Liquidity Risk and Currency Premia

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Abstract
The currency market is the world's largest financial market by trading volume. We show that even in this highly liquid market exposure to liquidity risk commands a non-trivial risk premium of up to 3.6% per year. Liquidity risk is not subsumed by existing currency risk factors and successfully prices the cross-section of currency excess returns. Moreover, we find that liquidity risk and carry trade premia are correlated, although this correlation is limited to static rather than dynamic carry trades. Building upon this result, we propose a liquidity-based explanation for the carry trade, which adds significant explanatory power beyond existing theories.

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1. Introduction

Trading volume in the foreign exchange (FX) market amounts to \$7.5 trillion every day.[1] This makes the FX market the largest financial market in the world. Precisely because of its sheer size and despite its decentralised nature, the FX market is commonly known as one of the most liquid and resilient trading venues. However, a clear understanding of whether FX *liquidity risk* matters for asset prices is still missing. This paper aims to fill this void by providing the first systematic study of the pricing implications of FX liquidity risk.[2]

Starting from a simple liquidity adjusted capital asset pricing model (see Acharya and Pedersen, 2005), we derive four candidate sources of liquidity risks: commonality in illiquidity, systematic illiquidity (i.e., the average illiquidity across individual exchange rates), commonality in market returns, and currency-specific illiquidity. Our main results are threefold: First, we show that sorting currency pairs based on their exposure to systematic (marketwide) and currency-specific illiquidity risk generates a non-trivial risk adjusted return. Second, we show that augmenting an asset pricing model that includes the dollar and carry factor (see Verdelhan, 2017) by either of these two liquidity risk factors significantly improves the fit of the baseline model. This effect is particularly strong during the period after the global financial crisis when interest rate differentials were compressed across countries. Third, we find that only systematic and currency-specific liquidity risk are correlated with the infamous carry trade. Motivated by this observation, we explore a liquidity risk based explanation of the carry trade premium. In particular, we show that on average our liquidity-based story contains additional explanatory power of about 26% relative to the existing theories.

Understanding the cross-sectional asset pricing implications of FX liquidity risk is important for at least three reasons. First, the currency market is the world's largest financial market and facilitates international trade and investment every day. Second, the FX market is a shock absorber that helps to restore efficiency and no arbitrage conditions across financial markets including equities, bonds, and derivatives (Pasquariello, 2014). Third, due to its decentralised over-the-counter (OTC) nature, the FX market is characterised by limited transparency, heterogeneity of market participants, and market fragmentation leading to unprecedented price and liquidity patterns that require scientific study. For instance, Karnaukh, Ranaldo, and Söderlind (2015) show that currency liquidity systematically deteriorates in crisis periods while commonality in FX illiquidity increases at the same time.

The contribution of this paper to the FX asset pricing and international finance literature is fourfold. First, it provides a methodological contribution to the identification of potential sources of FX liquidity risk. To be specific, we adapt the Acharya and Pedersen (2005) liquidity adjusted capital asset pricing model to the FX market by incorporating currency-specific

[1] See "Triennial central bank survey — global foreign exchange market turnover in 2022," Bank for International Settlements, September 2022.

[2] Liquidity risk and expected (il)liquidity are conceptually different: the former captures the co-movement of asset returns and market or asset specific illiquidity (i.e., Acharya and Pedersen, 2005), whereas the latter matters because investors are concerned about returns net of transaction costs (i.e., Amihud and Mendelson, 1986).

illiquidity as an additional source of liquidity risk. We use this framework to organise several theories about how liquidity risk can affect currency returns. In particular, we identify four potential sources of FX liquidity risk: i) commonality in currency liquidity and systematic liquidity (i.e., Mancini, Ranaldo, and Wrampelmeyer, 2013; Abankwa and Blenman, 2021), ii) return sensitivity to systematic liquidity (i.e., Pástor and Stambaugh, 2003; Banti, Phylaktis, and Sarno, 2012), iii) commonality in currency liquidity and market returns (Acharya and Pedersen, 2005), and iv) return sensitivity to currency-specific liquidity (e.g., Amihud, 2002). Eventually, we also identify empirical counterparts of systematic and currency-specific FX liquidity.

The second contribution is to sort currency pairs into tradeable portfolios based on their exposure (i.e., 'betas') to the four above sources of FX liquidity risk. Note that we control for the notorious correlation of illiquidity and volatility by orthogonalising measures of illiquidity against currency-specific and systematic volatility, respectively. The goal of these projections is to capture the variation in illiquidity that is not driven by volatility and hence should truly capture *illiquidity*. Two clear results emerge from these portfolio sorts. First, sorting currency pairs based on their exposure to systematic and currency-specific liquidity risk generates significant risk-adjusted returns ranging from 3.3–3.6% per year. Importantly, the excess returns to systematic and currency-specific illiquidity risk are neither subsumed by the dollar base factor and carry factor (see Lustig and Verdelhan, 2007; Lustig, Roussanov, and Verdelhan, 2011), respectively, nor by the volatility risk factor (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012a). Second, all four liquidity risk factors significantly load on the dollar factor, whereas only systematic and currency-specific illiquidity sorted portfolios are significantly exposed to carry trade returns.

The third contribution is to test if the liquidity-based risk factors can explain the cross-section of currency returns. To explore this, we run a horse race of different asset pricing models including traditional and liquidity-based risk factors. Following the evidence in the most recent literature on cross-sectional asset pricing in currency markets (e.g., Lustig et al., 2011; Menkhoff et al., 2012a; Verdelhan, 2017) we use a two-factor SDF consisting of the dollar base and carry trade factors. There are two key takeaways from running these asset pricing tests. First, replacing the carry trade factor by our systematic (marketwide) or currency-specific liquidity risk factor yields a parsimonious asset pricing model that performs on par with the two factor benchmark. Second, augmenting the benchmark model by either of the two liquidity factors improves the fit of the asset pricing model. In particular, a direct comparison of nested models with and without liquidity risk factors suggests that the differences are especially relevant for the period after the global financial crisis in 2008/09. Third, we follow the methodology in Barillas and Shanken (2016) to show that none of our results are driven by our choice of test assets. In sum, these results lend support to the idea that exposures to liquidity risk can serve as an alternative explanation for the carry trade anomaly.

The fourth contribution is to explore whether the carry trade risk premium is, at least partially, a compensation for liquidity risk. This hypothesis is motivated by the observation that carry trade premia and two of our liquidity beta based factors are not just correlated but also exhibit similar asset pricing properties. Hence, we conjecture that this result hinges on the fact that liquidity risk is a first order determinant of uncovered interest rate parity deviations and consequently of carry trade returns. Note that the link between carry trade returns and our liquidity risk factors is non-trivial. This is because ex ante it is not clear whether interest rate differentials and *liquidity risk* are correlated. On the contrary, prior literature suggests that the *level* of illiquidity (e.g., transaction costs) plays an important role for explaining carry trade returns. For instance, Burnside (2009) argues that liquidity frictions may explain the profitability of the carry trade since liquidity spirals can amplify currency crashes. Mancini et al. (2013) provide suggestive empirical evidence in favour of this statement over the short and unprecedented period of the global financial crisis 2007-09. Moreover, Brunnermeier, Nagel, and Pedersen (2008) and Bakshi and Panayotov (2013) show that changes in US dollar funding liquidity can predict carry trade payoffs. We complement this literature by showing that carry trade returns are primarily driven by cross-sectional differences in currency pairs' exposure to illiquidity risk rather than in the level of illiquidity. Against this backdrop, our analysis proceeds in four steps.

To begin with, we provide direct empirical evidence that liquidity risk is a pivotal determinant of uncovered interest rate parity deviations. In particular, we find that currencies that are more exposed to systematic liquidity risk significantly appreciate against the US dollar. This result is fully consistent with our hypothesis that high interest rate currencies appreciate against the US dollar due to being more exposed to liquidity risk and thereby propelling uncovered interest rate parity deviations and ultimately carry trade returns.

In the second step, we regress the carry factor on each of the four liquidity beta based risk factors. In line with the evidence on cross-sectional asset pricing, we find that only systematic (marketwide) and currency-specific liquidity risk are significantly correlated with carry trade returns. However, unlike Mancini et al. (2013), we find no evidence of commonality in illiquidity being correlated with carry trade returns after controlling for volatility risk. Taken together, the systematic and currency-specific liquidity risk explain up to 40% of the time series variation in carry trade premia. Moreover, we provide evidence that the carry trade tertile portfolios exhibit a monotonically increasing factor loading from low to high interest rate portfolios. Importantly, the high interest rate (i.e., investment) currencies in the top tertile portfolio are the ones that are the most exposed to liquidity risk. This result corroborates the idea that high interest rate currencies do not depreciate sufficiently against the US dollar due to being more exposed to global liquidity risk.

In the third step, we compare the performance of the liquidity-based explanation of the carry trade to existing *risk-based* theories. In particular, we focus on the more recent literature that considers global imbalances (Della Corte, Riddiough, and Sarno, 2016), intermediary leverage (Fang, 2018), and network centrality (Richmond, 2019) as alternative explanations for carry trade premia.[3] Our results show that a liquidity-based view outperforms the afore-

[3]Some additional sources of risk include innovations in currency volatility (Menkhoff et al., 2012a), skewness

mentioned interpretations of carry trade profitability based on simple statistical grounds such as coefficients of determination or pricing errors. Moreover, in line with Chernov, Dahlquist, and Lochstoer (forthcoming), we also find that direct conditional projections of the stochastic discount factor have a significant explanatory power for carry trade returns.

In the fourth step, we decompose carry trade returns into the static, dynamic, and dollar trade following Hassan and Mano (2018). We do this, because we want to shed some light on which constituents of the carry trade are more closely related to liquidity risk than others. Regressing the three building blocks of the carry trade on the systematic and currency-specific liquidity risk factors delivers an interesting insight: These two liquidity risk factors (and systematic illiquidity risk in particular) can explain substantial amounts of the variation in the static and dollar trade but much less of the dynamic trade. This suggests that liquidity risk premia and carry trade returns are only similar to each other on average because the classic carry trade combines both dynamic and static components.[4]

Therefore, our analysis of carry trade components also adds to the broader literature studying the economic origins of carry trade returns. For example, Christiansen, Ranaldo, and Söderlind (2011) and Jeanneret (2019) adopt a smooth transition regression model with factor betas that are governed by FX market volatility and illiquidity, respectively. They find that carry trades are more exposed to the stock market and commodity prices conditional on FX volatility and illiquidity being high. Consistent with these observations, Copeland and Lu (2016) show that most profits of carry trades are attributed to low FX volatility periods. Similarly, Atanasov and Nitschka (2014), Dobrynskaya (2014), and Lettau, Maggiori, and Weber (2014) show that downside stock market risk can explain high returns to carry trades. Ahmed and Valente (2015) decompose the Menkhoff et al. (2012a) global FX volatility factor into short-run and long-run components and show that only the long-run component carries a risk premium. Byrne, Ibrahim, and Sakemoto (2018) find that the common information embedded in several of the previous factors better explains carry trade returns than innovations in exchange rate volatility or downside stock market returns. Recently, Bekaert and Panayotov (2019) show that crash-risk explanations only apply to the standard carry trade but not to "good" carry trades that do *not* involve some of the typical carry currencies like the Australian dollar or the Japanese yen.

The paper is organised as follows. Section 2 describes the theoretical background and derives four candidate sources of FX illiquidity risk. Section 3 describes the data and construction of currency pair specific and global illiquidity measures. Section 4 sorts currency pairs into portfolios based on their exposure to illiquidity risk. Section 5 contains standard cross-sectional asset pricing tests. Section 6 provides evidence of a liquidity-based explanation for carry trade premia. Section 7 concludes with recommended future work.

(Rafferty, 2012), correlation (Mueller, Stathopoulos, and Vedolin, 2017), and commodity imports/ exports (Ready, Roussanov, and Ward, 2017). Hu, Pan, and Wang (2013) show that the treasury noise measure is a priced risk factor in the cross-section of hedge fund returns and find that it can also explain the returns to currency carry trades. Orlov (2016) compares liquidity in equities to the FX market and shows that the former is the dominant factor in determining carry trade returns.

[4]Note that by construction the carry trade is equal to the sum of the dynamic and static trade.

2. Theoretical Background

Here, we introduce the basic idea of a liquidity adjusted capital asset pricing model that builds on the work by Acharya and Pedersen (2005). We use this approach to organise several theories about how liquidity risk might affect the cross-section of currency returns. Specifically, this framework can explain the empirical findings that commonality in liquidity (Mancini et al., 2013), return sensitivity to market liquidity (Pástor and Stambaugh, 2003), and average liquidity (Amihud and Mendelson, 1986; Amihud, 2002) are priced.

2.1. Liquidity Adjusted Asset Pricing Model

Following the framework in Acharya and Pedersen (2005) the conditional expected net excess return (i.e., rx^i) for currency pair i can be defined as

$$\mathrm{E}(rx^i) = \mathrm{E}(r^i - c^i) = \lambda \frac{cov(r^i - c^i, r^M - c^M)}{var(r^M - c^M)}, \tag{1}$$

where r^i is the currency excess return on buying a foreign currency in the forward market and then selling it in the spot market after one month (i.e., 22 business days), c^i is the relative illiquidity cost, λ is the market risk premium, r^M is the currency market return, and c^M is the corresponding measure of FX market illiquidity costs. Notice that throughout this paper we suppress the time and currency pair subscripts t and i, respectively, unless they are needed for clarity. In the context of currencies one could also think of $\mathrm{E}(rx^i)$ as the after "illiquidity-cost" excess return that is, by construction of currency excess returns, net of the interest rate differential between the foreign and domestic risk-free rates.

Next, since the covariance is a linear operator, we can rewrite Eq. (1) as follows:

$$\mathrm{E}(rx^i) = \lambda\beta^M + \lambda\beta^1 - \lambda\beta^2 - \lambda\beta^3. \tag{2}$$

This expression states that the net required excess return is simply given by the sum of four betas times the market risk premium, which we will compute by using the two factor model in Verdelhan (2017) as the baseline (discussed in detail below). Hence, the first covariance is the standard market beta, whereas the three additional betas can be regarded as different forms of *systematic* liquidity risks.[5] Note that we will control for the notorious correlation between illiquidity and volatility risk by orthogonalising illiquidity against global and currency-specific measures of volatility, respectively.

By nature, the liquidity adjusted capital asset pricing model in Acharya and Pedersen (2005) only focuses on sources of *systematic* liquidity risk. However, given that the number of tradeable currency pairs is relatively small (compared to the number of investable stocks)

[5]Notice that these are not traditional regression betas but rather just scaled covariances that have the same denominator (i.e., $var(r^M - c^M)$). Clearly, this distinction does not matter for any cross-sectional sorting since the regressors are the same for each currency pair.

there is limited scope for diversification. As a result, the factor model in Eq. (2) may not fully explain currency returns due to some residual currency-specific (i.e., idiosyncratic) liquidity risk. To take this into account, we consider the covariance between currency excess return r^i and currency-specific illiquidity c^i (i.e., $cov(r^i, c^i)$) as an additional source of liquidity risk. Note that this approach is also consistent with the equity market literature, which defines idiosyncratic volatility based on the CAPM-residuals (Ang, Hodrick, Xing, and Zhang, 2006). Hence, we are effectively augmenting the asset pricing model in Eq. (2) by an additional liquidity beta (i.e., β^4), which captures any non-systematic sources of liquidity risk:

$$\mathrm{E}(rx^i) = \lambda^M \beta^M + \lambda^1 \beta^1 - \lambda^2 \beta^2 - \lambda^3 \beta^3 - \lambda^4 \beta^4, \tag{3}$$

where, in line with the empirical approach in Acharya and Pedersen (2005), we allow the five betas to have different risk premia and hence are relaxing the model restriction in Eq. (2) that $\lambda^M = \lambda^1 = -\lambda^2 = -\lambda^3$. Put differently, we entertain the possibility that not all sources of FX liquidity risk are equally relevant empirically. Therefore, the key empirical challenge is twofold: First, how to define r^M, c^M, r^i, and c^i in the context of currency pairs. Second, estimate the risk premium associated with each of the five beta terms in Eq. (3). We tackle these empirical identification issues in the next section.

2.2. *Four Covariances*

The following points and Table 1 provide a brief summary of the economic intuition for the *systematic* (i.e., β^1, β^2, and β^3) and *currency-specific* (i.e., β^4) liquidity covariances:

1. **Commonality in illiquidity risk** $\beta^1 : cov(c^i, c^M)$, the required return increases with the covariance between the asset's illiquidity and the market illiquidity. This is because investors want to be compensated for holding a security that becomes illiquid when the market is illiquid. This is known as commonality in illiquidity (Mancini et al., 2013).

2. **Systematic illiquidity risk** $\beta^2 : cov(r^i, c^M)$, the required return increases as the covariance between the asset's return and the market illiquidity decreases (and hence β^2 enters Eq. (3) with a minus sign). This inverse relation arises because investors require a higher return on an asset with a low return in times when the market becomes more illiquid in general (Pástor and Stambaugh, 2003).

3. **Commonality in market risk** $\beta^3 : cov(c^i, r^M)$, the required return increases as the covariance between an asset's illiquidity and the market return decreases (and hence β^3 enters Eq. (3) with a minus sign). This effect stems from the fact that investors are unwilling to accept a lower expected return on an asset that is illiquid in a down market. Hence, an investor requires a higher return on financial assets with high illiquidity costs in states of poor market returns (Acharya and Pedersen, 2005).

4. **Asset-specific illiquidity risk** $\beta^4 : cov(r^i, c^i)$, the required return increases as the covariance between the asset's return and its asset-specific illiquidity decreases (and hence β^4

enters Eq. (3) with a minus sign). This is because agents require higher returns on assets that yield low returns in times when they are illiquid and thus riskier (Amihud, 2002).

Table 1: Four Sources of Liquidity Risk

Risk of	Name (Abbreviation)	Covariance	Compensation for
becoming illiquid	**C**ommonality in **I**lliquidity **R**isk (CIR)	$\beta^1 : cov(c^i, c^M)$	lower liquidity in *bad* times
lower returns	**S**ystematic **I**lliquidity **R**isk (SIR)	$\beta^2 : cov(r^i, c^M)$	lower returns in *illiquid* times
becoming illiquid	**C**ommonality in **M**arket **R**isk (CMR)	$\beta^3 : cov(c^i, r^M)$	lower liquidity in *bad* times
lower returns	**A**sset-specific **I**lliquidity **R**isk (AIR)	$\beta^4 : cov(r^i, c^i)$	lower returns in *illiquid* times

To study the beta terms described above we follow the tradition in the FX asset pricing literature (e.g., Lustig et al., 2011; Mancini et al., 2013) and construct investable trading strategies (portfolio sorts) that mimic the time series variation of the betas in Eq. (3). It is worth noting that the aim of the portfolio sorts approach is not to estimate the level of illiquidity costs but rather how various sources of liquidity risk are priced in the cross-section of currency returns. The main advantage of this approach is threefold: First, it allows us to study the pricing of *tradeable* liquidity risk factors that are not prone to any lookahead bias. Second, relative to cross-sectional regressions, the portfolio sorts are robust to non-linearities in the cross-sectional ranking of currency returns. Third, it enables us to overcome the issue that many empirical liquidity estimates (especially those that can be applied to long samples) are measured on a different scale than currency returns. The Amihud (2002) illiquidity measure is a notable exception to this but would require volume data for estimation. However, due to the decentralised nature of the FX market comprehensive volume data are unfortunately not available for a long enough sample period. Thus, we will follow Karnaukh et al. (2015) instead to estimate currency-specific illiquidity (see the next section for details) because it has the highest correlation with the effective cost of trading.

3. Data and Liquidity Measures

This section gives a brief description of the data and of how to measure currency-specific and market wide FX liquidity. Later sections discuss how this information is used to calculate liquidity betas and eventually trading strategies.

3.1. *Data*

We collect hourly nominal exchange rates (i.e., mid, bid, and ask quotes) against the US dollar (USD) for 15 major emerging and developed markets: Australia (AUD), Canada (CAD), Denmark (DKK), Euro area (EUR), Hong Kong (HKD), Israel (ILS), Japan (JPY), Mexico (MXP), New Zealand (NZD), Norway (NOK), Singapore (SGD), South Africa (ZAR), Sweden (SEK), Switzerland (CHF), and United Kingdom (GBP) for the period of 3 January 1994 to 30 September 2022 from Olsen Data, which is the standard source for academic research on high frequency FX rates.[6] For the same set of currency pairs and time frame we retrieve forward rates from Bloomberg. The cross-sectional dimension of our data set is driven by two key considerations: First, we want to ensure a consistent data quality and availability across currency pairs for the entire sample period. Second, we want to study the asset pricing implications of FX liquidity risk by creating tradeable currency risk factors and hence, we focus on some of the most important currency pairs in terms of FX trading activity. Note that prior to 1999 we use the German mark instead of the euro.

3.2. *Returns and Liquidity Measures*

In line with the FX asset pricing literature (e.g., Lustig and Verdelhan, 2007; Lustig et al., 2011) we define the (log) *currency excess return* (r) as

$$r_t = (f_{t-22,t} - s_t)/22, \tag{4}$$

where f and s are the (daily data on) 1-month log forward and spot rates quoted indirectly as foreign currency per unit of USD, e.g., 0.74 EUR per USD. This creates overlapping returns, which we later handle with robust standard errors following Newey and West (1987). Moreover, we define FX rate volatility v as the absolute spot return, $v_t = |s_t - s_{t-22}|$.

The relevant *'market' return* (r^M) for the currency market is not self evident. However, Verdelhan (2017) shows that the dollar (DOL) and carry (CAR) factors jointly account for up to 80% of the variation in monthly FX rate movements. We therefore define r^M as the excess return on the tangency portfolio from those factors. Based on the full-sample estimates of the covariance matrix and the corresponding mean excess returns we get the following weights for the tangency portfolio:

$$w_r = \{w_{DOL}, w_{CAR}\} = \{-0.49, 1.49\}. \tag{5}$$

As a robustness check, we have also experimented with tangency portfolio weights ranging from -1 to 2 and found consistent results for all portfolio sorts in Section 4. Note that following Eq. (1) these weights only affect the liquidity premium associated with β^3. See the online Appendix for these additional results.

The *currency pair specific measure of illiquidity* (c^i) is estimated as an average of the relative bid-ask spread and the spread measure by Corwin and Schultz (2012), respectively. Both measures are standardized before the averaging. This approach is similar to Karnaukh et al. (2015) who show that this measure most accurately proxies the effective cost of trading. Since higher values of this measure correspond to larger spreads, it is effectively a measure of *illiquidity* rather than *liquidity*.[7]

[6] As a robustness check, we have also used spot and forward rates from Refinitiv Datastream for a broad cross-section of up to 27 currency pairs. All findings are qualitatively unchanged and largely unaffected by the choice of data source. We document summary statistics tables in the online Appendix.

[7] As a robustness check, in the online Appendix we document portfolio sorts that are based on either the bid-

To construct these liquidity measures we use daily high ask and low bid quotes as well as close bid and ask prices that we compute from hourly data. The bid-ask spread is the difference between the ask and bid price relative to the midquote. The Corwin-Schultz spread estimator is derived from high and low transaction prices over two consecutive days, assuming that the high price is buyer initiated and that the low price is seller initiated. The standardization is done my subtracting a recursively estimated (an expanding window with an initial size of 252 days) mean and dividing by a similarly estimated standard deviation. This ensures that none of our liquidity betas suffers from any look-ahead bias.

The measure of *market wide (global) FX illiquidity* (c^M) follows the approach in Karnaukh et al. (2015), that is, we calculate global FX illiquidity as an unweighted average of the currency-specific illiquidities. In line with Menkhoff et al. (2012a), we apply the same approach to construct a measure of *market wide (global) FX volatility* (v^M).

4. Portfolio Sorts

This section describes how we construct portfolio sorts based on the four liquidity covariances that we have outlined above in Section 2.2. Within this context, the significant correlation of global volatility (Menkhoff, Sarno, Schmeling, and Schrimpf, 2012b) and systematic (market) illiquidity poses a major challenge for identifying liquidity risk. For instance, in our sample the correlation coefficient is around 52.1%. Hence, to overcome this issue we will orthogonalise measures of illiquidity against volatility. The resulting (residual) illiquidity measures capture the time series and cross-sectional variation in illiquidity that is presumably unrelated to volatility. Put differently, by performing orthogonalisations we aim to derive clean liquidity measures that are independent from volatility.

The remainder of this section proceed in three steps: First, we describe how to orthogonalise global and currency-specific measures of illiquidity risk against global and currency-specific measures of volatility risk.[8] Second, we outline how to estimate the time-varying systematic exposure (i.e., 'betas') with respect to marketwide and currency-specific factors, respectively. Third, we document the out-of-sample performance of sorting currency pairs based on the above four liquidity betas.

In the first step, we orthogonalise 22-day changes in systematic illiquidity Δc^M against changes in global volatility Δv^M by estimating the following regression equation using an expanding data window:

$$\Delta c^M = \alpha + \delta \Delta v^M + \Delta \tilde{c}^M, \tag{6}$$

where the initial window length is equal to 252 days. The last term (residual) is the orthogonalised series which we use further on. Note that all our portfolio sorts yield qualitatively

ask spread or the CS spread as the sole liquidity measure. We find that the portfolio excess return associated with β^1 is mainly driven by cross-sectional variation in the CS spread, whereas the risk factors based on β^2 and β^4 are mostly stemming from the variation in bid-ask spreads.

[8] In the online Appendix we also document the results of our portfolio sorts without applying any orthogonalisation to global (marketwide) and currency-specific measures of illiquidity risk.

similar results when using a rolling instead of an expanding window for the orthogonalisation. Following the Frisch-Waugh-Lovell theorem, orthogonalising is equivalent to including volatility as a control variable in the beta representation (see Eq. (3)).[9] Analogously, we can use the same approach to orthogonalise changes in currency-specific illiquidity Δc^i against changes in the currency-specific volatility Δv^i.

In the second step, we want to retrieve a time series of the four scaled liquidity covariances (i.e., β^1, β^2, β^3, β^4) to which, for simplicity, we will hereinafter refer to as *liquidity betas*. Specifically, we estimate the following (rolling window) regressions:

$$\Delta\tilde{c}^i = \alpha + \beta^1 \Delta\tilde{c}^M + \varepsilon, \tag{7}$$

$$r^i = \alpha + \beta^2 \Delta\tilde{c}^M + \varepsilon, \tag{8}$$

$$\Delta\tilde{c}^i = \alpha + \beta^3 r^M + \varepsilon, \tag{9}$$

$$r^i = \alpha + \beta^4 \Delta\tilde{c}^i + \varepsilon, \tag{10}$$

where $\Delta\tilde{c}^i$ and $\Delta\tilde{c}^M$ have been orthogonalised (see Eq. (6)) against currency pair specific (i.e., Δv^i) and global volatility factors (i.e., Δv^M), respectively. Note that we consider 22-day changes as illiquidity is persistent (Acharya and Pedersen, 2005); the first order autocorrelation of global illiquidity, for instance, is 77.8% at the daily frequency. These regressions are daily and we repeat them for every currency pair i.

Clearly, estimating betas and (scaled) covariances will yield identical results in terms of sorting if the regressors are the same for each currency pair. This applies to the first three regressions but not to the last one. As a robustness check we estimate (scaled) covariances instead of regression betas in Eq. (10) and find virtually identical results for the portfolio sorts. In addition, our results are robust to using an expanding window. However, the advantage of the rolling estimation is the fact that it allows for the possibility that the betas are time-varying. In each of these regressions in Eqs (7) to (10) we use a 252-day rolling window. All our results are qualitatively unchanged when using a longer or shorter window.

In Table 2 we report the collinearity concerning our measures of liquidity risk, bid-ask spreads, and interest rate differentials. Most correlations are economically insignificant with the notable exceptions of $corr(\beta^1, \beta^3)$ and $corr(\beta^2, \beta^4)$, respectively. Therefore, in practice, it should be possible to disentangle the effects of overall illiquidity and individual illiquidity betas. Moreover, we find that more illiquid currency pairs (i.e., higher bid-ask spread) also have higher illiquidity *risk* as they tend to exhibit smaller values of β^2 and β^4, respectively. Thus, a currency pair that is illiquid in absolute terms, also tends to be more risky as it has a lower return sensitivity to systematic (i.e., $cov(r^i, c^M)$) and currency-specific (i.e., $cov(r^i, c^i)$) illiquidity. This result is reminiscent of the adage pointed out, for example, by Admati and Pfleiderer (1988), that "liquidity begets liquidity" or put differently that there is "flight to

[9] As a robustness check we have also orthogonalised systematic illiquidity against the bond yield on AAA-rated US corporate debt, the TED spread, and the Chicago Board Options Exchange's volatility index (i.e., VIX), respectively. See the online Appendix for these additional results.

liquidity." Lastly, notice that high interest rate currencies (i.e., positive forward premium) are on average also more illiquid (i.e., higher bid-ask spread).

Table 2: Beta Correlations

	$\beta^{1,i}$	$\beta^{2,i}$	$\beta^{3,i}$	$\beta^{4,i}$	$f_t - s_t$
$\beta^{2,i}$	18.72				
$\beta^{3,i}$	***−85.32	−21.29			
$\beta^{4,i}$	5.72	***81.01	−5.83		
$f_t - s_t$	**−39.14	***−49.11	**41.29	−16.27	
bas	−13.83	***−86.84	12.01	***−59.54	**44.28

Note: This table reports the cross-sectional correlations (in %) of the median β^1, β^2, β^3, and β^4 (based on 252-day rolling window estimates), median relative bid-ask spread $bas = (ask - bid)/mid$, and median interest rate differential $f_t - s_t$ (i.e., forward discount/ premium) for 15 USD–based currency pairs. Significant correlations at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The sample covers the period from 21 February 1995 to 30 September 2022.

In the final step, we use each of the four rolling window liquidity betas to form traditional tertile portfolios ($T1, T2$, and $T3$). To minimise the impact of noise, we smooth the rolling window regression betas over a ten day moving window before translating them to trading signals. Moreover, we lag all trading signals by 22 business days to ensure the implementability based on 1-month forward contracts.[10] To be precise, we construct dollar-neutral long–short portfolios by going long the currency pairs in the top tertile ($T3$) and short the currency pairs in the bottom tertile ($T1$). Each tertile portfolio consists of five currency pairs at most, where each of them receives an equal weight. Our findings are robust to using a rank or value based weighting scheme. Following the terminology in Table 1, we dub the four liquidity beta based trading strategies as follows: **C**ommonality in **I**lliquidity **R**isk CIR-β^1, **S**ystematic **I**lliquidity **R**isk SIR-β^2, **C**ommonality in **M**arket **R**isk CMR-β^3, and **A**sset-specific **I**lliquidity **R**isk AIR-β^4, respectively.

Table 3 reports summary statistics for these four liquidity beta based portfolios as well as four common FX risk factors, namely dollar DOL, carry CAR, volatility VOL, and tangency TAN. Specifically, DOL is based on an equally weighted long portfolio of all USD currency pairs (Lustig et al., 2011), CAR on the forward discount/ premium (Lustig and Verdelhan, 2007), VOL is based on currency pairs' exposure to the global volatility factor β^v (Menkhoff et al., 2012a), and TAN is a strategy that sorts on exposures to the market portfolio β^M in Eq. (5) (Markowitz, 1952). IML is a trading strategy that sorts currency pairs into long-short portfolios based on the level of relative bid-ask spreads. To estimate a currency pair's sensitivity to global volatility β^v and market risk β^M, respectively, we run regressions in a

[10]Our results are very similar when we rebalance our portfolios on a monthly rather than daily basis. Thus, we do not incorporate any transaction costs in the form of bid-ask spreads, which is also in line with Lustig and Verdelhan (2007) and Menkhoff, Sarno, Schmeling, and Schrimpf (2017), respectively.

similar vein to those in Eqs (7) to (10).

Two out of the four liquidity beta sorted trading strategies exhibit non-trivial mean excess returns. In particular, sorting currencies based on systematic (SIR-β^2) and currency-specific illiquidity (AIR-β^4) risk generates significant risk-adjusted returns ranging from 3.3–3.6% per year. Both liquidity risk based trading strategies exhibit negative mean excess returns, which is in line with the signs of the liquidity betas in Eq. (3). On the contrary, the mean returns associated with commonality in illiquidity (CIR-β^1) and market risk (CMR-β^3) are insignificant and much smaller (in absolute terms).[11] Overall, our findings are in line with the equity market literature and in particular Chordia, Roll, and Subrahmanyam (2000), Amihud (2002), Pástor and Stambaugh (2003), and Hameed, Kang, and Viswanathan (2010). What is more, the liquidity risk premia SIR-β^2 and AIR-β^4 are significantly larger than the premium on illiquid minus liquid currency pairs (i.e., IML). Put differently, sorting on the level of illiquidity does not fully account for the cross-sectional heterogeneity in illiquidity risk. This is noteworthy, given the fact that illiquid currency pairs (e.g., higher relative bid-ask spread) tend to exhibit more liquidity risk (i.e., lower β^2 and β^4 in Table 2).

In Table 4 we estimate the correlation between our four liquidity beta based trading strategies and several common risk factors documented in FX asset pricing literature. In particular, we add long-short portfolios based on momentum (Menkhoff et al., 2012b), value (Menkhoff et al., 2017), skewness risk (Rafferty, 2012), and the output gap (Colacito, Riddiough, and Sarno, 2020). We construct these factors analogously to the ones in Table 3 using data from Bloomberg, Datastream, and the OECD.[12] The correlation table conveys a clear message: our liquidity beta based trading strategies are largely unrelated to other common FX risk factors. In particular, the absolute pairwise correlations are less than 20% with the notable exception of the dollar, carry, and IML, respectively. Hence, for the remainder of the paper, we will treat these three factors as the main benchmarks for our liquidity beta based strategies.

Next, we test in Table 5 if any of the four liquidity beta based trading strategies (i.e., CIR-β^1, SIR-β^2, CMR-β^3, AIR-β^4) is subsumed by existing FX risk factors. Specifically, we control for common FX risk factors that exhibit a relatively high correlation with our liquidity factors in Table 4, that is, the USD–based currency pairs basket (i.e., DOL), carry trade (i.e., CAR), and liquidity level risk factor (i.e., IML). In addition, we also include volatility risk (i.e., VOL) as a regressor to test the effectiveness of our orthogonalisation procedure.

In line with the mean excess returns in Table 3, both systematic (i.e., SIR-β^2) and currency-specific liquidity risk (i.e., AIR-β^4) factors deliver statistically and economically significant risk-adjusted returns (i.e., 'alphas'). Most importantly, the alpha is statically different from

[11]Note that the mean excess return with respect to currency-specific liquidity risk increases as the number of currency pairs decreases within the long and short leg of the portfolio (see Table B.12 in the online Appendix for the case of sorting currency pairs into quintiles instead of tertiles). This suggests that adding currency-specific liquidity risk to the beta representation in Eq. (2) is indeed meaningful due to the limited scope of diversification.

[12]We choose these other risk factors based on two criteria: i) replicability of the trading signals using publicly accessible data sources and ii) orthogonality of the factors in the sense that at this point we want to focus on risk factors that are not subsumed by carry trade returns. See the online Appendix for a comprehensive description as well as summary statistics tables of these additional FX risk factors.

Table 3: Summary Statistics Portfolio Sorts

	DOL	*CAR*	*VOL*	*TAN*	*IML*	*CIR*-β^1	*SIR*-β^2	*CMR*-β^3	*AIR*-β^4
Mean in %	0.10	***4.39	*−2.25	**3.29	*1.87	0.41	***−3.34	−1.02	***−3.55
	[0.09]	[3.43]	[1.92]	[2.44]	[1.77]	[0.40]	[2.84]	[1.17]	[3.39]
σ	6.80	8.10	7.49	8.61	6.85	6.72	7.58	5.78	6.83
SR	0.02	***0.54	*−0.30	**0.38	*0.27	0.06	***−0.44	−0.18	***−0.52
	[0.09]	[3.11]	[1.89]	[2.32]	[1.69]	[0.40]	[2.69]	[1.18]	[3.33]
Skewness	−0.21	−0.97	0.24	−0.75	−0.88	0.37	0.55	−0.10	0.07
Kurtosis-3	1.95	4.90	2.18	3.22	5.06	1.20	4.70	1.14	1.97
Min	−1.55	−2.16	−1.27	−1.88	−1.91	−0.77	−1.45	−1.13	−1.27
Max	0.91	1.68	1.56	1.27	1.12	1.20	1.92	0.69	1.35
MDD in %	31.98	28.60	24.06	26.11	17.79	33.99	26.73	16.36	17.28
Scaled MDD	22.05	16.57	15.06	14.22	12.18	23.74	16.54	13.27	11.87
#Obs	6865	6865	6865	6865	6865	6865	6865	6865	6865

Note: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., *CIR*-β^1, *SIR*-β^2, *CMR*-β^3, *AIR*-β^4) as well as common FX risk factors such as dollar *DOL*, carry *CAR*, volatility *VOL*, and tangency *TAN*. *DOL* is based on an equally weighted long portfolio of all USD currency pairs, *CAR* on the forward discount/ premium $f_t - s_t$ (Lustig et al., 2011), *VOL* is based on currency pairs' exposure to the global volatility factor β^v (Menkhoff et al., 2012a), and *TAN* is a strategy that sorts on exposures to the tangency portfolio β^M (Markowitz, 1952). *IML* is a trading strategy that sorts currencies into long-short portfolios based on the level of relative bid–ask spreads. Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*) and standard deviation (σ) in %, annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). To annualise the SR we multiply by $\sqrt{252/22}$ since using 1-month forward rates reduces the standard deviation of daily currency excess returns by a factor of $\sqrt{22}$. The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

zero when controlling for the volatility risk factor, suggesting that sorting on recursive projections is successful at disentangling liquidity and volatility risk.[13] Moreover, it is worth highlighting that the alpha with respect to *IML* is significant for both liquidity risk factors. This supports the notion that sorting on exposures to liquidity risk is indeed different from sorting on the level of transactions costs. The only exceptions to the case of a non-zero alpha are the specifications that control for the carry trade.[14] In particular, both liquidity factors are significantly exposed to *CAR*, which explains around 40% of the variation in *SIR*-β^2 and 29% of the variation in *AIR*-β^4, respectively. This suggests that part of the returns from liquidity beta sorted strategies is related to carry, but part of it is driven by a different source of predictability that is in liquidity betas, but not in interest rate differentials. Consistent with this observation, the joint hypothesis that $\alpha = 0$ and $\beta = 1$ is strongly rejected across all

[13] In line with this result, we find no evidence that the mean return for both *SIR*-β^2 and *AIR*-β^4 is statistically different during high and low volatility periods.

[14] In the online Appendix we show that the alpha is significantly different from zero when using spot and forward rates from Refinitiv Datastream for the same set of 15 currencies against the US dollar.

Table 4: Correlation of Liquidity Risk and Common FX Risk Factors

	CIR-β^1	SIR-β^2	CMR-β^3	AIR-β^4
SIR-β^2	**−11.33			
CMR-β^3	***−31.91	−4.86		
AIR-β^4	***−16.84	***73.20	−2.54	
DOL	***54.58	***−27.08	***−15.98	***−22.94
VOL	−0.70	***34.65	−6.51	***34.70
CAR	−2.52	***−63.34	1.86	***−54.02
MOM	−1.62	3.76	−1.30	−3.90
RER	***18.90	−12.33	**12.30	−10.02
SKW	***−15.20	−13.52	7.22	***−20.39
IML	3.40	***−57.59	2.18	***−46.81
GAP	1.19	*−7.69	−6.41	−6.30

Note: This table reports the correlations (in %) of the four liquidity beta sorted strategies (i.e., CIR-β^1, SIR-β^2, CMR-β^3, AIR-β^4) and other common FX risk factors. We include factors pertaining to the dollar (Lustig and Verdelhan, 2007, DOL), carry (Lustig et al., 2011, CAR), volatility (Menkhoff et al., 2012a, VOL), momentum (Menkhoff et al., 2012b, MOM), value (Menkhoff et al., 2017, RER), skewness (Rafferty, 2012, SKW), level of illiquidity (i.e., relative bid–ask spreads, IML), and the output gap (Colacito et al., 2020, GAP). The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The inference is based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

specifications including the ones that involve the carry trade.

Taken together, the results reported so far establish that at least two liquidity risk factors (i.e., SIR-β^2 and AIR-β^4) have economically meaningful excess returns overall and that these returns are negatively, albeit imperfectly correlated with carry trade returns. The lack of a perfect correlation is consistent with the hypothesis that liquidity risk potentially enters the currency pricing kernel. To test this, we now turn to standard cross-sectional asset pricing tests and run a horse race across different asset pricing models based on traditional and liquidity-based risk factors.

5. Does Liquidity Risk Price Currency Excess Returns?

The goal of this section is to compare the empirical performance of a model with liquidity risk against the traditional FX 'market model' based on Lustig and Verdelhan (2007) and Lustig et al. (2011). Thus, the benchmark model is based on the dollar DOL and carry CAR factor. The rationale for this model is the empirical observation that the first two principal components of the cross-section of currency returns are highly correlated with the dollar and carry factor, respectively (see Lustig et al., 2011; Verdelhan, 2017). We have also experimented with augmenting the two factor model by accounting for global volatility risk VOL (Menkhoff et al., 2012a). However, the increase in the explanatory power of the augmented factor model is just marginal (see top right subplot in Figure 1).

Table 5: Exposure Regressions

	CIR-β^1					SIR-β^2				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
α in %	0.410	0.355	0.502	0.396	0.348	***−3.343	***−3.312	−0.737	**−2.553	**−2.148
	[0.397]	[0.410]	[0.474]	[0.386]	[0.330]	[2.837]	[2.933]	[0.742]	[2.265]	[2.198]
DOL		***0.539					***−0.302			
		[13.685]					[3.691]			
CAR			−0.021					***−0.593		
			[0.424]					[10.635]		
VOL				−0.006					***0.351	
				[0.102]					[4.825]	
IML					0.033					***−0.637
					[0.658]					[9.859]
$\bar{R}^2$ in %		29.79	0.06	0.00	0.12		7.33	40.13	12.00	33.17
IR	0.02	0.02	0.02	0.02	0.02	−0.13	−0.13	−0.04	−0.11	−0.10
$F_{\alpha,\beta}$		69	224	134	196		152	544	40	355
#Obs	6865	6865	6865	6865	6865	6865	6865	6865	6865	6865
	CMR-β^3					AIR-β^4				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
α in %	−1.017	−1.003	−1.075	−1.130	−1.051	***−3.552	***−3.528	*−1.552	***−2.840	***−2.678
	[1.173]	[1.169]	[1.210]	[1.314]	[1.190]	[3.385]	[3.458]	[1.666]	[2.896]	[2.834]
DOL		***−0.136					***−0.230			
		[3.062]					[4.118]			
CAR			0.013					***−0.455		
			[0.265]					[10.562]		
VOL				−0.050					***0.316	
				[0.938]					[5.884]	
IML					0.018					***−0.466
					[0.341]					[9.902]
$\bar{R}^2$ in %		2.55	0.03	0.42	0.05		5.26	29.18	12.04	21.91
IR	−0.05	−0.05	−0.05	−0.06	−0.05	−0.15	−0.16	−0.08	−0.13	−0.13
$F_{\alpha,\beta}$		336	210	192	179		253	688	82	511
#Obs	6865	6865	6865	6865	6865	6865	6865	6865	6865	6865

Note: This table shows the results of regressing daily gross excess returns associated with the four liquidity beta based trading strategies (i.e., CIR-β^1, SIR-β^2, CMR-β^3, AIR-β^4) on excess returns associated with common FX risk factors. DOL is based on an equally weighted long portfolio of all USD currency pairs, CAR is based on the forward discount/ premium $f_t - s_t$ (Lustig et al., 2011), VOL is based on currency pairs' exposure to the global volatility factor β^v (Menkhoff et al., 2012a), and IML is a strategy that sorts on the level of illiquidity (i.e., relative bid–ask spreads, IML). The intercept (α) has been annualised ($\times$252). The information ratio (IR) is defined as α divided by the residual standard deviation. $F_{\alpha,\beta}$ denotes the F-test for the null hypothesis that $\alpha = 0$ and $\beta = 1$. The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Newey and West, 1987) correcting for correlation up to 22 lags.

Next, we propose an alternative model that replaces the carry factor CAR by one of the four liquidity risk factors. Since all our factors are tradeable, we can evaluate the performance of these competing factor models by comparing the actual versus model implied mean currency excess return across factor models. In particular, we estimate individual time series regressions of the form:

$$rp^i = \alpha + \delta\,\mathbf{f} + \varepsilon, \tag{11}$$

where $\mathbf{f}$ may contain both 'traditional' and liquidity-based FX risk factors. Following the common practice in the FX asset pricing literature (e.g., Lustig et al., 2011; Menkhoff et al., 2012a; Della Corte et al., 2016), we use the tertile (or quintile) portfolios (i.e., $T1, T2$, and $T3$) of eleven currency trading strategies as the dependent variable (i.e., rp^i). Our result are also robust to including individual currency excess returns for the 15 exchange rates against the USD that we use for the portfolio sorts. In particular, we include portfolios sorted based on volatility (Menkhoff et al., 2012a), value (Menkhoff et al., 2017), level of transaction costs IML, three-months momentum (Menkhoff et al., 2012b), skewness risk (Rafferty, 2012), global dollar risk (Verdelhan, 2017), intermediary leverage (Fang, 2018), import ratio (Ready et al., 2017), network centrality (Richmond, 2019), output gap (Colacito et al., 2020), and global imbalances (Della Corte et al., 2016). This yields a total of 36 currency portfolios that we use as test assets. In the online Appendix we provide a detailed description of how we construct each of these common FX trading strategies. The model in Eq. (11) is estimated using ordinary least squares (OLS) and standard errors are based on Newey and West (1987) heteroskedasticity- and autocorrelation-consistent standard errors correcting for serial correlation up to 22 lags.

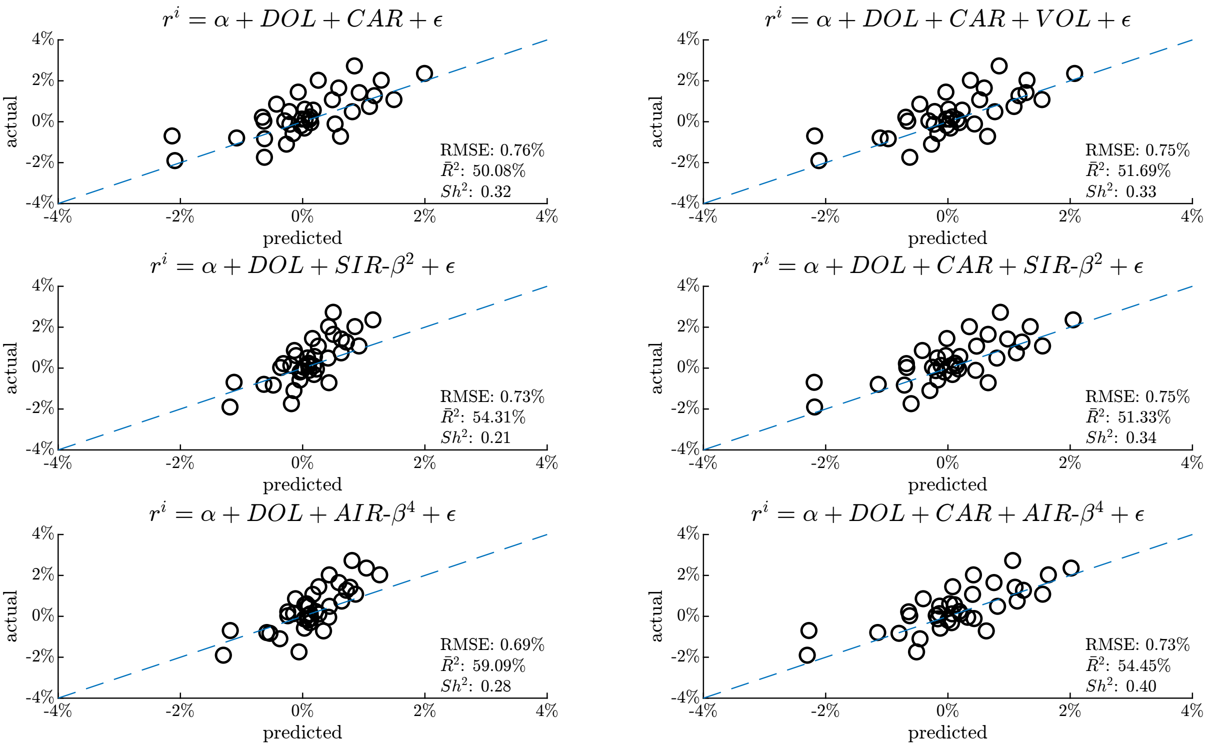
Figure 1 plots the model implied versus actual annualised mean currency excess return for six factor models. The baseline model is the one including the dollar and carry factor (top left corner), whereas the subplots on the right are nested versions of it. Given the evidence in Table 5 we only include systematic or currency-specific liquidity risk as additional factors. There are three key takeaways: First, replacing CAR by systematic (i.e., SIR-β^2) or currency-specific liquidity risk (i.e., AIR-β^4) factors delivers an asset pricing model that somewhat outperforms our baseline in terms of pricing error (i.e., RMSE) and coefficient of determination (i.e., $\bar{R}^2$), respectively. Second, augmenting our baseline model by either of the two liquidity factors (i.e., SIR-β^2 or AIR-β^4) improves the fit of the asset pricing model. Third, we follow the methodology in Barillas and Shanken (2016) to show that these results do not hinge on our choice of test assets. In particular, the squared Sharpe ratio (i.e., Sh^2) of the tangency portfolio implied by the factor models is higher across nested models that include both CAR and SIR-β^2 or AIR-β^4, respectively.

Taken together, the findings suggest that the carry factor and the liquidity beta based factors are not just correlated but also exhibit similar asset pricing properties. Hence, it is warranted to ask whether liquidity risk drives out carry in a horse race. To test his, we use a statistical procedure that is inspired by Cochrane (1996) and compare the test statistic of a Wald test across nested models with and without liquidity risk. In particular, we test whether the pricing errors (i.e., alphas) in Eq. (11) are jointly zero across all test assets. Eventually, we use the following χ^2 difference test to compare restricted and unrestricted models:

$$J_T(restricted) - J_T(unrestricted) \sim \chi^2(\text{\# of restrictions}), \tag{12}$$

where $J_T = \alpha' V^{-1} \alpha$ is defined as a Wald test statistic where V is the heteroskedasticity- and autocorrelation-consistent estimate of the covariance matrix that we estimate by GMM using

Figure 1: Realised Versus Predicted Excess Return



Note: These figures plot the actual versus model implied annualised ($\times 252$) mean currency excess return for six competing factor models of the form $rp^i = \alpha + \delta\,\mathbf{f} + \varepsilon$, where $\mathbf{f}$ may contain both 'traditional' and liquidity-based FX risk factors. The test assets are 36 currency portfolios that are constructed based on eleven common FX trading strategies. The model specifications are given in the titles of every subfigure. *RMSE* denotes the root-mean-square error, $\bar{R}^2$ the adjusted coefficient of determination, and Sh^2 the annualised squared Sharpe ratio associated with the tangency portfolio implied by each of the six factor models. The sample covers the period from 21 February 1995 to 30 September 2022.

the moment conditions pertaining to standard OLS (Cochrane, 2005).[15]

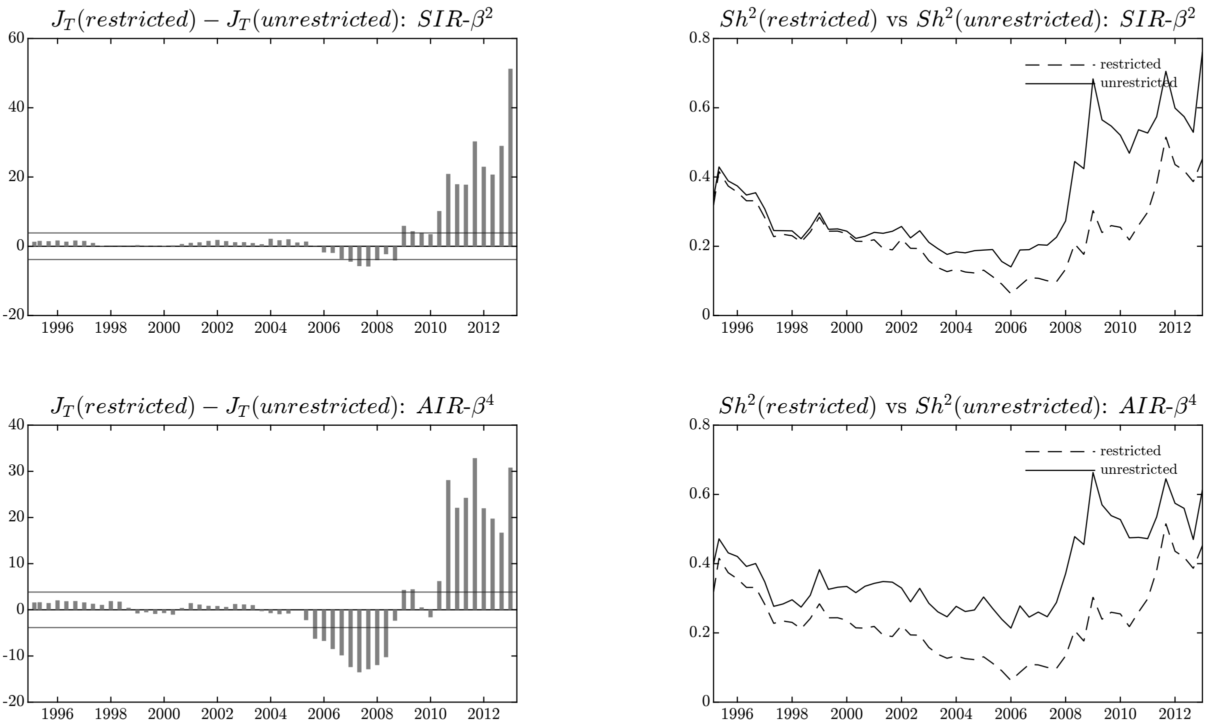
Figure 2 plots the difference between the *restricted* (i.e., dollar and carry) and *unrestricted* (dollar, carry, and either $SIR\text{-}\beta^2$ or $AIR\text{-}\beta^4$) models along two dimensions. First, the bar plots on the left show the value of the χ^2 test in Eq. (12). Second, the line plots on the right graph the annualised squared Sharpe ratio (i.e., Sh^2) associated with the tangency portfolio implied by the restricted and unrestricted model, respectively. We estimate both statistics conditional on choosing different cut-off dates for pruning the sample. The horizontal axis shows the starting points of the pruned sample periods. The end date is always 30 September 2022.

There are three main implications of these four sub-figures: First, asset pricing models with and without liquidity risk factors perform similarly for large swathes of the sample

[15] Note that the choice of weighting matrix is not relevant for our application as we estimate an exactly identified system where the number of moment conditions is equal to the number of parameter estimates. Moreover, the number of restrictions depends on how the returns are generated under the null hypothesis. In particular, if the additional factor (liquidity risk in this case) is priced by the benchmark factors (i.e., dollar and carry) then we only have one restriction. Contrarily, if (under the null hypothesis) the betas on the extra factor are zero then the number of restrictions is equal to the number of test assets.

period. Second, starting after the global financial crisis in 2007-09 the unrestricted models significantly outperform the baseline (restricted) model, which only includes the dollar and carry factor. This result is presumably driven by the fact that carry trade returns are mostly driven by interest rate differentials (Lustig et al., 2011) rather than spot rate changes. In particular, the post-crisis period is characterised by an ultra low interest rate environment resulting into a contraction of interest rate differentials across countries and ultimately carry trade premia.[16] Third, the divergence in terms of annualised squared Sharpe ratio across models with and without liquidity risk factors suggests that the previous finding is not driven by our choice of test assets. Thus, we conclude that liquidity risk is part of the currency pricing kernel during times of compressed interest rate differentials. This conclusion follows directly from the fact that all our risk factors are excess returns and hence the stochastic discount factor (SDF) performance (i.e., pricing error) is proportional to a traditional alpha from a linear factor model (Jagannathan and Wang, 2002).

Figure 2: Liquidity Risk Factors and the Currency Pricing Kernel



Note: The two bar plots on the left show the difference between the restricted model including only the dollar and carry factor and the unrestricted model that additionally includes either the systematic (i.e., SIR-β^2) or currency-specific liquidity risk (i.e., AIR-β^4) factor. The horizontal lines mark the critical values at the 5% confidence level (i.e., $\chi^2(1) = 3.84$) under the null hypothesis that the liquidity factors are priced by the dollar and carry factor, respectively. The two bar plots on the right show the annualised squared Sharpe ratio (i.e., Sh^2) associated with the tangency portfolio across models with and without liquidity risk factors. The estimates across the four plots are based on pruning the sample based on different start dates (horizontal axis). The first estimate is based on the full sample that covers the period from 21 February 1995 to 30 September 2022.

[16] The annualised mean excess return of the carry trade factor is 1.4 percentage points lower after January 2009 relative to the pre-crisis period.

Our central result in this section is that systematic and currency-specific liquidity risk explain a large fraction of the cross-sectional variation in currency excess returns. Importantly, the explanatory power of our liquidity risk factors is not confined to portfolios sorted on interest rate differentials (i.e., carry trade portfolios) but extends to a broad cross-section of currency portfolios that includes, among others, portfolio sorts on currency value, momentum, and skewness risk premia. This result clearly supports a risk-based view of exchange rate determination. However, we also find that liquidity risk and carry trade premia are correlated with each other, especially, during times of large interest rate differentials. Taken together, these findings give rise to the idea that the returns to carry trades are a compensation for time-varying fundamental risk, and thus carry traders can be viewed as taking on global liquidity risk. In particular, we conjecture that high (*low*) interest rate currencies earn higher (*lower*) expected returns due to being more exposed to liquidity risk. The next section will explore this possibility in more depth.

6. Liquidity Risk and Carry Trade Premia

In the previous section we have provided evidence that carry trade premia and at least two of our liquidity beta based factors are not just correlated but also exhibit similar asset pricing properties. In particular, we find that an alternative asset pricing model using liquidity beta based risk factors performs at least as well as the 'standard' FX asset pricing model based on the dollar and carry factor (Verdelhan, 2017). We conjecture that this result hinges on the fact that liquidity risk is a first order determinant of uncovered interest rate parity (UIP) deviations. In particular, we hypothesise that currencies that are more exposed to liquidity risk depreciate less against the US dollar and thereby fuelling deviations from UIP and hence, also carry trade returns.

To test the above hypothesis, we consider the following extended UIP regression:

$$\Delta s_t = \mu_t + a_i + b_1(f_t - s_t)_{t-22} + b_2\Delta\beta_t^2 + b_4\Delta\beta_t^4 + \gamma\Delta\mathbf{x}_t + \epsilon, \tag{13}$$

where both dependent and independent variables (except for the forward discount $f_t - s_t$ and the real exchange rate RER_t) enter our regression as 22-day changes (i.e., $\Delta = 22$). The dependent variable captures spot rate changes expressed as foreign currency units per US dollar. The regressors include the lagged (relative) forward discount $f_t - s_t$, rolling window estimates of systematic β_t^2 and currency-specific liquidity risk β_t^4 as well as control variables in $\mathbf{x}_t$ that are inspired by Jiang (2021). μ_t and a_i denote time and currency pair fixed effects, respectively. We standardise every time series by dividing by the standard deviation of the respective variable across all currency pairs. Hence, all variables are in units of standard deviation across currency pairs. Notice that standardising does neither alter the relative sizes between currencies nor change the sign or significance of the regression estimates. The frequency of this regression is daily and robust standard errors are computed based on Driscoll and Kraay (1998) allowing for random clustering and serial correlation up to 22 lags.

Table 6 reports the estimation results of the panel regression in Eq. (13). Three results emerge from our analysis. First, in line with our hypothesis above, a higher exposure to systematic (i.e., β_t^2) or currency-specific (i.e., β_t^4) liquidity risk is accompanied by an appreciation of foreign currencies against the US dollar. Second, an increase in the interest rate differential $f_t - s_t$ is associated with US dollar depreciation. This is the classic UIP puzzle (see, e.g., Hansen and Hodrick, 1980; Fama, 1984). These results are robust to including changes in real exchange rates RER_t and covered interest rate parity deviations $|CIP_t|$ as control variables. Third, to mitigate potential endogeneity issues concerning our two liquidity risk measures we employ lagged values of the TED spread as an instrument in the last two columns. The latter is a well-established indicator of perceived credit risk in the general economy. Following the work by Brunnermeier and Pedersen (2008) on liquidity spirals, a deterioration in funding liquidity can have an adverse effect on market liquidity. The exclusionary restriction is that changes in the TED spread do not directly affect exchange rates but only via the funding liquidity channel. Given that our sample focuses on developed economies it appears plausible to assume that the TED spread does not directly affect exchange rates by impacting sovereign (credit) risk.

In sum, Table 6 fully supports the idea that liquidity risk is a significant determinant of UIP deviations and thus carry trade returns. Beyond doubt, the importance of the carry trade factor is empirically well established. However, there is little consensus on how to interpret the carry trade risk premium. For instance, Lustig and Verdelhan (2007) argue that high interest rate currencies are riskier because they are more exposed to consumption growth risk, whereas the opposite holds for low interest rate currencies. Burnside, Eichenbaum, and Rebelo (2011) suggest that risk alone does not account for carry trade excess returns and explore an alternative explanation based on price pressure in FX trading. Following the more recent literature, other potential economic explanations for the carry trade are global imbalances (Della Corte et al., 2016), intermediary leverage (Fang, 2018), and network centrality (Richmond, 2019). Chernov et al. (forthcoming) construct conditional projections of the SDF and show that this novel econometric approach successfully prices individual exchange rates as well as a host of prominent currency trading strategies.[17] Therefore, the goal of this section is to provide empirical evidences in favour of an alternative view based on liquidity risk and to contrast it with the aforementioned interpretations.

The first step in our analysis is to show which of the four liquidity risk factors (i.e., CIR-β^1, SIR-β^2, CMR-β^3, AIR-β^4) can be used to explain the returns to the currency carry trade (i.e., CAR). If any of the four liquidity risk factors can explain carry trade returns, it should co-

[17]We apply the methodology in Chernov et al. (forthcoming) (hereinafter CDL) to daily 22-day returns by i) recursively estimating the prediction equations of currency excess returns and by ii) computing a moving 22-day window of the covariance matrix combined with the same type of shrinkage towards constant correlation as in CDL and using the same "updating" as in the RiskMetrics approach. Eventually, the $UMVE$ portfolio is scaled to have the same unconditional variance as the DOL factor. Note that the $UMVE$ is not a traditional long-short portfolio since the sum of absolute portfolio weights is time-varying. Moreover, our (pre-)sample starts in 1984 (not 1976 as in CDL) and we use G10 currency pairs in terms of cross-section to be consistent with CDL.

Table 6: UIP Regressions and Liquidity Risk

	OLS					2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$(f_t - s_t)_{t-22}$	*−0.048	−0.043	−0.045	−0.038	−0.038	−0.057	−0.074
	[1.762]	[1.530]	[1.596]	[1.040]	[1.028]	[0.873]	[0.952]
$\Delta b2$		***−0.103		**−0.103		**−1.182	
		[2.687]		[2.343]		[2.135]	
$\Delta b4$			**−0.063		*−0.059		−0.064
			[2.049]		[1.646]		[1.014]
$log(RER)_t - log(RER)_{t-5\text{ years}}$				***0.095	***0.095	**0.130	−1.041
				[3.649]	[3.680]	[2.296]	[1.204]
$\Delta\|CIP\|$				0.012	*0.012	*0.030	0.030
				[1.598]	[1.668]	[1.736]	[1.594]
R^2 in %	0.13	1.21	0.61	2.10	1.42	N/A	N/A
Adj. R^2 in %	0.11	1.20	0.60	2.08	1.40	N/A	N/A
Avg. #Time periods	7125	6874	6874	6687	6687	6687	6687
Currency FE	yes	yes	yes	yes	yes	yes	yes
Time series FE	yes	yes	yes	yes	yes	no	no

Note: This table reports results from daily fixed effects panel regressions of the form $\Delta s_t = \mu_t + a_i + b_1(f_t - s_t)_{t-22} + b_2\Delta\beta_t^2 + b_4\Delta\beta_t^4 + \gamma\Delta\mathbf{x}_t + \epsilon$, where the dependent variable is the spot rate change expressed as foreign currency units. The regressors include the lagged (relative) forward discount $f_t - s_t$, the rolling window estimates of systematic β_t^2 and currency-specific liquidity risk β_t^4, real exchange rates RER_t, and covered interest rate parity deviations $|CIP_t|$. Both dependent and independent variables (except for the forward discount $f_t - s_t$ and the real exchange rate RER_t) enter our regressions as 22-day changes (i.e., $\Delta = 22$). The last two columns present the second stage results of employing the lagged value of the TED spread as an instrument for $\Delta b2$ and $\Delta b4$, respectively. We standardise every time series by dividing by the standard deviation of the respective variable across currency pairs. μ_t and a_i denote time series and cross-sectional fixed effects, respectively. The sample covers the period from 21 February 1995 to 30 September 2022. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation up to 22 lags are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively.

move with and subsume the excess returns to the carry factor CAR. To test this hypothesis, we regress the carry factor on each of the four liquidity risk factors:

$$CAR = \alpha + \gamma\,\mathbf{f} + \epsilon, \tag{14}$$

where $\mathbf{f}$ may contain both 'traditional' and liquidity-based FX risk factors. The results are presented in Table 7. We find that only SIR-β^2 and AIR-β^4 are correlated with CAR, with a significant slope coefficient of -0.68 and -0.64 and an $\bar{R}^2$ of 40.1% and 29.1%, respectively. The unexplained excess returns (α) are significant but small economically and range from 2.12% to 2.13% annually. The other two liquidity beta based risk factors, CIR-β^1 and CMR-β^3, have almost no explanatory power for carry trade returns and hence, we drop these two factors from all subsequent analyses. In column 5 we propose an encompassing model that includes both systematic (i.e., SIR-β^2) and currency-specific (i.e., AIR-β^4) liquidity risk factors. The adjusted R^2 of this model is 41.4% and hence, relatively high.[18]

Compared to the liquidity risk based specification in column 5, the four alternative stories in columns 6-9 based on network centrality (PMC, Richmond, 2019), intermediary leverage (UML, Fang, 2018), global imbalances (IMB, Della Corte et al., 2016), and conditional projections ($UMVE$, Chernov et al., forthcoming) exhibit adjusted R^2s that are 2.1-32.2 percentage points lower and pricing errors (i.e., α) that are 1.4-2.4 percentage points larger, except for $UMVE$ that exhibits the lowest pricing error among all specifications. Note that the number of observations is smaller for the IMB and UML factors because global imbalance measures and bank leverage ratios are not available after 2017 and 2016, respectively. All results are qualitatively unchanged when pruning our sample to the overlapping period (i.e., from 1994 to 2016). The row titled "Nested $\bar{R}^2$ in %" reports the adjusted R^2 of model that includes both systematic and currency-specific liquidity risk factors (i.e., SIR-β^2 and AIR-β^4) in addition to PMC, UML, IMB or $UMVE$. The average increase in the adjusted R^2 across the four benchmark models is 26.1 percentage points. In the last column we build a nested model that extends the liquidity risk based specification in column 5 by including the long-short portfolios associated with the four alternative stories (i.e., PMC, UML, IMB, $UMVE$). In sum, the specification in column 10 corroborates the idea that the liquidity risk based story indeed provides additional explanatory power relative to the existing theories.

Systematic and currency-specific liquidity risk factors explain an ample amount of carry trade returns. This is consistent with a risk-based interpretation if high interest rate currencies have a higher loading on liquidity risk in absolute terms than low interest rate currencies. To test this hypothesis, we form tertile portfolios (i.e., $T1$, $T2$, and $T3$) based on the forward discount and regress them individually on the systematic (marketwide) and currency-specific liquidity beta based risk factors (i.e., SIR-β^2 and AIR-β^4). In line with our conjecture, Table 8 documents that the carry trade tertile portfolios show a monotonically increasing factor loading from low to high interest rate portfolios and unexplained excess returns are insignificant. Importantly, it is above all the high interest rate (i.e., investment) currencies in the top tertile portfolio $T3$ that are the most exposed to liquidity risk. Note that this is fully consistent with the evidence in Table 6: currencies that are more exposed to liquidity risk appreciate against the US dollar and thereby propel UIP deviations and ultimately carry trade premia. Therefore, the difference between sorting on interest rate differentials (i.e., carry trade strategy) and sorting on exposures to liquidity risk is in the short leg of the carry trade portfolio: the countries with the lowest interest rates are not necessarily the safest countries in terms of liquidity risk (i.e., high liquidity beta).[19] The fact that liquidity risk matters for carry trade returns is consistent with the idea of liquidity spirals (Brunnermeier and Pedersen, 2008) and

[18] As a robustness check, we have also used the IMX factor (see Ready et al., 2017) as a dependent variable in Eq. (14) and found consistent results that we document in the online Appendix. In contrast to CAR, the IMX factor sorts currencies into long-short portfolios based on the import ratio as it is defined in Ready et al. (2017). This is motivated by the fact that import ratios and interest rate differentials are highly correlated. We would like to thank Nick Roussanov for generously providing access to their data.

[19] Note that here we compare the short leg of the carry trade portfolio to the long leg of the liquidity beta sorted portfolios. This is because liquidity risk and carry trade premia have opposite signs.

Table 7: Explanatory Regressions for Carry Trade Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept (α) in %	***4.404	**2.131	***4.418	*2.116	*1.867	***3.545	**3.299	***4.303	1.721	0.012
	[3.438]	[2.102]	[3.463]	[1.896]	[1.867]	[3.260]	[2.529]	[3.145]	[1.369]	[0.013]
$CIR\text{-}\beta^1$	-0.030									
	[0.431]									
$SIR\text{-}\beta^2$		***-0.676			***-0.547					***-0.263
		[12.374]			[6.941]					[4.267]
$CMR\text{-}\beta^3$			0.026							
			[0.265]							
$AIR\text{-}\beta^4$				***-0.641	***-0.196					*-0.083
				[10.395]	[3.200]					[1.683]
PMC						***0.744				***0.464
						[12.736]				[8.908]
IMB							***0.671			***0.218
							[9.180]			[4.964]
UML								***0.552		***0.366
								[8.048]		[9.404]
$UMVE$									***0.380	***0.233
									[4.452]	[5.909]
$\bar{R}^2$ in %	0.05	40.12	0.02	29.17	41.37	39.29	22.09	17.43	9.17	67.42
Nested $\bar{R}^2$ in %						52.68	47.05	46.40	46.30	
#Obs	6865	6865	6865	6865	6865	5954	5706	5458	6865	5458

Note: This table shows the results of regressing daily gross carry trade returns CAR on four liquidity beta based risk factors (i.e., $CIR\text{-}\beta^1$, $SIR\text{-}\beta^2$, $CMR\text{-}\beta^3$, $AIR\text{-}\beta^4$) and alternative carry trade determinants (i.e., PMC, IMB, UML, $UMVE$). PMC is the peripheral minus central factor based on trade network analysis (Richmond, 2019), IMB is the imbalanced minus balanced factor that is long the currencies of debtor nations with mainly foreign-currency-denominated external liabilities and short the currencies of creditor nations with mainly domestic-currency-denominated external liabilities (Della Corte et al., 2016), UML is the unlevered minus levered factor that is a long-short strategy that exploits cross-sectional variation in countries' bank leverage (Fang, 2018), and $UMVE$ is the unconditional mean variance efficient portfolio building on conditional projections of the stochastic discount factor (Chernov et al., forthcoming). The row titled "Nested $\bar{R}^2$ in %" reports the adjusted R^2 of a model that includes both $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$ in addition to PMC, UML, IMB or $UMVE$. The intercept (α) has been annualised ($\times 252$). The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

spillover effects (Mancini et al., 2013). However, our key contribution is to show that exposures to systematic (i.e., $SIR\text{-}\beta^2$) and currency-specific liquidity risk (i.e., $AIR\text{-}\beta^4$) rather than commonality in liquidity risk (i.e., $CIR\text{-}\beta^1$) are the main drivers of carry trade returns over a considerably long sample period of more than 25 years.

In a next step, we decompose the carry trade into the static, dynamic, and dollar trade (Hassan and Mano, 2018). This is useful to shed light on which components are more related to liquidity risk than others. To make the carry trade from Hassan and Mano (2018) comparable to the traditional carry trade (e.g., Lustig and Verdelhan, 2007) we modify the original decomposition to accommodate traditional equally weighted long-short portfolios.[20]

[20] The portfolio weights for the dynamic trade are given by the difference between "dollar neutral" long-short carry trade weights and the static weights. The latter are derived from sorting currency pairs into long-short portfolios based on the average forward discount/ premium from 3 January 1994 to 20 February 1995, or when data is missing (i.e., for the USDILS and USDMXP) on the first few available data points.

Table 8: Time Series Regressions of Carry Trade Portfolios on Liquidity Risk Factors

	$T1$	$T2$	$T3$	CAR
Intercept (α) in %	-1.819	-0.529	0.049	*1.867
	[1.624]	[0.454]	[0.037]	[1.867]
SIR-β^2	0.051	**-0.160	***-0.496	***-0.547
	[0.828]	[2.002]	[4.607]	[6.941]
AIR-β^4	0.055	-0.096	*-0.141	***-0.196
	[0.824]	[1.428]	[1.763]	[3.200]
$\bar{R}^2$ in %	1.00	5.75	24.00	41.37
#Obs	6865	6865	6865	6865

Note: This table shows the results of regressing daily gross carry trade premia CAR and individual carry trade tertile portfolios (i.e., $T1$, $T2$, and $T3$) on two liquidity beta based risk factors (i.e., SIR-β^2 and AIR-β^4). Note that by construction the return on the high-minus-low carry trade portfolio CAR is given by the top tertile $T3$ minus the bottom tertile $T1$. The intercept (α) has been annualised ($\times 252$). The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

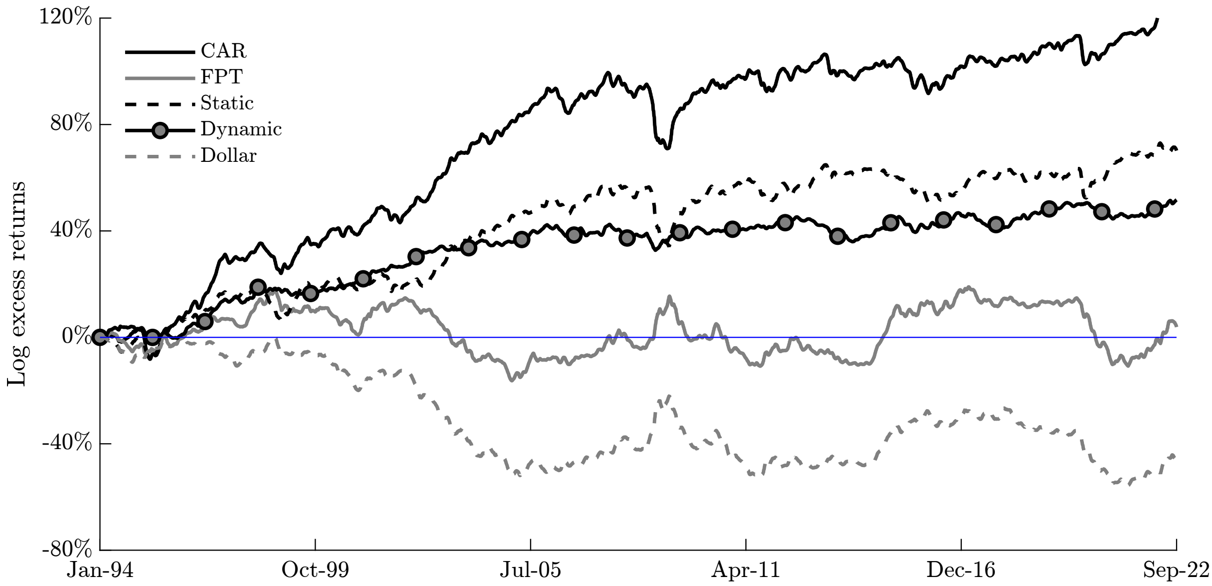
To be specific, we consider two types of 'carry' trades as outlined in Hassan and Mano (2018). One of them is the classic carry trade that exploits the correlation between currency returns and forward premia conditional on time fixed effects (e.g., Lustig and Verdelhan, 2007; Lustig et al., 2011). The other is the forward premium trade that weights each currency by the deviation of its current forward premium from its currency-specific mean (e.g., Cochrane, 2005; Bekaert and Hodrick, 2014). Hence, the forward premium trade is not necessarily "dollar neutral" since the long and short leg may contain a different number of currencies.[21]

Figure 3 depicts the cumulative excess returns associated with the carry and forward premium trade plus their three constituents, that is, the static, dynamic, and dollar trade, respectively. The forward premium trade and the carry trade are inversely related, whereas the carry and static trade as well as the forward premium and dollar trade exhibit correlated time series patterns. The time variation in the dynamic trade shows a unique pattern that seems to be unrelated to both the static and dollar trade. Note that the static and dynamic trade account for around 60% and 40% of total carry trade returns, respectively. To see this, compare across the elements of the last line in Table 9 that reports the annualised mean excess return associated with the carry and forward premium trade as well as their three constituents (i.e., static, dynamic, and dollar trade).

Table 9 shows results from regressing the carry trade (CAR), forward premium trade (FPT), and the associated building blocks (i.e., static, dynamic, and dollar trade) on our two liquidity risk factors, that is, SIR-β^2 and AIR-β^4, respectively. Notice that by construction the carry trade is equal to the sum of the dynamic and the static trade, whereas the forward premium trade is given by the sum of the dynamic and the dollar trade. The liquidity factors

[21]The weights for the forward premium trade are given by the sum of the weights on the dollar (carry) trade (i.e., Lustig, Roussanov, and Verdelhan, 2014) plus the weights on the dynamic trade.

Figure 3: Equity Curves for Carry Trade, Forward Premium Trade, and Constituents



Note: This figure plots the cumulative gross (log) excess returns of the carry trade (CAR), forward premium trade (FPT), and the associated building blocks (i.e., static, dynamic, and dollar trade) following the Hassan and Mano (2018) decomposition. The sample covers the period from 3 January 1994 to 30 September 2022.

(SIR-β^2 in particular) can explain an ample amount of the variation in the static and the dollar trade but largely fail to explain the dynamic trade. Thus, SIR-β^2 and AIR-β^4 can explain the average excess returns to both the carry and forward premium trade, respectively. Therefore, liquidity risk and carry trade premia are similar to each other on average because the carry trade returns are a combination of both dynamic and static components. This is in line with existing papers on the economics of the carry trade (e.g., Fang, 2018; Richmond, 2019) which also distinguish between unconditional and conditional forward discount sorted portfolios that are conceptually similar to the static and dynamic components in Hassan and Mano (2018). In sum, our findings suggest that a liquidity-based explanation only holds for the static carry trade, whereas the dynamic trade is a compensation for risks that are presumably unrelated to liquidity (risk).

Figure 4 illustrates how the correlation between CAR and SIR-β^2 or AIR-β^4 is driven by similarities in the portfolio weights associated with each currency pair. Specifically, the solid black and dashed grey lines depict the rolling window cross-sectional correlation coefficient between the portfolio weights of the carry trade and liquidity risk factors based on 22-day and 1008-day moving averages, respectively. There are two observation that deserve to be highlighted: First, the average correlation coefficient over longer horizons (i.e., 1008 days) is almost twice as large as over shorter ones (i.e., 22 days). This is fully consistent with the fact that the static trade is based on average interest rate differentials, whereas the dynamic trade sorts currency pairs based on yesterday's realisations. Put differently, one can think of the moving window correlations based on 22 and 1008 days as being a proxy for the portfolio

Table 9: Time series Regression: Carry Trade Decomposition

	CAR	FPT	Static trade	Dynamic trade	Dollar trade
Intercept (α) in %	*1.867	0.456	0.492	**1.375	-0.919
	[1.867]	[0.387]	[0.557]	[2.333]	[0.815]
SIR-β^2	***-0.547	0.136	***-0.475	**-0.072	**0.209
	[6.941]	[1.645]	[6.873]	[2.434]	[2.447]
AIR-β^4	***-0.196	-0.072	***-0.152	-0.044	-0.028
	[3.200]	[1.045]	[2.803]	[1.368]	[0.441]
$\bar{R}^2$ in %	41.37	0.99	39.90	4.09	4.44
#Obs	6865	6865	6865	6865	6865
Mean in %	***4.392	0.255	**2.619	***1.772	-1.518
	[3.433]	[0.224]	[2.397]	[2.963]	[1.415]

Note: This table reports the results from decomposing carry trade returns into the dynamic, static, and dollar trade (Hassan and Mano, 2018) and regressing the components on two liquidity risk factors, that is, SIR-β^2 and AIR-β^4, respectively. The last row reports the annualised mean excess returns of each carry trade component. The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

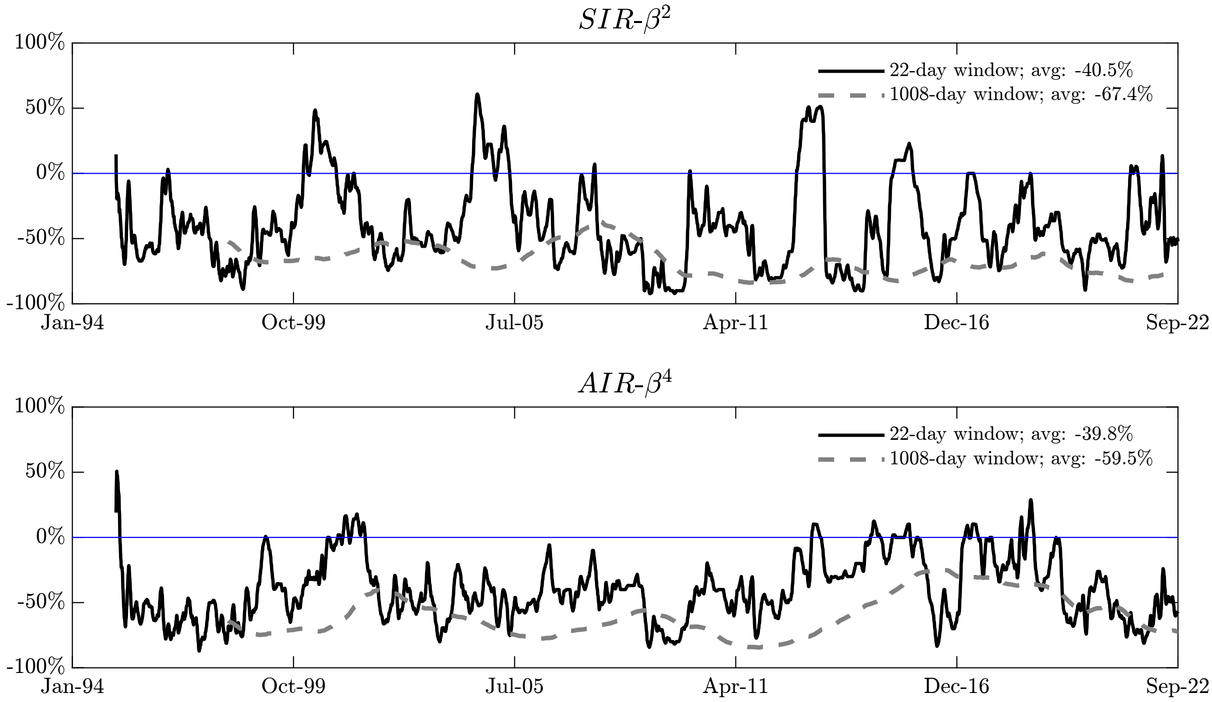
weights of the static and dynamic trade, respectively. Second, during times of market stress, such as the global financial crisis, the correlation between the portfolio weights increases for both liquidity risk factors (i.e., SIR-β^2 and AIR-β^4). Moreover, the 22-day moving window estimates temporarily (e.g., in August 2009) even exceed the ones based on 1008 days. These findings are also consistent with Mancini et al. (2013) who are the first showing that commonality in liquidity risk (i.e., CIR-β^1) and carry trade returns are strongly correlated during the short and unprecedented period of the global financial crisis.

To summarise, we shall highlight two features of the liquidity-based explanation for the carry trade. First, it performs at least as well as alternative explanations of carry trade profitability based on simple statistical grounds like adjusted R^2s and pricing errors. Second, commonality in liquidity risk and carry trade returns is confined to the static but not the dynamic component of the carry trade.

7. Conclusion

Using low-frequency measures of liquidity, this paper provides a comprehensive investigation of FX liquidity risk and carry trade returns. Our contribution is threefold: First, we show that sorting currency pairs into portfolios based on their exposure to systematic (i.e., β^2) and currency-specific liquidity risk (i.e., β^4) yields non-trivial risk-adjusted returns. Second, we find that augmenting an asset pricing model that includes the dollar and carry factor by either of our two aforementioned liquidity risk factors significantly improves the fit of the baseline model. This effect is especially pronounced during the period after the global financial crisis that is characterised by a tightening of interest rate differentials across countries. Third,

Figure 4: Cross-sectional Correlation of Moving Average Weights



Note: This figure plots the rolling window cross-sectional correlation coefficient between the portfolio weights of CAR and SIR-β^2 or AIR-β^4 based on 22-day (solid black line) and 1008-day (dashed grey line) moving averages, respectively. The sample covers the period from 21 February 1995 to 30 September 2022.

motivated by the observation that carry trade returns and our two liquidity beta based factors are not just correlated but also exhibit similar asset pricing properties we provide evidence in favour of a liquidity-based view of carry trade premia. While we cannot conclusively disprove alternative explanations, the evidence in this paper suggests that exposures to liquidity risk play a significant role for carry trade returns. In particular, our liquidity risk based story provides significant additional explanatory power relative to the existing theories based on measures of global imbalances, intermediary leverage, and network centrality, respectively. Moreover, we shed novel light on which components of the carry trade are more related to liquidity risk than others. To do this, we decompose carry trade returns into the static, dynamic, and dollar trade, respectively. We show that only the static and dollar trade are subsumed by systematic and currency-specific liquidity risk, whereas the dynamic trade does not load on either of these two liquidity risk factors. A promising avenue for future research would be to test the liquidity-based explanation for different implementations of the carry trade (e.g., Bekaert and Panayotov, 2019). In particular, it would be interesting to contrast approaches with different samples of currencies, weighting schemes, and also distinguishing whether the long and short sides of the trade are equal.

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Online Appendix to "Liquidity Risk and Currency Premia"

Appendix A. Common FX Trading Strategies

This section describes how we construct common FX trading strategies based on interest rate differentials (Lustig and Verdelhan, 2007; Lustig et al., 2011, CAR), volatility risk (Menkhoff et al., 2012a, VOL), value (Menkhoff et al., 2017, RER), three-month momentum (Menkhoff et al., 2012b, MOM), skewness risk (Rafferty, 2012, SKW), global dollar risk (Verdelhan, 2017, $GDOL$), intermediary leverage (Fang, 2018, UML), import ratios (Ready et al., 2017, IMX), network centrality (Richmond, 2019, PMC), output gap (Colacito et al., 2020, GAP), and global imbalances (Della Corte et al., 2016, IMB). We use most of these currency portfolios as test assets in our empirical asset pricing analysis in Section 5. All our trading strategies are rebalanced daily, unless the trading signals are only available at lower frequencies (e.g., monthly or yearly). To minimise the impact of noise, we smooth all the sorting variables (e.g., forward discounts in case of the carry trade) over a ten day moving window before translating them to trading signals. Moreover, we lag all trading signals by 22 business days to ensure the implementability based on 1-month forward contracts. Table A.1 provides detailed summary statistics for each of the FX trading strategies described below.

Appendix A.1. Carry Trade Portfolios (CAR)

We construct carry trade portfolios following the recent literature in this area (e.g. Lustig and Verdelhan, 2007; Lustig et al., 2011). In particular, we allocate currencies to three portfolios on the basis of their forward discounts (i.e., $f_t - s_t$). Each tertile portfolio consists of five currency pairs at most, where each of them receives an equal weight. This exercise implies that currencies with the lowest forward discounts (or lowest interest rate differential relative to the United States) are assigned to the first tertile portfolio $T1$, and currencies with the highest forward discounts (or highest interest rate differential relative to the United States) are assigned to the third tertile portfolio $T3$. The strategy that is long $T3$ and short $T1$ is referred to as the carry trade factor, or simply CAR.

Appendix A.2. Volatility Risk Portfolios (VOL)

Inspired by Menkhoff et al. (2012a), we form tertile portfolios based on currency pairs' exposure to the global volatility factor β^v. The volatility betas β^v are estimated individually for each currency pair using a 252-day rolling window. Each tertile portfolio consists of five currency pairs at most, where each of them receives an equal weight. We assign one third of all currencies with the lowest lagged volatility betas to the first tertile portfolio $T1$ (investment currencies), and one third of all currencies with the highest lagged volatility betas to the third tertile portfolio $T3$ (hedging currencies).

Table A.1: Summary Statistics Common FX Trading Strategies

	DOL	*CAR*	*VOL*	*RER*	*MOM*	*SKW*
Mean in %	0.10	***4.39	*−2.25	**2.14	−0.33	***2.75
	[0.09]	[3.43]	[1.92]	[2.02]	[0.33]	[2.62]
σ	6.80	8.10	7.49	6.64	6.95	6.87
SR	0.02	***0.54	*−0.30	**0.32	−0.05	***0.40
	[0.09]	[3.11]	[1.89]	[2.06]	[0.33]	[2.69]
Skewness	−0.21	−0.97	0.24	0.43	0.05	0.53
Kurtosis-3	1.95	4.90	2.18	1.59	1.43	4.36
Min	−1.55	−2.16	−1.27	−0.82	−1.10	−0.85
Max	0.91	1.68	1.56	1.24	1.49	2.09
MDD in %	31.98	28.60	24.06	19.24	33.53	17.39
Scaled MDD	22.05	16.57	15.06	13.59	22.62	11.88
#Obs	6865	6865	6865	6700	6865	6865
	GDOL	*UML*	*IMX*	*PMC*	*IMB*	*GAP*
Mean in %	1.21	0.52	**2.72	1.25	**3.20	*1.84
	[1.06]	[0.48]	[2.06]	[1.06]	[2.45]	[1.91]
σ	7.34	6.34	8.25	6.91	8.53	5.81
SR	0.16	0.08	**0.33	0.18	**0.38	*0.32
	[1.07]	[0.47]	[1.97]	[1.04]	[2.46]	[1.89]
Skewness	0.11	−0.44	−0.85	−0.62	0.01	−0.14
Kurtosis-3	0.40	1.11	3.40	5.70	1.89	1.62
Min	−0.87	−0.98	−2.13	−2.09	−1.70	−1.07
Max	1.07	0.91	1.00	1.10	1.34	1.02
MDD in %	19.11	39.72	25.59	31.77	21.62	16.66
Scaled MDD	12.21	29.39	14.56	21.58	11.89	13.46
#Obs	6865	5458	6451	5954	6731	5706

Note: This table presents the performance of portfolio sorts based on interest rate differentials (Lustig and Verdelhan, 2007; Lustig et al., 2011, *CAR*), volatility risk (Menkhoff et al., 2012a, *VOL*), value (Menkhoff et al., 2017, *RER*), one-month momentum (Menkhoff et al., 2012b, *MOM*), skewness risk (Rafferty, 2012, *SKW*), global dollar risk (Verdelhan, 2017, *GDOL*), intermediary leverage (Fang, 2018, *UML*), import ratios (Ready et al., 2017, *IMX*), network centrality (Richmond, 2019, *PMC*), output gap (Colacito et al., 2020, *GAP*), and global imbalances (Della Corte et al., 2016, *IMB*). Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*) and standard deviation (σ) in %, annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). To annualise the SR we multiply by $\sqrt{252/22}$ since using 1-month forward rates reduces the standard deviation of daily currency excess returns by a factor of $\sqrt{22}$. The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

Appendix A.3. Value Portfolios (RER)

Following Menkhoff et al. (2017), we form three tertile portfolios based on the lagged five-year real exchange rate return as in Asness, Moskowitz, and Pedersen (2013). Each tertile portfolio consists of five currency pairs at most, where each of them receives an equal weight. We assign one third of all currencies with the lowest lagged real exchange rate return to the first tertile portfolio $T1$ (overvalued currencies), and one third of all currencies with the highest lagged real exchange rate returns to the third tertile portfolio $T3$ (undervalued currencies). We compute the real exchange rate using information on purchase power parity from the OECD and Bloomberg, respectively.

Appendix A.4. Momentum Portfolios (MOM)

Following Menkhoff et al. (2012b), we form three tertile portfolios based on exchange rate returns for the previous three months. Each tertile portfolio consists of five currency pairs at most, where each of them receives an equal weight. We assign one third of all currencies with the lowest lagged exchange rate returns to the first tertile portfolio $T1$ (loser currencies), and one third of all currencies with the highest lagged exchange rate returns to the third tertile portfolio $T3$ (winner currencies). We construct three short-term momentum portfolios.

Appendix A.5. Skewness Risk Portfolios (SKW)

We form three tertile portfolios based on currency pairs' exposure to global skewness risk. In particular, we define our global skewness measure in line with Rafferty (2012) as the unweighted average across all 15 currency pairs in our sample (the sign of individual currency pair specific skewness measures is determined by the sign of forward discount $f_t - s_t$). We compute skewness for each currency pair and calendar month and estimate each currency pair's exposure to global skewness risk using a 252-day rolling window. The global skewness measure enters these regressions with a lag of one month (i.e., 22 trading days on average). Each tertile portfolio consists of five currency pairs at most, where each of them receives an equal weight. We assign one third of all currencies with the lowest lagged skewness betas to the first tertile portfolio $T1$ (risky currencies), and one third of all currencies with the highest lagged skewness betas to the third tertile portfolio $T3$ (hedging currencies).

Appendix A.6. Global Dollar Risk Portfolios (GDOL)

In accordance with Verdelhan (2017), we form tertile portfolios based on currency pairs' exposure to the dollar factor DOL, which is defined as an equally weighted long portfolio of all USD currency pairs (Lustig et al., 2011). In particular, we estimate each currency pair's exposure to DOL from a 252-day rolling window regression that includes both DOL and CAR as regressors. Each tertile portfolio consists of five currency pairs at most, where each of them receives an equal weight. We assign one third of all currencies with the lowest lagged global dollar beta to the first tertile portfolio $T1$ (safe currencies), and one third of all currencies with the highest lagged global dollar beta to the third tertile portfolio $T3$ (risky currencies).

Appendix A.7. Intermediary Leverage Portfolios (UML)

Following Fang (2018) we form tertile portfolios based on intermediary leverage differentials. We are very grateful to Xiang Fang for sharing his data on bank capital ratios (i.e., capital plus reserves over total assets) with us. These data are yearly and not available after 2016. Each tertile portfolio consists of five currency pairs at most, where each of them receives an equal weight. We assign one third of all currencies with the highest lagged leverage ratio to the first tertile portfolio $T1$ (levered currencies), and one third of all currencies with the lowest leverage ratio to the third tertile portfolio $T3$ (unlevered currencies).

Appendix A.8. Import Ratio Portfolios (IMX)

Following Ready et al. (2017), we form tertile portfolios based on the import ratio that is defined as the ratio of net imports of complex goods plus net exports of basic goods divided by total complex manufacturing output. We would like to thank Nick Roussanov for generously providing access to their data. These data are yearly and not available after 2020. Each tertile portfolio consists of five currency pairs at most, where each of them receives an equal weight. We assign one third of all currencies with the lowest lagged import ratio to the first tertile portfolio $T1$ (producer currencies), and one third of all currencies with the highest import ratio to the third tertile portfolio $T3$ (commodity currencies).

Appendix A.9. Network Centrality Portfolios (PMC)

Following Richmond (2019), we form tertile portfolios based on trade network centrality that is defined as the bilateral trade intensity between two countries (foreign and domestic country) at a given point in time scaled by the export share of the home country. We are grateful to Rob Richmond for sharing the network centrality measures with us. These data are yearly and not available after 2018. Each tertile portfolio consists of five currency pairs at most, where each of them receives an equal weight. We assign one third of all currencies with the highest lagged network centrality measure to the first tertile portfolio $T1$ (core countries), and one third of all currencies with the lowest network centrality measure to the third tertile portfolio $T3$ (periphery countries).

Appendix A.10. Output Gap Portfolios (GAP)

Following Colacito et al. (2020), we form quintile portfolios based on the output gap that is defined as the log of the difference between the actual and potential output, which is computed as the fitted value from a linear regression (Hamilton, 2018). Output is defined as industrial production, which is available at the monthly frequency via the OECD Revision Analysis Dataset. Each quintile portfolio consists of three currency pairs at most, where each of them receives an equal weight. We assign the 20% of all currencies with the lowest lagged output gap (relative to the US) to the first quintile portfolio $T1$ (weak economies), and the

20% of all currencies with the highest output gap to the fifth quintile portfolio $T5$ (strong economies).

Appendix A.11. Global Imbalance Portfolios (IMB)

Following Della Corte et al. (2016) we construct global imbalance portfolios as follows: we first group currencies into two baskets based on net foreign assets positions, and then re-order currencies within each basket using the proportion of external liabilities denominated in domestic currency. Hence, we allocate currencies based on this dependent double sort to four portfolios such that portfolio $P1$ corresponds to creditor countries whose external liabilities are primarily denominated in domestic currency (safest currencies), whereas $P4$ comprises debtor countries whose external liabilities are primarily denominated in foreign currency (riskiest currencies). Della Corte et al. (2016) refer to these portfolios as the global imbalance portfolios. As for all other currency portfolios, we compute the excess return for each portfolio as an equally weighted average of the currency excess returns within that portfolio. To construct a long–short portfolio we assume that investors go short foreign currencies in $P1$ and long foreign currencies in $P4$. We obtain end-of-year series on foreign assets and liabilities and gross domestic product (GDP) from Lane and Milesi-Ferretti (2001, 2007). In addition, we also use end-of-year series on the proportion of external liabilities denominated in domestic currency from Bénétrix, Lane, and Shambaugh (2015), who have updated the data from Lane and Shambaugh (2010). Both data sets are publicly available via Augustín Bétérix' website.[22] These data are yearly and not available after 2017.

Appendix B. Additional Empirical Results

Appendix B.1. Single Sorting

Tables B.1 to B.3 document the mean excess return of liquidity-based risk factors as well as their exposure to traditional FX risk factors using daily spot and forward rates from Refinitiv Datastream. The cross-section of currency pairs is increasing as follows:

- Table B.1 is based on 15 countries' currency against the US dollar: Australia (AUD), Canada (CAD), Denmark (DKK), Euro area (EUR), Hong Kong (HKD), Israel (ILS), Japan (JPY), Mexico (MXP), New Zealand (NZD), Norway (NOK), Singapore (SGD), South Africa (ZAR), Sweden (SEK), Switzerland (CHF), and United Kingdom (GBP).
- Table B.2 is based on 21 countries' currency against the US dollar: Australia (AUD), Canada (CAD), Denmark (DKK), Euro area (EUR), Hong Kong (HKD), Israel (ILS), Japan (JPY), Mexico (MXP), New Zealand (NZD), Norway (NOK), Singapore (SGD), South Africa (ZAR), Sweden (SEK), Switzerland (CHF), United Kingdom (GBP), India (INR), Korea (KRW), Poland (PLN), Russia (RUB), Turkey (TRY), and Taiwan (TWD).

[22]See https://agustinbenetrix.org/data/.

- Table B.3 is based on 27 countries' currency against the US dollar: Australia (AUD), Canada (CAD), Denmark (DKK), Euro area (EUR), Hong Kong (HKD), Israel (ILS), Japan (JPY), Mexico (MXP), New Zealand (NZD), Norway (NOK), Singapore (SGD), South Africa (ZAR), Sweden (SEK), Switzerland (CHF), United Kingdom (GBP), India (INR), South Korea (KRW), Poland (PLN), Russia (RUB), Turkey (TRY), Taiwan (TWD), Hungary (HUF), Indonesia (IDR), Myanmar (MYR), Czech Republic (CZK), Thailand (THB), and Philippines (PHP).

These cross-sectional choices of currency pairs are motivated by each currency pair's share in terms of global foreign exchange turnover.[23] Put differently, the share of global FX trading volume covered by each cross-section increases monotonically from Table B.1 to Table B.3.

Figure B.1 depicts the cumulative out-of-sample log excess returns of the four liquidity beta based strategies (top figure) in addition to the four common risk factors (bottom figure). The four liquidity beta based strategies exhibit some similarities in the return patterns if we ignore the sign of the cumulative returns. The direction of the cumulative returns (i.e., positive or negative) is consistent with the economic intuition in Section 2.2. With respect to the common risk factors, two observations deserve to be highlighted. First, the four liquidity risk factors exhibit a very different cumulative return pattern compared to the volatility risk factor VOL (Menkhoff et al., 2012a). Second, the carry trade factor CAR (Lustig et al., 2011) outperforms both liquidity beta based and traditional FX risk factors.

Motivated by the observation in Figure 4 that the correlation between the carry trade and our liquidity risk factors is time-varying we also explore a state-dependent regression model. In particular, we regress the static (CAR^S) or the dynamic (CAR^D) component of the carry trade on our two liquidity risk factors (i.e., $SIR\text{-}\beta^4$ and $AIR\text{-}\beta^4$) and include an interaction dummy that is equal to 1 in periods of markets stress and zero otherwise. Our *stress factor* is simply the average across the bond yield on AAA-rated US corporate debt, the TED spread, and the VXY FX volatility index.[24] Each of these measures captures a different dimension of market stress: the AAA corporate bond yield measures the expected return on AAA prime rated companies; the TED spread captures the perceived credit risk in the economy and is defined as the difference between the 3-month LIBOR rate and 3-month T-bill rate; the VXY is the Global FX Volatility index measuring the FX market's expectation of uncertainty based on option prices. To be precise, we estimate a regression of the form:

$$CAR^{\{S,D\}} = \alpha_L + \alpha_H \cdot Z + \delta DOL + (\gamma_{L,2} + \gamma_{H,2} \cdot Z)SIR\text{-}\beta^2 + (\gamma_{L,4} + \gamma_{H,4} \cdot Z)AIR\text{-}\beta^4 + \epsilon, \quad \text{(B.1)}$$

where we also allow the intercept (α) to be different across low ('L') and high ('H') periods of market stress that we capture by a dummy Z that is equal to 1 if the stress factor is above its 75% quantile in period t. The other regressors are the dollar factor DOL as well as the systematic and currency-specific liquidity beta based risk factors (i.e., $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$).

[23]See "Triennial central bank survey — global foreign exchange market turnover in 2022," Bank for International Settlements, September 2022.

[24]We standardise each time series by first subtracting the mean and then scaling by the standard deviation.

Table B.1: Exposure Regressions: 15 Currency Pairs from Refinitiv Datastream

	CIR-β^1					SIR-β^2				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
α in %	1.197	1.172	0.671	1.187	0.665	***−4.315	***−4.302	**−2.168	***−3.791	***−3.317
	[1.190]	[1.381]	[0.647]	[1.168]	[0.657]	[4.001]	[4.141]	[2.286]	[3.623]	[3.345]
DOL		***0.512					***−0.256			
		[12.567]					[3.931]			
CAR			**0.126					***−0.515		
			[2.345]					[10.165]		
VOL				−0.005					***0.266	
				[0.085]					[3.784]	
IML					***0.250					***−0.469
					[3.959]					[7.850]
$\bar{R}^2$ in %		29.71	2.34	0.00	6.84		6.23	32.45	7.66	20.07
IR	0.05	0.06	0.03	0.05	0.03	−0.18	−0.18	−0.11	−0.16	−0.15
$F_{\alpha,\beta}$		72	142	136	77		207	625	55	392
#Obs	6865	6865	6865	6865	6865	6865	6865	6865	6865	6865
	CMR-β^3					AIR-β^4				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
α in %	−0.016	−0.019	−0.727	−0.137	−0.388	***−3.593	***−3.583	**−2.409	***−3.124	***−2.986
	[0.019]	[0.023]	[0.831]	[0.156]	[0.454]	[3.595]	[3.698]	[2.463]	[3.205]	[3.047]
DOL		0.068					***−0.198			
		[1.481]					[3.882]			
CAR			***0.171					***−0.284		
			[4.021]					[6.369]		
VOL				−0.062					***0.238	
				[1.246]					[4.234]	
IML					***0.175					***−0.285
					[3.515]					[5.106]
$\bar{R}^2$ in %		0.73	5.97	0.69	4.67		4.51	12.00	7.47	9.03
IR	0.00	0.00	−0.04	−0.01	−0.02	−0.16	−0.17	−0.12	−0.15	−0.14
$F_{\alpha,\beta}$		210	243	272	161		277	495	92	314
#Obs	6865	6865	6865	6865	6865	6865	6865	6865	6865	6865

Note: This table shows the results of regressing daily gross excess returns associated with the four liquidity beta based trading strategies (i.e., CIR-β^1, SIR-β^2, CMR-β^3, AIR-β^4) on excess returns associated with common FX risk factors. DOL is based on an equally weighted long portfolio of all USD currency pairs, CAR is based on the forward discount/ premium $f_t - s_t$ (Lustig et al., 2011), VOL is based on currency pairs' exposure to the global volatility factor β^v (Menkhoff et al., 2012a), and IML is a strategy that sorts on the level of illiquidity (i.e., relative bid–ask spreads, IML). The intercept (α) has been annualised ($\times 252$). The information ratio (IR) is defined as α divided by the residual standard deviation. $F_{\alpha,\beta}$ denotes the F-test for the null hypothesis that $\alpha = 0$ and $\beta = 1$. The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Newey and West, 1987) correcting for correlation up to 22 lags.

Table B.4 reports the results from estimating Eq. (B.1) for the static (CAR^S) and the dynamic (CAR^D) part of the carry trade, respectively. There are three key takeaways from these multiple regressions: First, the risk-adjusted excess returns ('alphas') are only significant for the dynamic trade in normal times but not during periods of market stress ($\alpha_L + \alpha_H$ is close to zero and statistically insignificant). Second, the correlation of the static trade with SIR-β^2 and AIR-β^4 is almost twice as large during periods of uncertainty as otherwise. We interpret this as evidence that carry and liquidity risk premia are prone to commonality in bad times. Third, the correlation between the dynamic component of the carry trade and our two liq-

Table B.2: Exposure Regressions: 21 Currency Pairs from Refinitiv Datastream

	$CIR\text{-}\beta^1$					$SIR\text{-}\beta^2$				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
α in %	1.303	1.327	1.429	1.358	0.756	***−3.184	***−3.114	−0.051	**−2.633	−1.112
	[1.153]	[1.358]	[1.231]	[1.212]	[0.657]	[2.977]	[2.992]	[0.049]	[2.479]	[1.128]
DOL		***0.528					***−0.229			
		[11.869]					[3.927]			
CAR			−0.020					***−0.462		
			[0.342]					[9.490]		
VOL				0.023					***0.245	
				[0.337]					[3.987]	
IML					**0.129					***−0.441
					[2.338]					[10.019]
$\bar{R}^2$ in %		26.28	0.04	0.05	1.76		5.31	26.58	6.58	22.38
IR	0.05	0.06	0.06	0.06	0.03	−0.14	−0.14	0.00	−0.12	−0.05
$F_{\alpha,\beta}$		57	163	107	130		255	634	76	628
#Obs	6665	6665	6665	6665	6665	6865	6865	6865	6865	6865
	$CMR\text{-}\beta^3$					$AIR\text{-}\beta^4$				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
α in %	−0.777	−0.802	**−2.269	−1.005	−1.373	***−3.154	***−3.122	**−2.125	***−2.814	**−2.337
	[0.873]	[0.908]	[2.546]	[1.116]	[1.521]	[3.208]	[3.199]	[1.987]	[2.861]	[2.372]
DOL		*0.082					**−0.104			
		[1.811]					[2.281]			
CAR			***0.220					***−0.152		
			[4.930]					[3.281]		
VOL				**−0.101					***0.151	
				[2.236]					[3.055]	
IML					***0.127					***−0.174
					[2.872]					[4.168]
$\bar{R}^2$ in %		1.01	9.02	1.68	2.77		1.33	3.47	3.03	4.20
IR	−0.04	−0.04	−0.12	−0.05	−0.07	−0.15	−0.15	−0.10	−0.13	−0.11
$F_{\alpha,\beta}$		215	187	306	215		303	431	148	443
#Obs	6865	6865	6865	6865	6865	6865	6865	6865	6865	6865

Note: This table shows the results of regressing daily gross excess returns associated with the four liquidity beta based trading strategies (i.e., $CIR\text{-}\beta^1$, $SIR\text{-}\beta^2$, $CMR\text{-}\beta^3$, $AIR\text{-}\beta^4$) on excess returns associated with common FX risk factors. DOL is based on an equally weighted long portfolio of all USD currency pairs, CAR is based on the forward discount/ premium $f_t - s_t$ (Lustig et al., 2011), VOL is based on currency pairs' exposure to the global volatility factor β^v (Menkhoff et al., 2012a), and IML is a strategy that sorts on the level of illiquidity (i.e., relative bid–ask spreads, IML). The intercept (α) has been annualised ($\times 252$). The information ratio (IR) is defined as α divided by the residual standard deviation. $F_{\alpha,\beta}$ denotes the F-test for the null hypothesis that $\alpha = 0$ and $\beta = 1$. The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Newey and West, 1987) correcting for correlation up to 22 lags.

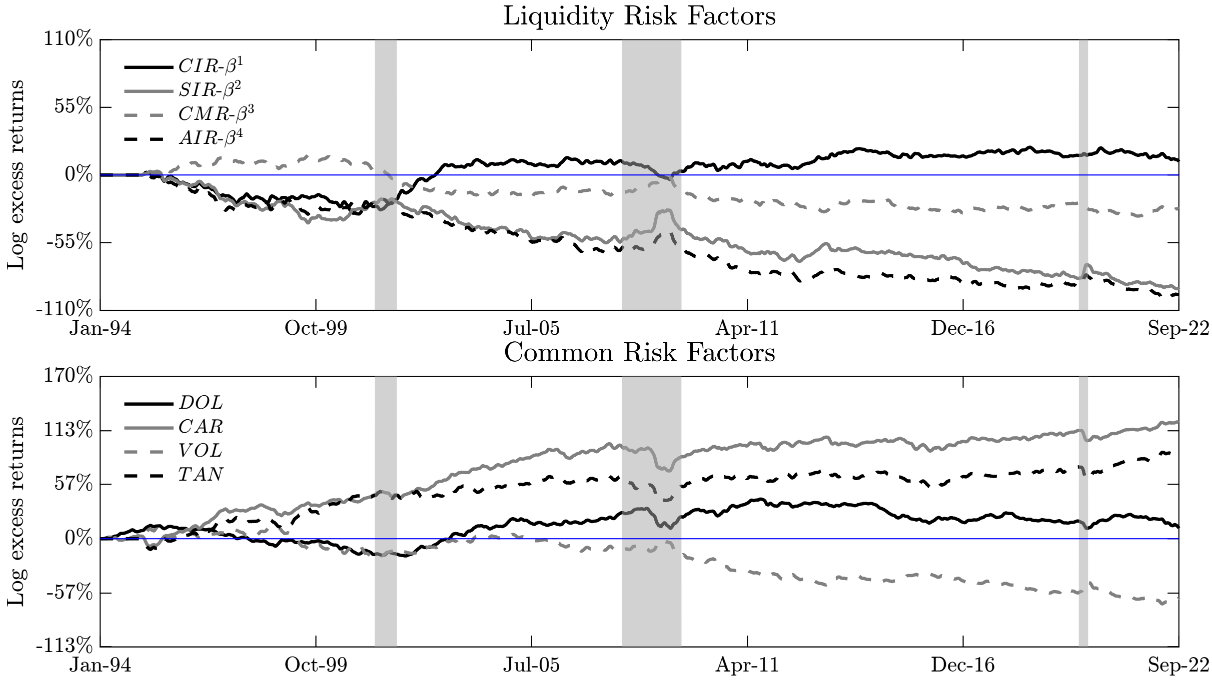
uidity factors is independent of market stress. Put differently, the dynamic component of the carry trade is a truly orthogonal risk factor to $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$, respectively.

Table B.3: Exposure Regressions: 27 Currency Pairs from Refinitiv Datastream

	$CIR\text{-}\beta^1$					$SIR\text{-}\beta^2$				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
α in %	0.330	0.016	−0.080	0.326	−0.699	***−3.537	***−3.463	−0.974	***−3.330	**−1.996
	[0.304]	[0.019]	[0.069]	[0.303]	[0.648]	[3.586]	[3.556]	[1.007]	[3.412]	[2.153]
DOL		***0.611					***−0.145			
		[15.719]					[3.022]			
CAR			0.065					***−0.408		
			[1.059]					[8.736]		
VOL				−0.002					**0.112	
				[0.025]					[2.015]	
IML					***0.204					***−0.305
					[4.844]					[9.945]
$\bar{R}^2$ in %		36.20	0.41	0.00	5.36		2.47	19.36	1.46	14.48
IR	0.01	0.00	0.00	0.01	−0.03	−0.16	−0.16	−0.05	−0.16	−0.10
$F_{\alpha,\beta}$		50	131	95	191		300	588	132	1020
#Obs	6865	6865	6865	6865	6865	6865	6865	6865	6865	6865
	$CMR\text{-}\beta^3$					$AIR\text{-}\beta^4$				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
α in %	−0.400	−0.361	−0.948	−0.413	−0.114	***−2.772	***−2.726	**−1.947	***−2.456	***−2.299
	[0.479]	[0.433]	[1.083]	[0.490]	[0.132]	[3.363]	[3.334]	[2.249]	[3.034]	[2.789]
DOL		**−0.074					**−0.090			
		[2.062]					[2.224]			
CAR			**0.087					***−0.131		
			[2.152]					[3.198]		
VOL				−0.007					***0.171	
				[0.183]					[4.041]	
IML					−0.056					**−0.094
					[1.343]					[2.508]
$\bar{R}^2$ in %		0.93	1.27	0.01	0.71		1.37	2.87	4.85	1.95
IR	−0.02	−0.02	−0.05	−0.02	−0.01	−0.15	−0.15	−0.11	−0.14	−0.13
$F_{\alpha,\beta}$		456	292	326	344		366	465	193	460
#Obs	6865	6865	6865	6865	6865	6865	6865	6865	6865	6865

Note: This table shows the results of regressing daily gross excess returns associated with the four liquidity beta based trading strategies (i.e., $CIR\text{-}\beta^1$, $SIR\text{-}\beta^2$, $CMR\text{-}\beta^3$, $AIR\text{-}\beta^4$) on excess returns associated with common FX risk factors. *DOL* is based on an equally weighted long portfolio of all USD currency pairs, *CAR* is based on the forward discount/ premium $f_t - s_t$ (Lustig et al., 2011), *VOL* is based on currency pairs' exposure to the global volatility factor β^v (Menkhoff et al., 2012a), and *IML* is a strategy that sorts on the level of illiquidity (i.e., relative bid–ask spreads, *IML*). The intercept (α) has been annualised ($\times 252$). The information ratio (IR) is defined as α divided by the residual standard deviation. $F_{\alpha,\beta}$ denotes the F-test for the null hypothesis that $\alpha = 0$ and $\beta = 1$. The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Newey and West, 1987) correcting for correlation up to 22 lags.

Figure B.1: Equity Curves for Liquidity and Common Risk Factors



Note: These figures plot the cumulative gross (log) excess returns of the four liquidity beta sorted portfolios (i.e., CIR-β^1, SIR-β^2, CMR-β^3, AIR-β^4; top figure) as well as four common FX risk factors (i.e., DOL, CAR, VOL, and TAN; bottom figure). Grey shaded areas correspond to recession periods as they are defined by the National Bureau of Economic Research (NBER). The sample covers the period from 3 January 1994 to 30 September 2022.

Table B.4: Commonality in Carry Trade and Liquidity Premia in Distressed Markets

	Static trade, CAR^S			Dynamic trade, CAR^D		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept LOW (α_L) in %	1.357	*1.517	1.077	***1.832	***1.908	***1.787
	[1.546]	[1.710]	[1.245]	[2.913]	[2.893]	[2.777]
Intercept HIGH (α_H) in %	−0.102	−0.926	0.120	−1.363	−1.600	−1.381
	[0.052]	[0.415]	[0.062]	[1.030]	[1.187]	[1.048]
DOL	***0.277	***0.325	***0.273	***−0.118	***−0.109	***−0.120
	[7.799]	[6.700]	[7.734]	[4.185]	[3.812]	[4.202]
SIR-β^2 LOW	***−0.415		***−0.312	***−0.101		**−0.085
	[7.728]		[4.624]	[3.400]		[2.204]
SIR-β^2 HIGH−LOW	***−0.199		***−0.258	−0.055		−0.013
	[3.219]		[2.734]	[1.388]		[0.218]
AIR-β^4 LOW		***−0.385	***−0.165		***−0.087	−0.026
		[7.657]	[2.736]		[2.825]	[0.671]
AIR-β^4 HIGH−LOW		**−0.180	0.099		*−0.085	−0.060
		[1.998]	[1.030]		[1.899]	[0.961]
$\bar{R}^2$ in %	47.04	38.15	47.86	8.00	7.07	8.41
#Obs	6756	6756	6756	6756	6756	6756

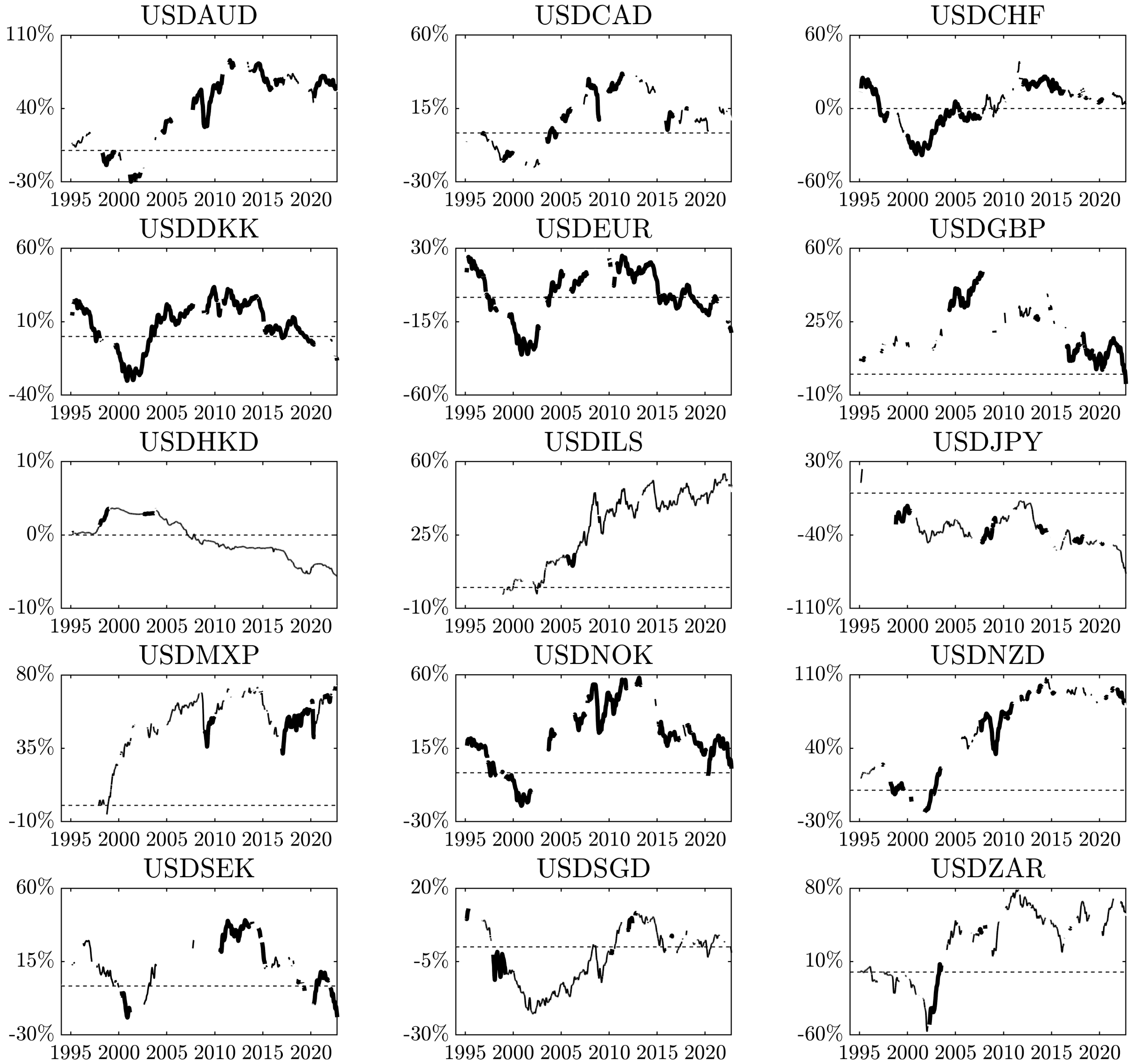
Note: This table reports the results from estimating a multiple linear regression of the form $CAR^p = \alpha_L + \alpha_H \cdot Z + \delta DOL + (\gamma_{L,2} + \gamma_{H,2} \cdot Z)SIR\text{-}\beta^2 + (\gamma_{L,4} + \gamma_{H,4} \cdot Z)AIR\text{-}\beta^4 + \epsilon \;\; \forall p \in \{S, D\}$, where the dependent variable is either the static (CAR^S) or the dynamic (CAR^D) part of the carry trade and the regressors are the dollar factor DOL and our liquidity factors SIR-β^2 and AIR-β^4, respectively. In addition, we include interaction terms based on a dummy D that is equal to 1 if the stress factor is above its 75% quantile in period t. Our stress factor is the average across the bond yield on AAA-rated US corporate debt, the TED spread, and the VXY FX volatility index, respectively. Note that we standardise each time series by first subtracting the mean and then scaling by the standard deviation. The intercept (α) has been annualised ($\times$252). The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

Table B.5: Sensitivity Table for Tangency Portfolio Weights

w_{DOL}	w_{CAR}	CIR-β^1	SIR-β^2	CMR-β^3	AIR-β^4
−1.00	2.00	0.41	***−3.34	−1.22	***−3.55
		[0.40]	[2.84]	[1.40]	[3.39]
−0.75	1.75	0.41	***−3.34	−1.13	***−3.55
		[0.40]	[2.84]	[1.29]	[3.39]
−0.50	1.50	0.41	***−3.34	−1.02	***−3.55
		[0.40]	[2.84]	[1.18]	[3.39]
−0.25	1.25	0.41	***−3.34	−1.28	***−3.55
		[0.40]	[2.84]	[1.53]	[3.39]
0.00	1.00	0.41	***−3.34	*−1.51	***−3.55
		[0.40]	[2.84]	[1.82]	[3.39]
0.25	0.75	0.41	***−3.34	**−2.01	***−3.55
		[0.40]	[2.84]	[2.41]	[3.39]
0.50	0.50	0.41	***−3.34	**−2.22	***−3.55
		[0.40]	[2.84]	[2.47]	[3.39]
0.75	0.25	0.41	***−3.34	−1.26	***−3.55
		[0.40]	[2.84]	[1.39]	[3.39]
1.00	0.00	0.41	***−3.34	−1.19	***−3.55
		[0.40]	[2.84]	[1.26]	[3.39]
1.25	−0.25	0.41	***−3.34	−1.52	***−3.55
		[0.40]	[2.84]	[1.61]	[3.39]
1.50	−0.50	0.41	***−3.34	−1.05	***−3.55
		[0.40]	[2.84]	[1.13]	[3.39]
1.75	−0.75	0.41	***−3.34	−1.05	***−3.55
		[0.40]	[2.84]	[1.12]	[3.39]
2.00	−1.00	0.41	***−3.34	−1.28	***−3.55
		[0.40]	[2.84]	[1.38]	[3.39]

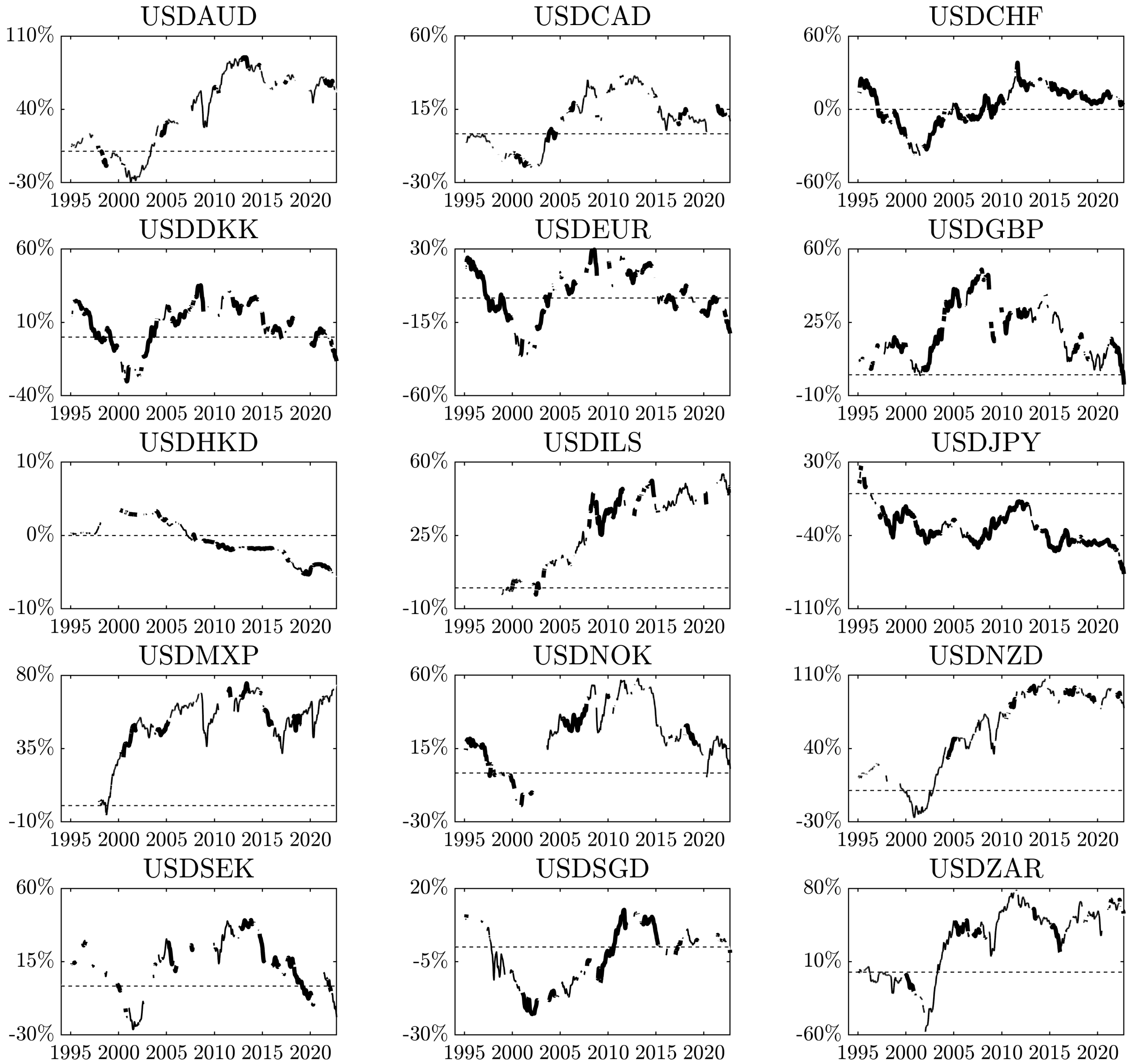
Note: This table presents the performance sensitivity of the portfolio sorts based on the four liquidity betas (i.e., CIR-β^1, SIR-β^2, CMR-β^3, AIR-β^4) to the tangency portfolio weights associated with each market factor (i.e., w_{DOL} and w_{CAR}) in Eq. (5). The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return being equal to zero based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

Figure B.2: Cumulative Excess Returns by Currency Pair (CIR-β^1)



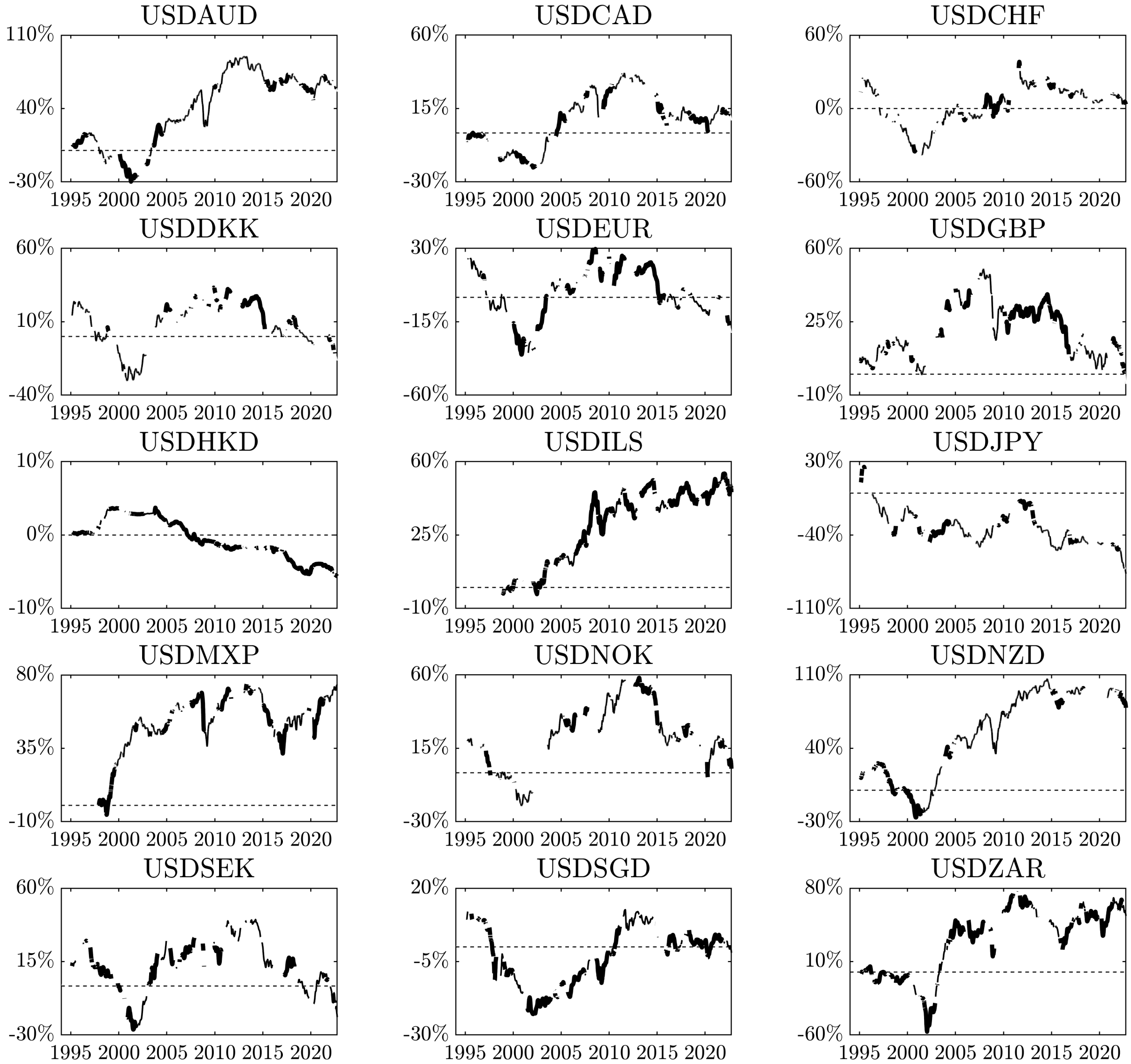
Note: This figure shows the cumulative daily excess returns from trading each currency against the US dollar (as shown at the top of the plot). The thin portions of each line correspond to periods when the respective foreign currency was held short in the CIR-β^1 trade. Similarly, the thick portions correspond to periods when the foreign currency was held long in the trade. Empty gaps correspond to periods where the foreign currency was *not* invested at all and hence received a zero weight in the portfolio allocation. The sample covers the period from 3 January 1994 to 30 September 2022.

Figure B.3: Cumulative Excess Returns by Currency Pair (SIR-β^2)



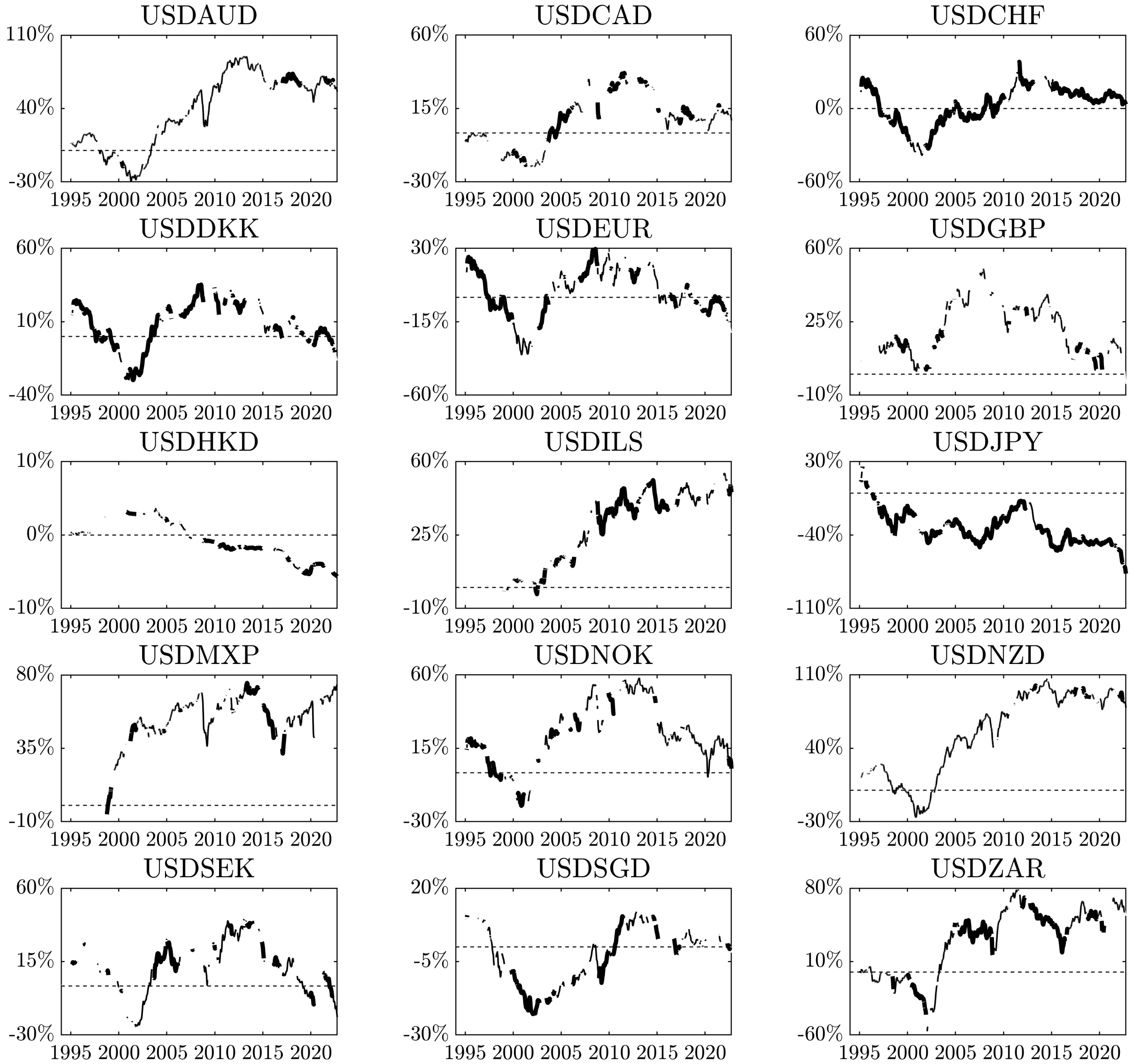
Note: This figure shows the cumulative daily excess returns from trading each currency against the US dollar (as shown at the top of the plot). The thin portions of each line correspond to periods when the respective foreign currency was held short in the SIR-β^2 trade. Similarly, the thick portions correspond to periods when the foreign currency was held long in the trade. Empty gaps correspond to periods where the foreign currency was *not* invested at all and hence received a zero weight in the portfolio allocation. The sample covers the period from 3 January 1994 to 30 September 2022.

Figure B.4: Cumulative Excess Returns by Currency Pair (CMR-β^3)



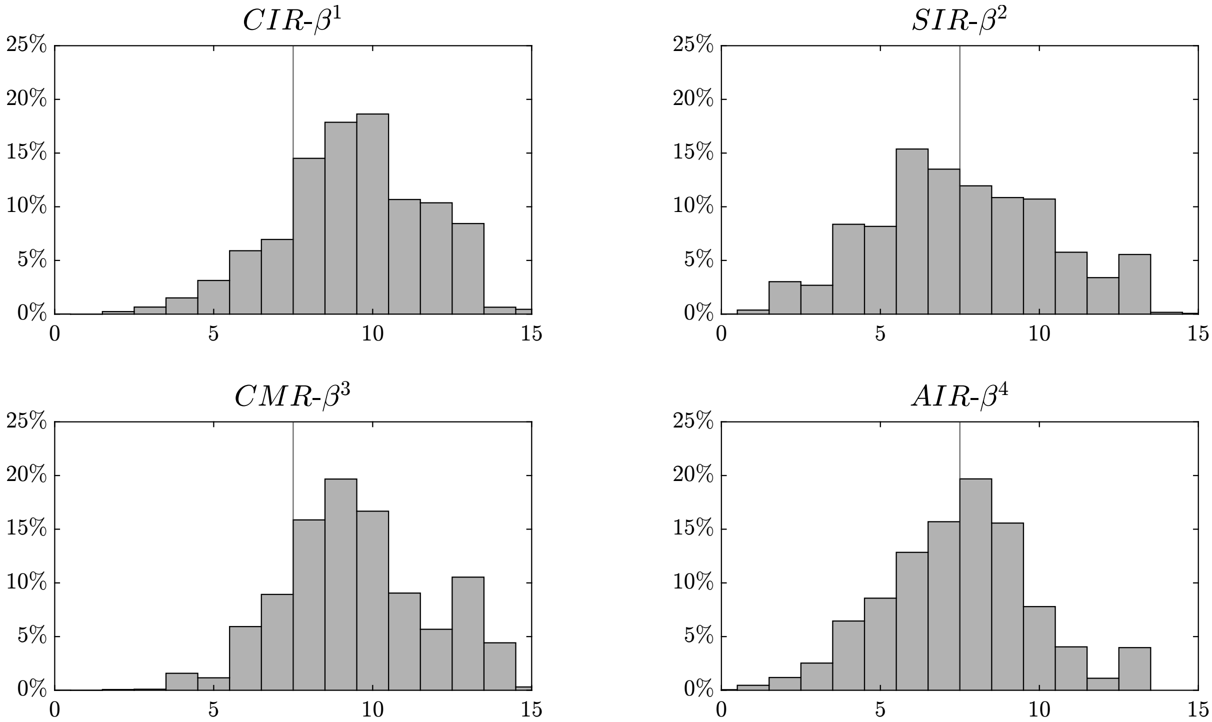
Note: This figure shows the cumulative daily excess returns from trading each currency against the US dollar (as shown at the top of the plot). The thin portions of each line correspond to periods when the respective foreign currency was held short in the CMR-β^3 trade. Similarly, the thick portions correspond to periods when the foreign currency was held long in the trade. Empty gaps correspond to periods where the foreign currency was *not* invested at all and hence received a zero weight in the portfolio allocation. The sample covers the period from 3 January 1994 to 30 September 2022.

Figure B.5: Cumulative Excess Returns by Currency Pair (AIR-β^4)



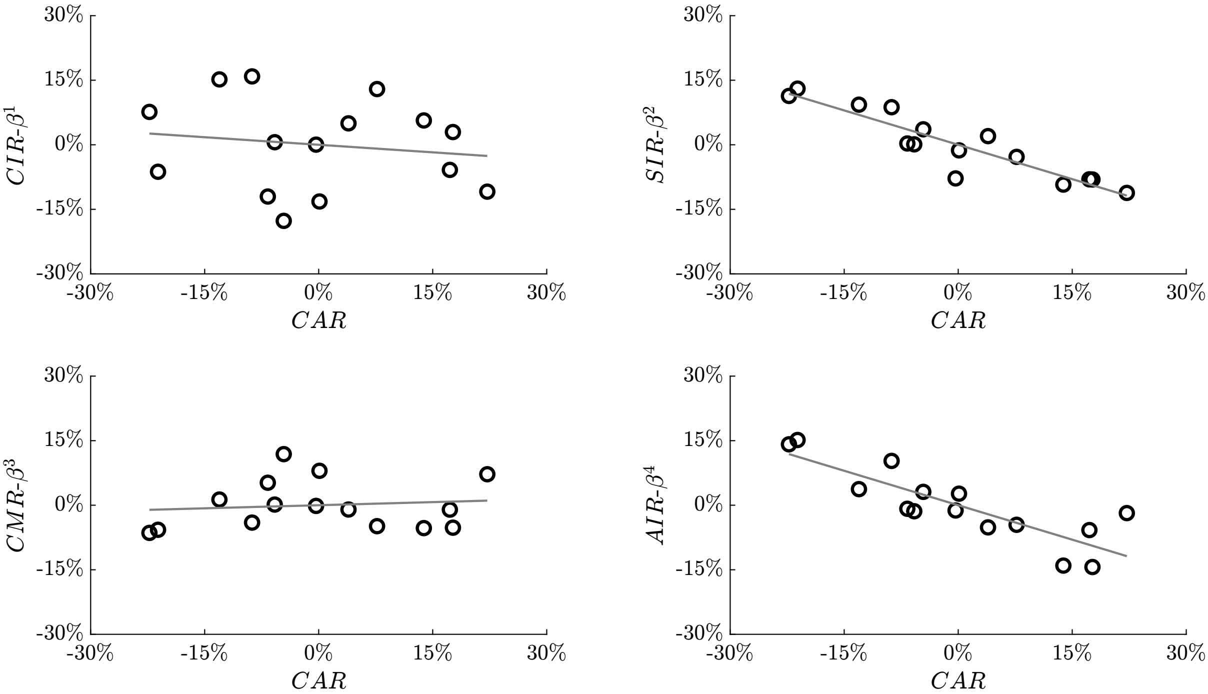
Note: This figure shows the cumulative daily excess returns from trading each currency against the US dollar (as shown at the top of the plot). The thin portions of each line correspond to periods when the respective foreign currency was held short in the AIR-β^4 trade. Similarly, the thick portions correspond to periods when the foreign currency was held long in the trade. Empty gaps correspond to periods where the foreign currency was *not* invested at all and hence received a zero weight in the portfolio allocation. The sample covers the period from 3 January 1994 to 30 September 2022.

Figure B.6: Histogram of Overlapping Weights in Carry and Liquidity Risk Factors



Note: The numbers on the x-axis refer to the total number of available currency pairs minus the number of currency pairs that either receive opposite weights in CAR and CIR-β^1, SIR-β^2, CMR-β^3, AIR-β^4, respectively, or are not invested at all. The percentages on the y-axis show the relative frequency of each possible combination of overlapping portfolio weights. The sample covers the period from 21 February 1995 to 30 September 2022.

Figure B.7: Average Weights in Carry Trade and Liquidity Risk Factors



Note: The numbers on the x-axis (*y-axis*) refer to the average portfolio weight in CAR ($CIR\text{-}\beta^1$, $SIR\text{-}\beta^2$, $CMR\text{-}\beta^3$, or $AIR\text{-}\beta^4$) associated with a particular currency pair (black circles). The sample covers the period from 21 February 1995 to 30 September 2022.

Table B.6: Summary Statistics Portfolio Sorts - BA Spread

	DOL	CAR	VOL	TAN	$CIR\text{-}\beta^1$	$SIR\text{-}\beta^2$	$CMR\text{-}\beta^3$	$AIR\text{-}\beta^4$
Mean in %	0.10	***4.39	*−2.25	**3.29	0.00	***−3.52	−0.56	***−3.87
	[0.09]	[3.43]	[1.92]	[2.44]	[0.00]	[2.97]	[0.64]	[3.55]
σ	6.80	8.10	7.49	8.61	6.45	7.60	5.79	7.09
SR	0.02	***0.54	*−0.30	**0.38	0.00	***−0.46	−0.10	***−0.55
	[0.09]	[3.11]	[1.89]	[2.32]	[0.00]	[2.78]	[0.64]	[3.43]
Skewness	−0.21	−0.97	0.24	−0.75	0.30	0.70	0.13	0.19
Kurtosis-3	1.95	4.90	2.18	3.22	0.87	5.32	0.84	3.53
Min	−1.55	−2.16	−1.27	−1.88	−0.75	−1.41	−0.83	−1.41
Max	0.91	1.68	1.56	1.27	1.00	2.15	0.98	1.54
MDD in %	31.98	28.60	24.06	26.11	37.94	24.10	17.97	16.54
Scaled MDD	22.05	16.57	15.06	14.22	27.58	14.87	14.55	10.94
#Obs	6865	6865	6865	6865	6865	6865	6865	6865

Note: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., $CIR\text{-}\beta^1$, $SIR\text{-}\beta^2$, $CMR\text{-}\beta^3$, $AIR\text{-}\beta^4$) as well as common FX risk factors such as dollar DOL, carry CAR, volatility VOL, and tangency TAN. Systematic (market) and currency pair specific liquidity are based on the relative bid–ask spread. DOL is based on an equally weighted long portfolio of all USD currency pairs, CAR on the forward discount/ premium $f_t - s_t$ (Lustig et al., 2011), VOL is based on currency pairs' exposure to the global volatility factor β^v (Menkhoff et al., 2012a), and TAN is a strategy that sorts on exposures to the tangency portfolio β^M (Markowitz, 1952). Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*) and standard deviation (σ) in %, annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). To annualise the SR we multiply by $\sqrt{252/22}$ since using 1-month forward rates reduces the standard deviation of daily currency excess returns by a factor of $\sqrt{22}$. The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

Table B.7: Summary Statistics Portfolio Sorts - CS Spread

	DOL	CAR	VOL	TAN	CIR-β^1	SIR-β^2	CMR-β^3	AIR-β^4
Mean in %	0.10	***4.39	*−2.25	**3.29	0.86	**−2.53	*−1.47	**−2.26
	[0.09]	[3.43]	[1.92]	[2.44]	[0.76]	[2.14]	[1.80]	[2.45]
σ	6.80	8.10	7.49	8.61	7.16	7.66	5.46	6.04
SR	0.02	***0.54	*−0.30	**0.38	0.12	**−0.33	*−0.27	**−0.37
	[0.09]	[3.11]	[1.89]	[2.32]	[0.76]	[2.08]	[1.83]	[2.41]
Skewness	−0.21	−0.97	0.24	−0.75	0.21	0.45	−0.40	0.21
Kurtosis-3	1.95	4.90	2.18	3.22	1.25	3.81	2.72	1.52
Min	−1.55	−2.16	−1.27	−1.88	−1.14	−1.31	−1.41	−0.87
Max	0.91	1.68	1.56	1.27	1.30	1.92	0.77	1.08
MDD in %	31.98	28.60	24.06	26.11	29.88	30.41	19.74	15.61
Scaled MDD	22.05	16.57	15.06	14.22	19.57	18.63	16.95	12.12
#Obs	6865	6865	6865	6865	6865	6865	6865	6865

Note: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., CIR-β^1, SIR-β^2, CMR-β^3, AIR-β^4) as well as common FX risk factors such as dollar DOL, carry CAR, volatility VOL, and tangency TAN. Systematic (market) and currency pair specific liquidity are based on the CS spread (Corwin and Schultz, 2012). DOL is based on an equally weighted long portfolio of all USD currency pairs, CAR on the forward discount/ premium $f_t - s_t$ (Lustig et al., 2011), VOL is based on currency pairs' exposure to the global volatility factor β^v (Menkhoff et al., 2012a), and TAN is a strategy that sorts on exposures to the tangency portfolio β^M (Markowitz, 1952). Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*) and standard deviation (σ) in %, annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). To annualise the SR we multiply by $\sqrt{252/22}$ since using 1-month forward rates reduces the standard deviation of daily currency excess returns by a factor of $\sqrt{22}$. The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

Table B.8: Summary Statistics Portfolio Sorts - AAA Bond Yield

	DOL	*CAR*	*AAA*	*TAN*	*CIR*-β^1	*SIR*-β^2	*CMR*-β^3	*AIR*-β^4
Mean in %	0.10	***4.39	−0.41	**3.29	0.94	***−3.65	−1.02	***−3.55
	[0.09]	[3.43]	[0.37]	[2.44]	[0.91]	[3.04]	[1.17]	[3.39]
σ	6.80	8.10	7.11	8.61	6.67	7.81	5.78	6.83
SR	0.02	***0.54	−0.06	**0.38	0.14	***−0.47	−0.18	***−0.52
	[0.09]	[3.11]	[0.37]	[2.32]	[0.92]	[2.82]	[1.18]	[3.33]
Skewness	−0.21	−0.97	−0.57	−0.75	0.31	0.79	−0.10	0.07
Kurtosis-3	1.95	4.90	2.84	3.22	0.78	5.12	1.14	1.97
Min	−1.55	−2.16	−1.51	−1.88	−0.79	−1.27	−1.13	−1.27
Max	0.91	1.68	0.89	1.27	1.03	2.20	0.69	1.35
MDD in %	31.98	28.60	37.64	26.11	37.80	26.70	16.36	17.28
Scaled MDD	22.05	16.57	24.84	14.22	26.57	16.03	13.27	11.87
#Obs	6865	6865	6865	6865	6865	6865	6865	6865

Note: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., *CIR*-β^1, *SIR*-β^2, *CMR*-β^3, *AIR*-β^4) as well as common FX risk factors such as dollar *DOL*, carry *CAR*, volatility *AAA*, and tangency *TAN*. *DOL* is based on an equally weighted long portfolio of all USD currency pairs, *CAR* on the forward discount/ premium $f_t - s_t$ (Lustig et al., 2011), *AAA* is based on currency pairs' exposure to the bond yield on AAA-rated US corporate debt, and *TAN* is a strategy that sorts on exposures to the tangency portfolio β^M (Markowitz, 1952). To compute the illiquidity betas β^1, β^2, and β^3 we orthogonalise systematic illiquidity c^M against the yield on AAA-rated US corporate debt. Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*) and standard deviation (σ) in %, annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). To annualise the SR we multiply by $\sqrt{252/22}$ since using 1-month forward rates reduces the standard deviation of daily currency excess returns by a factor of $\sqrt{22}$. The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

Table B.9: Summary Statistics Portfolio Sorts - TED Spread

	DOL	*CAR*	*TED*	*TAN*	*CIR*-β^1	*SIR*-β^2	*CMR*-β^3	*AIR*-β^4
Mean in %	0.10	***4.39	**−2.82	**3.29	0.64	***−3.34	−1.02	***−3.55
	[0.09]	[3.43]	[2.53]	[2.44]	[0.65]	[2.77]	[1.17]	[3.39]
σ	6.80	8.10	7.19	8.61	6.46	7.80	5.78	6.83
SR	0.02	***0.54	**−0.39	**0.38	0.10	***−0.43	−0.18	***−0.52
	[0.09]	[3.11]	[2.47]	[2.32]	[0.65]	[2.59]	[1.18]	[3.33]
Skewness	−0.21	−0.97	0.28	−0.75	0.30	0.77	−0.10	0.07
Kurtosis-3	1.95	4.90	2.57	3.22	0.87	4.78	1.14	1.97
Min	−1.55	−2.16	−1.02	−1.88	−0.75	−1.27	−1.13	−1.27
Max	0.91	1.68	1.82	1.27	1.03	2.08	0.69	1.35
MDD in %	31.98	28.60	22.55	26.11	34.54	26.64	16.36	17.28
Scaled MDD	22.05	16.57	14.71	14.22	25.07	16.02	13.27	11.87
#Obs	6865	6865	6865	6865	6865	6865	6865	6865

Note: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., CIR-β^1, SIR-β^2, CMR-β^3, AIR-β^4) as well as common FX risk factors such as dollar DOL, carry CAR, volatility TED, and tangency TAN. DOL is based on an equally weighted long portfolio of all USD currency pairs, CAR on the forward discount/ premium $f_t - s_t$ (Lustig et al., 2011), TED is based on currency pairs' exposure to the spread between the 3-month LIBOR rate and 3-month T-bill rate, and TAN is a strategy that sorts on exposures to the tangency portfolio β^M (Markowitz, 1952). To compute the illiquidity betas β^1, β^2, and β^3 we orthogonalise systematic illiquidity c^M against the TED spread. Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*) and standard deviation (σ) in %, annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). To annualise the SR we multiply by $\sqrt{252/22}$ since using 1-month forward rates reduces the standard deviation of daily currency excess returns by a factor of $\sqrt{22}$. The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

Table B.10: Summary Statistics Portfolio Sorts - VIX Index

	DOL	CAR	VIX	TAN	CIR-β^1	SIR-β^2	CMR-β^3	AIR-β^4
Mean in %	0.10	***4.39	*−2.15	**3.29	−0.24	***−2.94	−1.02	***−3.55
	[0.09]	[3.43]	[1.71]	[2.44]	[0.24]	[2.84]	[1.17]	[3.39]
σ	6.80	8.10	8.00	8.61	6.52	6.76	5.78	6.83
SR	0.02	***0.54	*−0.27	**0.38	−0.04	***−0.43	−0.18	***−0.52
	[0.09]	[3.11]	[1.66]	[2.32]	[0.24]	[2.72]	[1.18]	[3.33]
Skewness	−0.21	−0.97	0.62	−0.75	0.29	0.39	−0.10	0.07
Kurtosis-3	1.95	4.90	3.88	3.22	0.80	4.00	1.14	1.97
Min	−1.55	−2.16	−1.42	−1.88	−0.79	−1.08	−1.13	−1.27
Max	0.91	1.68	1.92	1.27	1.11	1.82	0.69	1.35
MDD in %	31.98	28.60	23.73	26.11	44.59	22.65	16.36	17.28
Scaled MDD	22.05	16.57	13.91	14.22	32.05	15.73	13.27	11.87
#Obs	6865	6865	6865	6865	6865	6865	6865	6865

Note: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., CIR-β^1, SIR-β^2, CMR-β^3, AIR-β^4) as well as common FX risk factors such as dollar DOL, carry CAR, volatility VIX, and tangency TAN. DOL is based on an equally weighted long portfolio of all USD currency pairs, CAR on the forward discount/ premium $f_t - s_t$ (Lustig et al., 2011), VIX is based on currency pairs' exposure to the Chicago Board Options Exchange's volatility index, and TAN is a strategy that sorts on exposures to the tangency portfolio β^M (Markowitz, 1952). To compute the illiquidity betas β^1, β^2, and β^3 we orthogonalise systematic illiquidity c^M against the VIX volatility index. Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*) and standard deviation (σ) in %, annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). To annualise the SR we multiply by $\sqrt{252/22}$ since using 1-month forward rates reduces the standard deviation of daily currency excess returns by a factor of $\sqrt{22}$. The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

Table B.11: Summary Statistics Portfolio Sorts Without Orthogonalisation

	DOL	CAR	VOL	TAN	CIR-β^1	SIR-β^2	CMR-β^3	AIR-β^4
Mean in %	0.10	***4.39	*−2.25	**3.29	1.61	***−3.16	*−1.54	***−3.40
	[0.09]	[3.43]	[1.92]	[2.44]	[1.54]	[2.58]	[1.78]	[2.99]
σ	6.80	8.10	7.49	8.61	6.72	7.93	5.60	7.34
SR	0.02	***0.54	*−0.30	**0.38	0.24	**−0.40	*−0.27	***−0.46
	[0.09]	[3.11]	[1.89]	[2.32]	[1.57]	[2.42]	[1.76]	[2.86]
Skewness	−0.21	−0.97	0.24	−0.75	0.45	0.85	0.18	0.43
Kurtosis-3	1.95	4.90	2.18	3.22	1.38	5.00	1.96	3.96
Min	−1.55	−2.16	−1.27	−1.88	−0.79	−1.27	−1.13	−1.50
Max	0.91	1.68	1.56	1.27	1.20	2.20	1.00	1.57
MDD in %	31.98	28.60	24.06	26.11	21.73	27.18	19.42	16.07
Scaled MDD	22.05	16.57	15.06	14.22	15.16	16.08	16.26	10.27
#Obs	6865	6865	6865	6865	6865	6865	6865	6865

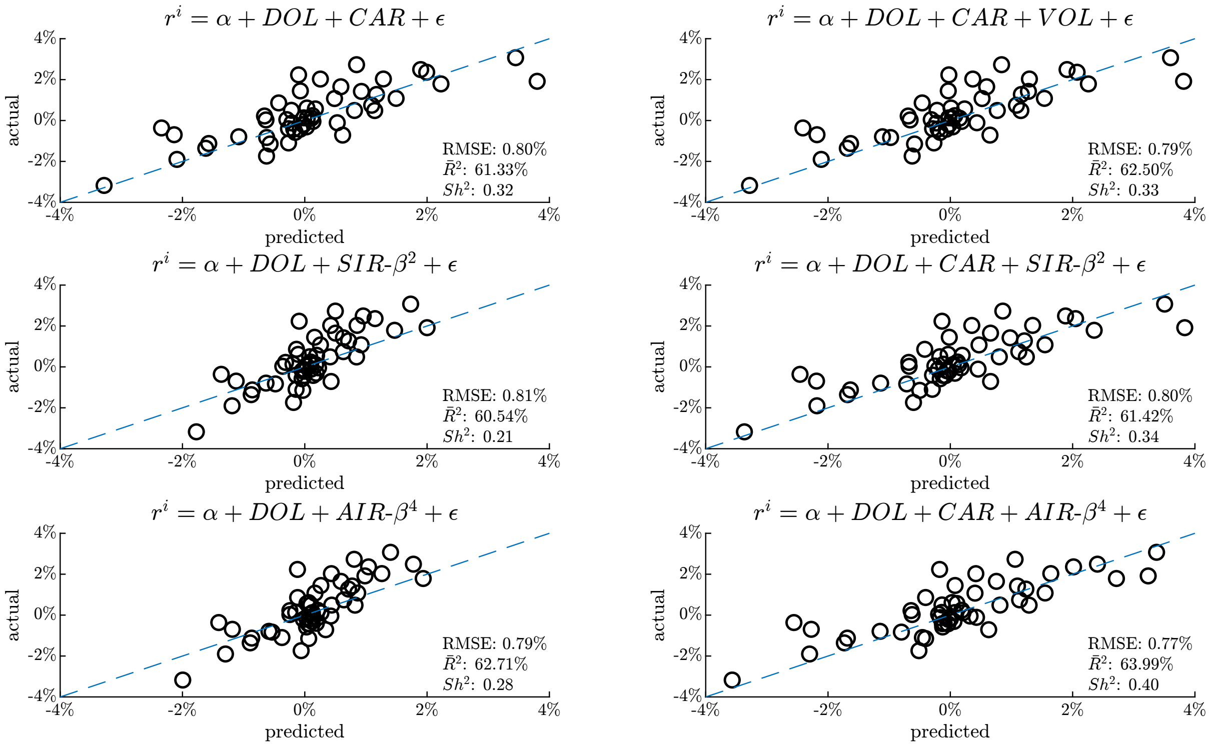
Note: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., CIR-β^1, SIR-β^2, CMR-β^3, AIR-β^4) as well as common FX risk factors such as dollar DOL, carry CAR, volatility VOL, and tangency TAN. DOL is based on an equally weighted long portfolio of all USD currency pairs, CAR on the forward discount/ premium $f_t - s_t$ (Lustig et al., 2011), VOL is based on currency pairs' exposure to the global volatility factor β^v (Menkhoff et al., 2012a), and TAN is a strategy that sorts on exposures to the tangency portfolio β^M (Markowitz, 1952). Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*) and standard deviation (σ) in %, annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). To annualise the SR we multiply by $\sqrt{252/22}$ since using 1-month forward rates reduces the standard deviation of daily currency excess returns by a factor of $\sqrt{22}$. The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

Table B.12: Summary Statistics Portfolio Sorts - Quintiles

	DOL	*CAR*	*VOL*	*TAN*	*IML*	*CIR*-β^1	*SIR*-β^2	*CMR*-β^3	*AIR*-β^4
Mean in %	0.10	***5.39	−2.34	***4.89	**3.08	0.82	***−4.27	*−2.09	***−5.50
	[0.09]	[3.18]	[1.55]	[2.86]	[2.53]	[0.62]	[2.94]	[1.82]	[3.96]
σ	6.80	10.94	9.60	10.85	7.94	8.56	9.37	7.73	9.04
SR	0.02	***0.49	−0.24	***0.45	**0.39	0.10	***−0.46	*−0.27	***−0.61
	[0.09]	[2.98]	[1.52]	[2.69]	[2.43]	[0.63]	[2.79]	[1.83]	[3.71]
Skewness	−0.21	−0.66	0.35	−0.77	−0.56	0.30	0.52	−0.17	0.50
Kurtosis-3	1.95	3.14	3.16	3.74	2.49	1.55	4.59	1.63	4.62
Min	−1.55	−2.64	−1.78	−2.69	−1.59	−1.45	−1.68	−1.71	−1.78
Max	0.91	1.99	2.36	1.78	1.57	1.85	2.45	1.28	2.45
MDD in %	31.98	34.69	31.91	37.86	20.83	41.73	27.58	18.84	25.39
Scaled MDD	22.05	14.88	15.58	16.36	12.31	22.88	13.81	11.43	13.18
#Obs	6865	6865	6864	6864	6864	6863	6865	6857	6864

Note: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., *CIR*-β^1, *SIR*-β^2, *CMR*-β^3, *AIR*-β^4) as well as common FX risk factors such as dollar *DOL*, carry *CAR*, volatility *VOL*, and tangency *TAN*. *DOL* is based on an equally weighted long portfolio of all USD currency pairs, *CAR* on the forward discount/ premium $f_t - s_t$ (Lustig et al., 2011), *VOL* is based on currency pairs' exposure to the global volatility factor β^v (Menkhoff et al., 2012a), and *TAN* is a strategy that sorts on exposures to the tangency portfolio β^M (Markowitz, 1952). *IML* is a trading strategy that sorts currencies into long-short portfolios based on the level of relative bid–ask spreads. Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*) and standard deviation (σ) in %, annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). To annualise the SR we multiply by $\sqrt{252/22}$ since using 1-month forward rates reduces the standard deviation of daily currency excess returns by a factor of $\sqrt{22}$. The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

Figure B.8: Realised Versus Predicted Excess Return



Note: These figures plot the actual versus model implied annualised ($\times$252) mean currency excess return for six competing factor models of the form $rp^i = \alpha + \delta\,\mathbf{f} + \varepsilon$, where $\mathbf{f}$ may contain both 'traditional' and liquidity-based FX risk factors. The test assets are 36 tertile portfolios of twelve common FX trading strategies plus the 15 US dollar currency pairs listed in Section 3.1. The model specifications are given in the titles of every subfigure. *RMSE* denotes the root-mean-square error, $\bar{R}^2$ the adjusted coefficient of determination, and Sh^2 the annualised squared Sharpe ratio associated with the tangency portfolio implied by each of the six factor models. The sample covers the period from 21 February 1995 to 30 September 2022.

Table B.13: Explanatory Regressions for IMX Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept (α) in %	**2.601	0.622	**2.670	0.163	0.022	*2.046	1.867	**3.078	-0.053	-0.948
	[1.979]	[0.571]	[2.036]	[0.149]	[0.021]	[1.873]	[1.526]	[2.298]	[0.040]	[1.018]
$CIR\text{-}\beta^1$	**0.157									
	[2.454]									
$SIR\text{-}\beta^2$		***-0.632			***-0.327					-0.052
		[12.043]			[4.502]					[0.900]
$CMR\text{-}\beta^3$			-0.044							
			[0.479]							
$AIR\text{-}\beta^4$				***-0.730	***-0.460					***-0.349
				[13.642]	[8.322]					[7.152]
PMC						***0.677				***0.394
						[12.832]				[7.752]
IMB							***0.706			***0.286
							[10.697]			[6.610]
UML								***0.465		***0.288
								[6.693]		[6.819]
$UMVE$									***0.367	***0.153
									[4.224]	[3.813]
$\bar{R}^2$ in %	1.65	35.20	0.08	37.73	41.99	33.80	25.51	12.93	8.60	62.03
#Obs	6451	6451	6451	6451	6451	5954	5706	5458	6451	5458

Note: This table shows the results of regressing daily gross IMX returns (Ready et al., 2017) on four liquidity beta based risk factors (i.e., $CIR\text{-}\beta^1$, $SIR\text{-}\beta^2$, $CMR\text{-}\beta^3$, $AIR\text{-}\beta^4$) and alternative carry trade determinants (i.e., PMC, IMB, UML,$UMVE$). PMC is the peripheral minus central factor based on trade network analysis (Richmond, 2019), IMB is the imbalanced minus balanced factor that is long the currencies of debtor nations with mainly foreign-currency-denominated external liabilities and short the currencies of creditor nations with mainly domestic-currency-denominated external liabilities (Della Corte et al., 2016), UML is the unlevered minus levered factor that is a long-short strategy that exploits cross-sectional variation in countries' bank leverage (Fang, 2018), and $UMVE$ is the unconditional mean variance efficient portfolio building on conditional projections of the stochastic discount factor (Chernov et al., forthcoming). The intercept (α) has been annualised ($\times 252$). The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

Table B.14: Explanatory Regressions for Carry Trade Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept (α) in %	***4.404	**2.131	***4.418	*2.116	*1.867	**2.138	1.693	*2.110	0.034	0.012
	[3.438]	[2.102]	[3.463]	[1.896]	[1.867]	[2.247]	[1.557]	[1.894]	[0.034]	[0.013]
CIR-β^1	-0.030									
	[0.431]									
SIR-β^2		***-0.676			***-0.547	***-0.337	***-0.509	***-0.456	***-0.549	***-0.263
		[12.374]			[6.941]	[5.063]	[6.150]	[4.774]	[6.260]	[4.267]
CMR-β^3			0.026							
			[0.265]							
AIR-β^4				***-0.641	***-0.196	***-0.150	-0.083	***-0.195	**-0.152	*-0.083
				[10.395]	[3.200]	[2.759]	[1.240]	[2.964]	[2.524]	[1.683]
PMC						***0.515				***0.464
						[9.480]				[8.908]
IMB							***0.427			***0.218
							[6.848]			[4.964]
UML								***0.349		***0.366
								[5.787]		[9.404]
$UMVE$									***0.282	***0.233
									[5.243]	[5.909]
$\bar{R}^2$ in %	0.05	40.12	0.02	29.17	41.37	52.68	47.05	46.40	46.30	67.42
#Obs	6865	6865	6865	6865	6865	5954	5706	5458	6865	5458

Note: This table shows the results of regressing daily gross carry trade returns CAR on four liquidity beta based risk factors (i.e., CIR-β^1, SIR-β^2, CMR-β^3, AIR-β^4) and alternative carry trade determinants (i.e., PMC, IMB, UML, $UMVE$). PMC is the peripheral minus central factor based on trade network analysis (Richmond, 2019), IMB is the imbalanced minus balanced factor that is long the currencies of debtor nations with mainly foreign-currency-denominated external liabilities and short the currencies of creditor nations with mainly domestic-currency-denominated external liabilities (Della Corte et al., 2016), UML is the unlevered minus levered factor that is a long-short strategy that exploits cross-sectional variation in countries' bank leverage (Fang, 2018), and $UMVE$ is the unconditional mean variance efficient portfolio building on conditional projections of the stochastic discount factor (Chernov et al., forthcoming). The intercept (α) has been annualised ($\times 252$). The sample covers the period from 21 February 1995 to 30 September 2022. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

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