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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 an economically significant 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 on this result, we propose a liquidity-based explanation for the carry trade, which adds significant explanatory power to existing theories.

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Keywords: currency portfolios • carry trade returns • FX liquidity risk • liquidity risk premium

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 decentralized 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 (Acharya and Pedersen 2005), we identify 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. Commonality in illiquidity and commonality in market returns capture the risk of a currency becoming illiquid in illiquid times and bad times, respectively, whereas systematic and currency-specific illiquidity pick up the risk of experiencing low returns in illiquid times. 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 economically significant risk adjusted returns. Second, we show that augmenting an asset pricing model that includes the dollar and carry factor (Verdelhan 2017) by either of these two liquidity risk factors significantly improves the fit of the 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 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 22% relative to 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, because of its decentralized over-the-counter (OTC) nature, the FX market is characterized by limited transparency, heterogeneity of market participants, and market fragmentation leading to unprecedented price and liquidity patterns that require scientific study. For instance, Karnaukh et al. (2015) show that currency liquidity systematically deteriorates in crisis periods,

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whereas 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, we adapt the Acharya and Pedersen (2005) liquidity adjusted capital asset pricing model to the FX market by incorporating currency-specific illiquidity as an additional source of liquidity risk. We use this framework to organize several theories about how liquidity risk can affect currency returns. The key intuition is that transaction costs have a first order impact on the profitability of currency trading strategies (Maurer et al. 2024), and thus, investors care about the risks affecting changes in currency liquidity. In particular, we identify four potential sources of FX liquidity risk: (i) commonality in currency liquidity and systematic liquidity (Mancini et al. 2013, Abankwa and Blenman 2021), (ii) return sensitivity to systematic liquidity (Pástor and Stambaugh 2003, Banti et al. 2012), (iii) commonality in currency liquidity and market returns (Acharya and Pedersen 2005), and (iv) return sensitivity to currency-specific liquidity (Amihud 2002). Eventually, we also identify empirical counterparts of systematic and currency-specific FX liquidity, respectively.

The second contribution is to sort currency pairs into tradeable portfolios based on their exposure (i.e., betas) to the four sources of FX liquidity risk. We control for the notorious correlation of illiquidity and volatility by orthogonalizing 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 of minus 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 (Lustig and Verdelhan 2007, Lustig et al. 2011), respectively, nor by the volatility risk factor (Menkhoff et al. 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 whether 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 (Lustig et al. 2011, Menkhoff et al. 2012a, Verdelhan 2017), we use a two-factor stochastic discount 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 2008/2009. 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 significant determinant of carry trade returns. The link between carry trade returns and our liquidity risk factors is nontrivial. 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 because liquidity spirals can amplify currency crashes. Mancini et al. (2013) provide suggestive empirical evidence in favor of this statement over the short and unprecedented period of the global financial crisis 2007–2009. Moreover, Brunnermeier et al. (2008) and Bakshi and Panayotov (2013) show that changes in U.S. 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 three steps.

To begin with, 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, 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 more negative factor loading from low to

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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 U.S. dollar due to being more exposed to global liquidity risk.

In the second 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 et al. 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 aforementioned interpretations of carry trade profitability based on simple statistical grounds such as coefficients of determination or pricing errors. Moreover, we also explore the possibility that our liquidity-based risk factors are a relevant determinant of the latest advances in global asset pricing factors (Sandulescu et al. 2020; Maurer et al. 2021, 2022; Orłowski et al. 2021; Aloosh and Bekaert 2022; Chernov et al. 2022; Korsaye et al. 2023). Empirically, we focus on the unconditional mean-variance efficient portfolio (*UMVE*) in Chernov et al. (2022), the covariance and spread adjusted carry (*CSCAR*) in Maurer et al. (2021, 2022), and the benchmark currency stochastic discount factor (*BCSDF*) in Orłowski et al. (2021) and show that these global SDFs significantly load on both systematic and currency-specific liquidity risk.[4]

In the third 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.

Therefore, our analysis of carry trade components also adds to the broader literature studying the economic origins of carry trade returns. For example, Christiansen et al. (2011) and Jeanneret and Sokolovski (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 et al. (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 et al. (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 organized 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.

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 organize 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 idiosyncratic 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

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

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). Under covered interest rate parity, this return is equivalent (in log terms) to buying a foreign risk-free bond at the beginning of the month (financed by borrowing domestically) and selling it at the end of the month to repay the loan. Put differently, the currency excess return equals approximately the interest rate differential less

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the depreciation rate of the domestic currency (Lustig and Verdelhan 2007, Lustig et al. 2011). We provide a formal definition of currency excess returns in Equation (4) in the next section. Moreover, c^i denotes 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. 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, because the covariance is a linear operator, we can rewrite Equation (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 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 later). 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] We will control for the notorious correlation between illiquidity and volatility risk by orthogonalizing 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 with the number of investable stocks) there is limited scope for diversification. As a result, the factor model in Equation (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. This approach is also consistent with the equity market literature, which defines idiosyncratic volatility based on the CAPM residuals (Ang et al. 2006). Hence, we are effectively augmenting the asset pricing model in Equation (2) by an additional liquidity beta (i.e., β^4), which captures any nonsystematic 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 Equation (2) that $\lambda = \lambda^M = \lambda^1 = -\lambda^2 = -\lambda^3$. 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 Equation (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 the expected sign of λ^2 in Equation (3) is negative). 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 the expected sign of λ^3 in Equation (3) is negative). 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).

Table 1. Four Sources of Liquidity Risk

Risk of	Name (abbreviation)	Covariance	Compensation for	Sign of λ
Becoming illiquid	Commonality in illiquidity risk (CIR)	$\beta^1 : cov(c^i, c^M)$	Lower liquidity in *illiquid* times	+
Lower returns	Systematic illiquidity risk (SIR)	$\beta^2 : cov(r^i, c^M)$	Lower returns in *illiquid* times	−
Becoming illiquid	Commonality in market risk (CMR)	$\beta^3 : cov(c^i, r^M)$	Lower liquidity in *bad* times	−
Lower returns	Asset-specific illiquidity risk (AIR)	$\beta^4 : cov(r^i, c^i)$	Lower returns in *illiquid* times	−

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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 the expected sign of λ^4 in Equation (3) is negative). This is because agents require higher returns on assets that yield low returns illiquid times and thus, are riskier (Amihud 2002).

To study the beta terms described previously, we follow the tradition in the FX asset pricing literature (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 Equation (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 nonlinearities 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, because of the decentralized nature of the FX market comprehensive volume data are unfortunately not available for a long enough sample period. Thus, we follow Karnaukh et al. (2015) instead to estimate currency-specific illiquidity (see the next section for details) because their illiquidity measure 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., close mid, bid, and ask quotes, as well as high ask and low bid prices) against the U.S. 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 January 3, 1994, to September 30, 2022 from Olsen Data, which is the standard source for academic research on high frequency FX rates.[6] Our sample starts in 1994 due to the availability of high ask and low bid prices from Olsen Data. 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 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 largest currency pairs in terms of FX trading activity. 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 (Lustig and Verdelhan 2007, Lustig et al. 2011), we define the *currency excess (log) return* (r) as

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

where f and s are the (daily data on) one-month log forward and spot rates quoted indirectly as foreign currency per unit of USD, for example, 0.74 EUR per USD. This creates overlapping returns, which we later handle with robust standard errors following Hodrick (1992). However, the main advantage of using daily (rather than monthly) data for estimating the liquidity betas in Section 4 is the added precision in the point estimates. 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 two 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 also experimented with using global SDFs as our market return. In particular, we focus on the unconditional mean-variance efficient portfolio (*UMVE*) in Chernov et al. (2022) and the covariance and spread adjusted carry (*CSCAR*) in Maurer et al. (2021, 2022). Moreover, we also consider the weights associated with each currency pair in *UMVE* and *CSCAR* when constructing market wide (global) measures of FX liquidity and volatility. As a result, the weights in Equation (5) will also affect the liquidity premium associated with β^1 and β^2 rather than just β^3. In addition, we also explored varying the tangency portfolio weights from -1 to 2. Across all these specification, we have found consistent results for all portfolio sorts in Section 4. See the online appendix for these additional results.

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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. Because higher values of this measure correspond to larger spreads, it is effectively a measure of *illiquidity* rather than *liquidity*.[7]

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 hourly high ask and low bid prices from Olsen Data are based on tick level data and thus, the maximum (*minimum*) of 24 hourly high ask (*low bid*) prices accurately reflects the highest ask (*lowest bid*) price on a particular day. 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 daily 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 by 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 outlined in Section 2.2. Within this context, the significant correlation of global volatility (Menkhoff et al. 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 orthogonalize 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 orthogonalizations we aim to derive clean liquidity measures that are independent of volatility.

The remainder of this section proceeds in three steps: First, we describe how to orthogonalize global and currency-specific measures of illiquidity against global and currency-specific measures of volatility. 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 previous four liquidity betas.

In the first step, we orthogonalize 22-day changes in global 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 orthogonalized series that we use further on. All our portfolio sorts yield qualitatively similar results when using a rolling instead of an expanding window for the orthogonalization. Following the Frisch-Waugh-Lovell theorem, orthogonalizing is equivalent to including volatility as a control variable in the beta representation (see Equation (3)).[8] Analogously, we can use the same approach to orthogonalize 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 four (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 orthogonalized (see Equation (6)) against currency pair specific (i.e., Δv^i) and global volatility factors (i.e., Δv^M), respectively. 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 based on 22-day changes of daily data 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 Equation (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 Equations (7)–(10), we use a 252-day rolling window. All our results are qualitatively unchanged when using a longer or shorter window.

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In Table 2, we report the collinearity concerning our measures of liquidity risk, bid-ask spreads, and interest rate differentials. Most correlations of the betas are economically insignificant with the notable exceptions of $corr(\beta^1, \beta^3)$ and $corr(\beta^2, \beta^4)$, respectively. Overall, 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 (i.e., more negative) values of β^2 and β^4, respectively. Thus, a currency pair that is illiquid, 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 liquidity." Last, high interest rate currencies (i.e., positive forward premium) are on average also more illiquid (i.e., higher bid-ask spread).

In the final step, we use each of the four rolling window liquidity betas to form traditional tertile portfolios ($T1, T2,$ and $T3$). To minimize the impact of noise, we smooth the betas over a 10-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 one-month forward contracts.[9] To be precise, we construct dollar-neutral long–short portfolios by going long the currency pairs in the top tertile ($T3$, high illiquidity beta) and short the pairs in the bottom tertile ($T1$, low illiquidity beta). 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: commonality in illiquidity risk $CIR\text{-}\beta^1$, systematic illiquidity risk $SIR\text{-}\beta^2$, commonality in market risk $CMR\text{-}\beta^3$, and asset-specific illiquidity risk $AIR\text{-}\beta^4$, respectively.

Table 3 reports summary statistics for these four liquidity beta based portfolios and four common FX risk factors: 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 Equation (5) (Markowitz 1952). To estimate a currency pair's sensitivity to global volatility β^v and market risk β^M, respectively, we run regressions in a similar vein to those in Equations (7)–(10). *IML* is a trading strategy that sorts currency pairs into long-short portfolios based on the level of relative bid-ask spreads.

Two of the four liquidity beta sorted trading strategies exhibit statistically significant mean excess returns. In particular, sorting currencies based on systematic ($SIR\text{-}\beta^2$) and currency-specific illiquidity ($AIR\text{-}\beta^4$) risk generates significant risk-adjusted returns of minus 3.3%–3.6% per year. These negative mean excess returns are in line with the expected signs of the liquidity risk premia (i.e., λ) in Table 1. Thus, our empirical result is consistent with the theoretical intuition in Section 2: Currency pairs that exhibit low returns in illiquid times are riskier and hence investors require higher expected returns. On the contrary, the mean returns associated with commonality in illiquidity ($CIR\text{-}\beta^1$) and market risk ($CMR\text{-}\beta^3$) are insignificant and much smaller (in absolute terms).

Overall, our findings are in line with the equity market literature, and in particular, Chordia et al. (2000), Amihud (2002), Pástor and Stambaugh (2003), and Hameed et al. (2010). What is more, the liquidity risk premia $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$ are significantly larger than the premium on illiquid minus liquid currency pairs (i.e., *IML*). Put differently, sorting on the level of illiquidity costs 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., more negative values of 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 the FX asset pricing literature. In particular, we add long-short portfolios

Table 2. Beta Correlations

	$\beta^1 : cov(c^i, c^M)$	$\beta^2 : cov(r^i, c^M)$	$\beta^3 : cov(c^i, r^M)$	$\beta^4 : cov(r^i, c^i)$	*bas*
$\beta^{2,i}$	18.72				
$\beta^{3,i}$	−85.32***	−21.29			
$\beta^{4,i}$	5.72	81.01***	−5.83		
bas	−2.91	−43.01***	4.05	−17.93**	
$f_t - s_t$	−13.83	−86.84***	12.01	−59.54***	43.82**

Notes. 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. The sample covers the period from February 21, 1995, to September 30, 2022.
*, **, *** Significant correlations at the 90%, 95%, and 99% levels, respectively.

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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***
	[0.08]	[2.80]	[1.58]	[2.01]	[1.48]	[0.33]	[2.33]	[1.00]	[2.82]
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***
	[0.08]	[2.53]	[1.55]	[1.92]	[1.41]	[0.34]	[2.21]	[1.00]	[2.77]
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
Minimum	−1.55	−2.16	−1.27	−1.88	−1.91	−0.77	−1.45	−1.13	−1.27
Maximum	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
No. of observations	6,865	6,865	6,865	6,865	6,865	6,865	6,865	6,865	6,865

Notes. 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*) and 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 annualized average (simple) excess return (*Mean*) and standard deviation (σ) in %, annualized Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Minimum), maximum (Maximum), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (No. of observations). To annualize the SR we multiply by $\sqrt{252/22}$ because using one-month forward rates reduces the standard deviation of daily currency excess returns by a factor of $\sqrt{22}$. The sample covers the period from February 21, 1995, to September 30, 2022. 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 (Hodrick 1992) correcting for serial correlation up to 22 lags.

*, **, *** Significant correlations at the 90%, 95%, and 99% levels, respectively.

based on momentum (Menkhoff et al. 2012b), value (Menkhoff et al. 2017), skewness risk (Rafferty 2012), and the output gap (Colacito et al. 2020). We construct these factors analogously to the ones in Table 3 using data from Bloomberg, Datastream, and the OECD. The correlation table conveys a clear message: Our liquidity beta-based trading strategies are largely unrelated to other common FX risk factors. Specifically, the absolute pairwise correlations are less than 20% with the notable exception of the dollar, carry, and *IML*, respectively. Hence, for the rest 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 whether 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 orthogonalization 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 zero when controlling for the volatility risk factor, suggesting that sorting on recursive projections is successful at disentangling liquidity and volatility risk.[10] 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

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	−4.14	6.39	−6.01	−1.74
RER	19.08**	−12.06	12.24*	−9.62
SKW	−15.16**	−13.53	7.30	−20.46**
IML	3.40	−57.59***	2.18	−46.81***
GAP	1.19	−7.69	−6.41	−6.30

Notes. 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 February 21, 1995, to September 30, 2022. The inference is based on heteroskedasticity- and autocorrelation-consistent standard errors (Hodrick 1992) correcting for serial correlation up to 22 lags.

*, **, *** Significant correlations at the 90%, 95%, and 99% levels, respectively.

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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*
	[0.335]	[0.344]	[0.401]	[0.324]	[0.278]	[2.329]	[2.427]	[0.617]	[1.879]	[1.822]
DOL		0.539***					−0.302***			
		[11.551]					[3.059]			
CAR			−0.021					−0.593***		
			[0.351]					[8.830]		
VOL				−0.006					0.351***	
				[0.083]					[3.948]	
IML					0.033					−0.637***
					[0.566]					[8.140]
$\overline{R}^2$ 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
$F_{\alpha=0,\,\lvert\beta\rvert=1}$		49	140	87	145		25	21	36	11
	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**
	[0.997]	[0.994]	[1.033]	[1.116]	[1.013]	[2.818]	[2.889]	[1.400]	[2.430]	[2.347]
DOL		−0.136***					−0.230***			
		[2.625]					[3.398]			
CAR			0.013					−0.455***		
			[0.218]					[8.872]		
VOL				−0.050					0.316***	
				[0.766]					[4.854]	
IML					0.018					−0.466***
					[0.285]					[8.508]
$\overline{R}^2$ 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
$F_{\alpha=0,\,\lvert\beta\rvert=1}$		140	135	106	117		67	59	61	48
No. of observations	6,865	6,865	6,865	6,865	6,865	6,865	6,865	6,865	6,865	6,865

Notes. This table shows the results of regressing daily 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 annualized ($\times 252$). The information ratio (IR) is defined as α divided by the residual standard deviation. $F_{\alpha=0,\,\lvert\beta\rvert=1}$ denotes the *F*-test for the null hypothesis that $\alpha = 0$ and $\lvert\beta\rvert = 1$. The sample covers the period from February 21, 1995, to September 30, 2022. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Hodrick 1992) correcting for serial correlation up to 22 lags.

*, **, *** Significant correlations at the 90%, 95%, and 99% levels, respectively.

indeed different from sorting on the level of transactions costs. The only exceptions to the case of a nonzero alpha are the specifications that control for the carry trade.[11] 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 $\lvert\beta\rvert = 1$ is strongly rejected across all specifications including the ones that involve the carry trade.

Taken together, the results reported thus far establish that 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, respectively.

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

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that the first two principal components of the cross section of currency returns are highly correlated with the dollar and carry factor, respectively (Lustig et al. 2011, Verdelhan 2017). We 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).

Next, we propose an alternative model that replaces the carry factor *CAR* by one of our liquidity risk factors. Because 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:

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

where **f** may contain both traditional and liquidity-based FX risk factors. Following the common practice in the FX asset pricing literature (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 11 currency trading strategies as the dependent variable (i.e., rp^j). In particular, we include portfolios sorted based on volatility (Menkhoff et al. 2012a), value (Menkhoff et al. 2017), level of transaction costs *IML*, three-month 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. Our results are also robust to including individual currency excess returns for the 15 exchange rates against the USD that we use for the portfolio sorts. The model in Equation (11) is estimated using ordinary least squares (OLS), and standard errors are based on Hodrick (1992) heteroskedasticity- and autocorrelation-consistent standard errors correcting for serial correlation up to 22 lags.

Figure 1 plots the model implied versus actual annualized mean currency excess return for eight-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., $SIR\text{-}\beta^2$) or currency-specific liquidity risk (i.e., $AIR\text{-}\beta^4$) 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., $\overline{R}^2$), respectively. Second, augmenting our baseline model by either of the two liquidity factors (i.e., $SIR\text{-}\beta^2$ or $AIR\text{-}\beta^4$) improves the fit of the asset pricing model. Moreover, comparing the subplots in the second and third row to the ones in the bottom row suggests that $AIR\text{-}\beta^4$ matters somewhat more in terms of cross-sectional asset pricing relative to $SIR\text{-}\beta^2$. 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 $SIR\text{-}\beta^2$ or $AIR\text{-}\beta^4$, respectively.

Taken together, the findings above 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 this, we proceed using two approaches: First, we present cross-sectional asset pricing tests for currency portfolios (i.e., rp^j) and illiquidity risk factors based on two-pass regressions (Cochrane 2005). Second, we use a statistical procedure that is inspired by Harvey and Liu (2021) and compare the test statistic of a Wald test across nested models with and without liquidity risk.

For the first approach, we estimate a beta pricing model in which the expected excess return on currency portfolio j is equal to the price of risk λ times the factor loadings b^j:

$$E[rp^j] = \lambda' b^j, \tag{12}$$

where λ and b^j are estimated using the generalised method of moments (GMM) of Hansen (1982). In particular, we first estimate the b's of the proposed liquidity factors $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$ and then in a second step run cross-sectional regressions to estimate risk premia. To implement GMM, we use the pricing errors as moment conditions and a weighting matrix that is equal to the identity matrix. The intuition is that with an identity weighting matrix GMM attempts to price all currency portfolios equally well. Moreover, our GMM approach appropriately accounts for the fact that the betas in the first stage have been estimated, as well as serial correlation in the returns (using the covariance matrix in Hodrick (1992)).

Table 6 presents the cross-sectional asset pricing test results. In line with Figure 1, we use the same cross section of 36 currency portfolios as test assets. There are three key takeaways from this table: First, the estimated risk premia (i.e., "lambdas") have the correct sign and are statistically significant and economically in line with the mean returns reported in Table 3. Second, both systematic and currency-specific liquidity risk (i.e., $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$) are priced even when controlling for both

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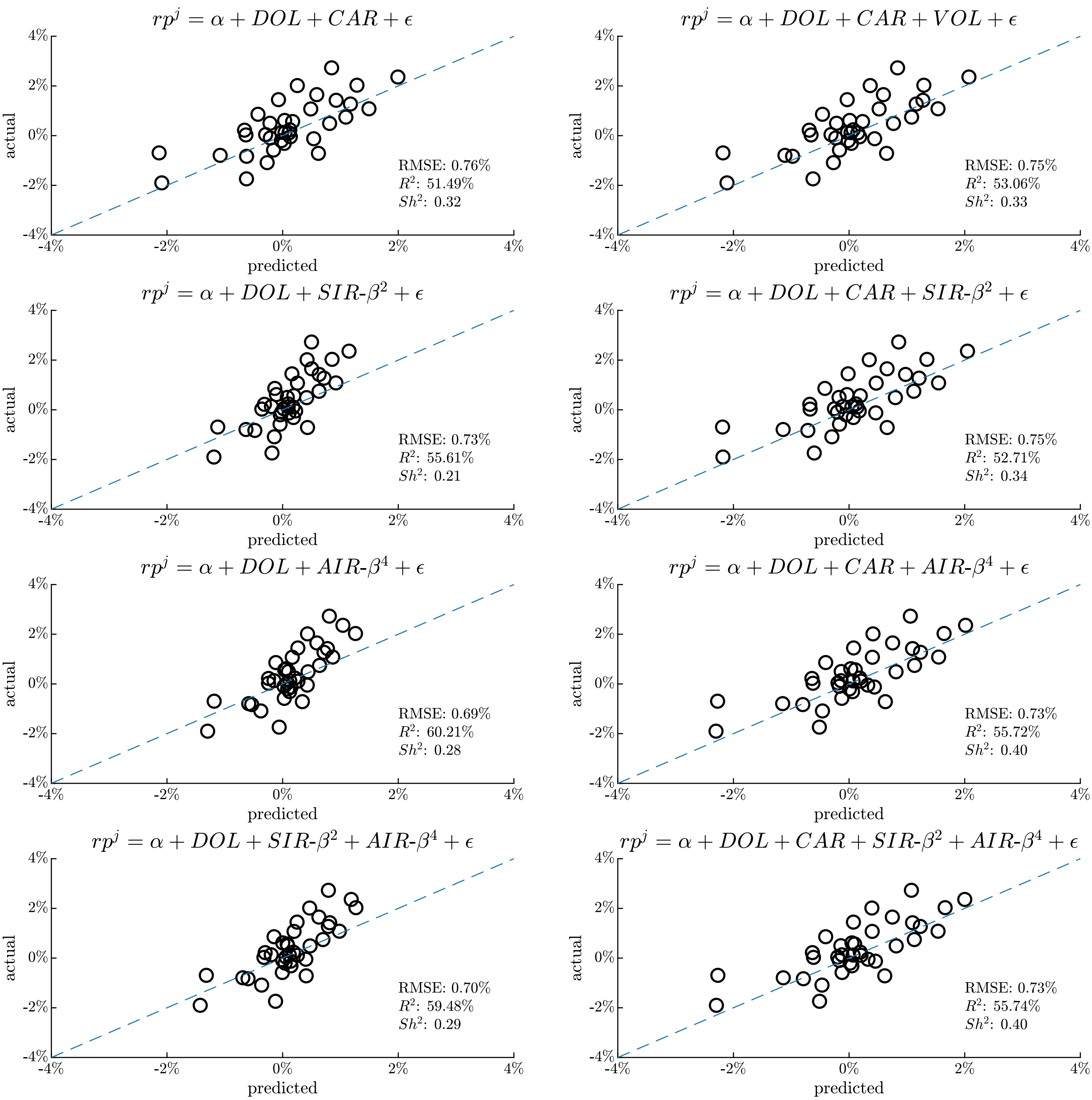
Figure 1. (Color online) Realized vs. Predicted Excess Return



Notes. These figures plot the actual vs. model implied annualized (×252) mean currency excess return for eight factor models of the form $rp^j = \alpha + \delta\,\mathbf{f} + \varepsilon$, where **f** may contain both traditional and liquidity-based 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 subplot. *RMSE*, root-mean-square error; R^2, coefficient of determination; Sh^2, annualized squared Sharpe ratio associated with the tangency portfolio implied by each model. The sample covers the period from February 21, 1995, to September 30, 2022.

the dollar and carry factor in columns 5–7. Third, including the two liquidity risk factors $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$ along the carry *CAR* and *DOL* factor improves the cross-sectional R^2 of the asset pricing model by 15% and lowers the *RMSE* by almost 8%. Overall, the evidence in Table 6 supports not only the idea that liquidity risk explains a significant fraction of the cross-sectional variation in currency excess returns but also that it contains additional explanatory power relative to the carry trade.

For the second approach, we use a statistical procedure that is inspired by Cochrane (1996) and compare the test statistic of a Wald test across nested models with

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Table 6. Asset Pricing Tests: Currency Strategies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DOL	0.409	0.383	0.363	0.299	0.357	0.284	0.282
	[0.008]	[0.008]	[0.007]	[0.006]	[0.007]	[0.006]	[0.006]
CAR		3.950*			3.250*	3.049	3.059
		[1.861]			[1.720]	[1.582]	[1.644]
SIR-β^2			−5.309***		−6.005***		−4.592***
			[3.229]		[10.054]		[7.798]
AIR-β^4				−5.455***		−6.120***	−6.115***
				[2.936]		[5.023]	[4.193]
R^2 in %	16.96	53.01	56.42	60.67	56.63	60.91	60.91
RMSE in %	1.00	0.75	0.72	0.69	0.72	0.68	0.68
No. of observations	6,865	6,865	6,865	6,865	6,865	6,865	6,865

Notes. This table presents asset pricing results (i.e., estimated risk premia) for currency strategies sorted on past information. The test assets are 36 currency portfolios that are constructed based on eleven common FX trading strategies. The set of pricing factors includes the dollar *DOL*, carry *CAR*, systematic *SIR*-β^2, and currency-specific *AIR*-β^4 liquidity risk factor, respectively. We report the market price of risk ("lambdas") in %, the cross-sectional R^2 of the pricing errors, and the root-mean-square error *RMSE*. Excess returns ("lambdas") are in annual terms (×252) and not adjusted for transaction costs. The sample covers the period from February 21, 1995, to September 30, 2022. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Hodrick 1992) correcting for heteroskedasticity and serial correlation up to 22 lags.
*, **, *** Significant correlations at the 90%, 95%, and 99% levels, respectively.

and without liquidity risk. In particular, we test whether the pricing errors (i.e., alphas) in Equation (11) are jointly zero across all test assets and then compare models with and without liquidity risk factors:

$$\Delta J_T = J_T(\text{without liquidity risk}) - J_T(\text{with liquidity risk}), \tag{13}$$

where $J_T = \alpha' V^{-1} \alpha$ is defined as the Wald test statistic of the null hypothesis that all alphas are zero. V is the heteroskedasticity- and autocorrelation-consistent estimate of the covariance matrix of the alphas that we estimate by GMM using the moment conditions pertaining to standard OLS (Cochrane 2005).[12]

Figure 2 plots the difference between a model *without liquidity* (i.e., dollar and carry) and *with liquidity* (i.e., dollar, carry, and either *SIR*-β^2 or *AIR*-β^4) along two dimensions. First, the bar plots on the left show the value of ΔJ_T in Equation (13). Second, the bar plots on the right show the (unconditional) difference between the annualized squared Sharpe ratio (i.e., Sh^2) associated with the tangency portfolio implied by the models with and without liquidity, respectively. We estimate both statistics by choosing different cutoff dates for pruning the sample. The horizontal axis shows the starting points of the pruned sample periods. The end date is always September 30, 2022. For both tests we use a block bootstrap procedure inspired by Harvey and Liu (2021) to do inference. In particular, the bootstrap approach imposes the null hypothesis that liquidity risk is priced by the benchmark factors (i.e., dollar and carry) and accounts for autocorrelation, cross-sectional correlation, and heteroskedasticity.

There are three main implications of these four subfigures: First, asset pricing models with and without liquidity risk factors perform similarly for large swathes of the sample period. Second, starting after the global financial crisis in 2007–2009 the models with liquidity significantly outperform the baseline 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 postcrisis period is characterized by an ultra low interest rate environment resulting in a contraction of interest rate differentials across countries and ultimately carry trade premia.[13] Third, the divergence in terms of annualized 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.[14] Thus, we conclude that liquidity risk is presumably part of the currency pricing kernel during times of compressed interest rate differentials. This conclusion follows from the fact that all our risk factors are excess returns and hence the SDF performance (i.e., pricing error) is proportional to the alpha from a linear factor model (Jagannathan and Wang 2002).

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 an illiquidity 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.

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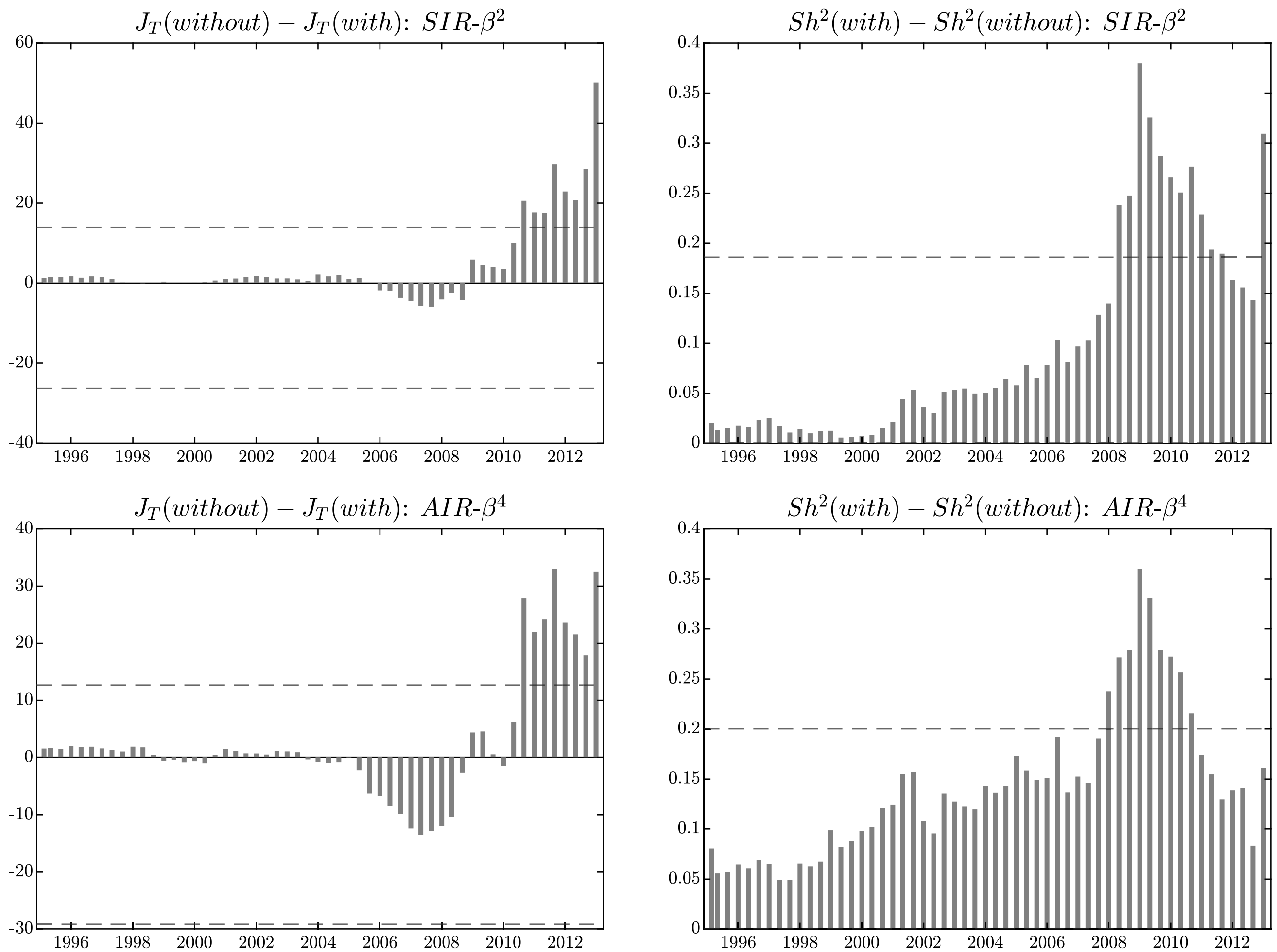
Figure 2. Liquidity Risk Factors and Currency Pricing Kernel



Notes. The two bar plots on the left show the difference in the Wald test statistic J_t between a model (*without* liquidity) including only the dollar and carry factor and a model (*with* liquidity) that additionally includes either the systematic (i.e., *SIR*-β^2) or currency-specific liquidity risk (i.e., *AIR*-β^4) factor, respectively. The two bar plots on the right show the difference between the annualized squared Sharpe ratio (i.e., Sh^2) associated with the tangency portfolio across models with and without liquidity factors. The estimates across the four plots are based on pruning the sample at different start dates (horizontal axis). The first estimate is based on the full sample that covers the period from February 21, 1995, to September 30, 2022. The horizontal dotted lines mark the bootstrapped critical values at the 5% and 95% confidence level, respectively. We use a block bootstrap procedure inspired by Harvey and Liu (2021) that imposes the null hypothesis that the liquidity factors (i.e., *SIR*-β^2 and *AIR*-β^4) are priced by the dollar and carry factor. We draw blocks of 22 days to preserve the serial correlation in portfolio returns. To account for the pruning of the sample we use half of the resampled time indices at each simulation.

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 affected by liquidity risk. The next section will explore this possibility in more depth.

6. Liquidity Risk and Carry Trade Premia

In the previous section, we 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 significant determinant of 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 et al. (2011) suggest that risk alone does not account

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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).[15] Therefore, the goal of this section is to provide empirical evidence 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 establish that systematic (i.e., $SIR\text{-}\beta^2$) and currency-specific liquidity risk (i.e., $AIR\text{-}\beta^4$) can successfully explain the returns to the carry trade (i.e., *CAR*). To show this, we regress the carry factor on our liquidity risk factors:

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

where **f** may contain both "traditional" and liquidity-based FX risk factors. The results are presented in Table 7. In line with Table 5, we find that both $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$ are correlated with *CAR*, with a significant slope coefficient of −0.68 and −0.64 and an $\overline{R}^2$ of 40.1% and 29.1%, respectively. The unexplained excess returns (α) are borderline significant but small economically and range around 2.1% annually. In column 3, we propose an encompassing model that includes both systematic (i.e., $SIR\text{-}\beta^2$) and currency-specific (i.e., $AIR\text{-}\beta^4$) liquidity risk factors. The adjusted R^2 of this model is 41.4% and hence relatively high.[16]

Compared with the liquidity risk based specification in column 3, the three alternative stories in columns 4–6 based on network centrality (*PMC*; Richmond 2019), intermediary leverage (*UML*; Fang 2018), and global imbalances (*IMB*; Della Corte et al. 2016) exhibit adjusted R^2s that are 19.3–32.2 percentage points lower and pricing errors (i.e., α) that are 1.4–2.4 percentage points larger. 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 $\overline{R}^2$ in %" reports the adjusted R^2 of a model that includes both systematic and currency-specific liquidity risk factors (i.e., $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$) in addition to *PMC*, *UML* or *IMB*. The average increase in the adjusted R^2 across the three benchmark models is about 22 percentage points. In the last column, we build a nested model that extends the liquidity risk based specification in column 3 by including the returns associated with the three alternative stories (i.e., *PMC*, *UML*, *IMB*). In sum, the specification in column 7 corroborates the idea that the liquidity risk based story indeed provides additional explanatory power relative to 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 load more negatively on liquidity risk than low interest rate currencies. To study this

Table 7. Explanatory Regressions for Carry Trade Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept (α) in %	2.131*	2.116	1.867	3.545***	3.299**	4.303**	1.986*
	[1.718]	[1.550]	[1.527]	[2.686]	[2.063]	[2.542]	[1.805]
$SIR\text{-}\beta^2$	−0.676***		−0.547***				−0.246***
	[10.157]		[5.750]				[3.412]
$AIR\text{-}\beta^4$		−0.641***	−0.196***				−0.111*
		[8.648]	[2.705]				[1.864]
PMC				0.744***			0.466***
				[10.572]			[7.931]
IMB					0.671***		0.259***
					[7.688]		[4.994]
UML						0.552***	0.370***
						[6.902]	[7.474]
$\overline{R}^2$ in %	40.12	29.17	41.37	39.29	22.09	17.43	64.01
Nested $\overline{R}^2$ in %				52.68	47.05	46.40	
No. of observations	6,865	6,865	6,865	5,954	5,706	5,458	5,458

Notes. This table shows the results of regressing daily carry trade returns *CAR* on two liquidity risk factors (i.e., $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$) and other carry trade determinants (i.e., *PMC*, *IMB*, *UML*). *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), and *UML* is the unlevered minus levered factor that is a long-short strategy that exploits cross-sectional variation in countries' bank leverage (Fang 2018). The row titled "Nested $\overline{R}^2$ 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*, *IMB* or *UML*. The intercept (α) has been annualized (×252). The sample covers the period from February 21, 1995 to September 30, 2022. The numbers inside the brackets are the corresponding test statistics based on heteroskedasticity- and autocorrelation-consistent standard errors (Hodrick 1992) correcting for serial correlation up to 22 lags.

*, **, *** Significant correlations at the 90%, 95%, and 99% levels, respectively.

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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., $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$). In line with our conjecture, Table 8 documents that the carry trade tertile portfolios show a monotonically more negative 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. 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).[17] The fact that liquidity risk matters for carry trade returns is consistent with the idea of liquidity spirals (Brunnermeier and Pedersen 2008) and spillover effects (Mancini et al. 2013). In line with this intuition, we show that exposures to systematic (i.e., $SIR\text{-}\beta^2$) and currency-specific liquidity risk (i.e., $AIR\text{-}\beta^4$) are one of the main drivers of carry trade returns over a considerably long sample period of more than 25 years.

Given the success of our liquidity-based risk factors in explaining the carry trade, it is warranted to ask whether liquidity risk is also a relevant determinant of the latest advances in global asset pricing factors. Chernov et al. (2022) construct conditional projections of the SDF and show that this novel approach successfully prices individual exchange rates and a host of prominent currency trading strategies.[18] Maurer et al. (2021, 2022) build mean-variance optimised portfolios (*CSCAR*) that are capable of pricing a rich cross section of average currency returns. Orłowski et al. (2021) estimate a minimum-dispersion stochastic discount factor (*BCSDF*) under leverage constraints and find that their SDF delivers strong out-of-sample pricing performance. Table 9 shows that these global SDFs significantly load on both systematic and currency-specific liquidity risk. Specifically, systematic and currency-specific liquidity risk can explain up to 2%, 12%, and 8% of the variation in *UMVE*, *CSCAR*, and *BCSDF*, respectively. Overall, our results support the idea that the cross-sectional pricing abilities of these global SDFs might at least partially stem from their loading on liquidity risk.

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 (Lustig and Verdelhan 2007), we modify the original decomposition to accommodate traditional equally weighted long-short portfolios.[19] 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 (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 (Cochrane 2005, Bekaert and Hodrick 2014). Hence, the forward premium trade is not necessarily "dollar neutral" because the long and short leg may contain a different number of currencies.[20]

Table 10 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, $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$, respectively. 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. Specifically, the static and dynamic trade account for around 60% and 40% of total carry trade returns, respectively (Table 10). The liquidity factors ($SIR\text{-}\beta^2$ 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. Moreover, $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$ can explain the average excess returns to both the carry and forward premium trade, respectively. This is in line with existing papers on the economics of the carry trade (Fang 2018, Richmond 2019) that 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

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

	T1	*T2*	*T3*	*CAR*
Intercept (α) in %	−1.819	−0.529	0.049	1.867
	[1.333]	[0.373]	[0.030]	[1.527]
$SIR\text{-}\beta^2$	0.051	−0.160*	−0.496***	−0.547***
	[0.715]	[1.768]	[3.908]	[5.750]
$AIR\text{-}\beta^4$	0.055	−0.096	−0.141	−0.196***
	[0.709]	[1.277]	[1.533]	[2.705]
$\overline{R}^2$ in %	1.00	5.75	24.00	41.37
No. of observations	6,865	6,865	6,865	6,865

Notes. This table shows the results of regressing daily carry trade returns *CAR* and individual carry trade tertile portfolios (i.e., $T1$, $T2$, and $T3$) on two liquidity beta based risk factors (i.e., $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$). 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 annualized (×252). The sample covers the period from February 21, 1995, to September 30, 2022. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Hodrick 1992) correcting for serial correlation up to 22 lags.

*, **, *** Significant correlations at the 90%, 95%, and 99% levels, respectively.

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Table 9. Explanatory Regressions for Global SDFs

	UMVE			*CSCAR*			*BCSDF*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept (α) in %	19.655***	19.339***	19.357***	3.622	3.655	3.125	4.133***	4.067***	3.998***
	[9.045]	[9.310]	[9.276]	[0.696]	[0.749]	[0.616]	[3.722]	[3.608]	[3.598]
$SIR\text{-}\beta^2$	−0.147*		0.030	−1.134***		−0.839***	−0.199***		−0.115*
	[1.787]		[0.202]	[4.770]		[2.862]	[4.767]		[1.825]
$AIR\text{-}\beta^4$		−0.228***	−0.253		−1.118***	−0.423		−0.215***	−0.120
		[2.783]	[1.627]		[4.429]	[1.341]		[4.097]	[1.494]
$\overline{R}^2$ in %	0.92	2.19	1.92	11.22	9.13	11.52	7.67	7.59	8.42
No. of observations	331	331	331	331	331	331	308	308	308

Notes. This table shows the results of regressing monthly nonoverlapping returns to the unconditional mean-variance efficient portfolio (*UMVE*) in Chernov et al. (2022), the covariance and spread adjusted carry (*CSCAR*) in Maurer et al. (2021, 2022), and the benchmark currency stochastic discount factor (*BCSDF*) in Orłowski et al. (2021) on two liquidity beta based risk factors (i.e., $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$). The intercept (α) has been annualized (×252). The sample covers the period from February 21, 1995, to September 30, 2022. The numbers inside the brackets are the corresponding test statistics based on heteroskedasticity- and autocorrelation-consistent standard errors (Hodrick 1992) correcting for serial correlation up to one lag.
*, **, *** Significant correlations at the 90%, 95%, and 99% levels, respectively.

dynamic trade is a compensation for risks that are presumably unrelated to liquidity (risk).

Figure 3 illustrates how the correlation between *CAR* and $SIR\text{-}\beta^2$ or $AIR\text{-}\beta^4$ is driven by similarities in the portfolio weights associated with each currency pair. Specifically, the solid black and dashed gray 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 1,008-day moving averages, respectively. There are two observations that deserve to be highlighted: First, the average correlation coefficient over longer horizons (i.e., 1,008 days) is almost twice as large as over shorter ones (i.e., 22 days). This is consistent with the fact that the static trade is based on average interest rate differentials, whereas the dynamic trade sorts currency pairs based on recent interest rate differentials. Put differently, one can think of the moving window correlations based on 22 and 1,008 days as being a proxy for the portfolio 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., $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$). Moreover, the 22-day moving window estimates temporarily (e.g., in August 2009) even exceed the ones based on 1,008 days. These findings are also consistent with Mancini et al. (2013), who are the first showing that commonality in liquidity risk (i.e., $CIR\text{-}\beta^1$) and carry trade returns are strongly correlated during the short and unprecedented period of the global financial crisis.

Motivated by the observation in Figure 3 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 carry trade (*CAR*) or one of its two constituents, that is, the static (CAR^S) and the dynamic (CAR^D) trade on our two liquidity factors (i.e., $SIR\text{-}\beta^4$ and $AIR\text{-}\beta^4$) and also include a dummy variable that is equal to one in periods of markets stress and zero otherwise. Our *stress factor* is simply

Table 10. 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
	[1.527]	[0.323]	[0.456]	[1.928]	[0.671]
$SIR\text{-}\beta^2$	−0.547***	0.136	−0.475***	−0.072**	0.209**
	[5.750]	[1.461]	[5.837]	[2.081]	[2.117]
$AIR\text{-}\beta^4$	−0.196***	−0.072	−0.152**	−0.044	−0.028
	[2.705]	[0.945]	[2.437]	[1.179]	[0.394]
$\overline{R}^2$ in %	41.37	0.99	39.90	4.09	4.44
No. of observations	6,865	6,865	6,865	6,865	6,865
Mean in %	4.392***	0.255	2.619**	1.772**	−1.518
	[2.802]	[0.186]	[1.976]	[2.434]	[1.157]

Notes. 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, $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$. The last row reports the annualized mean excess returns of each carry trade component. The sample covers the period from February 21, 1995, to September 30, 2022. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Hodrick 1992) correcting for serial correlation up to 22 lags.
*, **, *** Significant correlations at the 90%, 95%, and 99% levels, respectively.

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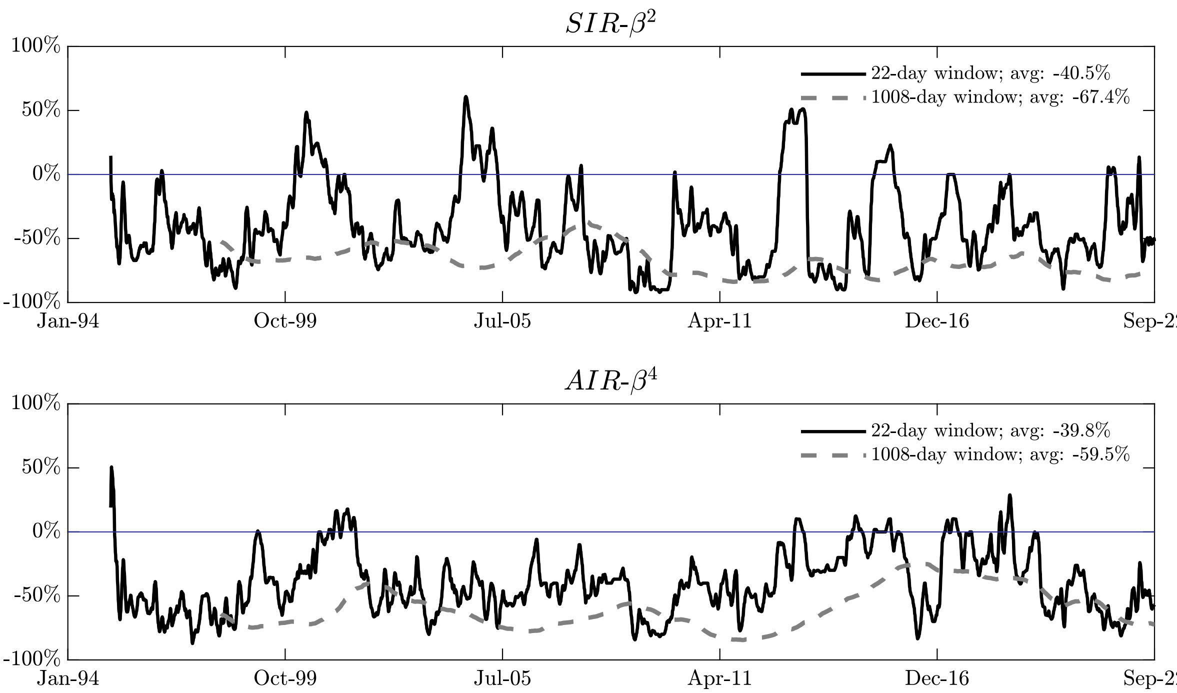
Figure 3. (Color online) Cross-Sectional Correlation of Moving Average Weights



Notes. 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 1,008-day (dashed gray line) moving averages, respectively. The sample covers the period from February 21, 1995, to September 30, 2022.

the average across the bond yield on AAA-rated U.S. corporate debt, the TED spread, and the VXY FX volatility index.[21] To be precise, we estimate regressions of the form

$$CAR = (\alpha_L + \alpha_H \cdot Z) + \delta DOL + (\gamma_{L,2} + \gamma_{H,2} \cdot Z)SIR\text{-}\beta^2 + (\gamma_{L,4} + \gamma_{H,4} \cdot Z)AIR\text{-}\beta^4 + \epsilon, \quad (15)$$

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 one if the stress factor is above its 75% percentile in period t. The other regressors are the dollar factor *DOL* and the systematic and currency-specific liquidity beta based risk factors (i.e., *SIR*-β^2 and *AIR*-β^4).

Table 11 reports the results from estimating Equation (15) for the carry trade (*CAR*) and its two components: the static (CAR^S) and the dynamic (CAR^D) trade. There are three key takeaways from these multiple regressions: First, the risk-adjusted excess returns (alphas) are only (marginally) significant for the dynamic trade in normal times and not at all during periods of market stress ($\alpha_L + \alpha_H$ is close to zero and statistically insignificant). Second, the slope coefficient of the carry trade on *SIR*-β^2 and *AIR*-β^4 is almost twice as large during periods of uncertainty as otherwise. This effect is primarily driven by the static rather than the dynamic part of the carry trade. We interpret this result as evidence that carry and liquidity risk premia are prone to covariation in bad times. Third, the correlation between the dynamic component of the carry trade and our two liquidity factors is independent of market stress. Put differently, the dynamic component of the carry trade is a truly orthogonal risk factor to *SIR*-β^2 and *AIR*-β^4, respectively.

To summarize, 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, the comovement in liquidity risk and carry trade returns stems from periods of high market stress and is confined to the static but not the dynamic component of the carry trade.

7. Conclusion

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 economically significant 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

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Table 11. Carry Trade and Liquidity Risk Premia in Distressed Markets

	Carry trade, CAR			Static trade, CAR^S			Dynamic trade, CAR^D		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept LOW (α_L) in %	3.189***	3.425***	2.864**	1.357	1.517	1.077	1.832**	1.908**	1.787**
	[2.576]	[2.709]	[2.370]	[1.300]	[1.452]	[1.043]	[2.408]	[2.393]	[2.299]
Intercept HIGH (α_H) in %	−1.465	−2.526	−1.261	−0.102	−0.926	0.120	−1.363	−1.600	−1.381
	[0.524]	[0.788]	[0.459]	[0.043]	[0.339]	[0.050]	[0.861]	[0.991]	[0.879]
DOL	0.159***	0.216***	0.153***	0.277***	0.325***	0.273***	−0.118***	−0.109***	−0.120***
	[3.145]	[3.195]	[3.055]	[6.637]	[5.750]	[6.597]	[3.461]	[3.165]	[3.483]
$SIR\text{-}\beta^2$ LOW	−0.516***		−0.397***	−0.415***		−0.312***	−0.101***		−0.085*
	[6.989]		[3.877]	[6.370]		[3.867]	[2.915]		[1.861]
$SIR\text{-}\beta^2$ HIGH–LOW	−0.254***		−0.270*	−0.199***		−0.258**	−0.055		−0.013
	[2.699]		[1.812]	[2.668]		[2.343]	[1.188]		[0.186]
$AIR\text{-}\beta^4$ LOW		−0.472***	−0.192**		−0.385***	−0.165**		−0.087**	−0.026
		[7.110]	[2.118]		[6.406]	[2.345]		[2.462]	[0.577]
$AIR\text{-}\beta^4$ HIGH–LOW		−0.265**	0.040		−0.180*	0.099		−0.085	−0.060
		[2.127]	[0.297]		[1.683]	[0.892]		[1.623]	[0.828]
$\overline{R}^2$ in %	43.37	33.88	44.41	47.04	38.15	47.86	8.00	7.07	8.41
No. of observations	6,756	6,756	6,756	6,756	6,756	6,756	6,756	6,756	6,756

Notes. This table reports the results from estimating a regression of the form $CAR^* = (\alpha_L + \alpha_H \cdot Z) + \delta DOL + (\gamma_{L,2} + \gamma_{H,2} \cdot Z)SIR\text{-}\beta^2 + (\gamma_{L,4} + \gamma_{H,4} \cdot Z)AIR\text{-}\beta^4 + \epsilon$, where the dependent variable CAR^* is either the carry trade (CAR) or one of its two components, that is, the static (CAR^S) or the dynamic (CAR^D) trade and the regressors are the dollar factor DOL and our liquidity factors $SIR\text{-}\beta^2$ and $AIR\text{-}\beta^4$, respectively. In addition, we include interaction terms based on a dummy Z that is equal to 1 if the stress factor is above its 75% percentile 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. We standardize each time series by first subtracting the mean and then scaling by the standard deviation. The intercept (α) has been annualized (×252). The sample covers the period from February 21, 1995, to September 30, 2022. The numbers inside the brackets are the corresponding test statistics based on robust standard errors (Hodrick 1992) correcting for serial correlation up to 22 lags.

*, **, *** Significant correlations at the 90%, 95%, and 99% levels, respectively.

especially pronounced during the period after the global financial crisis, which is an episode characterized by a tightening of interest rate differentials across countries. Third, 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. Although 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 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 (Bekaert and Panayotov 2019). In particular, it would be interesting to contrast approaches with different samples of currencies, weighting schemes, and distinguishing whether the long and short sides of the trade are equal.

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Endnotes
[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 (Acharya and Pedersen 2005), whereas the latter matters because investors are concerned about returns net of transaction costs (Amihud and Mendelson 1986).

[3] Some additional sources of risk include innovations in currency volatility (Menkhoff et al. 2012a), skewness (Rafferty 2012), correlation (Mueller et al. 2017), and commodity imports/exports (Ready et al. 2017). Hu et al. (2013) show that the treasury noise measure is a priced risk factor in the cross section of hedge fund returns and

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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 We are especially grateful to Thomas Maurer and Valeri Sokolovski for generously providing access to their data and replication code.

5 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.

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-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 As a robustness check we have also orthogonalized systematic illiquidity against the bond yield on AAA-rated U.S. 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.

9 Our results are very similar when we rebalance our portfolios once every month using monthly nonoverlapping return data. 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 et al. (2017).

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

11 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 U.S. dollar.

12 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.

13 The annualized mean excess return of the carry trade factor is 1.4 percentage points lower after January 2009 relative to the precrisis period.

14 We get both quantitatively and qualitatively similar results when comparing nonnested models based on the approach in Barillas et al. (2019).

15 We thank Xiang Fang for generously sharing the intermediary leverage factor with us.

16 As a robustness check, we have also used the *IMX* factor (Ready et al. 2017) as a dependent variable in Equation (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 thank Nick Roussanov for generously providing access to their data.

17 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.

18 We apply the methodology in Chernov et al. (2022) to daily 22-day returns by (i) recursively estimating the prediction equations of currency excess returns and (ii) computing a moving 22-day window of the covariance matrix combined with shrinkage toward constant correlation and using the same "updating" as in the RiskMetrics approach. The *UMVE* portfolio is scaled to have the same unconditional variance as the *DOL* factor. The *UMVE* is not a traditional long-short portfolio because the sum of absolute portfolio weights is time varying. Moreover, our (pre-)sample starts in 1984, and we exclude the *HKD* from the cross section of currencies.

19 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 January 3, 1994, to February 20, 1995, or when data are missing (i.e., for the USDILS and USDMXP) on the first few available data points.

20 The weights for the forward premium trade are given by the sum of the weights on the dollar (carry) trade (Lustig et al. 2014) plus the weights on the dynamic trade.

21 We standardize each time series by first subtracting the mean and then scaling by the standard deviation.

References

Abankwa S, Blenman LP (2021) Measuring liquidity risk effects on carry trades across currencies and regimes. *J. Multinational Financial Management* 60:100683.

Acharya VV, Pedersen LH (2005) Asset pricing with liquidity risk. *J. Financial Econom.* 77(2):375–410.

Admati AR, Pfleiderer P (1988) A theory of intraday patterns: Volume and price variability. *Rev. Financial Stud.* 1(1):3–40.

Ahmed S, Valente G (2015) Understanding the price of volatility risk in carry trades. *J. Bank. Finance* 57:118–129.

Aloosh A, Bekaert G (2022) Currency factors. *Management Sci.* 68(6):4042–4064.

Amihud Y (2002) Illiquidity and stock returns: Cross-section and time-series effects. *J. Financial Marketing* 5(1):31–56.

Amihud Y, Mendelson H (1986) Asset pricing and the bid-ask spread. *J. Financial Econom.* 17(2):223–249.

Ang A, Hodrick RJ, Xing Y, Zhang X (2006) The cross-section of volatility and expected returns. *J. Finance* 61(1):259–299.

Atanasov V, Nitschka T (2014) Currency excess returns and global downside market risk. *J. Internat. Money Finance* 47: 268–285.

Bakshi G, Panayotov G (2013) Predictability of currency carry trades and asset pricing implications. *J. Financial Econom.* 110(1): 139–163.

Banti C, Phylaktis K, Sarno L (2012) Global liquidity risk in the foreign exchange market. *J. Internat. Money Finance* 31(2): 267–291.

Barillas F, Shanken J (2016) Which alpha? *Rev. Financial Stud.* 30(4):1316–1338.

Barillas F, Kan R, Robotti C, Shanken J (2019) Model comparison with sharpe ratios. *J. Financial Quant. Anal.* 55(6):1840–1874.

Bekaert G, Hodrick RJ (2014) *International Financial Management* (Pearson Education Limited, Essex, UK).

Bekaert G, Panayotov G (2019) Good carry, bad carry. *J. Financial Quant. Anal.* 55(4):1063–1094.

Brunnermeier MK, Pedersen LH (2008) Market liquidity and funding liquidity. *Rev. Financial Stud.* 22(6):2201–2238.

Brunnermeier MK, Nagel S, Pedersen LH (2008) Carry trades and currency crashes. *NBER Macroeconom. Annu.* 23(1):313–348.

Burnside C (2009) Comment on "Carry trades and currency crashes". *NBER Macroeconom. Annu.* 23(1):349–359.

Burnside C, Eichenbaum M, Rebelo S (2011) Carry trade and momentum in currency markets. *Annu. Rev. Financial Econom.* 3(1):511–535.

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Byrne JP, Ibrahim BM, Sakemoto R (2018) Common information in carry trade risk factors. *J. Internat. Financial Marketing Inst. Money* 52:37–47.

Chernov M, Dahlquist M, Lochstoer L (2022) Pricing currency risks. *J. Finance* 78(2):693–730.

Chordia T, Roll R, Subrahmanyam A (2000) Commonality in liquidity. *J. Financial Econom.* 56(1):3–28.

Christiansen C, Ranaldo A, Söderlind P (2011) The time-varying systematic risk of carry trade strategies. *J. Financial Quant. Anal.* 46(04):1107–1125.

Cochrane JH (1996) A cross-sectional test of an investment-based asset pricing model. *J. Political Econom.* 104(3):572–621.

Cochrane JH (2005) *Asset Pricing* (Princeton University Press, Princeton, NJ).

Colacito R, Riddiough SJ, Sarno L (2020) Business cycles and currency returns. *J. Financial Econom.* 137(3):659–678.

Copeland L, Lu W (2016) Dodging the steamroller: Fundamentals vs. the carry trade. *J. Internat. Financial Marketing Inst. Money* 42:115–131.

Corwin SA, Schultz P (2012) A simple way to estimate bid-ask spreads from daily high and low prices. *J. Finance* 67(2):719–760.

Della Corte P, Riddiough SJ, Sarno L (2016) Currency premia and global imbalances. *Rev. Financial Stud.* 29(8):2161–2193.

Dobrynskaya V (2014) Downside market risk of carry trades. *Rev. Finance* 18(5):1885–1913.

Fang X (2018) Intermediary leverage and currency risk premium. Preprint, submitted December 9, https://dx.doi.org/10.2139/ssrn.3290317.

Hameed A, Kang W, Viswanathan S (2010) Stock market declines and liquidity. *J. Finance* 65(1):257–293.

Hansen LP (1982) Large sample properties of generalized method of moments estimators. *Econometrica* 50(4):1029.

Harvey CR, Liu Y (2021) Lucky factors. *J. Financial Econom.* 141(2):413–435.

Hassan TA, Mano RC (2018) Forward and spot exchange rates in a multi-currency world. *Quart. J. Econom.* 134(1):397–450.

Hodrick RJ (1992) Dividend yields and expected stock returns: Alternative procedures for inference and measurement. *Rev. Financial Stud.* 5(3):357–386.

Hu GX, Pan J, Wang J (2013) Noise as information for illiquidity. *J. Finance* 68(6):2341–2382.

Jagannathan R, Wang Z (2002) Empirical evaluation of asset-pricing models: A comparison of the SDF and beta methods. *J. Finance* 57(5):2337–2367.

Jeanneret A, Sokolovski V (2019) Commodity prices and currencies. Preprint, submitted September 14, https://dx.doi.org/10.2139/ssrn.4564504.

Karnaukh N, Ranaldo A, Söderlind P (2015) Understanding FX liquidity. *Rev. Financial Stud.* 28(11):3073–3108.

Korsaye SA, Trojani F, Vedolin A (2023) The global factor structure of exchange rates. *J. Financial Econom.* 148(1):21–46.

Lettau M, Maggiori M, Weber M (2014) Conditional risk premia in currency markets and other asset classes. *J. Financial Econom.* 114(2):197–225.

Lustig H, Verdelhan A (2007) The cross section of foreign currency risk premia and consumption growth risk. *Amer. Econom. Rev.* 97(1):89–117.

Lustig H, Roussanov N, Verdelhan A (2011) Common risk factors in currency markets. *Rev. Financial Stud.* 24(11):3731–3777.

Lustig H, Roussanov N, Verdelhan A (2014) Countercyclical currency risk premia. *J. Financial Econom.* 111(3):527–553.

Mancini L, Ranaldo A, Wrampelmeyer J (2013) Liquidity in the foreign exchange market: Measurement, commonality, and risk premiums. *J. Finance* 68(5):1805–1841.

Markowitz H (1952) Portfolio selection. *J. Finance* 7(1):77–91.

Maurer TA, Pezzo L, Taylor MP (2024) Importance of transaction costs for asset allocations in FX markets. *J. Financial Econom*. Forthcoming.

Maurer T, Tô T-D, Tran N-K (2021) Pricing implications of covariances and spreads in currency markets. *Rev. Asset Pricing Stud.* 12(1):336–388.

Maurer TA, Tô T-D, Tran N-K (2022) Market timing and predictability in FX markets. *Rev. Finance* 27(1):223–246.

Menkhoff L, Sarno L, Schmeling M, Schrimpf A (2012a) Carry trades and global foreign exchange volatility. *J. Finance* 67(2):681–718.

Menkhoff L, Sarno L, Schmeling M, Schrimpf A (2012b) Currency momentum strategies. *J. Financial Econom.* 106(3):660–684.

Menkhoff L, Sarno L, Schmeling M, Schrimpf A (2017) Currency value. *Rev. Financial Stud.* 30(2):416–441.

Mueller P, Stathopoulos A, Vedolin A (2017) International correlation risk. *J. Financial Econom.* 126(2):270–299.

Orlov V (2016) Currency momentum, carry trade, and market illiquidity. *J. Bank. Finance* 67:1–11.

Orłowski P, Sokolovski V, Sverdrup E (2021) Benchmark currency stochastic discount factors. Preprint, submitted October 19, https://dx.doi.org/10.2139/ssrn.3945075.

Pasquariello P (2014) Financial market dislocations. *Rev. Financial Stud.* 27(6):1868–1914.

Pástor Ľ, Stambaugh RF (2003) Liquidity risk and expected stock returns. *J. Political Econom.* 111(3):642–685.

Rafferty B (2012) Currency returns, skewness and crash risk. Preprint, submitted March 16, https://dx.doi.org/10.2139/ssrn.2022920.

Ready R, Roussanov N, Ward C (2017) Commodity trade and the carry trade: A tale of two countries. *J. Finance* 72(6):2629–2684.

Richmond RJ (2019) Trade network centrality and currency risk premia. *J. Finance* 74(3):1315–1361.

Sandulescu M, Trojani F, Vedolin A (2020) Model-free international stochastic discount factors. *J. Finance* 76(2):935–976.

Verdelhan A (2017) The share of systematic variation in bilateral exchange rates. *J. Finance* 73(1):375–418.