Importance of Transaction Costs for Asset Allocation in Foreign Exchange Markets*

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Abstract

Transaction costs have a first-order effect on the performance of currency portfolios. Proportional costs based on quoted bid-ask spread are relatively small, but when a fund is large, costs due to the trading volume price impact are sizable and quickly erode returns, leaving many popular strategies unprofitable. A mean-variance-transaction-cost optimized approach (MVTC) that accounts for costs in the optimization efficiently tackles the problem with only relatively minor negative implications on before-cost profitability. MVTC is robust even when the price impact of trading is severe. Finally, we introduce an accurate extrapolation approach to expand the sample of the realized Amihud measure of Ranaldo and Santucci de Magistris (2022) from 12 to 26 currencies and from 2012 back in time to 1986.

JEL-Classification: F31, G11, G15.
Keywords: Transaction Costs, Price Impact, realized Amihud, Mean-Variance, Optimization, Asset Allocation, Foreign Exchange, Carry Trade.

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1 Introduction

We analyze the importance of transaction costs for investors in foreign exchange (FX) markets. The contribution of our analysis is threefold. We first document that the trading volume price impact can lead to significant transaction costs with first-order negative implications on the profitability of currency trading strategies despite the relatively high trading volume and liquidity in FX markets. Most importantly, while proportional costs based on quoted bid-ask spreads are relatively small, the performance of many popular strategies is sensitive to the price impact of trading. For some strategies – such as the currency carry trade, momentum, and mean-variance optimized currency portfolios – costs due to the trading volume price impact quickly erode returns, rendering the strategies unprofitable.

For instance, the monthly rebalancing of a simple carry trade strategy implies a relatively large monthly turnover of 57% of its notional value. When a fund's initial assets under management (AUM) reaches USD 100 million or even 1 billion, then trade orders on average account for 3% or even 10% of the daily trading volume. This implies that sell and buy orders of such a fund significantly move bid and ask quotes, and in turn, costs due to the price impact are large. The carry trade strategy provides a Sharpe ratio of 0.79 before accounting for costs and 0.74 after deducting proportional costs, which is consistent with the literature. In contrast, for a fund with an initial AUM of USD 80 million, the costs due to the trading volume price impact reduce the Sharpe ratio to 0.5, which is comparable to the performance of the US stock market. Moreover, when the AUM reaches USD 660 million or more, costs due to the price impact dominate the average returns and the strategy is unprofitable.

It is an important contribution to document the sensitivity of currency strategies to the price impact of trading. So far the literature on FX trading strategies and international portfolio management has only considered the relatively small proportional trading costs captured by quoted bid-ask spreads. The main insight of the literature is that popular strategies are robust to proportional costs as illustrated in the previous paragraph. Our finding provides a new perspective that the trading volume price impact poses a severe challenge for investors, and popular strategies even turn unprofitable if a fund reaches a certain size. In addition, our results provide a natural motivation to explain illiquidity premia in FX markets as documented by, for instance, Mancini et al. (2013) and Soderlind and Somogyi (2023). That is, investors care about FX liquidity and dislike to be exposed to liquidity risk since the price impact of trading has a first-order quantitative negative effect on the profitability of currency strategies.

Second, we provide a mean-variance-transaction-cost optimization approach ($MVTC$) that efficiently mitigates trading costs with only relatively minor negative effects on the before-cost optimality. MVTC builds on the mean-variance optimized currency portfolio of Maurer et al. (2023) and uses the framework of Dybvig and Pezzo (2020) to tackle costs. The optimization ensures that the portfolio stays "close enough" to the optimal before-cost balance between expected return and risk, while reducing trading activity (especially in less liquid and more expensive currencies) and thus minimizing costs. Our cost-optimized portfolio performs well out-of-sample. It is robust to a price impact of trading and remains profitable even under severe conditions. Specifically, even when the initial AUM of a fund reaches USD 1 billion the after-cost Sharpe ratio is still 0.75, which is comparable with the before-cost Sharpe ratio of the simple carry trade (0.79). Moreover, its capacity is large. It outperforms the US stock market as long as the initial AUM does not exceed USD 6 billion, and its after-cost average returns are positive even when the AUM of a fund exceeds USD 1 trillion.

Intuitively, we can understand our findings using an analogy from basic portfolio diversification. Idiosyncratic risks can be a first-order component of an asset's volatility. Hence, it is important for investors to tackle idiosyncratic risks and construct a diversified portfolio. Once idiosyncratic risks are diversified away, they have no (or only a negligible) effect on the performance. Similarly, we show that transaction costs (and specifically the price impact of trading) can significantly affect the profitability of currency trading strategies. Accordingly, it is important for investors to optimally tackle transaction costs in the portfolio construction. Once investors adopt efficient cost-mitigation techniques (following $MVTC$), trading costs have a small effect on performance.

Third, we contribute to the FX market literature on illiquidity by expanding the sample of the realized Amihud illiquidity measure of Ranaldo and Santucci de Magistris (2022) to a large cross-section of currencies against the USD (26 instead of 12) and a long time-series (starting in 1986 instead of 2012).[1] Ranaldo and Santucci de Magistris (2022) and Lacava et al. (2023) show that this measure is accurate and robust, and as such arguably more suitable for our analysis than alternatives in the literature. The daily realized Amihud measure is the ratio of the daily exchange rate growth variation and the trading volume. Olsen intraday exchange rate quotes are available for a large panel of currencies, and it is straightforward to estimate daily exchange rate growth variations. In contrast, volume data from Continuous Linked Settlement Group (CLS) is available for 12 currencies against the USD and starting in 2012. Although these currencies represent a substantial share of the global trading volume, we propose novel extrapolations of the trading volume data to further expand this panel to a larger cross-section of currencies and back to 1986. Specifically, we show that trading volume can be accurately extrapolated using the proportional bid-ask spread as a conditioning variable.[2] The use of the bid-ask spread as a conditioning variable is consistent with the finding of Karnaukh et al. (2015) that the bid-ask spread is a useful proxy for liquidity in Electronic Broking Services (EBS) data.

Our paper is related to a growing literature on FX market illiquidity that uses CLS volume and Olsen intrady price data. Fischer and Ranaldo (2011) show that FX trading volume increases after FOMC meetings. Ranaldo and Somogyi (2021) estimate a VAR model similar to the stock market model of Hasbrouck (1991a,b) and find substantial information asymmetry across participants, time and currency pairs, and they estimate a sizeable asymmetric information risk premium. Hasbrouck and Levich (2021) document that more central agents trade at better conditions (centrality premium), and provide evidence that this is a compensation for providing liquidity in the market. Hasbrouck and Levich (2019) compute the Amihud (2002) illiquidity measure and show that it is closely related to price impact estimates based on high-frequency EBS data. Ranaldo and Santucci de Magistris (2022) introduce the *realized* Amihud illiquidity measure – a refinement of the Amihud (2002) measure. They find that this novel illiquidity measure is decreasing in market depth, and increasing

[1] We make our estimations/extrapolations available on our websites.

[2] In the main text of the paper in section 2.4.1 we only show the extrapolation in the cross-section. Section B.3 in the Internet Appendix provides details about the extrapolation in the panel (cross-section and time-series) using data from CLS or the BIS Triennial Surveys.

in bid-ask spreads, money market stress, uncertainty, risk aversion, and price inefficiencies. Lacava et al. (2023) further provide an in-depth theoretical discussion of the realized Amihud measure, and demonstrate its accuracy and robustness. Cespa et al. (2022) examine the information content of FX volume and find a stronger daily return reversal for currency pairs with abnormally low volume. Somogyi (2022) shows that trading against the USD is generally cheaper than other bilateral trades and argues that part of the USD dominance in terms of order volume can be attributed to the cost advantage of trading against the USD. Roussanov and Wang (2023) document that FX dealers trade without delay on monetary policy announcements. In contrast, funds and non-bank financials are slower and only react 3 to 5 days later. This evidence provides a channel for the delayed adjustment of exchange rates to monetary news. Finally, using CLS data on FX forwards Bräuer and Hau (2023) show that FX hedging demands have a significant impact on exchange rates.

Another strand of the literature uses datasets other than the volume data from CLS. Evans and Lyons (2002, 2008) use interdealer order flow data from Reuters Dealing 2000-1 and show that order flow is a strong determinant of exchange rates, and even more so after the release of macro news. Froot and Ramadorai (2005) estimate a VAR model to disentangle intrinsic-value from expected return shocks, and show that institutional-investor FX flows only correlate with expected return shocks. Hau et al. (2010) document that a change in the MSCI Global Equity Index has triggered large uninformed order flows in FX markets, which in turn has a significant price impact on exchange rates. Using EBS data, Karnaukh et al. (2015) show that FX market illiquidity correlates with funding constraints and global risk. Mancini et al. (2013) (using EBS data) and Soderlind and Somogyi (2023) (using estimates of effective bid-ask spreads) document that illiquidity in FX markets is priced in the cross-section of returns. Breedon et al. (2016) use data from Reuters and EBS and show that order flows have a significant effect on FX risk premia. Using disaggregated Norwegian central bank data Evans and Rime (2016) show that order flows predict exchange rate fluctuations over relatively long horizons, and most of the predictability is attributed to the time-variation in the risk premium. Menkhoff et al. (2016) use end-user data from a top FX dealer and document that orders of demand-side investment managers forecast currency returns, while corporates and individual investors appear uninformed. Krohn and Sushko

(2022) document a tight link between FX spot and swap market liquidity, and further show that banks' funding liquidity has a significant impact on FX market liquidity. Hau et al. (2021) use EU regulatory data and find that there is price discrimination across clients in forward FX markets, i.e., dealers charge significantly smaller spreads to more sophisticated clients. Camanho et al. (2022) use fund-level holdings data and show that funds rebalance their international allocation in response to realized returns with the aim to maintain their original risk exposure. In turn, the flows due to rebalancing have a significant impact on exchange rates. Using data from the BIS Triennial Survey Aloosh and Bekaert (2022) find that aggreagte trading volume explains a significant part of the common variation of exchange rate changes. Korsaye et al. (2023) show that trading frictions (proxied by bid-ask spreads) are important in constructing robust global factors that correctly price international asset returns. Bechtel et al. (2023) propose and test a new channel that connects liquidity risk and interest rates in short-term funding markets. Finally, Krohn et al. (2023) show that the USD tends to appreciate in the run-up to FX fixes and depreciates afterwards, leading to a W-shaped intraday return pattern.

While this literature makes an effort to understand liquidity in FX markets,[3] we are agnostic about the determinants of liquidity. We use the realized Amihud measure of Ranaldo and Santucci de Magistris (2022) for its simplicity and robustness to quantify the price impact of trading, and then analyze its implications on the profitability of popular FX trading strategies.

Finally, our paper is related to the literature on portfolio optimization in the presence of transaction costs. For brevity, we refer to Dybvig and Pezzo (2020) for a review of this literature.

The rest of the paper is structured as follows. Section 2 provides details about the data and the investment opportunity set in FX markets, including the specification of transaction costs. In section 3, we briefly describe seven popular trading strategies from the literature, and introduce our novel mean-variance-transaction-cost optimized strategy $MVTC$. Section 4 provides the main results, and documents that the price impact has first-order effects on

[3]That is, quantifying the impact of order flows on exchange rates, measuring illiquidity, understanding the heterogeneity of market participants, risk sharing, and the role of dealers, etc.

the profitability of most trading strategies. In section 5, we outline the robustness checks detailed in the Internet Appendix B. Section 6 concludes. Additional results, robustness checks, details about the theory of $MVTC$, and details about the data are in the Internet Appendix.

2 Investment Opportunity Set in FX Markets

2.1 Data

We take the view of a US investor. The short-term bond denominated in the U.S. dollar (USD) is the risk-free asset. For the universe of risky assets, we use currency returns for N_t currencies against the USD. Depending on data availability at time t, the number of currencies N_t changes through time.

Following the literature, we include the currencies of 26 countries in our analysis. Of these, 13 belong to the set of countries classified as developed in Lustig et al. (2011), while the remaining 13 are classified as emerging. The 13 developed countries and currency codes are: Australia (AUD), Canada (CAD), the Euro Area (EUR), France (FRF), Germany (DEM), Italy (ITL), Japan (JPY), Netherlands (NLG), New Zealand (NZD), Norway (NOK), Sweden (SEK), Switzerland (CHF), United Kingdom(GBP). The 13 emerging countries and currency codes are: Brazil (BRL), Czech Republic (CZK), Greece (GRD), Hungary (HUF), Ireland (IEP), Mexico (MXN), Poland (PLN), Portugal (PTE), Singapore (SGD), South Africa (ZAR), South Korea (KRW), Spain (ESP), and Taiwan (TWD). We provide details about data sources and filters in Internet Appendix D.

We obtain daily bid, ask and mid quotes for spot and forward exchange rates with 1- and 3-month maturities from Barclays Bank International and Reuters (B&R) via Datastream. In the following, we focus on forwards with 1-month maturity but all computations are analogous for 3-month contracts. We denote by $X_{i,t}^{BR}$ and $F_{i,t}^{BR}$ the spot and forward exchange rates from B&R as USD per unit of currency i on day t. We add superscripts b and a to indicate bid and ask quotes. We also collect hourly spot exchange rates from Olsen, and denote by $X_{i,t,\tau}^{O}$ the USD per unit of currency i at hour τ on day t. We have Olsen spot quotes against the USD from February 1986 to January 2024, while the B&R data for spot and forwards against the USD is available starting in October 1983 and ending in January 2024. Our analysis is conducted over the sample covered by both sources, i.e., starting in February 1986 and ending in January 2024.

Spot quotes from Olsen are more comprehensive in terms of market coverage, and these data are usually regarded as more reliable and of superior quality compared to the B&R data. Comparing daily spot quotes of the two datasets, we find that mid-prices are the same

$$X_{i,t} = X_{i,t}^{BR} \approx X_{i,t}^{O}.$$

However, proportional bid-ask spreads are generally narrower in the Olsen data. This is consistent with the literature suggesting that bid-ask spreads in the B&R data are too wide (Lyons, 2001). Acknowledging this feature of the data we reconstruct the time series of spot bid and ask quotes as follows. For currency i against the USD we compute a daily estimate for the proportional bid-ask spread of Olsen by averaging the hourly spreads within day t, and denote it as $PBA_{i,t}^{S,O} = \frac{1}{H_t}\sum_\tau \ln\left(\frac{X_{i,t,\tau}^{a,O}}{X_{i,t,\tau}^{b,O}}\right)$, where H_t is the number of trading hours on day t. For the B&R data we use the daily bid and ask spot quotes to compute the spread $PBA_{i,t}^{S,BR} = \ln\left(\frac{X_{i,t}^{a,BR}}{X_{i,t}^{b,BR}}\right)$. We then define the adjusted daily spread as the minimum between the daily spreads of Olsen and B&R, and construct the corresponding adjusted daily ask and bid spot prices,

$$PBA_{i,t}^{S} = \min\left(PBA_{i,t}^{S,O}, PBA_{i,t}^{S,BR}\right), \tag{1}$$

$$X_{i,t}^{a} = X_{i,t}\exp\left\{0.5PBA_{i,t}^{S}\right\}, \quad X_{i,t}^{b} = X_{i,t}\exp\left\{-0.5PBA_{i,t}^{S}\right\},$$

Table 1 provides a summary of the spot quotes. The first three columns with the heading 'All Days' consider our full sample that combines data from B&R and Olsen, while the last five columns with the heading 'Days with B&R Data Coverage' focus on the sub-sample of days for which B&R data is available. The columns indicated by 'N Obs' reports the number of days for which we can construct $PBA_{i,t}^{S}$. For 19 out of our 26 currencies B&R provides bid and ask quotes for more than 98% of the days that are covered in our full sample. That is, Olsen quotes only fill small gaps. For KRW, MXN, TWD and ZAR B&R is missing roughly 10% of the data points in our full sample, and for ESP, GRD and PTE the B&R coverage is only 41%, 50% respectively 56% of the full sample. In these cases Olsen provides data to significantly increase our sample.

We further report in Table 1 the time-series average of the adjusted bid-ask spread $\overline{PBA}_i^S = \frac{1}{T}\sum_t PBA_{i,t}^S$ for our full sample (column 2) and the sub-sample of days with B&R coverage (column 6). For the latter sample we also compute the average bid-ask spread based on only B&R data, $\overline{PBA}_i^{S,BR} = \frac{1}{T}\sum_t PBA_{i,t}^{S,BR}$. B&R spreads $\overline{PBA}_i^{S,BR}$ are on average 48% larger than our adjusted spreads $\overline{PBA}_i^S$. Interestingly, the problem of too wide spreads in the B&R data appears worse for developed markets and more liquid currencies. For developed currencies B&R spreads $\overline{PBA}_i^{S,BR}$ are on average 67% wider compared to our adjusted spreads $\overline{PBA}_i^S$. In comparison, $\overline{PBA}_i^{S,BR}$ is on average only 30% larger than $\overline{PBA}_i^S$ for our set of emerging currencies. Moreover, for EUR, JPY, and GBP, which are the three most liquid currencies (i.e., high trading volume and low bid-ask spreads), we observe a $\overline{PBA}_i^{S,BR}$ that is 150%, 91%, respectively 54% larger than $\overline{PBA}_i^S$. Meanwhile, for CSK, HUF and PNL, which are among the most illiquid currencies in our sample (i.e., low trading volume and high bid-ask spreads), $\overline{PBA}_i^{S,BR}$ is only 11%, 5% respectively 14% larger than $\overline{PBA}_i^S$. Finally, the cross-sectional correlation between $\frac{\overline{PBA}_i^{S,BR}}{\overline{PBA}_i^S}$ and $\overline{PBA}_i^S$ is -.34, or similarly the correlation between $\frac{\overline{PBA}_i^{S,BR}}{\overline{PBA}_i^S}$ and the average daily trading volume of currency i is 0.68. Both correlations corroborate the finding that the issue of too wide B&R spreads is more prominent for more liquid currencies.

Forward quotes are only available from B&R, and therefore we can only compute the daily $PBA_{i,t}^{F,BR} = \ln\left(\frac{F_{i,t}^{a,BR}}{F_{i,t}^{b,BR}}\right)$ from daily bid and ask forward quotes. Accordingly, we cannot use the same procedure as for spots to address the concern that B&R spreads for forwards are too wide. Instead, we construct an adjusted bid-ask spread for forwards by re-scaling $PBA_{i,t}^{F,BR}$ by the average ratio of our adjusted spot spreads $PBA_{i,t}^S$ and the B&R spot spreads $PBA_{i,t}^{S,BR}$,

$$PBA_{i,t}^F = PBA_{i,t}^{F,BR}\frac{1}{T}\sum_t \frac{PBA_{i,t}^S}{PBA_{i,t}^{S,BR}}.$$

The assumption is that the issue of too wide B&R spreads is roughly the same across spots and forwards. We then define the daily mid, ask and bid forward prices:

$$F_{i,t} = F_{i,t}^{BR}, \quad F_{i,t}^{a} = F_{i,t} \exp\left\{0.5PBA_{i,t}^{F}\right\}, \quad F_{i,t}^{b} = F_{i,t} \exp\left\{-0.5PBA_{i,t}^{F}\right\}.$$

In addition to the price data we use quantity data to estimate the price impact of large trade orders on the bid and ask quotes (details on the price impact measure are in section 2.4). We obtain spot order flows from CLS via Quandl.com. Flows are defined as buy or sell orders of foreign currency against the USD, and they are measured in USD. The order flow data span the period of September 2012 until September 2021, and include the following currencies: AUD, CAD, EUR, JPY, MXN, NZD, NOK, SGD, ZAR, SEK, CHF, GBP.[4] CLS provides data across four categories: corporates, funds, non-bank financials, and total buy-side. We follow Ranaldo and Somogyi (2021) to identify banks acting as price takers by subtracting signed flows of corporates, funds, and non-bank financials from the total buy-side. Finally, on day t we aggregate the orders for currency i across all participants (i.e., corporates, funds, non-bank financials, and banks acting as price takers) to obtain the total spot trading volume $v_{i,t}^{S}$.

2.2 Monthly Returns and Trading Positions

Following the literature, we define the 1-month realized currency return as the return of an uncovered long position in the 1-month forward exchange rate contract of currency i against the USD (denominated in USD),

$$r_{i,t+1} \equiv \ln\left(\frac{X_{i,t+1}}{F_{i,t}}\right) = fd_{i,t} + \Delta x_{i,t+1},$$

where $fd_{i,t} = \ln\left(\frac{X_{i,t}}{F_{i,t}}\right)$ is the forward discount which is known at time t, and $\Delta x_{i,t+1} = \ln\left(\frac{X_{i,t+1}}{X_{i,t}}\right)$ is the spot exchange rate growth which is realized at time $t+1$. Note that $r_{i,t+1}$ is an excess return over the risk-free rate in USD. We use the last mid-price quotes of the

[4]Following Ranaldo and Somogyi (2021) we exclude HUF as its coverage starts only on November 7, 2015. We further exclude KRW due to the limited number of trades per price taker category.

month to compute monthly returns before accounting for trading costs.

For trading strategy j, currency i and time t we denote by $\theta^{\mathbf{0,j}}_{\mathbf{i,t}}$ the initial position before trading takes place, and by $\theta^{\mathbf{j}}_{\mathbf{i,t}}$ the portfolio weight after trading. We define θ as a fraction of a fund's assets under management (AUM), or more generally, a fraction of invested wealth. We measure the AUM or wealth in USD and denote it by W_t. Then, the trading activity in currency i is given by

$$\theta^{\mathbf{j}}_{\mathbf{i,t}} - \theta^{\mathbf{0,j}}_{\mathbf{i,t}} = \mathbf{\Delta}^{\mathbf{P+}}_{\mathbf{i,t}} + \mathbf{\Delta}^{\mathbf{P-}}_{\mathbf{i,t}} - \mathbf{\Delta}^{\mathbf{S-}}_{\mathbf{i,t}} - \mathbf{\Delta}^{\mathbf{S+}}_{\mathbf{i,t}}, \text{ with} \tag{2}$$

- $\mathbf{\Delta}^{\mathbf{P+}}_{\mathbf{i,t}} = \max\left\{\theta^{\mathbf{j}}_{\mathbf{i,t}} - \max(\theta^{\mathbf{0,j}}_{\mathbf{i,t}}, 0), 0\right\}$: opening new long forward positions,
- $\mathbf{\Delta}^{\mathbf{P-}}_{\mathbf{i,t}} = \max\left\{\min(\theta^{\mathbf{j}}_{\mathbf{i,t}}, 0) - \theta^{\mathbf{0,j}}_{\mathbf{i,t}}, 0\right\}$: closing existing short forward positions,
- $\mathbf{\Delta}^{\mathbf{S-}}_{\mathbf{i,t}} = \max\left\{\min(\theta^{\mathbf{0,j}}_{\mathbf{i,t}}, 0) - \theta^{\mathbf{j}}_{\mathbf{i,t}}, 0\right\}$: opening new short forward positions,
- $\mathbf{\Delta}^{\mathbf{S+}}_{\mathbf{i,t}} = \max\left\{\theta^{\mathbf{0,j}}_{\mathbf{i,t}} - \max(\theta^{\mathbf{j}}_{\mathbf{i,t}}, 0), 0\right\}$: closing existing long forward positions.

Similar to θ, $\mathbf{\Delta}$ are fractions of W_t. To obtain the USD amount traded we multiply $\mathbf{\Delta}$ by W_t.

We consider two types of transaction costs: (i) proportional costs PC_t in equation (6), and (ii) price impact of trading PI_t in equation (7). Both are measured in terms of a fraction of the invested wealth. To obtain trading costs in USD we need to multiply these quantities by the fund's current AUM, W_t. Proportional costs are characterized by the quoted bid-ask spread, and capture the costs that investors pay for small trading orders. The price impact of trading accounts for the widening in the bid-ask spread in response to large orders. When an investor places a large buy (sell) order and the market is not deep enough to fully absorb it at the current ask (bid) quote, then this order puts upward (downward) pressure on the ask (bid) price, and the cost to execute the order increases.

We denote by $\tilde{W}_t = W_t(1 - PC_t - PI_t)$ the wealth at time t after trading costs have been paid. Then, the wealth process is given by

$$
\begin{aligned}
W_t &= \sum_{i=1}^{N_t} \left(1 + r_{US,t-1} + r_{i,t}\right) \theta^{\mathbf{j}}_{\mathbf{i,t-1}} \tilde{W}_{t-1} + \left(1 + r_{US,t-1}\right) \left(1 - \sum_{i=1}^{N_t} \theta^{\mathbf{j}}_{\mathbf{i,t-1}}\right) \tilde{W}_{t-1} \\
&= \left(1 + r_{US,t-1} + \sum_{i=1}^{N_t} \theta^{\mathbf{j}}_{\mathbf{i,t-1}} r_{i,t}\right) \left(1 - PC_{t-1} - PI_{t-1}\right) W_{t-1},
\end{aligned}
$$

where $r_{US,t-1}$ denotes the risk-free rate in USD, and we use the fact that $1 - \sum_{i=1}^{N_t} \theta^{\mathbf{j}}_{\mathbf{i,t-1}}$ is invested in the risk-free asset in the USD. Therefore, we define the realized excess return before costs r_t^j and the equivalent after cost return $r_t^{j,c}$ as

$$
\begin{aligned}
r_t^j &= \sum_{i=1}^{N_t} r_{i,t} \theta^{\mathbf{j}}_{\mathbf{i,t-1}}, && (3) \\
r_t^{j,c} &= r_t^j - \left(1 + r_{US,t-1} + r_t^j\right) \left(PC_{t-1} + PI_{t-1}\right). && (4)
\end{aligned}
$$

From post-trading date $t-1$ to before-trading date t, the USD amount invested in currency i changes according to

$$
\theta^{\mathbf{0,j}}_{\mathbf{i,t}} W_t = \left(1 + r_{US,t-1} + r_{i,t}\right) \theta_{\mathbf{i,t-1}} \tilde{W}_{t-1}.
$$

Accordingly, the initial position in currency i at time t is given by

$$
\theta^{\mathbf{0,j}}_{\mathbf{i,t}} = \frac{1 + r_{US,t-1} + r_{i,t}}{1 + r_{US,t-1} + r_t^j} \theta_{\mathbf{i,t-1}}.
$$

Our setup only considers trades θ and $\boldsymbol{\Delta}$ against the USD. This ignores the possibility that it may be cheaper to trade directly between two non-USD currencies rather than twice against the USD. We address this limitation in robustness tests in section 5 and Internet Appendix B.3, and confirm that our main results are unaffected.

2.3 Proportional Costs

For the proportional costs, we follow the literature (Menkhoff et al., 2012b; Della Corte et al., 2016; Maurer et al., 2023), and account for quoted bid and ask spreads. Since it is relatively cheap to roll a contract over from month to month, the literature typically assumes no roll-over fees and only accounts for transaction costs if there is a change in a position.

Our measure of the per dollar proportional transaction costs to open new long positions ($\mathbf{C}_{\mathbf{i,t}}^{\mathbf{P}+}$), close existing short positions ($\mathbf{C}_{\mathbf{i,t}}^{\mathbf{P}-}$), open new short positions ($\mathbf{C}_{\mathbf{i,t}}^{\mathbf{S}-}$) and close existing long positions ($\mathbf{C}_{\mathbf{i,t}}^{\mathbf{S}+}$) are

$$\mathbf{C}_{\mathbf{i,t}}^{\mathbf{P}+} \equiv \ln\left(\frac{F_{i,t}^{a}}{F_{i,t}}\right), \quad \mathbf{C}_{\mathbf{i,t}}^{\mathbf{P}-} \equiv \ln\left(\frac{X_{i,t}^{a}}{X_{i,t}}\right), \quad \mathbf{C}_{\mathbf{i,t}}^{\mathbf{S}-} \equiv \ln\left(\frac{F_{i,t}}{F_{i,t}^{b}}\right), \quad \mathbf{C}_{\mathbf{i,t}}^{\mathbf{S}+} \equiv \ln\left(\frac{X_{i,t}}{X_{i,t}^{b}}\right). \tag{5}$$

In the data, bid-ask spreads of forward contracts are wider than spreads of spot exchange rates. Our measure of proportional costs accounts for these differences. The proportional costs to trade the N_t currencies at time t reduce the portfolio return by

$$PC_t = \sum_{i=1}^{N_t} \sum_{k \in \mathcal{K}} \underbrace{\mathbf{C}_{\mathbf{i,t}}^{\mathbf{k}}}_{\substack{\text{cost per} \\ \text{dollar traded}}} \overbrace{\mathbf{\Delta}_{\mathbf{i,t}}^{\mathbf{k}}}^{\substack{\text{quantity} \\ \text{traded}}}, \quad \text{where} \quad \mathcal{K} = \{P+, P-, S-, S+\}. \tag{6}$$

Recall that the proportional costs PC_t are measured in terms of a fraction of the invested wealth. To obtain trading costs in USD we need to multiply PC_t by W_t.

Figure 1 plots the time-series of the cross-currency median of the average proportional costs for the spot market, $med\left(0.5C_{i,t}^{S+} + 0.5C_{i,t}^{P-}\right)$ (solid line), and the forward market, $med\left(0.5C_{i,t}^{P+} + 0.5C_{i,t}^{S-}\right)$ (dashed line). Proportional costs are roughly between 0.5 and 7 basis points (bps), are slightly higher and more volatile for the 1-month forwards, and decrease over time after the year 2000. The highest spike (around 6.5 bps) in the forward time-series occurs during the 2008 financial crisis, while the most illiquid period for the spot market is between the 1997 Asian crisis and the Dot-com crisis in the early 2000s. Figures A2 and A3 in the Internet Appendix show the country specific time-series, confirming the fact that costs are generally lower in spot markets.

2.4 Price Impact of Trading

In our analysis we rebalance trading strategies once on the last day of the month and we implicitly assume that the execution of a trade is spread out over the course of the day. Therefore, the price impact captures the average pressure during the day. Our assumption follows the insight of Garleanu and Pedersen (2016) that it is optimal to trade continuously to minimize the price impact but the price impact function inversely scales with time.

We use the price impact functions $\Pi_{i,t}^k(\mathbf{\Delta}_{i,t}^k)$ for $\mathcal{K} = \{P+, P-, S-, S+\}$ to quantify changes in spot and forward ask and bid quotes induced by trading currency i on day t. These changes in quotes increase costs and are additive to the proportional costs. We separately construct price impact functions for ask and bid quotes in spot and forward markets, each currency i, and point in time t, as liquidity starkly varies across markets, currencies and time.

Closing existing short positions ($\mathbf{\Delta_{i,t}^{P-}}$) requires a buy order in the spot market. In response to buy order $\mathbf{\Delta_{i,t}^{P-}}$ the log-ask quote in the spot market for currency i at time t increases by $\Pi_{i,t}^{P-}(\mathbf{\Delta_{i,t}^{P-}})$. Recall that costs are defined as the difference between the effective ask price (at which trades are executed) and the mid-quote. Accordingly, an increase in ask quotes implies higher trading costs. Similarly, closing existing long positions requires a sell order in spot markets, and sell order $\mathbf{\Delta_{i,t}^{S+}}$ decreases the associated spot market log-bid quote by $\Pi_{i,t}^{S+}(\mathbf{\Delta_{i,t}^{S+}})$. Finally, opening new long ($\mathbf{\Delta_{i,t}^{P+}}$) or short positions ($\mathbf{\Delta_{i,t}^{S-}}$) requires trading in forward contracts, and forward log-ask quotes increase by $\Pi_{i,t}^{P+}(\mathbf{\Delta_{i,t}^{P+}})$, and log-bid quotes decrease by $\Pi_{i,t}^{S-}(\mathbf{\Delta_{i,t}^{S-}})$.

Equation (7) formalizes the price impact cost PI_t in terms of a fraction of the invested wealth to trade the N_t currencies at time t,

$$PI_t \;=\; \sum_{i=1}^{N_t} \sum_{k \in \mathcal{K}} \underbrace{\Pi_{i,t}^k(\mathbf{\Delta_{i,t}^k})}_{\substack{\textit{price impact per} \\ \textit{dollar traded}}} \overbrace{\mathbf{\Delta_{i,t}^k}}^{\substack{\textit{quantity} \\ \textit{traded}}} \quad \text{where} \;\; \mathcal{K} = \{P+, P-, S-, S+\}. \tag{7}$$

Equation (14) in section 2.4.2 provides more details and a linear functional form of $\Pi_{i,t}^k(\mathbf{\Delta_{i,t}^k})$.

2.4.1 Amihud Price Impact Measure

Our estimation of the price impact is based on the measure of Amihud (2002). The Amihud measure captures the percentage change in the price per dollar traded in the spot market. It can be interpreted as a proxy for the price impact parameter λ in Kyle (1985). In the context of FX markets, Ranaldo and Santucci de Magistris (2022) propose a daily realized Amihud measure for spot exchange rates using intraday price data from Olsen and trading volume data from CLS. Lacava et al. (2023) further provide an in-depth theoretical discussion of the realized Amihud measure, and demonstrate its accuracy and robustness.[5] We follow these papers and construct the realized Amihud measure of the spot exchange rate of currency i on day t as,

$$A_{i,t}^S = \frac{RPV_{i,t}}{v_{i,t}^S}, \tag{8}$$

where $RPV_{i,t} = \sum_{\tau=1}^{H_t} |\Delta x_{i,t,\tau}|$ is the sum of the H_t hourly absolute spot exchange rate growths (using mid-price quotes) within day t, and $v_{i,t}^S$ is the daily USD trading volume for spot transactions of currency i against the USD.

We have a good coverage of hourly price data from Olsen from February 1986 to January 2024, and it is straightforward to estimate $RPV_{i,t}$. In contrast, as explained in section 2.1, we have CLS volume data for spot transactions for a subset of 12 out of 26 currencies and only covering the period from September 2012 to September 2021. Accordingly, we need to extrapolate $v_{i,t}^S$ in the time dimension, and across currencies. In the following, we denote the set of the 12 currencies with CLS coverage by $\mathcal{I}$, and we define the complement set $\mathcal{I}^c$ containing the remaining 14 currencies without CLS volume data.[6] We further define the set of days with CLS coverage (September 2012 to September 2021) by $\mathcal{T}$, and the periods from February 1986 to August 2012 and October 2021 to January 2024 by $\mathcal{T}^c$.

[5] A possible alternative measure is the VAR approach of Ranaldo and Somogyi (2021). This measure has many useful features such as the possibility to differentiate the trading impact of diverse traders on market prices, i.e., the main feature exploited by the authors. However, we do not need to know the determinants but simply need an accurate measure of liquidity. The realized Amihud measure is precise, and in addition, it is straightforward to obtain a time-series of liquidity. For these reasons it is a suitable measure for our purposes.

[6] Specifically, $\mathcal{I} = \{AUD, EUR, GBP, NZD, CAD, CHF, JPY, NOK, SEK, MXN, SGD, ZAR\}$, and $\mathcal{I}^c = \{BRL, CZK, DEM, ESP, FRF, GRD, HUF, IEP, ITL, KRW, NLG, PLN, PTE, TWD\}$.

Before we explain our approach to extrapolate the volume data, note that our computation of the realized Amihud measure slightly differs from that of Ranaldo and Santucci de Magistris (2022). While both their and our measures use daily volume data from CLS for $v_{i,t}^S$, we use hourly data from Olsen and they use minute-level quotes to compute $RVP_{i,t}$. However, we find that our estimates are similar. For each currency $i \in \mathcal{I}$ we compute the correlation between our daily $A_{i,t}^S$ based on hourly Olsen quotes and the daily realized Amihud measure of Ranaldo and Santucci de Magistris (2022) that uses one-minute Olsen quotes for the sample $t \in \mathcal{T}$.[7] We report the results in Table 2 in the row indicated by 'Hourly Quotes'. The correlations range between 0.79 and 0.9, with the exception of the JPY, which has the lowest correlation of 0.6. While the estimates of Ranaldo and Santucci de Magistris (2022) based on minute-level data are more precise, the high correlations confirm that it is not a major concern that we use hourly data.

For the extrapolation in the time dimension we simply use the time-series average of the available volume data. That is, we set

$$v_{i,t}^S \quad = \quad \bar{v}_i^S \;\; \forall t \in \mathcal{T}^c, \tag{9}$$

where $\bar{v}_i^S$ is the average of the daily trading volume of currency i for $t \in \mathcal{T}$. The extrapolation backwards in time is conservative, as trading volume is generally increasing over time. For instance, the BIS Triennial Survey suggests that the trading volume of EUR/USD spot transactions for the survey years of 2013, 2016 and 2019 was more than twice the trading volume in the years 2001, 2004, and 2007. Other currencies have experienced a similar and often larger increase in trading volume over time. Thus, prior to 2012 our extrapolated Amihud measure $A_{i,t}^S$ in (8) is likely lower when we use $v_{i,t}^S = \bar{v}_i^S$, suggesting that we assume more liquidity and a lower price impact of trading than the actual market conditions. Accordingly, in the early years of our sample we likely underestimate the importance of the price impact, and in reality transaction costs likely had a more severe impact on the profitability of trading strategies than what we report. In section 5 and Internet Appendix B.3, we consider alternative extrapolations of $v_{i,t}^S$ that allow for time-variation. As expected, the time-series

[7]We are thankful to Angelo Ranaldo and Paolo Santucci de Magistris for sharing their daily realized Amihud estimates for the 12 currencies $i \in \mathcal{I}$ for the sample period from September 2012 to September 2021.

of the extrapolated volume data is increasing over time. In turn, this implies that the price impact in our baseline analysis is smaller and more conservative than in the robustness tests. However, we find that the choice of method for extrapolating the volume data does not have a material effect on our final results on the after-cost profitability of our strategies.

Setting $v_{i,t}^S = \bar{v}_i^S$ for all $t \in \mathcal{T}^c$ means that the Amihud measure $A_{i,t}^S$ in (8) is only dynamic due to the time-variation in $RPV_{i,t}$. To get a sense of whether this restriction is problematic, we compute again for each currency $i \in \mathcal{I}$ the correlation between our realized Amihud measure and the measure of Ranaldo and Santucci de Magistris (2022). However, this time we impose a time-invariant $v_{i,t}^S = \bar{v}_i^S$ for our measure. The row indicated by 'Constant Volume' in Table 2 reports the results. The correlations range between 0.62 and 0.81, with the exception of the JPY, which has the lowest correlation of 0.49. The generally high correlations indicate that most of the time-series variation in the realized Amihud measure stems from $RPV_{i,t}$, and it is unproblematic to impose a time-invariant $v_{i,t}^S = \bar{v}_i^S$ for the purpose of our extrapolations.

Recall that we have CLS volume data and we can compute $\bar{v}_i^S$ only for the 12 currencies $i \in \mathcal{I}$. To obtain $\bar{v}_i^S$ (and construct $v_{i,t}^S = \bar{v}_i^S$ and ultimately $A_{i,t}^S$ in (8)) for the 14 currencies $i \in \mathcal{I}^c$, we extrapolate in the cross-section. Karnaukh et al. (2015) show that bid-ask spreads are a good proxy for liquidity. Motivated by this insight, we use the proportional bid-ask spread as a conditioning variable for the cross-sectional extrapolation of $\bar{v}_i^S$. Specifically, for currency i we denote by $\overline{PBA}_i^S$ the time-series average from September 2012 to September 2021 of the daily proportional spot bid-ask spread $PBA_{i,t}^S$ (see definition in section 2.1). Then, we regress the natural logarithm of $\bar{v}_i^S$ on a constant and the natural logarithm of $\overline{PBA}_i^S$ for the 12 currencies $i \in \mathcal{I}$,

$$\ln\left(\bar{v}_i^S\right) \quad = \quad a + b\ln\left(\overline{PBA}_i^S\right) + \varepsilon_i, \tag{10}$$

where a and b are the regression coefficients estimated via OLS, and ε_i is the residual. Figure 2 plots $\ln\left(\bar{v}_i^S\right)$ against $\ln\left(\overline{PBA}_i^S\right)$ (indicated by asterisks), and visualizes the striking linear relation. The regression fit $R^2 = 0.8$ is astounding. The negative slope coefficient $b = -1.46$ is sensible and has a clear interpretation: lower levels of liquidity proxied by higher spreads are associated with lower traded volume. This provides confidence for the accuracy of a cross-sectional extrapolation based on bid-ask spreads.

Given the linear regression (10) we construct extrapolated average volumes for the 14 currencies $i \in \mathcal{I}^c$,

$$\bar{v}_i^S \;=\; \exp\left\{a + b \ln\left(\overline{PBA}_i^S\right)\right\}. \tag{11}$$

One complication is the availability of bid and ask quote data to compute $\overline{PBA}_i^S$. We only have daily bid and ask quotes between September 2012 and September 2021 for 6 of the 14 currencies $i \in \mathcal{I}^c$, namely BRL, CZK, HUF, KRW, PLN, and TWD. For these 6 currencies, we can readily use (11) to obtain extrapolated values $\bar{v}_i^S$, and thus construct $v_{i,t}^S = \bar{v}_i^S$ and $A_{i,t}^S$ in (8). We plot the extrapolated $\bar{v}_i^S$ in Figure 2 (indicated by circles). A nice feature of the extrapolation is that $\ln\left(\overline{PBA}_i^S\right)$ for $i \in \mathcal{I}$ spans a relatively large range from -9.74 to -7.39. BRL, KRW and TWD lie well within that range, and CSK, HUF and PLN are located just outside with HUF taking the most extreme value of -6.92. Therefore, the extrapolations do not require us to move far out on the estimated line.

The remaining 8 currencies (namely DEM, ESP, FRF, GRD, IEP, ITL, NLG, PTE; which we denote as the subset $\mathcal{I}_{EU}^c$) have joined the EUR, and it is only possible to compute average proportional bid-ask spreads based on data prior to January 1999. We denote this by $\overline{PBA}_{i,\text{pre-EUR}}^S$. As bid-ask spreads are generally decreasing over time, $\overline{PBA}_{i,\text{pre-EUR}}^S$ for $i \in \mathcal{I}_{EU}^c$ computed from data prior to 1999 are not comparable to $\overline{PBA}_i^S$ for $i \in \mathcal{I}$ constructed from data from September 2012 to September 2021. That is, if we simply plug in the pre-1999 $\overline{PBA}_{i,\text{pre-EUR}}^S$ in (11) then we obtain comparatively low extrapolated values of $\bar{v}_i^S$ for $i \in \mathcal{I}_{EU}^c$. Accordingly, we re-scale the extrapolated volumes such that they add up to the average volume of the EUR, $\sum_{i \in \mathcal{I}_{EU}^c} \bar{v}_i^S = \bar{v}_{EUR}^S$. The idea is that the currencies that join the EUR should collectively have a trading volume that is comparable to that of the EUR. Note that this implicitly assumes the same time-invariant extrapolation as in (9). The adjusted extrapolation formula for currencies $i \in \mathcal{I}_{EU}^{c}$ is,[8]

$$\bar{v}_i^S = \frac{\bar{v}_{EUR}^S \exp\left\{a + b\ln\left(\overline{PBA}_{i,\text{pre-EUR}}^S\right)\right\}}{\sum_{j\in\mathcal{I}_{EU}^c}\exp\left\{a + b\ln\left(\overline{PBA}_{j,\text{pre-EUR}}^S\right)\right\}}. \tag{12}$$

Finally, we construct the Amihud measure for forwards $A_{i,t}^F$ for each of the 26 currencies by re-scaling $A_{i,t}^S$ by $PBA_i^{F/S} = \frac{1}{T}\sum_t \frac{PBA_{i,t}^F}{PBA_{i,t}^S}$, which is the time-series average over the entire sample of the ratio between the proportional forward and the spot bid-ask spreads,

$$A_{i,t}^F = PBA_i^{F/S} A_{i,t}^S. \tag{13}$$

$PBA_i^{F/S}$ is greater than 1 for every currency, reflecting the well-known fact that the forward market is less liquid than the spot market. In turn, this consistently reflects a higher price impact per dollar traded in the forward market, i.e. $A_{i,t}^F > A_{i,t}^S\ \forall\{i,t\}$. The tight link between liquidity in spot and forward markets in (13) is closely related to the empirical findings of Krohn and Sushko (2022), albeit their data is on swaps rather than forwards.

Note that it would have been problematic to use forward price and volume data to construct $A_{i,t}^F$ analogously to $A_{i,t}^S$ in (8). The reason is that forward quotes are tightly linked to spot quotes due to no-arbitrage, and much of the variation in forward quotes is indirectly driven by fluctuations in spot prices (and thus spot order flow) rather than by order flows in forward markets. Indeed, hourly forward spreads (i.e., forward minus spot quotes) from Olsen have little variation, implying that spot and forward prices closely move together and have approximately the same variation. Bräuer and Hau (2023) further confirm in their analysis that the correlation is 0.99 between dollar forward and spot. To the extent that order flows in spot markets predominately drive spot and therefore also forward prices, a forward Amihud measure analogous to (8) would be grossly misspecified. As a simple example, consider a forward market that has no trading on a particular day. However, transactions in

[8] To the extent that GDP is a good proxy for the traded volume, we compared our re-scaling factor $\frac{\bar{v}_{EUR}^S}{\sum_{j\in\mathcal{I}_{EU}^c}\exp\left\{a+b\ln\left(PBA_{j,\text{pre-EUR}}^S\right)\right\}}$ to the average GDP of the EUR countries in our sample relative to the GDP of the Euro area over the period 1995 to 2021 using the data available from the OECD, https://stats.oecd.org/Index.aspx?DatasetCode=SNA_TABLE1#. This comparison produces results in line with our assumptions. First, relative GDP is very stable across time. Second, the correlation between our re-scaling factor and the average relative GDP is 0.7.

the corresponding spot market move spot prices, and market makers adjust forward quotes to preclude arbitrage. The Amihud measure for forwards according to (8) would be infinite on that day. In principle, this problem is also present in the construction of the Amihud measure for spot markets. In common with one strand of the literature, we therefore assume that order flows in spot markets are the main drivers while flows in corresponding forward markets are of secondary importance.[9] Accordingly, our construction of $A^F_{i,t}$ in equation (13) is arguably more sensible as it is based on the more precisely measured $A^S_{i,t}$, and uses a simple liquidity adjustment based on bid-ask spreads.

2.4.2 Linear Price Impact Function

Next, we construct a linear price impact function of the trade order size and derive a mapping to the Amihud measure. The linear price impact function is:

$$\Pi^k_{i,t}(\mathbf{\Delta^k_{i,t}}) \equiv \pi^k_{i,t}\mathbf{\Delta^k_{i,t}}, \quad \forall k \in \{P+, P-, S-, S+\}, \tag{14}$$

with $\pi^k_{i,t}$ specified in (15).

A linear functional form is popular in the literature (Kyle, 1985; Leland, 1985; Back, 1993; Garleanu and Pedersen, 2013, 2016; Kyle et al., 2018). However, we acknowledge that our specification has limitations. The linear specification in (14) and the independence across currencies in (7) are likely an accurate representation of FX markets when trade orders are of a moderate size. However, the same may not be true during turbulent times or when trade orders are very large. FX markets are OTC and liquidity is provided by a few global dealers that are simultaneously making the market for multiple currencies. It is plausible that the search costs and dealers' liquidity needs and inventory risks lead to commonalities in liquidity and non-linear cost functions with increasing marginal costs. These effects can have non-trivial implications on the costs of a trading strategy, in particular when multiple currencies are traded at the same time. Estimating commonalities and non-linearities in the price impact function is a difficult task and potentially comes with large estimation errors.

[9] For instance, Ranaldo and Santucci de Magistris (2022) implicitly assume the same. However, we acknowledge that for instance Bräuer and Hau (2023) provide evidence that FX hedging demands via forwards can have a significant impact on exchange rates. This introduces some errors in the spot Amihud measure.

We leave this for future research, and use the linear specification without cross-sectional interconnectedness that is simpler to estimate and is arguably subject to smaller estimation errors. To the extent that effects from non-linearity and interconnectedness likely increase trading costs, we expect that the findings of our analysis are conservative and understate the true problem of transaction costs.

Consider for now the buy order $\mathbf{\Delta_{i,t}^{P-}}$. The mapping between per dollar price impact measure $A_{i,t}^S$ and the parameter $\pi_{i,t}^{P-}$ is derived as follows. By definition of the Amihud measure $A_{i,t}^S$ buy order $\mathbf{\Delta_{i,t}^{P-}}$ of a fund with a current AUM of W_t pushes up the current log-ask price $\ln\left(X_{i,t}^a\right)$ to

$$\ln(\tilde{X}_{i,t}^a) \;\; = \;\; \ln(X_{i,t}^a) + A_{i,t}^S \mathbf{\Delta_{i,t}^{P-}} W_t.$$

It follows that the cost (as a fraction of the AUM) that the fund has to pay over and above the mid quote $X_{i,t}$ is

$$\ln\left(\frac{\tilde{X}_{i,t}^a}{X_{i,t}}\right)\mathbf{\Delta_{i,t}^{P-}} \;\; = \;\; \underbrace{\ln\left(\frac{X_{i,t}^a}{X_{i,t}}\right)\mathbf{\Delta_{i,t}^{P-}}}_{=\mathbf{C_{i,t}^{P-}}} + \underbrace{\ln\left(\frac{\tilde{X}_{i,t}^a}{X_{i,t}^a}\right)\mathbf{\Delta_{i,t}^{P-}}}_{=\mathbf{\Pi_{i,t}^{P-}}(\mathbf{\Delta_{i,t}^{P-}})}.$$

The first term is the proportional costs as described in equation (6), while the second term identifies the costs due to the price impact of trading related to equation (7). Dividing the second term by $\mathbf{\Delta_{i,t}^{P-}}$, and comparing it to the right-hand side of equation (14), we obtain

$$\pi_{i,t}^{P-} \;\; = \;\; A_{i,t}^S W_t.$$

Using a similar argument, we obtain price impact parameters $\pi_{i,t}^{S+}$ to sell currency i in the spot market to close existing long positions, and $\pi_{i,t}^{P+}$ and $\pi_{i,t}^{S-}$ to open new long, respectively short positions in the forward market,

$$\pi_{i,t}^{S+} = \pi_{i,t}^{P-} = A_{i,t}^S W_t, \;\; \text{and} \;\; \pi_{i,t}^{P+} = \pi_{i,t}^{S-} = A_{i,t}^F W_t, \tag{15}$$

where $A_{i,t}^S$ and $A_{i,t}^F$ are described in (8) and (13) and the discussion in section 2.4.1.

In Table 1 in the columns indicated by $\bar{A}_i^S$ we report the time-series average of our realized Amihud measure (equation (8)) for spot transactions. The reported numbers measure the bps change in the ask or bid price in response to a buy or sell order of USD 1 million. Not surprisingly $\bar{A}_i^S$ is smaller for developed than emerging currencies. Perhaps more surprisingly is the fact that $\bar{A}_i^S$ is over 150 times larger for the HUF (the least liquid currency in our sample) than the EUR (the most liquid currency).

To provide a sense of the severity of the transaction costs due to the trading volume price impact we revisit our discussion on the 'too wide' B&R bid-ask spreads in section 2.1. Recall that B&R spreads are on average 48% wider than our adjusted spreads. Similar to Lyons (2001) it follows a simple rule-of-thumb that B&R spreads should be reduced, and thus, transaction costs have a smaller impact on the profitability of trading strategies than what is reported in papers that only work with B&R data. However, this conclusion is misleading as it only considers proportional costs and ignores the price impact of trading. To address this issue we compute the break even trade order size

$$\mathbf{\Delta_i^k} W = \frac{\overline{PBA}_i^{S,BR} - \overline{PBA}_i^{S}}{2\bar{A}_i^S},$$

such that the transaction costs due to our adjusted proportional costs $0.5\overline{PBA}_i^{S}$ and due to the price impact of trading based on the Amihud measure $\bar{A}_i^S$ and the order size $\mathbf{\Delta_i^k} W$ are exactly equal to the B&R proportional costs $0.5\overline{PBA}_i^{S,BR}$ (i.e., the benchmark that is often used in the literature). We report this break even order size $\mathbf{\Delta_i^k} W$ (in million USD) in the last column of Table 1. For the EUR we need large orders of almost USD 300 million such that the trading costs are comparable to the wide B&R spreads. Similarly for some other developed currencies (e.g., JPY, CAD, FRF) orders have to be large (above USD 100 million) such that costs exceed the quoted B&R spreads. In contrast, for some developed (most notably the NOK and SEK) and many emerging currencies orders of less than USD 10 million, and in the case of the HUF an order of only USD 400k already imply trading costs that are higher than the proportional costs based on the B&R bid-ask spreads. To put the trade order size into perspective it is important to note that many popular FX trading strategies are concentrated, and thus, trade orders are a large fraction of the invested wealth.

Accordingly, a large fund that manages USD 1 billion or more often places large orders that easily exceed USD 100 million. Accordingly, contrary to the previous conclusion, showing that a strategy survives costs based on B&R spreads is not a conservative robustness analysis. Indeed, for many currencies the price impact of trading leads to much larger costs (compared to the proportional costs) when trade orders are large.

Finally, to visualize the price impact estimates, we plot the time-series $A^S_{i,t}\bar{z}^{funds}_i$ for spot transactions and $A^F_{i,t}\bar{z}^{funds}_i$ for forward transactions. $\bar{z}^{funds}_i = \frac{1}{T}\sum_t z^{funds}_{i,t}$ is the time-series average of $z^{funds}_{i,t} = \left|buy^{funds}_{i,t} - sell^{funds}_{i,t}\right|$, the absolute value of the daily order flow imbalance of funds. $buy^{funds}_{i,t}$ and $sell^{funds}_{i,t}$ represent the USD value of the sum of all CLS registered spot buy respectively sell orders of funds for currency i on day t.[10,11] The idea is to get a sense of the magnitude of the price impact (i.e., the increase in the ask or the decrease in the bid quote) in response to the average buy and sell imbalance of funds within a day. As such $\bar{z}^{funds}_i$ can be interpreted as the daily average of the aggregated $\mathbf{\Delta^k_i}W$ of all funds. Figure 3 plots the cross-currency median price impact (reported in bps) for the spot market (solid line) and the forward market (dashed line). As expected, the price impact is higher for the forward market (hovering around 7-8 bps) than the spot market (hovering around 4-5 bps). The price impact in spot and forward markets peaks around the 2008 financial crisis. We further notice a higher volatility of the price impact in the forward market. Finally, there is no downtrend in the price impact as we use a time-invariant volume to extrapolate the volume data in the time dimension. This feature, if anything, makes it more difficult to detect the effects of the price impact on the profitability of our trading strategies. The same insights are confirmed at the currency-level as reported in Figures A4 and A5 in the Internet Appendix.

[10]For currencies $i \in \mathcal{I}^c$ (for which we do not have CLS data) we extrapolate $\bar{z}^{funds}_i$ using an analogous approach as for the extrapolation of $\bar{v}^S_i$. Similar to the volume data we show in the Internet Appendix A that we can reliably extrapolate $\bar{z}^{funds}_i$.

[11]We only use the order imbalance $\bar{z}^{funds}_i$ for spot transactions. We do not generate an estimate for the forward order flows. This helps us to keep the price impact comparable across the two markets.

3 Trading Strategies

In section 3.1 we construct seven currency trading strategies that are well-known for delivering high returns. Six of these seven strategies rank currencies based on characteristics and construct (mostly equally weighted) long-short portfolios. The seventh strategy is a mean-variance optimized currency portfolio. In section 3.2 we introduce a mean-variance-transaction-cost optimized strategy that aims to achieve the optimal balance between rebalancing the portfolio to earn a high before-cost Sharpe ratio while reducing trading activity to lower transaction costs.

Following the literature, all our strategies are rebalanced monthly. Our strategies use the information available at the end of month t to construct portfolios that we then hold until the end of the subsequent month $t+1$. Accordingly, the returns are out-of-sample, and the trading strategies do not suffer from a look-ahead bias.

3.1 Strategies from the Literature

DOL: The dollar strategy (DOL) borrows in USD and equally invests in all other currencies (Lustig et al., 2011), $\theta_{i,t}^{DOL} = \frac{1}{N_t}$.

DDOL: The dollar carry ($DDOL$) takes a long position in DOL if the median exchange rate forward discount is positive, and a short position otherwise (Lustig et al., 2014), $\theta_{i,t}^{DDOL} = sign\left(median\left(\{fd_{j,t}\}_{j=1}^{N_t}\right)\right)\frac{1}{N_t}$.

HML: The carry (HML) sorts currencies according to the forward discount into quintiles and borrows in the bottom quintile and invests in the top quintile (Lustig and Verdelhan, 2007). Define $\mathcal{Q}_t^j$ as the set of forward discount sorted currencies in quintile j. $1_{i\in\mathcal{Q}_t^j}$ is an indicator function equal to 1 if currency i is in set $\mathcal{Q}_t^j$, and 0 otherwise. $Q_t^j = \sum_{i=1}^{N_t} 1_{i\in\mathcal{Q}_t^j}$ counts the number of currencies in quintile j at time t. Then, $\theta_{i,t}^{HML} = \frac{1_{i\in\mathcal{Q}_t^5}}{Q_t^5} - \frac{1_{i\in\mathcal{Q}_t^1}}{Q_t^1}$.

RB: As an alternative to HML we also consider the ranked-based (RB) version of the carry trade (Asness et al., 2013). In this strategy, the rescaled rank is used as the portfolio weight, $\theta_{i,t}^{RB} = \frac{\vartheta_{i,t}}{0.5\sum_{i=1}^{N_t}|\vartheta_{i,t}|}$ with $\vartheta_{i,t} = rank(fd_{i,t}) - \sum_{j=1}^{N_t}\frac{rank(fd_{j,t})}{N_t}$. As for HML, the notional value of the RB is equal to 2 by construction. The rank-based weights are not sensitive to the magnitude of forward discounts. As such, RB avoids the issue of extreme portfolio weights due to outliers, a desirable property that is shared with HML. In contrast to HML, RB may benefit from being less concentrated as all currencies are used in the portfolio construction, while HML only uses currencies in the top and bottom quintiles.

MOM: The momentum strategy MOM sorts currencies according to their past 12-month performance into quintiles and borrows in the bottom and invests in the top quintile (Burnside et al., 2011; Menkhoff et al., 2012b). Formally, the portfolio weights $\theta_{i,t}^{MOM}$ are defined analogously to $\theta_{i,t}^{HML}$.

VAL: The value strategy (VAL) sorts currencies according to the purchasing-power-parity-adjusted (PPP) or real exchange rate into quintiles, and borrows in the top quintile (overvalued currencies with high real exchange rates) and invests in the bottom quintile (undervalued currencies with low real exchange rates) (Bilson, 1984; Menkhoff et al., 2017). We estimate the real exchange rate of currency i against the USD by multiplying the PPP (which is the ratio of prices in currency i and the USD of a representative consumption bundle) by the nominal exchange rate $X_{i,t}$. Formally, the portfolio weights $\theta_{i,t}^{VAL}$ are defined analogously to $\theta_{i,t}^{HML}$.

MV: The mean-variance optimized portfolio (MV) solves,

$$\max_{\left\{\theta_{\mathbf{t}} \in \mathbb{R}^{N_t}\right\}} \left\{\theta_{\mathbf{t}}{}' \mu_{\mathbf{t}}^{\mathbf{e}} - \frac{\lambda}{2} \theta_{\mathbf{t}}{}' \mathbf{V_t} \theta_{\mathbf{t}}\right\}$$

where $\mu_{\mathbf{t}}^{\mathbf{e}} = E_t\left[r_{t+1}\right]$ is the $N_t \times 1$ vector of conditional expected currency returns, and $\mathbf{V_t}$ is the $N_t \times N_t$ covariance matrix. Maurer et al. (2023) show that this mean-variance optimization performs well out-of-sample, and outperforms other types of mean-variance optimized portfolios that impose risk limits or other constraints.

We follow the literature and use the current forward discount $fd_{i,t}$ as a proxy for $\mu_{\mathbf{i,t}}^{\mathbf{e}}$ (Baz et al., 2001; Della Corte et al., 2009; Daniel et al., 2017; Ackermann et al., 2016; Maurer et al., 2023, 2022). This is motivated by the random walk conjecture, i.e., the well-known empirical finding that exchange rate changes are difficult to predict over a short horizon, $E_t\left[\Delta x_{i,t+1}\right] \approx 0$ (Meese and Rogoff, 1983). Moreover, as demonstrated for instance by

Maurer et al. (2023), although there is evidence of predictability in $\Delta x_{i,t+1}$, it does not seem to hold any economic value. They employ a set of 18 predictors and conduct elastic net estimations to forecast $\Delta x_{i,t+1}$. Their results reveal an average out-of-sample R^2 of 0.36% for the monthly predictions. However, when applied to optimized portfolios, they document that the portfolio based on the predicted $\Delta x_{i,t+1}$ performs worse out-of-sample than the portfolio based on the random walk assumption.

With regard to the conditional covariance matrix $\mathbf{V_t}$, Maurer et al. (2023) show that the out-of-sample performance of MV substantially improves if we eliminate principal components that explain less than 1% of the common variation of the currency returns. This is motivated by the results of Lustig et al. (2011), who document a strong factor structure in FX markets. We first use daily returns over the previous 6 months to obtain the rolling window sample covariance matrix $\hat{\mathbf{V}}_\mathbf{t}$ at the end of month t. Then, we define the robust version of the covariance matrix as $\tilde{\mathbf{V}}_\mathbf{t} = \mathbf{W_t \Lambda_t W'_t}$, and its inverse as $\tilde{\mathbf{V}}_\mathbf{t}^{-1} = \mathbf{W_t \Lambda_t}^{-1}\mathbf{W'_t}$, where $\mathbf{W_t}$ is the matrix of eigenvectors and $\mathbf{\Lambda_t}$ is the diagonal matrix of eigenvalues of $\hat{\mathbf{V}}_\mathbf{t}$ after removing eigenvectors and eigenvalues which explain less than 1% of the common variation of the returns. Accordingly, the portfolio weights of MV are $\theta_\mathbf{t}^\mathbf{MV} = \frac{1}{\lambda}\tilde{\mathbf{V}}_\mathbf{t}^{-1} fd_t$.

Finally, we follow Maurer et al. (2023) and set $\lambda = 25$ to roughly match the unconditional volatility of 8% of the other currency trading strategies. Section 5 and A15 in the Internet Appendix analyze the effects of using other values for λ.

3.2 Mean-Variance-Transaction-Cost Optimization ($MVTC$)

We use the framework of Dybvig and Pezzo (2020) to optimize over costs within a myopic mean-variance setup. We denote this strategy as the Mean-Variance-Transaction-Cost optimized portfolio ($MVTC$).[12] We ignore potentially interesting implications of a dynamic model to keep the solution tractable. Therefore, our strategy in general leads to a sub-

[12] Garleanu and Pedersen (2013, 2016), Olivares-Nadal and DeMiguel (2016), Hautsch and Voigt (2019) and DeMiguel et al. (2020) provide alternative solution methods to transaction cost problems. One advantage of our approach is that we account for rebalancing due to realize returns that generate a difference between the initial position $\theta_\mathbf{i,t}^\mathbf{0,j}$ and $\theta_\mathbf{i,t-1}^\mathbf{j}$, and changes in the investment opportunity set that generate a difference between $\theta_\mathbf{i,t}^\mathbf{j}$ and $\theta_\mathbf{i,t-1}^\mathbf{j}$. The aforementioned papers ignore the first effect and assume $\theta_\mathbf{i,t}^\mathbf{0,j} = \theta_\mathbf{i,t-1}^\mathbf{j}$ to simplify the optimization problem.

optimal outcome. However, $MVTC$ is still resilient even to a severe price impact of trading and outperforms all other strategies in our analysis by a large margin. Accordingly, we are not concerned about its theoretical sub-optimality.

The optimization problem is:

Problem 1

$$\max_{\left\{\mathbf{\Delta^{k}_{i,t}}\geq 0\right\}^{k\in\mathcal{K}}_{i=\{1,\dots,N_t\}}} \left\{\theta^{\mathbf{MVTC}'}_{\mathbf{t}}\mu^{\mathbf{e}}_{\mathbf{t}} - \frac{\lambda}{2}\theta^{\mathbf{MVTC}'}_{\mathbf{t}}\mathbf{V}_{\mathbf{t}}\theta^{\mathbf{MVTC}}_{\mathbf{t}} - PC_t - PI_t\right\}$$

$$s.t.\ \theta^{\mathbf{MVTC}}_{\mathbf{i,t}} - \theta^{\mathbf{0,MVTC}}_{\mathbf{i,t}} = \mathbf{\Delta^{P+}_{i,t}} + \mathbf{\Delta^{P-}_{i,t}} - \mathbf{\Delta^{S-}_{i,t}} - \mathbf{\Delta^{S+}_{i,t}},$$

where PC_t and PI_t are defined in (6) and (7).

The economics of Problem 1 are well established in the literature. We refer to Internet Appendix C and Dybvig and Pezzo (2020) for a review of the economic properties. The first insight is that proportional costs ($PC_t > 0$) give rise to a no-trading region around $\theta^{\mathbf{MV}}_{\mathbf{t}}$, which identifies the optimal balance between expected return to risk before accounting for costs. If the initial position $\theta^{\mathbf{0,MV}}_{\mathbf{t}}$ is close enough to $\theta^{\mathbf{MV}}_{\mathbf{t}}$, then it is not worth paying costs to move closer to $\theta^{\mathbf{MV}}_{\mathbf{t}}$. The second insight is that a price impact ($PI_t > 0$) does not affect the shape or size of the no-trading region, but the optimal trades (which are initiated outside of the no-trading region) are different and we never end up at the border of the no-trading region.

The theoretical setup provides us with three predictions characterizing $MVTC$. First, we expect MV to outperform $MVTC$ if the performance is measured in returns before transaction costs. This is because, by definition, MV is the optimal portfolio when evaluated before transaction costs (in a single-period model). Second, we expect transaction costs to be larger for MV than for $MVTC$. Third, we expect $MVTC$ to outperform MV after transaction costs. Finally, the size of these differences between MV and $MVTC$ are expected to depend on the magnitude of the transaction costs.

3.2.1 Implementation

Problem 1 does not have a closed-form solution. However, it is a well-behaved quadratic program for which an accurate and fast converging numerical solution is readily available. We solve Problem 1 for θ_t^{MVTC} with three adjustments.

First, we set all proportional costs in (5) equal, $\mathbf{C^k_{i,t}} = \mathbf{C_{i,t}} = 0.25\sum_{h\in\mathcal{K}} \mathbf{C^h_{i,t}}$, $\forall k \in \mathcal{K}$. Second, we equalize the price impact parameters in (15), $\pi^k_{i,t} = \pi_{i,t} = 0.25\sum_{h\in\mathcal{K}} \pi^h_{i,t}$, $\forall k \in \mathcal{K}$, and thus, the price impact functions (14) are identical across order types, $\Pi^k_{i,t}(\mathbf{\Delta^k_{i,t}}) = \Pi_{i,t}(\mathbf{\Delta^k_{i,t}})$, $\forall k \in \mathcal{K}$. These adjustments simplify our optimization problem as we can now combine $\mathbf{\Delta^{P+}_{i,t}}$ and $\mathbf{\Delta^{P-}_{i,t}}$ to $\mathbf{\Delta^{P}_{i,t}} = \mathbf{\Delta^{P+}_{i,t}} + \mathbf{\Delta^{P-}_{i,t}}$, and similarly $\mathbf{\Delta^{S}_{i,t}} = \mathbf{\Delta^{S-}_{i,t}} + \mathbf{\Delta^{S+}_{i,t}}$. Then, equation (2) becomes $\theta^{\mathbf{MVTC}}_{\mathbf{i,t}} - \theta^{\mathbf{0,MVTC}}_{\mathbf{i,t}} = \mathbf{\Delta^{P}_{i,t}} - \mathbf{\Delta^{S}_{i,t}}$. Furthermore, the performance reduction due to proportional costs (6) simplifies to $PC_t^{(adj)} = \sum_{i=1}^{N_t} \mathbf{C_{i,t}}\left(\mathbf{\Delta^{P}_{i,t}} + \mathbf{\Delta^{S}_{i,t}}\right)$, and the cost due to the price impact (7) reduces to $PI_t^{(adj)} = \sum_{i=1}^{N_t} \pi_{i,t}\left(\mathbf{\Delta^{P}_{i,t}} + \mathbf{\Delta^{S}_{i,t}}\right)$.

In principle, it is possible to implement Problem 1 in its original formulation, but our empirical results are qualitatively unaffected. Accordingly, it is efficient to simplify the cost structure. Note that we use the approximate proportional costs $PC_t^{(adj)}$ and price impact $PI_t^{(adj)}$ in the optimization to construct θ_t^{MVTC}, but we use the actual cost function PC_t in (6) and PI_t in (7) (with the linear specification detailed in (14) and (15) in section 2.4.2) when we compute after-cost returns in our out-of-sample performance evaluation.

Third, the solution approach of Problem 1 requires the covariance matrix to be full rank. Unfortunately, $\mathbf{\tilde{V}_t}$ is not full rank. Therefore, we re-write Problem 1 to explicitly incorporate $\theta^{\mathbf{MV}}_{\mathbf{t}}$ as the target portfolio,

Problem 2 (Strategy $MVTC$**)**

$$\max_{\left\{\mathbf{\Delta^{P}_{i,t}}\geq 0, \mathbf{\Delta^{S}_{i,t}}\geq 0\right\}_{i=\{1,\ldots,N_t\}}} \left\{ \begin{array}{l} \frac{1}{2}\theta^{\mathbf{MV}\prime}_{\mathbf{t}} fd_t - \frac{\lambda}{2}\left(\theta^{\mathbf{MVTC}}_{\mathbf{t}} - \theta^{\mathbf{MV}}_{\mathbf{t}}\right)' \mathbf{\hat{V}_t} \left(\theta^{\mathbf{MVTC}}_{\mathbf{t}} - \theta^{\mathbf{MV}}_{\mathbf{t}}\right) \\ -PC_t^{(adj)} - PI_t^{(adj)} \end{array} \right\}$$

$$s.t.\ \theta^{\mathbf{MVTC}}_{\mathbf{i,t}} - \theta^{\mathbf{0,MVTC}}_{\mathbf{i,t}} = \mathbf{\Delta^{P}_{i,t}} - \mathbf{\Delta^{S}_{i,t}} \quad and \quad \theta^{\mathbf{MV}}_{\mathbf{t}} = \frac{1}{\lambda}\mathbf{\tilde{V}_t}^{-1} fd_t.$$

$\mathbf{\hat{V}_t}$ is the sample covariance matrix estimated from daily currency returns over the past 6 months (which is full rank), and $\tilde{\mathbf{V}}_{\mathbf{t}}^{-1}$ is the robust inverse of the covariance matrix $\hat{\mathbf{V}}_{\mathbf{t}}$ after removing principal components that explain less than 1% of the common variation of currency returns (see section 3.1 for details). In Internet Appendix C we provide details of the numerical algorithm used to solve Problem 2. Intuitively, $\theta_{\mathbf{t}}^{\mathbf{MVTC}}$ identifies the optimal trade-off between (i) minimizing the distance to the maximum (before-cost) Sharpe ratio portfolio $\theta_{\mathbf{t}}^{\mathbf{MV}}$, and (ii) minimizing trading costs when rebalancing from $\theta_{\mathbf{t}}^{\mathbf{0,MVTC}}$ to $\theta_{\mathbf{t}}^{\mathbf{MVTC}}$.

Formally, if we set $\tilde{\mathbf{V}}_{\mathbf{t}}^{-1} = \hat{\mathbf{V}}_{\mathbf{t}}^{-1}$, then Problem 2 is equivalent to Problem 1. This is because the objective function in Problem 2 in this case is an algebraic re-arrangement of that in Problem 1. Intuitively, in the formulation of Problem 2 the maximum (before-cost) Sharpe ratio portfolio $\theta_{\mathbf{t}}^{\mathbf{MV}}$ is surrounded by the no-trading region from Problem 1. In more practical terms, when our portfolio construction approach requires the inverse of the covariance matrix then we use the robust version $\tilde{\mathbf{V}}_{\mathbf{t}}^{\mathbf{-1}}$. Moreover, when our approach needs an estimate of the covariance matrix, and full rank is required, then we resort to $\hat{\mathbf{V}}_{\mathbf{t}}$. With this transformation we retain the feasibility of the approach of Dybvig and Pezzo (2020) while exploiting the superior performance of the robust mean-variance optimized portfolio of Maurer et al. (2022, 2023).

4 Performance of Trading Strategies

Section 4.1 summarizes the before cost performance of the eight strategies, and confirms the findings in the literature that they are profitable and achieve high Sharpe ratios. Section 4.2 quantifies the trading costs depending on the AUM of a fund, and section 4.3 analyzes the after-cost performance. The main results are in Table 3. Panel A considers the case when there are only proportional costs but no price impact of trading. This applies to funds with a small AUM and trading volume. Panel B and C show the performance for funds with initial AUM of USD 100 million and USD 1 billion in February 1987. These funds place sizable orders and the price impact of trading is non-trivial.

Note that the performance analysis of our strategies uses returns from February 1987 to January 2024 although our data starts in February 1986. The reason is that we require 12 months of data to construct MOM, and therefore we start all strategies in February 1987.

4.1 Performance Before Costs

We start our discussion with a comparison of the before-cost performance of MV, HML, RB, DOL, $DDOL$, VAL, and MOM. The first three rows of panel A in Table 3 report the annualized before-cost Sharpe ratio, average return, and volatility. Consistent with the literature, we find that most strategies have an attractive before-cost performance. MV dominates all other strategies with a before-cost Sharpe ratio of 1.12. The interest-rate-sorted RB and HML deliver substantially lower but still high before-cost Sharpe ratios of 0.81 and 0.79. The VAL, MOM, and $DDOL$ have relatively modest Sharpe ratios of 0.51, 0.36, and 0.32. Finally, the DOL is essentially unprofitable, with a Sharpe ratio of only 0.09. The stark before-cost outperformance of MV resonates with previous results in the literature (Baz et al., 2001; Della Corte et al., 2009; Daniel et al., 2017; Ackermann et al., 2016; Maurer et al., 2023, 2022; Chernov et al., 2023).

The Sharpe ratios of $DDOL$ (0.32) and MOM (0.36) are lower than the values in the original papers in the literature. Lustig et al. (2014) report a Sharpe ratio of 0.56 for $DDOL$ (and 0.66 if it is constructed from currencies of only developed countries), and Menkhoff et al. (2012b) find a Sharpe ratio of 0.61 for MOM.[13] The main difference is the sample period. The former study uses data from 1983 to 2010, the sample of the latter is from 1976 to 2010, while our sample starts in 1987 and ends in 2024. We find that $DDOL$ and MOM performed well until the global financial crisis (GFC), but since 2008 their average returns were low or even negative in the case of MOM.

In robustness checks reported in Section 5 and in Internet Appendix B.2, we analyze different sample periods. As a brief preview, the first plot in Figure 4 illustrates that the cumulative return of MOM is comparable to HML until 2008. After that, HML continues to earn relatively high average returns while MOM consistently makes losses. In addition, Table A5 in the Internet Appendix reproduces Table 3 for the sample period ending in

[13] They further find that MOM based on a shorter formation period is more profitable. For instance, if they use a 1-month formation period MOM achieves a Sharpe ratio of 0.95. In our sample we find that a 12-month formation period yields a more profitable MOM than a 1-month formation period.

December 2007.[14] The first row in panel A shows that the before-cost Sharpe ratios of $DDOL$ and MOM are 0.55 and 0.68, respectively, which are close to the values reported by Lustig et al. (2014) and Menkhoff et al. (2012b).

By construction, the annual volatilities are similar across all strategies, and range between 6.8% and 8.7%. The characteristic-sorted long-short strategies maintain a constant notional value of either one (DOL, $DDOL$) or two (HML, RB, VAL, MOM) resulting in comparable volatilities. RB has the lowest volatility of 6.8%. As pointed out in Section 3.1 RB invests in all currencies with less portfolio concentration, resulting in better diversification. This explains the lower volatility compared to HML or other characteristic-sorted long-short strategies that only invest in the top and bottom quintiles. In the construction of MV, we set $\lambda = 25$ to target a volatility that is comparable to the characteristic-sorted long-short strategies. Specifically, MV has a volatility of 7.95% (see Appendix B.4.2 for a sensitivity analysis of MV to different values of λ).

So far, our discussion refers to the values reported in panel A of Table 3. These results apply to sufficiently small funds that face no price impact of trading. However, the results generalize to any fund size and transaction costs. The reason is that MV, HML, RB, DOL, $DDOL$, VAL, and MOM do not account for transaction costs in their construction. As such, the portfolio holdings and the before-cost performance of these strategies are unaffected by the AUM or trading costs. Indeed, the values in the top three rows across panels A (small fund without price impact), B (initial fund size of USD 100 million) and C (initial fund size of USD 1 billion) are identical for the seven strategies. This illustrates that there are no implications of the fund size or transaction costs on the before-cost performance.

Next, we analyze the before-cost performance of $MVTC$, which is novel and has not been analyzed in the literature. As $MVTC$ accounts for trading costs in the optimization, theory predicts that it decreases the trading order size to reduce transaction costs. In terms of before-cost performance, this reduction in trading activity implies a sub-optimal rebalancing policy and asset allocation. Therefore, we expect that $MVTC$ underperforms MV when evaluated in before-cost returns, as the latter targets the highest before-cost Sharpe ratio

[14] 2008 appears to identify a structural break for the profitability of many FX trading strategies. After 2008 many strategies perform substantially worse than in the sample before the GFC.

irrespective of trading costs. We further conjecture that an increase in the AUM and costs due to the price impact of trading have negative implications on the before-cost performance of $MVTC$.

We confirm these predictions in the data. The before-cost Sharpe ratio of $MVTC$ is 1.08 in panel A of Table 3 when there is no price impact of trading. That is, $MVTC$ underperforms MV. However, the difference between the Sharpe ratios is small and insignificant, 1.08 for $MVTC$ and 1.12 for MV. Indeed, if there is no price impact of trading then MV and $MVTC$ are highly correlated, and they are very similar in terms of all performance measures listed in panel A of Table 3. It is interesting that MV and $MVTC$ are almost indistinguishable when there is no price impact. This means that proportional costs do not have a noticeable negative effect on the before-cost performance of $MVTC$.

In contrast, the negative implications of the price impact of trading on the before-cost performance of $MVTC$ are sizable. The before-cost Sharpe ratio of $MVTC$ decreases to 0.96 and 0.84 when the initial fund size is USD 100 million in panel B and USD 1 billion in panel C, respectively. In other words, the sub-optimal allocation of $MVTC$ in terms of before-cost performance becomes noticeable when a fund reaches a sufficiently large size and trading costs due to price impact are considerable.

The annual volatility of $MVTC$ is decreasing in the initial AUM. It is 7.8% when there is no price impact of trading (panel A), decreases to 7.3% when the initial AUM is USD 100 million (panel B), and further drops to 6.4% when the initial fund size is USD 1 billion (panel C). The decrease in volatility can be explained by the reduction in the trading activity of $MVTC$ in response to higher transaction costs. A lower turnover means more stability in the portfolio weights. This is similar to shrinkage methods that are designed to tackle estimation errors and reduce out-of-sample volatility (Olivares-Nadal and DeMiguel, 2016). However, this shrinkage effect is secondary, and the impact on volatility is relatively small. We observe a stronger effect of the fund size or trading costs on the before-cost average return of $MVTC$. When there is no price impact of trading the average annual return is 8.4% (panel A). It decreases to 6.9% and 5.4% when the initial AUM are USD 100 million and USD 1 billion, respectively. The stark decline in the average return dominates the relatively small effect on volatility, resulting in a before-cost Sharpe ratio that is decreasing in the fund size.

Our results are opposite to the key insights of Yoshimoto (1996), Olivares-Nadal and DeMiguel (2016), Hautsch and Voigt (2019) and Pezzo et al. (2023), who analyze the implications of transaction costs on portfolio choice in stock markets. These authors find that accounting for transaction costs in the construction of stock portfolios primarily introduces stability (similar to a shrinkage estimator), and therefore mitigates estimation error problems. The actual mitigation of transaction costs appears secondary in their analyses. It is particularly important to note that the negative effect of transaction costs on the before-cost Sharpe ratio of $MVTC$ is the opposite. That is, if an estimation error mitigation effect was present in our analysis (i.e., the dominant effect in the stock market literature), then the before-cost Sharpe ratio of MV would be smaller than the one of $MVTC$, and likely the before-cost Sharpe ratio of $MVTC$ would be increasing in transaction costs. Therefore, the insights of the stock market literature do not carry over to our analysis in FX markets.

The reason why the insights of the stock literature are not applicable is that estimation errors are not a (first-order) concern in FX markets, while it is a serious issue in stock markets. First of all, the literature has shown that interest rate differentials are a good proxy for conditional expected currency returns, and optimized portfolios based on this proxy perform well out-of-sample (Meese and Rogoff, 1983; Baz et al., 2001; Della Corte et al., 2009; Daniel et al., 2017; Ackermann et al., 2016; Maurer et al., 2023, 2022; Chernov et al., 2023). In contrast, it is difficult to find good estimates of conditional expected returns in stock markets. Second, FX strategies typically use a relatively small set of currencies (less than 30) compared to typical stock portfolios (several thousands). In addition, Lustig et al. (2011) show that there is a strong factor structure in FX markets while there is a large "factor zoo" in stock markets.[15] Accordingly, it is feasible to obtain precise estimates of the covariance matrix of returns in FX markets, while this is a formidable problem in stock markets.

Finally, we benchmark our currency strategies to the US stock market.[16] The buy-and-

[15]Subsequent to Lustig et al. (2011) the FX literature has introduced many additional factors beyond the DOL and HML. However, recently Sarno et al. (2023) and Liu et al. (2023) show that these additional factors in the literature are subsumed by DOL and HML.

[16]Stock market excess returns are downloaded from Kenneth French's website, https://mba.tuck.

hold value-weighted stock market portfolio has a before-cost Sharpe ratio of 0.52 during our sample period (February 1987 to January 2024). The annual average excess return and volatility are 8.1% and 15.6%, respectively. Accordingly, MV, $MVTC$, RB and HML outperform the US stock market in terms of before-cost Sharpe ratio. VAL has almost the same before cost Sharpe ratio at the US stock market. In contrast, DOL, $DDOL$, and MOM deliver an inferior performance.

The inferior performance does not necessarily mean that these strategies are undesirable. First, recall that before the Global Financial Crisis (GFC), $DDOL$ and MOM performed well with before-cost Sharpe ratios of 0.55 and 0.68, respectively. They only perform poorly after 2008. As a comparison, during the sample period from 1987 to December 2007, the US stock market earned a Sharpe ratio of only 0.45. Accordingly, pre-GFC $DDOL$ and MOM outperform the US stock market in terms of before-cost Sharpe ratio. Second, if the correlation between the strategies is sufficiently low, then a combination of the strategies may be more efficient than investing in a single strategy. In other words, even a strategy with a relatively low Sharpe ratio may improve the performance of the portfolio. This is particularly relevant when we consider currency portfolios and the US stock market, as the correlations between them are low.[17]

To sum up, the before-cost performance of $MVTC$ is virtually indistinguishable from MV when there are only proportional costs. However, when a fund has a large AUM and there is a price impact of trading, then the deviation is economically large of $MVTC$ from the optimal balance of before-cost expected return and risk, resulting in a noticeably lower before-cost Sharpe ratio. Furthermore, independent of the fund size, MV and $MVTC$ significantly outperform popular characteristic-sorted currency trading strategies in terms of before-cost returns. Finally, within our full sample, only MV, $MVTC$ and the carry trade strategies HML and RB deliver a higher before-cost Sharpe ratio than the value-weighted US stock market portfolio. The performance of VAL is identical to the US stock market.

`dartmouth.edu/pages/faculty/ken.french/data_library.html`.

[17]However, among currency portfolios Maurer et al. (2023, 2022) show that MV outperforms combinations of other currency strategies, and other strategies do not earn an abnormal return when MV is used as a pricing factor. As such MV on its own appears to be efficient (in terms of before cost returns) within the space of currency returns.

DOL, $DDOL$, and MOM underperform it.

4.2 Transaction Costs

Table 3 reports the average annualized trading costs, the monthly turnover, and the average notional value in the fourth to sixth rows in panels A, B, C. The costs are measured by $PC_t + PI_t$ and are measured as a percentage of the AUM of a fund. The monthly turnover of strategy S is defined as $\sum_{i=1}^{N_t} |\theta_{i,t}^{S} - \theta_{i,t}^{0,S}|$, and quantifies the fraction of the AUM that is traded every month. The notional value is $\sum_{i=1}^{N_t} |\theta_{i,t}^{S}|$, and identifies the combined notional value of all long and short forward positions as a fraction of the AUM. The ratio of the turnover to the notional value (TO-NV) determines the fraction of the portfolio's notional value that is traded every month.

MV has an average monthly turnover of 2.32, an average notional value of 3.07, and a TO-NV of 0.76. These quantities are independent of the fund size. The average annual costs incurred by MV are 1.1% when a fund is small and only pays proportional costs. The costs increase to 5.9% and even 11.5% when the initial AUM of a fund are USD 100 million or USD 1 billion. These costs are considerable given that the average before cost return of MV is 8.9%. While small funds (no price impact) are still profitable after costs, for larger funds the before-cost performance is quickly eroded by trading costs.

By construction, the portfolio holdings of a characteristic-sorted, long-short strategy are in general less sensitive to the time-series variation in forward discounts (conditional expected returns) and covariances than MV with its fine-tuned weights. Thus, it is reasonable to expect that the turnover and transaction costs are smaller for equally weighted strategies compared to MV. To illustrate this, we provide an intuitive argument. Consider a mean-variance optimized portfolio and an equally weighted portfolio which sorts assets according to expected returns and buys the top quintile and sells the bottom quintile. A time-series variation in the covariance matrix will only affect the portfolio weights of the optimized portfolio whereas the weights in the equally weighted portfolio remain constant. Moreover, small changes in expected returns will likely leave the allocation of the equally weighted portfolio unchanged, whereas the weights of the optimized portfolio may substantially change. In these scenarios the optimized portfolio has more turnover and higher costs than the equally weighted strategy.

Indeed, we document this insight in the data for all strategies. Among the characteristic-sorted strategies, HML has the highest average monthly turnover of 1.13 with a TO-NV of 0.57. These values are substantially lower than in the case of MV. RB and MOM have a slightly lower turnover of 0.95 each, and a TO-NV of 0.48. The turnover of $DDOL$ is roughly half (0.4), but given that its notional value is also only half of the other strategies, then the TO-NV remains comparable (0.4). The turnover and TO-NV are substantially lower for VAL (0.25 and 0.13) and DOL (0.03 and 0.03). This confirms our conjecture that the characteristic-sorted portfolios trade less aggressively than MV.

The average costs paid by the characteristic-sorted strategies are also considerably lower than MV. Nevertheless, the costs are far from negligible for most strategies. When the fund size is large (initial AUM of USD 1 billion) HML, MOM, and RB incur average costs of 7.5%, 5.6%, and 5.2%, respectively. These costs surpass (or in the case of RB are very close to) the average before-cost returns, implying that they are making losses (or are almost unprofitable) after accounting for costs. Even for a fund with initial AUM of USD 100 million, costs erode a significant part of the before-cost returns of these strategies. Thus, investors should be concerned about the price impact of trading.

DOL, $DDOL$, and VAL are more resilient to the price impact of trading and the costs are considerably lower, amounting to only 0.04%, 1.8%, and 2.5%, respectively, even in the case of a large fund with an initial AUM of USD 1 billion. It is important to note that this conclusion is based on the assumption that the price impact functions are linear and independent across currencies. As pointed out in the discussion in section 2.4.2 large trade orders in multiple currencies may come with a larger price impact than implied by our functional form. In such a case costs may be larger than reported in our analysis and DOL, $DDOL$, and VAL may not be as resilient.

Next, recall that $MVTC$ is designed to optimally reduce costs compared to MV, which trades irrespective of costs. Accordingly, we expect that $MVTC$ trades less and incurs lower trading costs than MV. We further expect that $MVTC$ reduces its trading activity (measured in terms of the fraction of the portfolio's notional value) as the AUM becomes larger and the price impact more severe. It is, however, ambiguous how costs of $MVTC$ are affected by the fund size. Holding trading activity constant, an increase in the AUM leads to higher costs due to the larger price impact. On the other side, if the reduction in trading activity is sufficiently large, then costs (as a percentage of the AUM) may still decrease as we increase the fund size, although the price impact becomes more severe.

We confirm our predictions in the data. When there is no price impact, $MVTC$ has an average monthly turnover of 1.5, an average notional value of 2.9, implying a TO-NV of 0.5. This is two-thirds of MV and comparable to HML, RB, and MOM. The trading activity drastically decreases with an average monthly turnover of 0.7 or 0.3, an average notional value of 2.6 or 2.2, and a TO-NV of only 0.26 or 0.13 when the initial AUM of a fund is USD 100 million or USD 1 billion. This means that $MVTC$'s trading aggressiveness is comparable to VAL when the fund size is large and the price impact of trading is severe.

The average costs incurred by $MVTC$ are 0.58% per year when there is no price impact, and 0.56% or 0.54% when the initial fund size is USD 100 million or USD 1 billion. With the exception of the DOL (which incurs almost zero trading costs) these costs are low compared to any of the other strategies, especially considering a large fund that is subject to a severe price impact. It is interesting that $MVTC$ reduces its trading activity to the extent that the AUM appears orthogonal to the average costs incurred by the fund. This means that the increase in the per-USD trading costs due to the more severe price impact is perfectly offset by the reduction in the trading aggressiveness in response to the higher per-USD costs. These costs are comparably small considering that the average before-cost return of $MVTC$ ranges between 5.4% and 8.4% (depending on the initial AUM). This is in stark contrast to MV, for which trading costs are a major concern.

Table 3 further reports, on rows seven and eight in panels B and C, the average amount traded by the strategy (average across currency-month observations with non-trivial trade) as a percentage of the average daily trading volume in the market (row seven), or in absolute terms as millions of USD (row eight). These metrics provide a reference to understand the trading activity of each strategy. In particular, the trade size relative to the daily trading volume in the market allows a cross-strategy comparison.

Most notably, MV, HML, RB, and MOM engage in large trades in the order of 1.5-3.2% or even 5.7-10.1% of the average daily trading volume in the market when the AUM of a fund is USD 100 million or 1 billion. This resonates with the finding that the price impact of trading is severe for these strategies. In comparison for the fund size of USD 100 million or 1 billion these percentages of the daily volume in the market are 0.5% or 3.7% for $DDOL$, 0.6% or 4.2% for VAL, 0.6% or 1.4% for $MVTC$, and only 0.02% or 0.2% for DOL. This illustrates again the resilience of $MVTC$ and DOL to the problem of transaction costs even when the size of a fund is large.

It is furthermore interesting that the average trade size of $MVTC$ is roughly half that of MV when measured in USD (USD 34 million versus 62 million for AUM of USD 100 million; USD 89 million versus 148 million for AUM of USD 1 billion), but it is less than a quarter when expressed as a percentage of the daily trading volume in the market (0.6% vs 3.0% for AUM of USD 100 million; 1.4% vs 5.7% for AUM of USD 1 billion). Similar patterns are also observed when we compare $MVTC$ to all other strategies. The reason is that $MVTC$ (compared to MV or other strategies) does not only reduce the overall trade size, it also specifically reduces the order size of expensive currencies. These expensive currencies are illiquid and the daily trading volume in the market is typically low. In contrast, $MVTC$ still trades aggressively (and comparable to MV or other strategies) in cheap currencies, which are liquid and have a high daily volume. Therefore, the average order size as a percentage of the daily trading volume should be much lower for $MVTC$ than MV or other strategies, while the USD difference in average order size may be relatively small.

As a final comparison, we consider the trading costs of the US stock market. For that purpose, we use the S&P 500 SPDR ETF (SPY) as a reference.[18] We have data for the SPY starting in April 1993. The correlation of monthly excess returns between the US value-weighted stock market portfolio and the SPY is 0.98 for the sample period from April 1993 to January 2024. Moreover, we find that the US stock market earns on average 0.12% more per year than the SPY. This is close to the SPY's advertised expense ratio of 0.09%. A buy-

[18]We download SPY data from Yahoo finance, https://finance.yahoo.com/.

and-hold investment in the SPY does not incur additional costs beyond the expense ratio.[19] Accordingly, we use 0.09% as the relevant costs for the US stock market, independent of the AUM. This is a small fraction of the costs incurred by our FX trading strategies.

To sum up, we document that the price impact of FX trading is a major concern for large funds. For most strategies, trading costs erode a large fraction of the average before-cost returns. Specifically, when the initial AUM of a fund is USD 1 billion MV, HML, and MOM incur costs that surpass the average before-cost returns, resulting in strategies that, on average, make losses after accounting for costs. Moreover, we observe that $MVTC$ significantly reduces its trading activity in response to transaction costs. It incurs substantially lower costs than MV and other popular FX trading strategies. This effect intensifies when we consider a higher initial AUM of a fund. As a result $MVTC$ efficiently tackles the transaction cost problem, resulting in costs that are a small fraction of its average returns.

4.3 Performance After Costs

As documented in the previous section, when the size of a fund is large, the price impact and trading costs are considerable and in some cases larger than the average before-cost returns. Therefore, the price impact of trading has a first-order impact on the profitability of most trading strategies. In the following, we analyze the after-cost performance of our strategies in more detail. The last seven rows in panel A, B, and C in Table 3 report the after-cost Sharpe ratio, the difference between the after-cost Sharpe ratio of a strategy and that of $MVTC$ (denoted by ΔSR), the after-cost annualized average return, annualized volatility, monthly skewness, maximum drawdown (MDD) measuring the largest negative return from peak to trough during our sample period, and the total return of the strategy over the sample period.

[19] The bid-ask spread and the price impact only have to be paid twice; once at the beginning and once at the end of the investment. Considering an investment period of 37 years these costs are negligible.

4.3.1 Mean-Variance Optimized Portfolio MV

We start with MV, which is the most profitable strategy in terms of before-cost returns. When there are only proportional costs, the after-cost Sharpe ratio of MV is 0.99, which is a 12% drop from the before-cost Sharpe ratio of 1.12. This suggests that trading costs are not a major concern for small funds that invest in MV.

In contrast, when a fund has an initial AUM of USD 100 million, then the after-cost Sharpe ratio of MV drops to 0.36. This is a 68% reduction from the before-cost Sharpe ratio. Interestingly, while MV outperforms the US stock market in terms of before-cost returns (1.12 vs 0.52) or after accounting for only proportional costs (0.99 vs 0.51), it performs considerably worse than the stock market (0.36 vs 0.51) when the initial fund size is USD 100 million.[20] Even worse, when the initial AUM is USD 1 billion then MV turns into a losing strategy with a negative after-cost Sharpe ratio of -0.27 (or an average excess return of -2.7% per year). Accordingly, when a fund is large, the costs due to the price impact of trading have a first-order impact on the profitability of MV.

The reduction in the Sharpe ratio of the MV is almost entirely explained by the direct implications of costs on the average return. The annual average return decreases from 8.9% before costs to 7.9% after deducting proportional costs, and 2.9% or even -2.7% after accounting for the price impact when a fund has an initial AUM of USD 100 million or 1 billion, respectively.

There is also a small effect of the price impact on volatility. The before-cost volatility of MV is 8.0%, and it slightly decreases to 7.9% after accounting for proportional costs. Interestingly, it increases to 8.1% or 10.0% when the initial AUM is USD 100 million or 1 billion, respectively. This increase in volatility negatively affects the after-cost Sharpe ratio but, as mentioned above, this effect is small compared to the direct effect of costs on the average return.

Similar to the effect on volatility, we observe a negative effect of the price impact on crash risks. However, while the effect on volatility is relatively modest, the crash risk implications

[20]The after-cost Sharpe ratio of 0.51 of the US stock market is almost identical to its before-cost Sharpe ratio of 0.52. The reason is that the US stock market has a low expense ratio of 0.09%.

are quantitatively large and concerning. The price impact leads to a reduction in the monthly skewness from -0.83 and the MDD from -26% (when there are only proportional costs) to -1.23 and -36% when the initial AUM is USD 100 million, or to -2.47 and -157% when the initial AUM is USD 1 billion.

Finally, we analyze the total increase in the AUM from February 1987 to January 2024 for a fund that invests in MV. A fund that started out with an AUM of USD 100 million achieves a total return of 641%. In comparison, a fund with an initial AUM of USD 1 billion has a total return of -14%. Note that these calculations account for the risk-free rate in the USD while the average returns reported above are excess returns. If these funds had to pay only proportional costs but there was no price impact of trading, then the total return would be 4,456%. Clearly, the cumulative costs over the 37-year horizon add up significantly, and the price impact of trading has a first-order effect.

Overall, trading costs are a major concern for large funds that face a non-trivial price impact of trading and intend to invest in MV. Transaction costs erode a large fraction of or even the entire expected return, and increase the crash risk at the same time.

4.3.2 Characteristic Sorted Long-Short Strategies

Next, we turn to the six characteristic-based long-short strategies HML, RB, DOL, $DDOL$, VAL, and MOM. In the previous section we established that, by construction, these strategies trade less aggressively and incur lower costs than MV. The proportional costs borne by these strategies are small, and after-cost Sharpe ratios are close to the respective before-cost Sharpe ratios. As such, a small fund (which does not face any price impact of trading) does not need to be concerned about trading costs. This is the standard conclusion from the literature, which only assesses the effect of proportional costs on the profitability of trading strategies.

In contrast, the after-cost Sharpe ratios substantially decrease when the initial AUM of the fund is large. The effect is the largest for HML, RB and MOM. In the case of HML, the before-cost Sharpe ratio is 0.79, while the after-cost Sharpe ratio decreases to 0.74 when there is no price impact, and to 0.46 or even -0.12 when the initial AUM is USD 100 million or USD 1 billion, respectively. Similarly, for RB and MOM the corresponding values are 0.81 and 0.36 before cost, 0.75 and 0.33 after cost without price impact, 0.59 and 0.18 when the initial AUM is USD 100 million, and 0.04 and -0.28 when the initial fund size is USD 1 billion. Also similarly to MV, HML and MOM underperform the US stock market (which has an after-cost Sharpe ratio of 0.51) when the fund size is USD 100 million, and all three strategies are unprofitable (with negative or barely positive average returns) after accounting for costs when the fund has an initial AUM of USD 1 billion.

The implications of the price impact of trading are less severe but still concerning for the $DDOL$ and VAL. These strategies have before-cost Sharpe ratios of 0.32 for $DDOL$ and 0.51 for VAL. Proportional costs reduce the Sharpe ratios of $DDOL$ and VAL to 0.29 and 0.49, while the price impact of a fund with an initial AUM of USD 100 million or USD 1 billion further reduces these ratios to 0.26 or 0.08 for $DDOL$ and 0.44 or 0.14 for VAL. While the after-cost Sharpe ratios remain positive even when the initial AUM reaches USD 1 billion, the performance is not attractive to an investor and these strategies underperform the US stock market by a large margin.

The costs incurred by DOL are negligible irrespective of the fund size, and the after-cost Sharpe ratio of DOL is virtually identical to the before-cost Sharpe ratio. As such, the DOL is very resilient to trading costs. However, we acknowledge that the DOL is not an attractive strategy to begin with.

It is clear that the intuitive advantage of characteristic-based long-short strategies to mitigate costs (as the investment policy is less sensitive to state variables than MV) does not work well. The reason is twofold. First, the before-cost performance of these strategies is much worse than the performance of MV, and we would need a lot of cost savings to make up for this. Second, although the characteristic-based long-short strategies are less sensitive to the price impact of trading than MV, they are not resilient enough. That is, when the size of a fund is large, they still suffer greatly from the price impact of trading and incur large transaction costs.

Similarly to MV, for the characteristic-based long-short strategies we also observe an increase in crash risk due to the price impact, albeit this effect appears only relevant when the fund size is sufficiently large. For instance, the skewness and MDD of HML are -0.77 and -32%, respectively, when there is no price impact, and these values decline to -0.83 and -33% when the initial AUM is USD 100 million, and to -0.91 and -115% when the initial AUM is USD 1 billion. The crash risk for a fund with an initial AUM of USD 100 million is almost identical to a small fund with no price impact. However, the crash risk rapidly increases as we increase the initial fund size from USD 100 million to USD 1 billion. The effect is similar for the other five characteristic-based long-short strategies.

To sum up, for large funds, transaction costs have first-order implications on the profitability of characteristic-based long-short strategies.

4.3.3 Mean-Variance-Transaction-Cost Optimized Portfolio $MVTC$

Finally, we investigate the after-cost performance of $MVTC$, which is designed to optimally tackle costs. In the previous sections, we showed that, compared to the high before-cost returns, average annual costs are relatively low even when the fund size is large. Accordingly, the Sharpe ratios are comparable before and after costs. When there are only proportional costs, the after-cost Sharpe ratio of $MVTC$ is 1.01, which is a 6% drop from the before-cost Sharpe ratio of 1.08. For a fund with an initial AUM of USD 100 million or USD 1 billion, the after-cost Sharpe ratios are 0.88 or 0.75, respectively, which is an 8% or 11% decrease from the before-cost Sharpe ratios of 0.96 or 0.84. This suggests that trading costs are not a major concern for investors in $MVTC$, independent of the fund size.

Consistent with the theory, we also observe that $MVTC$ always outperforms MV after accounting for costs, despite the fact that MV has a higher before-cost Sharpe ratio. In the case of only proportional costs, the difference between the after-cost Sharpe ratios of MV and $MVTC$, i.e., $\Delta SR = SR^{MV} - SR^{MVTC} = -0.02$, is small and statistically insignificant.[21] However, when the initial AUM is USD 100 million or USD 1 billion, these differences (i.e., ΔSR) are -0.52 or -1.02, respectively, and statistically significant at the 1% level. The differences in Sharpe ratios between all other strategies and the $MVTC$ are always (i.e.,

[21]To test for significance, we employ the test proposed by Ledoit and Wolf (2008), which uses block bootstrapping and is robust to heteroskedasticity and cross- and auto-correlation. We choose a block size of 5 observations for the block bootstrapping.

independent of the fund size) economically large and statistically significant, as indicated by ΔSR in Table 3. Furthermore, in comparison to the US stock market, $MVTC$ delivers a much more attractive Sharpe ratio.

Figure 4 further illustrates the after-cost outperformance of $MVTC$. We plot the cumulative after-cost excess returns of $MVTC$, MV, HML, and MOM.[22] First, $MVTC$ performs well independent of the fund size. Second, we note that there are no sudden discontinuities. That is, the strong performance of $MVTC$ is not driven by a few outlier months but it is continuous throughout the sample. While we generally observe a weakening of the FX strategies between October 2008 and December 2021,[23] $MVTC$ is still profitable during that period. Moreover, the performance during the final 2 years of our sample are exceptional. This demonstrates that FX strategies, and in particular $MVTC$, did not only perform well in the distant past but also deserve much attention nowadays. Moreover, table A6 shows that post-GFC the after cost Sharpe ratio of $MVTC$ is still 0.81 (no price impact), 0.76 (initial AUM of USD 100 million), and 0.59 (initial AUM of USD 1 billion).

The after-cost cumulative returns of MV are almost indistinguishable from $MVTC$ when there is no price impact of trading. In contrast, when the fund size is large and there is a non-trivial price impact of trading the outperformance of $MVTC$ over MV is obvious. When the initial AUM is USD 100 million, MV performs relatively well for the first 10 years but is essentially unprofitable after 1997. Even worse, when the initial AUM is USD 1 billion, MV makes large losses, especially in the 1990s, reports some small gains from 2000 to 2006, and is a losing strategy ever since.

$MVTC$ also outperform HML and MOM by a large margin. HML performs well throughout the sample when there is no price impact of trading. It performs relatively well until 2008 when the initial AUM is USD 100 million, but after that the performance is weak. Moreover, when the initial AUM is 1 billion, HML is a losing strategy almost throughout the entire sample. MOM performs similarly to HML until 2008. After 2008, even its before-cost average return turns negative, and it is unprofitable before and after costs.

[22] We do not plot the other strategies to keep the figure legible.

[23] We provide a more detailed analysis of pre- and post-2008 performance in robustness tests in Section 5 and Internet Appendix B.2.

Compared to the other strategies, we do not observe any worrisome effects of the fund size and trading costs on the risk of $MVTC$. The before-cost and after-cost volatilities are almost identical. The skewness and MDD are unaffected by the fund size. When there is no price impact, the monthly skewness of $MVTC$ is -0.76 and the MDD is -28%. When the initial fund size is USD 100 million or 1 billion, the skewness coefficients are -1.03 or -0.95, respectively, and the MDD are -26% or -30%. Moreover, this insight is also confirmed in Figure 4. Essentially, there is only a trend adjustment in the cumulative returns of $MVTC$ when we compare different fund sizes.

Finally, a fund that started out with an AUM of USD 100 million in February 1987 yields a total return of 2,600%. In comparison, a fund with an initial AUM of USD 1 billion has a total return of 1,449%. These total returns are a lot more attractive than the total returns of MV, i.e., 641% or -14%.

Overall, $MVTC$ efficiently reduces its trading activity to save costs while maintaining a strong performance. First, trading costs are much less problematic for $MVTC$ than all other strategies. Second, $MVTC$ is resilient to transaction costs even when the price impact of trading is severe.

Last but not least, we note that $MVTC$ is the solution in a single-period model. It does not take into account potentially interesting dynamics in a multi-period model. It is not obvious at the outset that $MVTC$ performs well out-of-sample when implemented in the data with many trading dates. It is an important empirical finding that (i) $MVTC$ performs significantly better than all other strategies, (ii) achieves a high after-cost Sharpe ratio, and (iii) is resilient even when the size of a fund is large and the price impact of trading is severe.

4.3.4 Capacities of Strategies: Effect of the Fund Size

Next, we vary the size of a fund to further investigate the resilience of $MVTC$ to the price impact of trading. Figure 5 plots the after-cost Sharpe ratio of a fund against its initial AUM. For the AUM we consider values up to USD 5 billion. The figure is complemented by Table A1 in the Internet Appendix, which provides more detailed values and considers a wider range for the AUM. All lines in Figure 5 are decreasing as a larger AUM implies larger trade orders and higher costs due to the trading volume price impact. Confirming the findings in Table 3, when the initial AUM of a fund is less than USD 100 million or 1 billion, $MVTC$ achieves an after-cost Sharpe ratio of at least 0.88 or at least 0.75, respectively.

Recall that the US stock market has an after-cost Sharpe ratio of 0.51 irrespective of the AUM as indicated by the red dotted line in the figure. A fund investing in $MVTC$ performs better than the US stock market as long as the initial AUM does not surpass USD 6 billion (or equivalently an AUM of USD 45 billion in January 2024). Moreover, $MVTC$ is still profitable (i.e., it earns a positive after-cost average return and a Sharpe ratio of more than 0.15) even when the initial AUM reaches USD 1 trillion. These numbers demonstrate that $MVTC$ has a large capacity and is resilient to even a very large fund size and a severe price impact of trading.

In contrast, all other strategies perform much worse. For instance, MV only outperforms the US stock market when the initial AUM is smaller than USD 60 million. Moreover, MV is unprofitable as soon as the initial AUM surpasses USD 340 million. Similarly, HML and RB underperform the US stock market or even turn completely unprofitable once the initial AUM is larger than USD 80 million or USD 180 million, respectively, or USD 660 million or USD 1.25 billion, respectively. As such, these strategies have relatively small capacities, especially if we take the US stock market as the benchmark. $MVTC$ clearly stands out as the only currency trading strategy that is resilient to a severe price impact of trading.

We conclude that transaction costs, and specifically the price impact of trading, are a first-order concern for currency investors. Costs quickly erode the expected returns of popular strategies in the literature, and these strategies are left unprofitable. Thus, addressing trading costs in the construction of the portfolio is essential to improve the overall performance. $MVTC$ efficiently reduces trading activity to mitigate costs. Accordingly, it is resilient to even a severe price impact of trading.

5 Robustness and Extensions

We perform several robustness checks and extensions, which we report in detail in the Internet Appendix B. It is reassuring that our main results continue to hold in all robustness analyses. In the following we provide a brief overview.

In Appendix B.1 we investigate whether intuitive rules-of-thumb are helpful in mitigating transaction costs. We consider two rules-of-thumb: (i) trading at a lower frequency, or (ii) removing high-cost currencies from our asset universe. Such rules reduce costs to some extent, but they are inefficient as they have significant negative implications on the performance of our strategies. Thus, our findings advise against the use of intuitive rules-of-thumb, as deviations from the optimal (before-cost) balance between expected return and risk have adverse consequences for the performance. If we invest in $MVTC$, which accounts for costs in portfolio optimization, the out-of-sample performance is significantly better. Moreover, $MVTC$ is far more resilient than the other analyzed strategies when we consider large funds that face a severe price impact.

In Section 4 we use the longest available sample period as our baseline as a longer sample period generally provides more accurate estimates of expected returns. Nevertheless, in Appendix B.2, we further show that our results are robust and continue to hold in the following sub-samples: (i) pre- and post-2008 global financial crisis (GFC), (ii) pre- and post-introduction of the Euro (January 1999), and (iii) in and out of NBER-defined US recessions. These robustness checks are important to ensure that our results are generally true, and not driven by a specific sub-sample under special economic conditions.

In Appendix B.3 we show that our results are robust and continue to hold for alternative estimations of the price impact functions. The choice of method used to estimate cost functions has little effect on the after-cost profitability of our strategies and, therefore, our results are not driven by the particular estimation of the costs. Recall that in the baseline analysis we keep the trading volume fixed through time and all time-series variation in the Amihud measure stems from the variation in absolute returns. In our robustness checks we first use the time-series average of our Amihud measure to construct a time-invariant price impact function. Second, we do a more elaborate extrapolation back in time and allow for time-varying volume. Finally, we cut all costs in half to conservatively address the concerns that our setup cannot handle indirect trades via the currency triangle. The idea is that it might be cheaper (and, in the best-case scenario, reduce costs by up to 50%) to trade directly between two non-USD currencies rather than twice against the USD.

A potential concern about $MVTC$ is that it instantly adjusts its portfolio holdings when there is a major shock to the investment opportunity set, while in reality this may not be possible. Therefore, in Appendix B.4.1, we implement an event study and illustrate that the crash risk exposure of $MVTC$ does not substantially increase even if it is impossible to unwind its risk exposure in turbulent periods.

Finally, in Appendix B.4.2 we show that reasonable choices of the λ parameter for the $MVTC$ strategy do not alter our results.

6 Conclusion

We show that, despite the high trading volume in FX markets, transaction costs have a first-order impact on the performance of currency portfolios. Specifically, while proportional costs are a minor concern (as documented in the literature), the price impact of trading is a first-order problem for popular FX trading strategies. Costs due to the price impact quickly erode average returns, and cause these strategies to underperform the US stock market or, even worse, turn them unprofitable. This is an important contribution, as the FX market literature has hitherto considered the profitability of currency strategies in the absence of price impact.

In contrast, if we optimally account for costs in the construction of our portfolio ($MVTC$), we find that the after-cost performance is attractive, and $MVTC$ consistently outperforms the US stock market. $MVTC$ is resilient to even a large fund size and a severe price impact of trading. Accordingly, transaction costs are a first-order problem, and it is vital for investors to optimally tackle them in the portfolio construction in order to obtain a robustly profitable strategy.

Our paper further contributes to the literature on liquidity in FX markets. Most importantly, we propose novel extrapolations of the realized Amihud measure introduced by Ranaldo and Santucci de Magistris (2022). This allows us to obtain estimates of the price impact for 26 instead of 12 currencies (against the USD) and for a sample going back to 1986 instead of 2012. In particular, we show that trading volume can be accurately extrapolated in the cross-section and in the time-series using the bid-ask spread as a conditioning variable.[24]

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[24]The results of the time-series extrapolation are in Section B.3 in the Internet Appendix.

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Table 1: **Average Trading Costs by Currency**

	All Days			Days with B&R Data Coverage				
Currency i	N Obs	$\overline{PBA}_i^S$	$\bar{A}_i^S$	N Obs	$\overline{PBA}_i^{S,BR}$	$\overline{PBA}_i^S$	$\bar{A}_i^S$	$\mathbf{\Delta_i^k}W$
AUD	9653	4.6	0.019	9638	8.1	4.6	0.019	91.8
BRL	7718	6.9	0.101	7714	7.3	6.9	0.101	1.6
CAD	9653	3.1	0.009	9631	5.4	3.1	0.009	127.8
CHF	9653	3.5	0.038	9653	5.6	3.5	0.038	28.1
CSK	7604	10.4	0.484	7604	11.6	10.4	0.484	1.2
DEM	3107	4.3	0.018	3065	6.4	4.3	0.018	60.1
ESP	3048	7.1	0.032	1261	5.9	5.6	0.035	5.3
EUR	6542	1.5	0.004	6521	3.7	1.5	0.004	293.7
FRF	3107	4.6	0.021	3065	9.6	4.7	0.021	115.6
GBP	9653	2.8	0.011	9652	4.3	2.8	0.011	70.1
GRD	3489	15.1	0.103	1761	9.4	7.7	0.12	7.1
HUF	7849	10.9	0.59	7849	11.4	10.9	0.59	0.4
IEP	3107	10.5	0.064	3065	18.6	10.4	0.064	63.6
ITL	3107	7.4	0.043	3065	11.6	7.4	0.043	47.7
JPY	9653	3.1	0.007	9650	5.9	3.1	0.007	187.8
KRW	8746	5	0.074	7819	6.7	5.2	0.082	8.9
MXN	9021	6.6	0.042	7849	7.8	7	0.048	9.1
NLG	3107	4.7	0.02	3065	6.4	4.7	0.02	41.2
NOK	9653	4.8	0.188	9652	5.8	4.8	0.187	2.9
NZD	9652	7.8	0.068	9604	12.2	7.9	0.068	32.5
PLN	7587	9.4	0.267	7587	10.7	9.4	0.267	2.4
PTE	2246	10.9	0.065	1261	7.9	7.5	0.067	3.2
SEK	9653	5.8	0.156	9652	8.2	5.8	0.156	7.4
SGD	9653	4.4	0.027	9651	7.2	4.4	0.027	51.1
TWD	8837	7.2	0.033	7825	7.8	6.8	0.037	13.8
ZAR	9628	12.7	0.093	8978	25.6	11.5	0.089	78.9

Notes: The table reports trading costs for each currency against the USD. The first three columns use data from our full sample, the last five columns considers the sub-sample of days for which B&R data is available. N obs reports the number of daily observations. $\overline{PBA}_i^{S,BR} = \frac{1}{T}\sum_t PBA_{i,t}^{S,BR}$ is the average proportional bid-ask spreads (in bps) computed from B&R data. $\overline{PBA}_i^S = \frac{1}{T}\sum_t PBA_{i,t}^S$ is the average adjusted spreads (in bps) according to equation (1). $\bar{A}_i^S = \frac{1}{T}\sum_t A_{i,t}^S$ is the average realized Amihud measure (in bps per USD 1 million traded) according to equation (8). $\mathbf{\Delta_i^k}W = \frac{\overline{PBA}_i^{S,BR} - \overline{PBA}_i^S}{2\bar{A}_i^S}$ is the trade order size (in million USD) that equalizes the trading costs if we only consider proportional costs constructed from B&R data $0.5\overline{PBA}_i^{S,BR}$ compared to the total costs considering the adjusted proportional costs $0.5\overline{PBA}_i^S$ and the price impact of trading given the realized Amihud measure $\bar{A}_i^S$ and the trade order size $\mathbf{\Delta_i^k}W$. The data are daily for the period from the 2st of February 1986 to the 31st of January 2024.

Table 2: **Correlations between Alternative Realized Amihud Measures**

	AUD	CAD	CHF	EUR	GBP	JPY
Hourly Quotes	0.83	0.9	0.83	0.79	0.89	0.6
Constant Volume	0.63	0.77	0.67	0.62	0.72	0.48
	MXN	NOK	NZD	SEK	SGD	ZAR
Hourly Quotes	0.88	0.88	0.8	0.79	0.84	0.79
Constant Volume	0.81	0.79	0.67	0.67	0.64	0.63

Notes: The table reports for the spot exchange rates of each currency $i \in \mathcal{I} = \{$AUD, EUR, GBP, NZD, CAD, CHF, JPY, NOK, SEK, MXN, SGD, ZAR$\}$ the correlations between the daily realized Amihud measure of Ranaldo and Santucci de Magistris (2022) and two versions of our daily $A^S_{i,t} = \frac{RPV_{i,t}}{v^S_{i,t}}$ in (8) for the time period from September 2012 to September 2021. Ranaldo and Santucci de Magistris (2022) use one-minute exchange rate quotes to compute the daily return variation $RPV_{i,t}$ and daily volume data for $v^S_{i,t}$. In the row indicated by 'Hourly Quotes' we use hourly exchange rate quotes to compute $RPV_{i,t}$ and daily volume data for $v^S_{i,t}$. In the row indicated by 'Constant Volume' we use hourly exchange rate quotes to compute $RPV_{i,t}$ and the time-series average of the daily volume (i.e., a constant) for $v^S_{i,t}$.

Table 3: **Performance of FX Strategies**

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
PANEL A: NO PRICE IMPACT								
Before cost SR	1.12	1.08	0.79	0.81	0.09	0.32	0.51	0.36
Before cost Mean (%)	8.92	8.40	6.55	5.50	0.70	2.45	3.50	3.15
Before cost Vol (%)	7.95	7.76	8.34	6.80	7.83	7.74	6.92	8.67
Mean Costs (%)	1.06	0.58	0.34	0.39	0.02	0.19	0.11	0.30
Turnover	2.32	1.49	1.13	0.95	0.03	0.40	0.25	0.95
Notional	3.07	2.93	2.00	2.00	1.00	1.00	2.00	2.00
SR	**0.99**	**1.01**	**0.74**	**0.75**	**0.09**	**0.29**	**0.49**	**0.33**
ΔSR	**-0.02**	**-**	**-0.27**	**-0.26**	**-0.92*****	**-0.72*****	**-0.52****	**-0.68*****
Mean (%)	7.85	7.81	6.20	5.11	0.68	2.25	3.39	2.85
Vol (%)	7.92	7.73	8.34	6.80	7.83	7.75	6.91	8.67
Skew	-0.83	-0.76	-0.77	-0.69	-0.41	-0.28	-0.20	-0.25
MDD (%)	-26.42	-28.02	-32.28	-31.43	-44.09	-18.30	-22.39	-54.73
Total return	44.56	44.23	23.73	16.32	2.37	4.87	8.25	6.13
PANEL B: $AUM_0 = 100$ **million**								
Before cost SR	1.12	0.96	0.79	0.81	0.09	0.32	0.51	0.36
Before cost Mean (%)	8.92	6.94	6.55	5.50	0.70	2.45	3.50	3.15
Before cost Vol (%)	7.95	7.25	8.34	6.80	7.83	7.74	6.92	8.67

Continued on next page

Table 3 – continued from previous page

	MV	$MVTC$	HML	RB	DOL	$DDOL$	VAL	MOM
Mean Costs (%)	5.92	0.56	2.63	1.46	0.02	0.41	0.46	1.58
Turnover	2.32	0.68	1.13	0.95	0.03	0.40	0.25	0.95
Notional	3.07	2.59	2.00	2.00	1.00	1.00	2.00	2.00
Avg USD Trade Size (millions)	62.15	33.60	63.40	32.25	0.39	9.50	10.83	36.45
Avg Relative Trade Size (%)	2.99	0.63	3.21	1.53	0.02	0.49	0.61	1.83
SR	**0.36**	**0.88**	**0.46**	**0.59**	**0.09**	**0.26**	**0.44**	**0.18**
ΔSR	**-0.52*****	**-**	**-0.42****	**-0.29***	**-0.80*****	**-0.62*****	**-0.44****	**-0.70*****
Mean (%)	2.92	6.37	3.90	4.04	0.68	2.04	3.04	1.56
Vol (%)	8.14	7.22	8.39	6.83	7.83	7.77	6.92	8.69
Skew	-1.23	-1.03	-0.83	-0.71	-0.41	-0.29	-0.21	-0.24
MDD (%)	-35.91	-25.53	-33.24	-31.88	-44.10	-18.98	-22.55	-80.47
Total return	6.41	26.00	9.58	10.66	2.37	4.42	7.16	3.44

PANEL C: $AUM_0 = 1$ **billion**

	MV	$MVTC$	HML	RB	DOL	$DDOL$	VAL	MOM
Before cost SR	1.12	0.84	0.79	0.81	0.09	0.32	0.51	0.36
Before cost Mean (%)	8.92	5.36	6.55	5.50	0.70	2.45	3.50	3.15
Before cost Vol (%)	7.95	6.41	8.34	6.80	7.83	7.74	6.92	8.67
Mean Costs (%)	11.49	0.54	7.51	5.16	0.04	1.82	2.47	5.57
Turnover	2.32	0.29	1.13	0.95	0.03	0.40	0.25	0.95
Notional	3.07	2.16	2.00	2.00	1.00	1.00	2.00	2.00
Avg USD Trade Size (millions)	148.06	88.84	220.87	151.91	3.92	73.14	76.39	169.02
Avg Relative Trade Size (%)	5.74	1.39	10.07	6.92	0.19	3.74	4.17	7.63

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Table 3 – continued from previous page

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
SR	**-0.27**	**0.75**	**-0.12**	**0.04**	**0.08**	**0.08**	**0.14**	**-0.28**
ΔSR	**-1.02*****	**-**	**-0.86*****	**-0.70*****	**-0.66*****	**-0.67*****	**-0.61*****	**-1.02*****
Mean (%)	-2.74	4.81	-1.01	0.31	0.66	0.63	1.02	-2.45
Vol (%)	10.03	6.44	8.82	7.09	7.83	7.99	7.20	8.86
Skew	-2.47	-0.95	-0.91	-0.83	-0.41	-0.42	-0.42	-0.24
MDD (%)	-157.21	-29.62	-115.01	-62.16	-44.14	-47.12	-28.37	-144.18
Total return	-0.14	14.49	0.71	1.94	2.34	2.20	2.91	0.00

Notes: The table reports summary statistics of monthly excess returns of our strategies in the FX market. The strategies are described in Section 3. Panel A summaries the performance when there are only proportional costs. Panel B and C report results when the initial AUM of a fund is USD 100 million respectively 1 billion and costs account for the price impact of trading. Before cost SR, Mean (%) and Vol (%) measure the annualized Sharpe ratio, and annualized average and volatility of the excess returns (reported in percentage points). Mean Costs (%) measures the average annualized trading costs as a percentage of the AUM. Turnover and Notional report the monthly turnover and the notional value as a fraction of the AUM. Avg Relative Trade Size (%) and Avg USD Trade Size (millions) measures the average amount traded per month (average across currency-month observations with non-trivial trade) as a percentage of the average daily trading volume in the market respectively in absolute terms as millions of USD. SR is the annualized after cost Sharpe ratio. ΔSR is the difference in the after-cost Sharpe ratio of a strategy and that of *MVTC*. Standard errors of ΔSR are estimated using block bootstrapping with a block size of 5 observations to account for heteroskedasticity, cross- and auto-correlation (Ledoit and Wolf, 2008). ***, **, * indicate a statistical significance at the 1%, 5%, 10% level. Mean (%) and Vol (%) are the annualized average and volatility of the after cost excess returns (reported in percentage points). Skew is the monthly skewness of the after cost excess returns, MDD (%) is the Maximum Draw Down (measured in percentage points). Total return is the return (including the risk-free rate) from February 1987 to January 2024. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

Proportional Costs

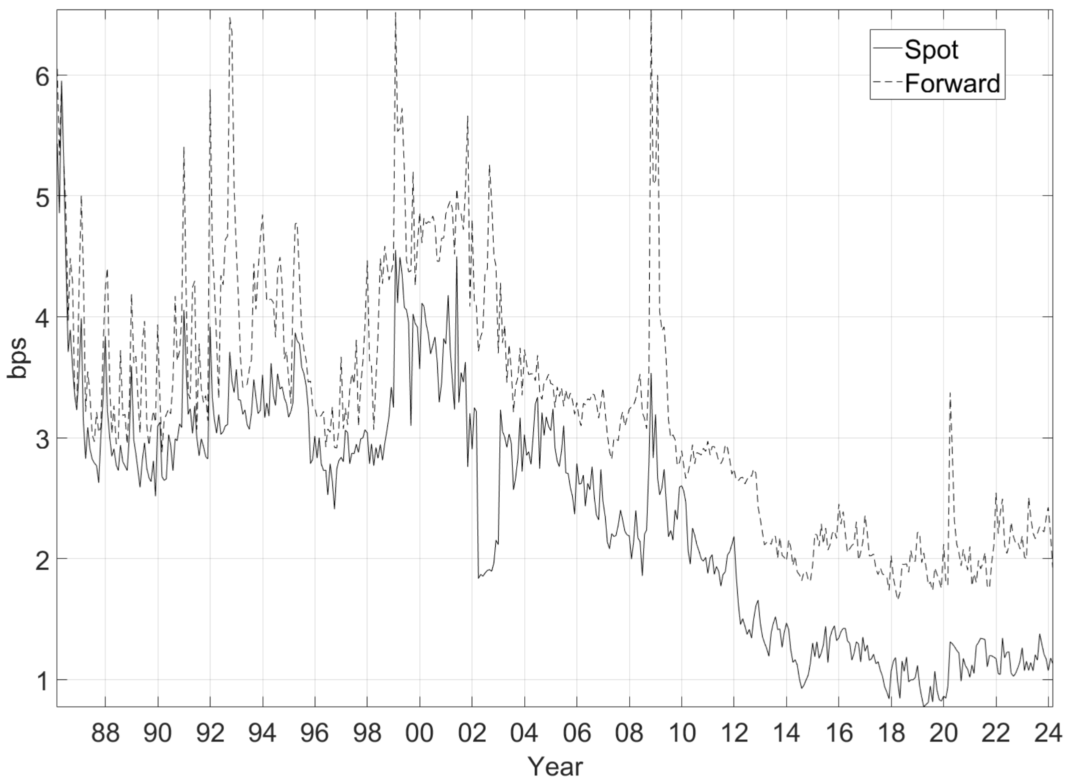

Figure 1: The figure plots the cross-currency median of the average proportional costs (section 2.3) for the spot market, $med\left(0.5C_{i,t}^{S+}+0.5C_{i,t}^{P-}\right)$ (solid line), and the forward market, $med\left(0.5C_{i,t}^{P+}+0.5C_{i,t}^{S-}\right)$ (dashed line). The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1986 to January 2024.

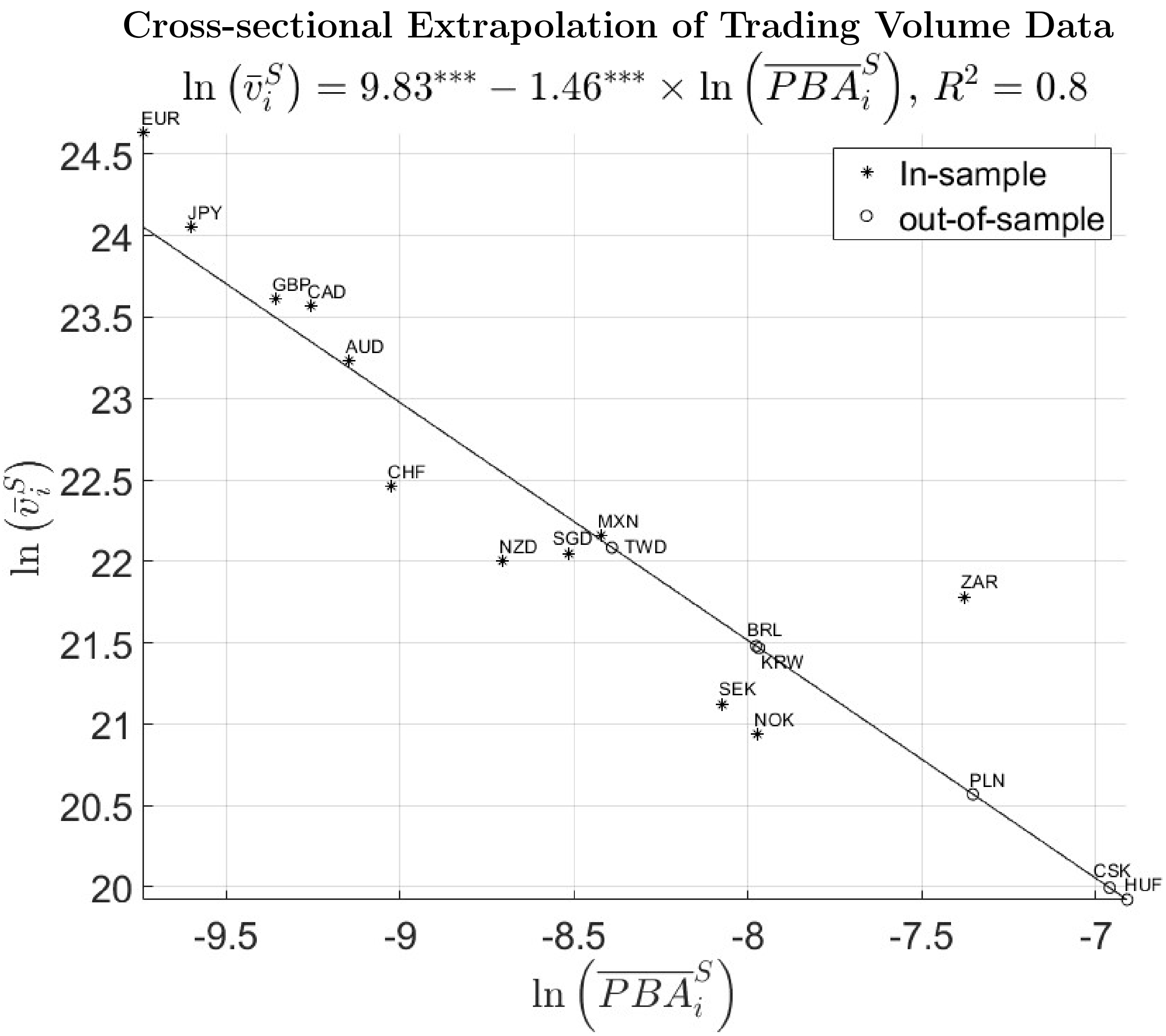

Figure 2: The asterisks in the figure plot the natural logarithm of the average volume $\ln\left(\bar{v}_i^S\right)$ against the natural logarithm of the average proportional bid-ask spread $\ln\left(\overline{PBA}_i^S\right)$ for the 12 currencies $i \in \mathcal{I} = \{$AUD, EUR, GBP, NZD, CAD, CHF, JPY, NOK, SEK, MXN, SGD, ZAR$\}$. The average is taken over the daily sample between September 3rd 2012 through September 24th 2021. The linear line is the fitted regression $\ln\left(\bar{v}_i^S\right) = 9.83 - 1.46 \ln\left(\overline{PBA}_i^S\right)$, and the circles on the line represent the fitted values $\ln\left(\bar{v}_i^S\right)$ corresponding to $\ln\left(\overline{PBA}_i^S\right)$ for the 6 currencies BRL, CZK, HUF, KRW, PLN, and TWD (for which CLS trading volume data is unavailable).

Price Impact

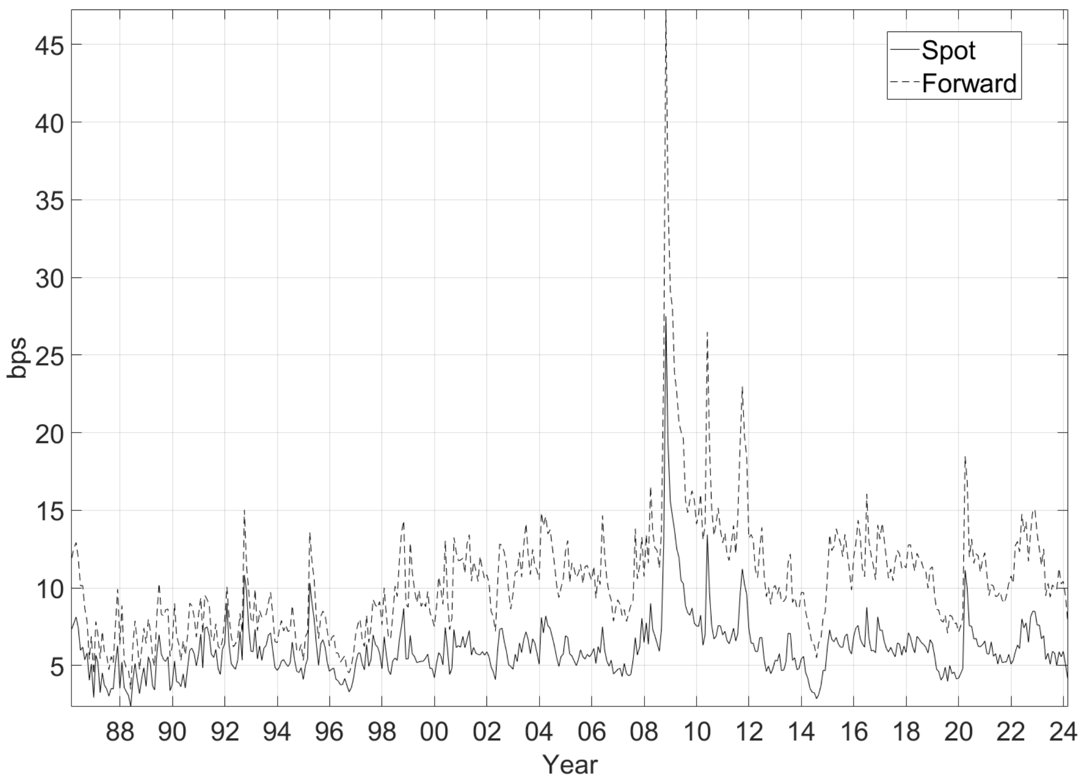

Figure 3: The figure plots the cross-currency median of $A^S_{i,t}\bar{z}^{funds}_i$ for spot (solid line) and $A^F_{i,t}\bar{z}^{funds}_i$ for forwards (dashed line). $A^S_{i,t}$ and $A^F_{i,t}$ are the realized Amihud measures for spot and forwards. $\bar{z}^{funds}_i$ is the time-series average of the absolute value of the daily order flow imbalance of funds. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1986 to January 2024.

Cumulative After-Cost Excess Returns

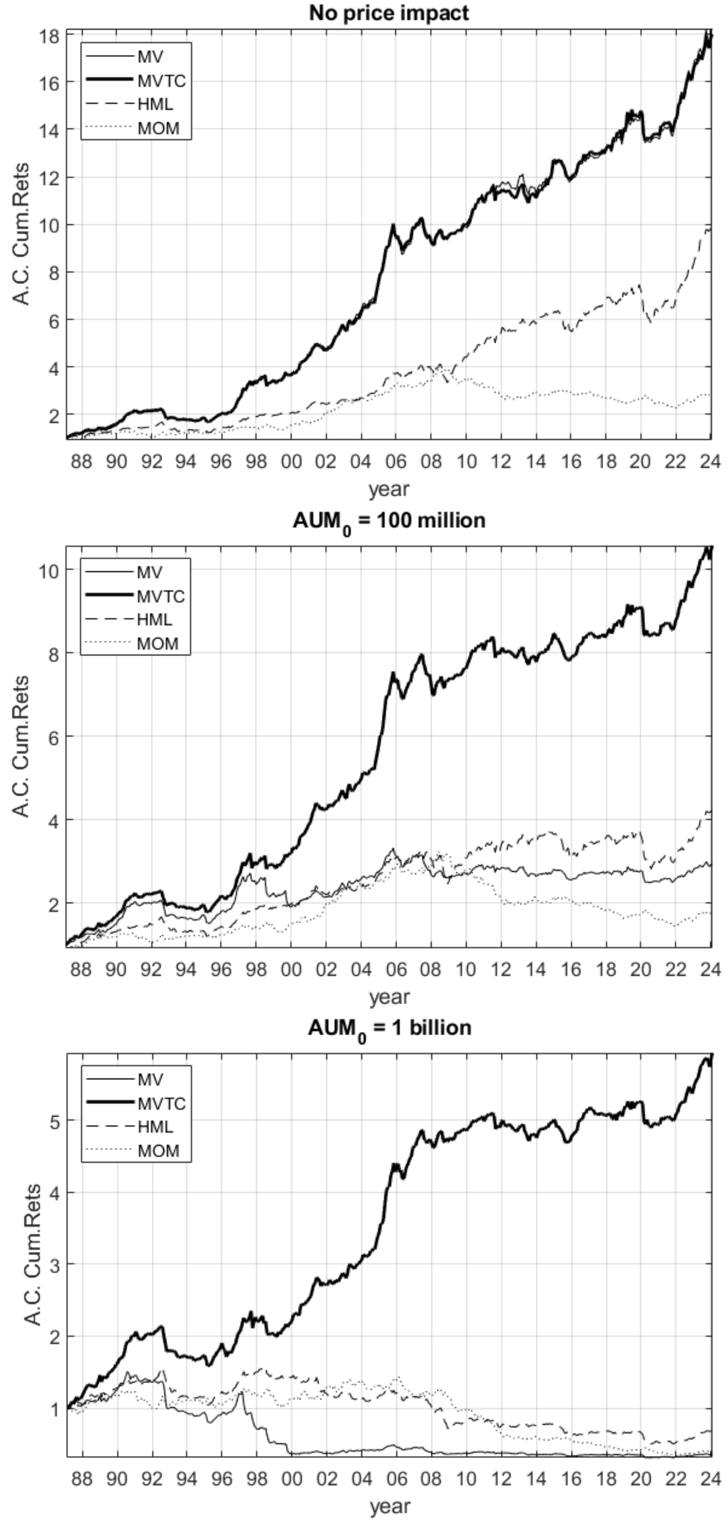

Figure 4: The figures plot the after-cost cumulative excess returns of MV (solid line), $MVTC$ (bold solid line), HML (dashed line), and MOM (dotted line). The strategies are described in Section 3. The top graph assumes no price impact, while the middle and bottom graphs assume an initial AUM of USD 100 million respectively 1 billion. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

Capacities of the Strategies: Effect of the Fund Size

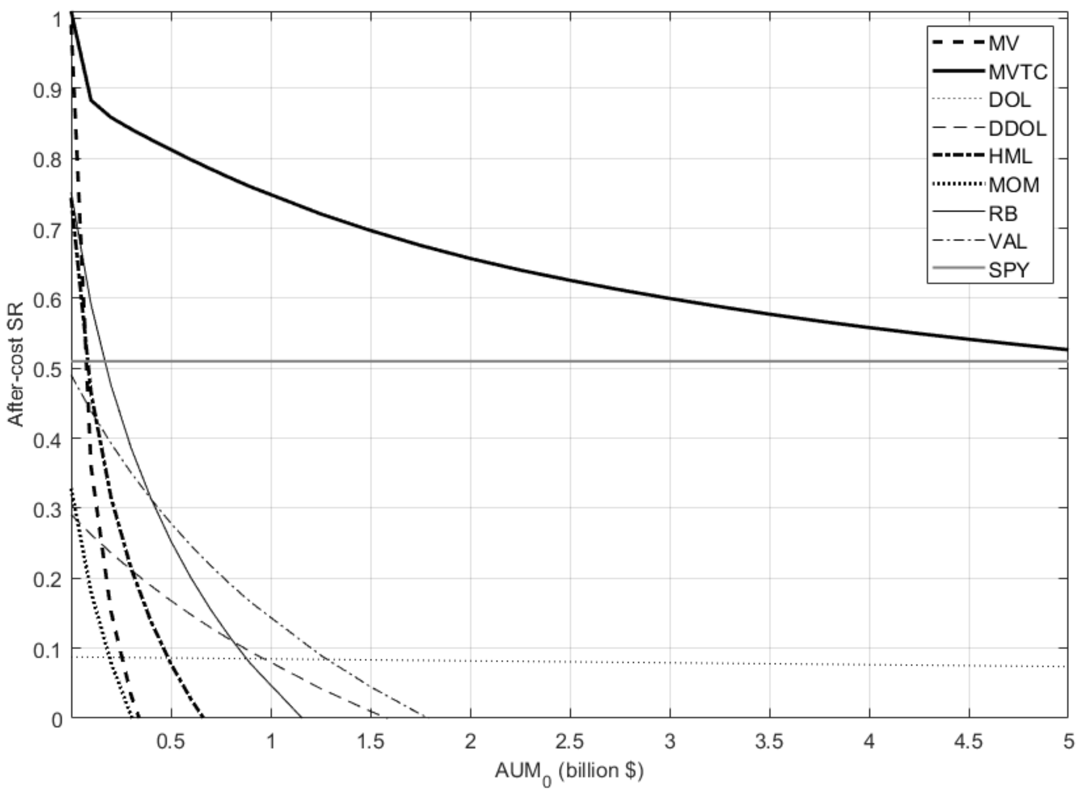

Figure 5: The figure plots the annualized after-cost Sharpe ratio as a function of the initial AUM of a fund for our FX trading strategies, and the US stock market (SPY; dotted red line). The FX strategies are described in Section 3. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

Internet Appendix

A Additional Results

For currencies $i \in \mathcal{I}^c$ (for which we do not have CLS data) we extrapolate $\bar{z}_i^{funds}$ using an analogous approach as for the extrapolation of $\bar{v}_i^S$. Figure A1 provides the regression results with a regression fit of 79%, and demonstrates that we can reliably extrapolate $\bar{z}_i^{funds}$.

Figures A2 to A5 show for each currency separately the proportional costs for spot and forwards, and $A_{i,t}^S \bar{z}_i^{funds}$ for spot and $A_{i,t}^F \bar{z}_i^{funds}$ for forwards. $A_{i,t}^S$ and $A_{i,t}^F$ are the realized Amihud measures for spot and forwards. $\bar{z}_i^{funds}$ is the time-series average of the absolute value of the daily order flow imbalance of funds and currency i.

Figure A6 shows the before cost performance of MV, $MVTC$, HML, and MOM.[25] MV and $MVTC$ clearly outperform the other strategies, and $MVTC$ slightly underperforms MV. It is reassuring that there are no notable jumps in the time-series of cumulative excess returns. This illustrates that our results are not driven by some large outliers. Instead, there is a clear trend. Moreover, the figure illustrates that our trading strategies are similarly or even more profitable in the past few years compared to before the GFC.

Figure A7 plots the cumulative costs incurred by $MVTC$, MV, HML, and MOM. It is apparent that the costs of MV are always higher than the costs of any other strategy. HML and MOM incur reasonably low costs when there is no price impact of trading, but costs are sizable for large funds which face a non-trivial price impact. In contrast, $MVTC$ manages to keep its costs low at all times, even if the price impact of trading is severe.

[25]We do not plot the other strategies to keep the figure legible.

B Robustness

B.1 Rules-of-Thumb to Address Transaction Costs

In this section, we investigate whether intuitive rules-of-thumb are helpful in mitigating transaction costs. We consider two rules-of-thumb: (i) trading at a lower frequency, or (ii) removing high-cost currencies from our asset universe. These rules reduce costs to some extent, but they are inefficient as they have significant negative implications on the performance of our strategies. Thus, our findings advise against the use of intuitive rules-of-thumb, as deviations from the optimal (before-cost) balance between expected return and risk have adverse consequences for the performance. If we invest in $MVTC$, which accounts for costs in the portfolio optimization, the out-of-sample performance is significantly better. Moreover, $MVTC$ is far more resilient than the other analyzed strategies when we consider large funds that face a severe price impact. This is an interesting contribution as the empirical finance literature as well as practitioners often employ rules-of-thumb. This is particularly important for the literature that investigates the after-cost profitability of (anomaly) portfolios. These results may be affected by the use of an (in)efficient approach to tackle trading costs. In addition, our findings provide important guidance for practitioners.

Note that the characteristic based long-short strategies can also be considered a rule-of-thumb to mitigate (among others) transaction costs.[26] However, we have established in the main text that these strategies significantly underperform $MVTC$ as their before cost performance is weaker and they still incur relatively high costs.

B.1.1 Trading at Lower Frequencies

It is intuitive that frequent trading leads to more turnover and higher transaction costs. Therefore, we investigate how the performance is affected if we reduce the trading frequency from monthly to quarterly in the hope of mitigating costs. Table A2 reports the quarterly performances of our eight strategies. The first two columns provide the before-cost and

[26] The leading reason to construct characteristic based long-short strategies is arguably to mitigate parameter uncertainty.

after-cost Sharpe ratios. We further report the difference between the Sharpe ratios of the strategies and $MVTC$ in the third column denoted by ΔSR. The last two columns report the quarterly turnover and average annual transaction costs.

We start our discussion with MV and the six characteristic-based long-short strategies (HML, RB, DOL, $DDOL$, VAL, MOM). As expected, trading at the quarterly frequency significantly reduces costs. In general, for the seven strategies, costs are roughly cut in half, or even more when price impact is considered. This reflects well on our simple and intuitive cost mitigation rule.

On the other hand, there is also a negative effect of quarterly trading. Generally, we find lower before-cost Sharpe ratios when we implement our strategies at the quarterly instead of the monthly frequency. This is due to both economic and statistical reasons. From an economic point of view, if a trading signal has only short-term predictive power then a strategy based on this signal is more (less) likely to be successful when we trade at a high (low) frequency. Consistent with this explanation, we observe lower average returns when we implement our strategies at the quarterly frequency. From a statistical point of view, the monthly variance is less than a third of the quarterly variance if monthly returns are positively auto-correlated (Lo, 2002). Consistent with this explanation, we observe that the annualized volatility of the quarterly strategies is higher compared to monthly rebalancing.

When there is no price impact, the negative effect on the before-cost performance outweighs the benefits of mitigating costs. That is, the after-cost Sharpe ratios of all strategies (except for VAL) are higher when we implement them at the monthly instead of at the quarterly frequency. The reason is that proportional costs are relatively small and, as such, are not a first-order issue. Accordingly, a small fund is better off investing at the monthly frequency.

The same is not always true for larger funds with a non-trivial price impact. In this case, costs are a major concern and cost reduction measures are relevant. For instance, when the initial AUM is USD 100 million, MV achieves an after-cost Sharpe ratio of 0.59 when implemented at the quarterly frequency, while it is only 0.36 when we trade monthly. Another example is RB. When the initial AUM is USD 1 billion then the monthly RB is unprofitable, with an after-cost Sharpe ratio of 0.04, while the quarterly version of RB is profitable, with a Sharpe ratio of 0.36. These examples illustrate that trading at a lower frequency can be helpful in mitigating costs and increasing the resilience of strategies to the price impact of trading. However, this is not generally true for all strategies. For instance, MOM performs consistently worse when implemented at the quarterly frequency.

The after-cost performance of the quarterly versions of MV and the six characteristic-based long-short strategies are relatively poor when the initial AUM is USD 1 billion. The best-performing and most resilient among the seven strategies is RB, with an after-cost Sharpe ratio of 0.36. This is significantly less than the Sharpe ratio achieved by investing in the US stock market. Moreover, as in our baseline analysis we find that MV and MOM are unprofitable (with negative average returns) when implemented at the quarterly frequency. Therefore, our previous insight remains unchanged. The price impact of trading is a major concern for sizable funds, as costs quickly erode returns and, as a result, popular strategies in the literature perform poorly after accounting for costs.

Next, we analyze the effect of the trading frequency on $MVTC$. We observe cost savings when we trade quarterly instead of monthly. This effect is, however, quantitatively small, especially relative to the high average returns earned by $MVTC$. The reason is that $MVTC$ efficiently reduces its trading activity and costs whether we implement it at a monthly or a quarterly frequency. As such, there is no benefit from overlaying the strategy with an intuitive rule-of-thumb in an attempt to manage costs. The (before-cost) performance somewhat suffers as we trade less frequently, and the after-cost Sharpe ratio of the quarterly $MVTC$ is slightly lower than its monthly counterpart.

Finally, a comparison between strategies clearly suggests that it is best to invest in the monthly $MVTC$. The after-cost Sharpe ratio of $MVTC$ always significantly dominates all other strategies (with the exception of MV when there is no price impact; in this case, MV and $MVTC$ are almost indistinguishable). Moreover, $MVTC$, and in particular the monthly version, is the only strategy that (i) is resilient to even a large fund size with a severe price impact, and (ii) consistently outperforms the US stock market.

To sum up, we find that trading at a lower frequency decreases the turnover and transaction costs, but changing the trading frequency also has a negative first-order effect on performance. Overall, it is not advisable to trade at the quarterly frequency. Instead, investors are better off trading at the monthly frequency and accounting for costs in the construction of the strategy, as suggested by $MVTC$.

B.1.2 Removing Currencies with High Transaction Costs

Our second rule-of-thumb builds on the intuition that transaction costs decrease if we restrict trading to currencies with low costs. We focus on the monthly trading frequency and either (i) restrict trading to the 13 developed currencies (as defined in Section 2.1), or (ii) sequentially eliminate the most expensive currencies from the set of admissible assets in every month t.

Table A3 shows the performance and the trading costs of our strategies when we invest in only the 13 developed currencies. The first two columns report the before-cost and after-cost Sharpe ratios. The third column reports the difference between the after-cost Sharpe ratios of all strategies and the $MVTC$. The last two columns report the monthly turnover and annual costs.

We find that the costs and after-cost Sharpe ratios are generally comparable if we use the 13 developed or the full set of 26 currencies. The exceptions are VAL, which improves, and MOM, which performs substantially worse when we restrict the set to the 13 developed currencies. While developed currencies are cheaper to trade than emerging currencies, reducing the asset universe by half (from 26 to 13 currencies) implies that the portfolio weights are twice the size. In turn, the increase in the portfolio concentration leads to larger trade orders or a more severe price impact, albeit in only developed and arguably more liquid currencies. It turns out that it does not matter whether we implement our strategies using only developed or the larger set of developed and emerging currencies; the after-cost performances are comparable.

To sum up, limiting the portfolio to a set of developed currencies is not an efficient rule to mitigate the issue of transaction costs. Popular strategies in the literature are still sensitive to the price impact of trading, and costs quickly erode the average returns, leaving popular strategies unprofitable. $MVTC$ (implemented either in the set of 13 developed or all 26 currencies) always earns the highest after-cost Sharpe ratio, and is the only strategy that is resilient when the size of a fund is large and the price impact is severe.

An alternative rule-of-thumb is to limit trading to only the cheapest currencies in every month t. Table A4 reports the Sharpe ratios before and after costs for MV, $MVTC$ and HML in columns 1 to 3 and 4 to 6.[27] The first row reports the performance of the strategies constructed from the full set of 26 currencies. The second row reports the results when we reduce our set of admissible currencies by one currency, i.e., in month t we drop the currency with the highest median transaction cost over the past 6 months.[28] Each subsequent row reduces the set of admissible currencies by an additional currency, i.e., in month t row i removes the $i-1$ currencies with the highest median costs over the past 6 months. Note that the data availability changes through time and we do not have data for all 26 currencies in every month. The maximum number of currencies we can drop is 10, in order to have at least two currencies with which to construct a portfolio every month.

For MV and HML, the differential between the before-cost and after-cost Sharpe ratios narrows as we remove expensive currencies (difference between columns 1 and 4 respectively 3 and 6). This indicates that costs are decreasing, which confirms that the rule-of-thumb mitigates costs as expected. For $MVTC$, however, we do not observe a similar monotonic decrease in the differences between before-cost and after-cost Sharpe ratios. This implies that $MVTC$ efficiently tackles costs and does not benefit from overlaying it with the intuitive cost-reducing rule-of-thumb.

More importantly, we document that the before-cost performance of all three strategies rapidly worsens as we remove currencies. MV, $MVTC$ and HML achieve before-cost Sharpe ratios of 1.12, 1.08 and 0.79, respectively, in our baseline analysis when we use all 26 currencies. These values almost monotonically decrease as we remove currencies. In the extreme case when we remove the 10 most expensive currencies, the Sharpe ratios are only 0.3, 0.3 and 0.45.[29] The reduction in the before-cost performance is of first-order importance, and

[27]We limit our attention to MV, $MVTC$, and HML for brevity. The results for the other strategies are similar.

[28]Changing the rolling window length does not affect our results.

[29]When we remove 10 currencies, for $MVTC$ the before-cost Sharpe ratio is 0.3 when there is no price impact, 0.3 when the initial AUM is USD 100 million, and 0.31 when the initial AUM is USD 1 billion.

outweighs the cost savings. For $MVTC$, the after-cost Sharpe ratio is consistently decreasing in the number of removed currencies. Thus, an investor should consider the full set of currencies when constructing $MVTC$. The same pattern holds for MV and HML when there is either no price impact or the initial AUM is USD 100 million. When the fund size is large (with an initial AUM of USD 1 billion) the after-cost Sharpe ratios of MV and HML are not decreasing in the number of dropped currencies, but they are consistently negative and, as such, these strategies are unprofitable in any case. Moreover, we find that MV is completely wiped out (i.e., loses the entire AUM) once during our sample period when the initial AUM is USD 1 billion and we remove 9 or 10 currencies. Again, there is no value for investors to follow a rule-of-thumb to remove high cost currencies from the asset universe.

We conclude that the rule-of-thumb to remove high cost currencies is inefficient. The exclusion of expensive currencies reduces costs, but it also leads to a decrease in before-cost performance. The latter effect generally dominates. The most sensible approach (which delivers the best out-of-sample performance) is the cost-optimized portfolio $MVTC$ implemented in the unrestricted set of 26 currencies.

B.2 Sub-samples

A longer sample period generally provides more accurate estimates of expected returns. Thus, we use the results in section 4 as our baseline. We further show that our results are robust and continue to hold in the following sub-samples: (i) pre- and post-2008 Global Financial Crisis (GFC), (ii) pre- and post-introduction of Euro (January 1999), and (iii) in and out of NBER recessions. These robustness checks are important to ensure that our results are generally true, and not driven by a specific sub-sample under special economic conditions.

B.2.1 Pre- versus Post-Global Financial Crisis

The GFC marks a regime shift. In particular MOM was profitable in terms of before cost returns right up to the GFC, and turns into a losing strategy afterwards. Similarly, we observe that the before cost average returns of $DDOL$ are significantly lower (but still positive) after the GFC. In this section we check whether the post-GFC sample is driving our baseline result that MV and the six characteristic based long-short strategies perform poorly after accounting for costs. In other words, we check whether our results are robust in the sub-sample from February 1986 to December 2007. A particular focus is on $DDOL$ and MOM.

Table A5 reports the results. All strategies but VAL deliver noticeably higher before cost Sharpe ratios before the GFC than in the full sample. In particular $DDOL$ and MOM have a before cost Sharpe ratios of 0.55 and 0.68, which compares to 0.32 and 0.36 in the full sample. As a comparison the Sharpe ratio of the US stock market is 0.45 during the sample of 1987 to 2007. Similar to the baseline analysis proportional costs are relatively small in the pre-GFC sample, while costs due to the price impact are a first order concern when a fund is large. When the initial AUM is USD 100 million most strategies perform relatively well after costs. In contrast, when the initial AUM is USD 1 billion MV, HML and MOM are essentially unprofitable. RB, DOL, $DDOL$ and VAL are more resilient with after cost Sharpe ratios between 0.24 and 0.37. However, despite that they are profitable they all underperform the US stock market, which has a Sharpe ratio of 0.45. $MVTC$ is by far the most resilient strategy outperforming all other strategies (including the US stock market). When the initial AUM is USD 1 billion the after cost Sharpe ratio of $MVTC$ is 0.94, and it is above 1.11 when the initial fund size is smaller than USD 100 million.

For completeness we also report the performance of the strategies in the sub-sample from January 2008 to January 2024 (table A6). Many strategies perform worse after the GFC. DOL, $DDOL$ and MOM are essentially unprofitable even before costs. VAL has a before cost Sharpe ratio of 0.58 and the after cost Sharpe ratio decreases to 0.38 when the initial fund size is USD 1 billion. MV, $MVTC$, HML, RB perform comparably well with after cost Sharpe ratios slightly above 0.86 when there is no price impact. These four strategies are relatively resilient with after cost Sharpe ratios between 0.68 and 0.76 when the initial AUM is USD 100 million. When the initial fund size is USD 1 billion MV turns unprofitable (negative Sharpe ratio), HML and RB have stronger Sharpe ratios of 0.21 and 0.41, but underperform the US stock market, which has a Sharpe ratio of 0.59. $MVTC$ has the most attractive after cost Sharpe ratio of 0.59 when the initial AUM is USD 1 billion, and over

0.76 for an initial AUM below USD 100 million. Accordingly, our main results continue to hold post-GFC. As a final note it is important to understand that the sub-sample from January 2008 to January 2024 is short and expected returns (or Sharpe ratios) are imprecisely measured. To this extend we have to be cautious about drawing strong conclusions from this sub-sample analysis.

B.2.2 Introduction of the Euro

The introduction of the Euro in January 1999, and thus, the replacement of several European currencies had a non-trivial effect on the investment opportunity set in FX markets. We show the robustness of our results in table A7 and A8. Our strategies achieve very similar (before and after costs) Sharpe ratios whether we use the full sample or the sub-sample ending in January 1999 or starting in February 1999.[30]

B.2.3 NBER Recessions

Finally, our results are robust during and outside of NBER recession periods as documented in Table A9. HML, DOL, $DDOL$ and MOM deliver low before cost Sharpe ratios during recessions. Interestingly, MV, $MVTC$, RB and VAL perform well before accounting for costs and appear recession-proof. However, when the fund size is large and the price impact is severe, all strategies except for $MVTC$ turn unprofitable. It is striking that $MVTC$ performs well and is resilient to even a severe price impact even during recession periods. This resonates and further strengthens our insight that investors should opt for a rigorous portfolio and cost optimization approach rather than characteristic sorted long-short strategies and intuitive rules-of-thumb.

Finally, the results outside of recession periods are almost identical to the results of the full sample. This is not surprising since there are only very few recession months in our sample.

[30]The only noticeable difference is the after cost Sharpe ratio of MV which is 0.74 post-introduction of the Euro versus 0.36 in the full sample when the initial AUM is USD 100 million.

B.3 Alternative Estimations of Transaction Costs

Our findings remain robust when employing different approaches to estimate the price impact functions. This robustness reinforces the notion that the performances of our strategies and the impact of transaction costs is largely independent of the specific cost estimation method, indicating that our conclusions are not driven by a specific estimation of costs.

B.3.1 Time-Invariant Price Impact

In this section we use the time-series average of our Amihud measure $\bar{A}_i^k = \frac{1}{T}\sum_t A_{i,t}^k$, for $k \in \{S, F\}$ to construct a time-invariant price impact function. Since the volume $v_{i,t}$ is time-invariant in section 2.4.1 the time-series average over the Amihud measure is equivalent to replacing the numerator in (8) by the time-series average of the exchange rate growth variation $\overline{RPV}_i = \frac{1}{T}\sum_t RPV_{i,t}$. This mitigates the concern that the results might be driven by certain episodes of high illiquidity or volatility. Table A10 reports the results, which are very similar to the results in table 3. Accordingly, our conclusions are the same whether we use the price impact estimates as described in section 2.4, or the time-invariant estimates of this robustness analysis.

B.3.2 Time-Series Extrapolation of Volume Data

In the baseline analysis in section 2.4.1 we keep the trading volume fixed through time $v_{i,t} = \bar{v}_i$ for $t \in \mathcal{T}^c$, and all time-series variation in the Amihud measure stems from the variation in $RPV_{i,t}$. This is to avoid potentially large errors when we attempt to extrapolate trading volume data in the time-series. In this section we perform such an extrapolation in the time dimension.

We denote the average of the daily trading volume and proportional bid-ask spread within a quarter q by $\tilde{v}_{i,q}^S = \frac{1}{Q_q}\sum_{t\in\mathcal{Q}_q} v_{i,t}^S$ and $\widetilde{PBA}_{i,q}^S = \frac{1}{Q_q}\sum_{t\in\mathcal{Q}_q} PBA_{i,t}^S$, where $\mathcal{Q}_q$ is the set of days in quarter q, $1_{\{t\in\mathcal{Q}_q\}}$ is an indicator function equal to 1 if day t is in quarter q and zero otherwise, and $Q_q = \sum_t 1_{\{t\in\mathcal{Q}_q\}}$ counts the number of days in quarter q. Then, for all currency-quarter (i, q) for which we have observations $\tilde{v}_{i,q}^S$ and $\widetilde{PBA}_{i,q}^S$ we run the following panel regression:

$$\ln\left(\tilde{v}_{i,q}^S\right) = \tilde{a} + \tilde{b}\ln\left(\widetilde{PBA}_{i,q}^S\right) + \tilde{\varepsilon}_{i,q}. \tag{16}$$

Figure A8 plots $\ln\left(\tilde{v}_{i,q}^S\right)$ against $\ln\left(\widetilde{PBA}_{i,q}^S\right)$ (indicated by asterisks). The regression fit $R^2 = 65\%$, and the slope coefficient $\tilde{b} = -1.16$ are similar to the cross-sectional regression (10).[31]

Then, for all currency-quarter (i, q) for which we do not observe $\tilde{v}_{i,q}^S$ but have an estimate of $\widetilde{PBA}_{i,q}^S$, we use the following extrapolation:

$$\tilde{v}_{i,q}^S = \exp\left\{\tilde{a} + \tilde{b}\ln\left(\widetilde{PBA}_{i,q}^S\right)\right\}.$$

Note that we can do this also for the currencies $i \in \mathcal{I}_{EU}^c$, and we do not have to do the re-scaling in (12). Next, we use the quarterly volume as a proxy for the daily volume on each day within the quarter, $v_{i,t}^S = \tilde{v}_{i,q}^S$, $\forall t \in \mathcal{Q}_q$. Finally, we plug the constructed panel of $v_{i,t}^S$ (together with the $RPV_{i,t}$ computed using Olsen data) into (8) to get the realized Amihud $A_{i,t}^S$. We then use the approach in (13) to obtain $A_{i,t}^F$ for forwards.

As expected the time-series of the extrapolated volume data is increasing over time. In turn, this implies that the realized Amihud measure and therefore the price impact in our baseline analysis in section 2.4 is smaller and more conservative than in this robustness section. Accordingly, the results in table A11 indicate that costs due to the price impact of trading have a slightly more detrimental effect on the profitability of the strategies. As before $MVTC$ is still robust to even a large fund size and a severe price impact. However, the difference in the results (table 3 vs A11) is relatively small, implying that the extrapolation method for the volume data does not affect our conclusions.

[31] Adding time fixed effects does not noticeably change the regression. The regression fit increases to $R^2 = 72\%$, the time fixed effects are close to zero, and the slope coefficient $\tilde{b} = -1.32$ is only slightly different from the regression without fixed effects.

B.3.3 BIS Volume Data

In this section we use volume data from the BIS Triennial Survey instead of the CLS data. An advantage of the BIS data is that it goes back until 1992, and thus, may be useful to obtain more accurate extrapolations before 2012. On the flip side, we need to interpolate between dates as the BIS data is only available for average trading volume in the month of April and only every three years. We denote by $\hat{v}^S_{i,y}$ the average daily volume in spot markets in April of year y, where we only have data for every third year.[32] Moreover, we denote by $\widehat{PBA}^S_{i,y}$ the average proportional bid-ask spread for spot transactions in year y, $\widehat{PBA}^S_{i,y} = \frac{1}{Y_y}\sum_{t\in\mathcal{Y}_y} PBA^S_{i,t}$, where $\mathcal{Y}_y$ is the set of days in year y, $1_{\{t\in\mathcal{Y}_y\}}$ is an indicator function equal to 1 if day t is in year y and zero otherwise, and $Y_y = \sum_t 1_{\{t\in\mathcal{Y}_y\}}$ counts the number of days in year y. Then, for all currency-year (i, y) for which we have observations $\hat{v}^S_{i,y}$ and $\widehat{PBA}^S_{i,y}$ we implement an analogous panel regression to (16),

$$\ln\left(\hat{v}^S_{i,y}\right) = \hat{a} + \hat{b}\ln\left(\widehat{PBA}^S_{i,y}\right) + \varepsilon^{BIS}_{i,y}. \tag{17}$$

Figure A9 plots $\ln\left(\hat{v}^S_{i,y}\right)$ against $\ln\left(\widehat{PBA}^S_{i,y}\right)$ (indicated by asterisks). The regression fit $R^2 = 52\%$, and the slope coefficient $\hat{b} = -1.64$ are similar to the cross-sectional regression (16).[33]

Then, for all currency-year (i, y) (where y includes only BIS Triennial survey years) for which we do not observe $\hat{v}^S_{i,y}$ but have an estimate of $\widehat{PBA}^S_{i,y}$, we use the following extrapolation:

$$\hat{v}^S_{i,y} = \exp\left\{\hat{a} + \hat{b}\ln\left(\widehat{PBA}^S_{i,y}\right)\right\}.$$

Next, we linearly interpolate between BIS Triennial survey years to obtain daily volume data $v^S_{i,t}$. Finally, we plug the constructed panel of $v^S_{i,t}$ (together with the $RPV_{i,t}$ computed using Olsen data) into (8) to get the realized Amihud measure $A^S_{i,t}$. We then use the approach in (13) to obtain $A^F_{i,t}$ for forwards.

[32] The survey years are 1992, 1995, 1998, 2001, 2004, 2007, 2010, 2013, 2016, 2019, 2022.

[33] As with the panel regression with the CLS data, adding time fixed effects as no material effect.

The results in table A12 are almost identical to the results in table A11. Accordingly, it does not make a difference whether we construct the realized Amihud measure from extrapolated CLS data or from BIS data, and our results are robust.

B.3.4 Cutting Costs in Half

In the main text we only consider trades θ and $\boldsymbol{\Delta}$ against the USD. This ignores the possibility that it may be cheaper to trade directly between two non-USD currencies rather than twice against the USD.

As an illustration suppose that we want to be long AUD and short JPY. In our analysis we open (i) a long position in an AUD forward against the USD, and (ii) a short position in a JPY forward against the USD.[34] Then, we add up the costs of the two trades. However, the USD positions in the two trades are offsetting, and we can directly enter a long AUD forward against JPY. The alternative trade only incurs transaction costs for one trade instead of two trades.

This does however not imply that our analysis necessarily overestimates trading costs. First, it is an empirical question whether it is cheaper to directly trade AUD against JPY, or indirectly AUD against USD and USD against JPY. Ranaldo and Santucci de Magistris (2022) and Somogyi (2022) document in the data that trading against the USD is generally cheaper than other bilateral trades. Somogyi (2022) further argues that part of the USD dominance in terms of order volume can be contributed to the cost advantage of trading against USD. Second, our illustrative example can be overturned if we consider multiple trading periods. Following the literature, in our analysis we assume there are no costs to roll a contract over from month to month. Suppose at time $t-1$ we are long AUD and short JPY, and at time t we want to remain long AUD but close our short JPY position. Effectively, this means that we need to convert the short JPY position into a short USD position. If we have entered long AUD against USD and short JPY against USD forwards at $t-1$, then at t we roll over the AUD against USD contract and close the existing short

[34]Alternatively, if there were any open AUD shorts, then we close a short position in an AUD against USD contract. Similarly, we close a long position in a JPY against USD contract if we were previously long. Whether we open new or close existing positions does not matter for the purpose of this illustration.

forward in JPY against USD. In contrast, if we have implemented the direct AUD against JPY at $t-1$, then at t we either roll the contract over and open a new long position in a JPY forward against USD, or we close the previous position and open a new long forward in AUD against USD. Clearly, at this point the latter trading strategy also requires two trades in forwards (one at $t-1$, and another at t). Thus, it loses its efficiency compared to trading AUD against USD and JPY against USD at $t-1$. Moreover, in the data it is generally the case that trading costs of AUD against USD plus USD against JPY are less than costs of AUD against JPY plus costs of JPY against USD (or AUD against USD). Accordingly, if we consider the total costs over a longer time horizon (rather than just at one point in time) and given that every position will be unwound eventually, the costs as computed in our analysis may not be higher than if we allow to trade all bilateral currency pairs.

From the point of view of implementing our analysis, using the currency triangle to reduce costs is a non-trivial problem. First, we have N_t currencies. Considering all possible combinations leads to $\frac{N_t(N_t-1)}{2}$ bilateral trades. In contrast in our analysis we only work with N_t possible trades against the USD. Second, as illustrated above the problem becomes difficult when we have an inter-temporal setting. To sum up, our assumption to trade only against the USD is not innocuous but it clearly simplifies our analysis, and if we consider multiple time periods it may be close to the efficient policy.

Nevertheless, the robustness analysis in this section addresses the limitation of our baseline setting. Following the logic of our illustrative example in the best case scenario bilateral trades can reduce the number of trades by 50% compared to our baseline analysis where only trading against the USD is possible. If all trades had the same costs, this would imply that total trading costs can be reduced at most by 50%. Recall that the literature suggests that trades against the USD are generally cheaper than trades against other currencies. Accordingly, if we consider a strategy that trades only against the USD but is subject to artificial costs that are only 50% of the true costs, then we obtain a lower bound to the total costs of the optimal cost minimizing strategy that trades in all bilateral currency pairs and is subject to the true transaction costs. Table A13 reports the results. Cutting costs in half implies that the capacity of every strategy approximately doubles. While this provides a boost to the strategies, the capacities of MV and the six characteristic based long-short strategies are still small, and they all perform poorly when the initial AUM of a fund reaches USD 1 billion. To this extent our conclusions do not differ from our baseline analysis in table 3.

B.4 Sensitivity Analyses

B.4.1 Event Study: Performance of $MVTC$ in Turbulent Times

Ceteris paribus in periods of high volatility a mean-variance optimized strategy unwinds its risk exposure. This is because the optimal weights are inversely related to risk. Nonetheless, unwinding positions in turbulent times might be costly or even impossible in practice. Accordingly, a potential concern is that the performance of $MVTC$ may be too optimistic as reported in table 3. Although we have shown that $MVTC$ is very resilient to the price impact, we now impose a stricter constraint. That is, we do not allow any rebalancing during turbulent times. This allows us to check whether $MVTC$ experiences big losses when unwinding or deleveraging is impossible during bad times.

We identify turbulent or bad times as episodes of high FX market volatility or illiquidity. We use the FX market volatility measure of Menkhoff et al. (2012a), and aggregate Corwin and Schultz (2012) effective exchange rate spreads to estimate illiquidity as suggested by Karnaukh et al. (2015). As illustrated in Figure A10 by the blue and red dots, we select the five highest (non-consecutive) peaks in volatility and illiquidity over a rolling window of 13 months. Moreover, we add four months which represent important and well-known crises that involve the FX markets (highlighted by the vertical black lines): September 1992 which contains the Black Wednesday, July 1997 which signifies the onset of the Asian Financial Crisis with the collapse of the Thai baht, September 2008 which marks the onset of the credit crunch with the collapse of Lehman Brothers, and March 2020 the recognition that COVID is a global pandemic and the start of lock-downs across the world. As it is visually apparent, all these events form 9 distinct points in time which represent turbulent months in our analysis.

Table A14 compares the Maximum Draw Downs (MDD) of $MVTC$ and BH, which is a buy and hold strategy that keeps the position of $MVTC$ fixed starting 1 month before and ending 12 months after a turbulent month. Column 2 through 4 of Table A14 report whether the month is turbulent because of a peak in the volatility, illiquidity or because it is a well-known crisis. Columns 5 to 10 report the MDD for $MVTC$ and BH when there is no price impact (columns 5 and 6), and when the initial AUM is USD 100 million (columns 7 and 8) and USD 1 billion (columns 9 and 10). The last row shows the average MDD for each strategy across the different event studies.

On average $MVTC$ experiences a maximum loss for BH of up to 1.9 times the loss of $MVTC$. The worst drawdowns are reported following the crisis in September 1992. The MDD of $MVTC$ is roughly -10% (slightly differing across the different AUMs) while it is between -28% and -21% for BH. Accordingly, crash risk increases if rebalancing is impossible for an extended period of time. However, it is still manageable and is relatively mild compared to high crash risk levels of other strategies. We conclude that $MVTC$ continues to perform well with manageable crash risk exposure even if it is impossible to rebalance within up to 12 months after a spike in volatility or illiquidity, or after the onset of a crisis.

B.4.2 Risk Aversion Coefficient λ

Finally, in Table A15 we show that the Sharpe ratio of $MVTC$ is increasing in the coefficient of risk aversion λ. This effect is stronger with a large fund size and a more severe price impact. The intuition is that when the risk aversion is large, then the investor does not take much risk and the portfolio holdings are close to zero. Therefore, rebalancing the portfolio does not require large trade orders and little costs are incurred, implying that the after cost Sharpe ratio is close to the before cost Sharpe ratio of MV. We believe $\lambda = 25$ is a reasonable value as it implies volatilities of MV and $MVTC$ that are comparable to the characteristic based long-short strategies. If we decrease λ to 10 or even 5, $MVTC$ delivers a lower Sharpe ratio than if $\lambda = 25$, but it is still resilient to a large fund size and a severe price impact and outperforms the US stock market. Decreasing λ even further would imply a volatility and a crash risk (and even the probability of losing everything) that probably no investor would be willing to bear.[35]

[35] In the case of an initial AUM of USD 1 billion and $\lambda = 5$ MV gets wiped out (i.e., loses its entire AUM) once during the sample period.

C Theory

C.1 Algorithm

We can rewrite Problem 2 as

$$\min_{\mathbf{x_t} \geq 0} \quad \mathbf{q_t}'\mathbf{x_t} + \frac{1}{2}\mathbf{x_t}'\mathbf{H_t}\mathbf{x_t}$$

where $\mathbf{q_t}' \equiv \mathbf{C_t}'\mathbf{\bar{I}}'_{\mathbf{2},\mathbf{t}} + \lambda(\theta^{\mathbf{0}}_{\mathbf{t}} - \theta^{\mathbf{MV}}_{\mathbf{t}})'\mathbf{\hat{V}}_t\mathbf{\bar{I}_t}$, with $\theta^{\mathbf{MV}}_{\mathbf{t}} = \frac{1}{\lambda}\mathbf{\tilde{V}_t^{-1}}\mathbf{fd_t}$, $\mathbf{H_t} = \mathbf{\bar{I}_t}'(\lambda\mathbf{\hat{V}}_t + \mathbf{\Pi_t})\mathbf{\bar{I}_t}$, $\mathbf{\bar{I}_t} \equiv [I_{N_t}, -I_{N_t}]$. $\mathbf{\Pi_t}$ is an $N_t \times N_t$ diagonal matrix with $2\pi_{i,t}$ (defined in section 3.2.1) as the ith element on the diagonal. $\mathbf{C_t}$ is an $N_t \times 1$ column vector with $\mathbf{C_{i,t}}$ (defined in section 3.2.1) as the ith element.

$\mathbf{\bar{I}_{2,t}} \equiv [I_{N_t}, I_{N_t}]$, and I_{N_t} is the $N_t \times N_t$ identity matrix for the N_t assets available at time t. The program returns $\mathbf{x_t} \equiv [\mathbf{\Delta^{P'}_t}, \mathbf{\Delta^{S'}_t}]$ and the unique optimal portfolio θ^{MVTC}_t is obtained by

$$\theta^{MVTC}_t = \theta^{\mathbf{0}}_{\mathbf{t}} + \mathbf{\bar{I}_t}\mathbf{x_t}.$$

Notice that solving this program at every t produces the strategy $MVTC$ (i) with no-price impact if $\mathbf{\Pi_t} = 0$, (ii) with linear price impact if $\mathbf{\Pi_t}$ is positive definite. In any case this is a well-behaved convex program, and we solve it using the Matlab Optimization ToolBox.

C.2 Economic Properties of Problem 1

In this section we briefly discuss some properties of Problem 1. The mean-variance portfolio MV, which does not account for transaction costs in the optimization, is a special case of Problem 1. If we set $PC_t = 0$, $PI_t = 0$, we obtain strategy MV, which maximizes the before-cost Sharpe ratio. The portfolio of MV is independent of the initial position $\theta^{\mathbf{0,MV}}_{\mathbf{t}}$, and it is always optimal to trade all the way to $\theta^{\mathbf{MV}}_{\mathbf{t}}$. In contrast, if there are transaction costs $PC_t > 0$ or $PI_t > 0$, then $\theta^{\mathbf{MVTC}}_{\mathbf{t}}$ crucially depends on the origin $\theta^{\mathbf{0,MVTC}}_{\mathbf{t}}$. Intuitively, there is a trade-off between paying transaction costs and utility gains to move towards $\theta^{\mathbf{MV}}_{\mathbf{t}}$.

Consider first the case of only proportional costs ($PC_t > 0$, $PI_t = 0$). If the initial allocation $\theta^{\mathbf{0,MVTC}}_{\mathbf{t}}$ is close enough to $\theta^{\mathbf{MV}}_{\mathbf{t}}$, it is optimal not to trade at all as the linear marginal cost required to move towards $\theta^{\mathbf{MV}}_{\mathbf{t}}$ is higher than the quadratic marginal utility.

Thus, there is a no-trading region around $\theta_{\mathbf{t}}^{\mathbf{MV}}$. If the initial allocation $\theta_{\mathbf{t}}^{\mathbf{0,MVTC}}$ is far enough from $\theta_{\mathbf{t}}^{\mathbf{MV}}$ (i.e., outside of the no trading region), then it is optimal to move towards $\theta_{\mathbf{t}}^{\mathbf{MV}}$ but only until $\theta_{\mathbf{t}}^{\mathbf{MVTC}}$. This is because the marginal utility of moving towards $\theta_{\mathbf{t}}^{\mathbf{MV}}$ is diminishing, and at the boundary of the no-trading region, where $\theta_{\mathbf{t}}^{\mathbf{MVTC}}$ is located, the marginal utility is equal to the relevant entries of the marginal cost vectors $\mathbf{C}_{\mathbf{t}}^{\mathbf{k}}$, $k \in \mathcal{K}$.

Figure A11 illustrates this in a setting with two risky assets. The horizontal axis describes the weight placed on asset 1 and the vertical axis the weight on asset 2. The weight on the risk-free asset is 1 minus the sum of the weights on the two risky assets. The green rectangle in the center represents the optimal portfolio $\theta_{\mathbf{t}}^{\mathbf{MV}}$ if there were no transaction costs. The blue parallelogram surrounding $\theta_{\mathbf{t}}^{\mathbf{MV}}$ defines the no trading region when the two assets are positively correlated. If the initial allocation $\theta_{\mathbf{t}}^{\mathbf{0}}$ is inside the no trading region (i.e., within the blue parallelogram), then there is no trade and $\theta_{\mathbf{t}}^{\mathbf{MVTC}} = \theta_{\mathbf{t}}^{\mathbf{0}}$, as the marginal cost to trade towards $\theta_{\mathbf{t}}^{\mathbf{MV}}$ exceeds the marginal utility. If the initial portfolio $\theta_{\mathbf{t}}^{\mathbf{0}}$ lies outside of the no trading region, then the investor wants to move towards $\theta_{\mathbf{t}}^{\mathbf{MV}}$ but stops trading once she reaches the boundary of the no trading region. The arrows indicate the direction of trade and the arrow heads show how far to trade. The purple, brown or red colors of the arrows indicate that only asset 1, 2 or both assets are traded.

If we construct the no trading region around MV ignoring the correlation between the assets, the region reduces to the yellow square in Figure A11. In a continuous time setup where assets are independent, the optimal dynamic strategy of Liu (2004) shares many qualitative properties with this approximate solution. It can be shown that ignoring correlations in the construction of the region is sub-optimal both theoretically and empirically.

In Figure A11 if the two assets are positively correlated, then the blue parallelogram no trading region of $MVTC$ is larger along the $-45°$ line than the yellow square no trading region if we were to set correlations equal to zero. This is because the two assets are substitutes if they are positively correlated, while they are not substitutable if they are uncorrelated. If the two assets were perfect substitutes (i.e., a correlation equal to 1 and identical volatilities), then selling asset 1 and at the same time buying asset 2 leaves our risk exposure unaffected. In the same spirit, if the two assets are imperfect substitutes (i.e., correlation between 0 and 1), then there is less benefit in selling one and at the same time buying the other asset than if they are not substitutable at all (i.e., correlation equal to 0). Since an initial position $\theta_{\mathbf{t}}^{\mathbf{0}}$ close to the $-45°$ line requires the investor to buy one and sell the other asset, the marginal utility from trading towards $\theta_{\mathbf{t}}^{\mathbf{MV}}$ is smaller and the no trading region larger if the two assets are positively correlated than if they are uncorrelated. Conversely, a similar argument can be applied to the case of a negative correlation, and the no trading region of $MVTC$ is relatively smaller along the $-45°$ line.

A price impact ($PI_t > 0$) does not affect the shape or size of the no-trading region, but the optimal trades (which are initiated outside of the no-trading region) are different and we never end up at the border of the no-trading region.[36] Furthermore, Dybvig and Pezzo (2020) show that the directions of the trades are neither guaranteed to be towards the no-trading region nor that it is optimal to trade less than if there is no price impact. The starting point $\theta_{\mathbf{t}}^{\mathbf{0,MVTC}}$ and the other model parameters determine the size and the direction of the optimal trades. Therefore, it is ultimately an empirical question how a price impact affects trading.

D Data Sources and Filters

In Table A16 we list the Datastream mnemonics for spot and forward exchange rate quotes against the USD. We collect daily data from Barclays and Reuters from January 1986 to January 2024. For the Australian dollar, Japanese yen, New Zealand dollar, Norwegian krone, Swedish krona, and Swiss franc, we replace the Barclays forward series with Reuters forward rates (in parenthesis) in January 1997 as the former are discontinued in the recent period. To obtain bid and ask exchange rate quotes the suffixes (EB) and (EO), and for high and low quotes the suffixes (EH) and (EL) are added to the corresponding mnemonics. We also collect hourly bid and ask quotes for spot exchange rates from Olsen from February 1986 to January 2024.

Following Menkhoff et al. (2012b) and Della Corte et al. (2016) we do not include cur-

[36] This is shown in Theorem 2 of Dybvig and Pezzo (2020) for the case of a linear price impact.

rencies that have a negative score on the capital account openness index of Chinn and Ito (2006) as those currencies are viewed as subject to major trading frictions coming from capital controls. In addition, we do not consider the Danish krone due to its low trading volume and low liquidity proxied by the Amihud measure. Details about the Amihud measure are in section 2.4. This is in line with Ranaldo and Santucci de Magistris (2022) who show that the Danish krone is very illiquid and has the largest price impact among all currencies in their sample. We further exclude the Icelandic krona, which has an average bid-ask spread of 45 bps (roughly 10 times the median spread across all currencies), and the Belgian franc due to limited data availability. Finally, following Maurer et al. (2023) we exclude a currency at time t if it is pegged to another currency, has proportional costs bigger than 0.5%, more than 20% of its daily exchange rate changes are missing over the past 6 months, or if the absolute value of the annualized forward discount $|fd_{i,t}|$ is larger than 20%. Forward discounts of more than 20% are rare and we believe that such large values likely indicate non-tradable outliers in the data, the presence of severe trading frictions, sizable sovereign default risk or an extraordinarily large expected currency devaluation. Under these conditions a currency trader is likely not able or willing to consider a currency as part of the investment opportunity set.

Data for the US stock market and the USD risk-free rate are from the Kenneth French data library, `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. Data for the S&P 500 SPDR ETF (SPY) are from Yahoo finance, `https://finance.yahoo.com/`.

Purchasing power parity (PPP) data for most of the 26 countries is provided by the OECD. For countries which are not covered by the OECD, we collect data from the World Bank. Annual PPP data is released in March and we assume PPP is constant from March until February in the following year in order to construct monthly observations. Data for Taiwan is unavailable for either source, and we use the series PPPTTLTWA618NUPN from the Federal Reserve Bank of St. Louis.

We collect the NBER recession time-series from the Federal Reserve Bank of St. Louis. NBER based Recession Indicators for the USA are defined as the Period following the Peak through the Trough.

E Tables and Figures

Table A1: **Capacities of the Strategies: Effect of the Fund Size**

$\overline{SR}$	MV	$MVTC$	HML	RB	DOL	$DDOL$	VAL	MOM
Panel A: Asset under Management in February 1987 (USD billions)								
0.00	0.34	>1000	0.66	1.25	40.00	1.75	2.00	0.31
0.05	0.28	>1000	0.55	0.98	15.00	1.25	1.50	0.24
0.10	0.24	>1000	0.46	0.84	0.00	0.87	1.25	0.18
0.15	0.20	>1000	0.38	0.71	0.00	0.59	0.97	0.13
0.20	0.17	60.00	0.32	0.60	0.00	0.35	0.77	0.08
0.25	0.15	35.00	0.26	0.51	0.00	0.15	0.59	0.05
0.30	0.12	25.00	0.21	0.42	0.00	0.00	0.44	0.02
0.35	0.10	20.00	0.17	0.35	0.00	0.00	0.30	0.00
0.40	0.09	15.00	0.14	0.28	0.00	0.00	0.18	0.00
0.45	0.07	8.50	0.11	0.23	0.00	0.00	0.08	0.00
0.50	0.06	6.00	0.08	0.18	0.00	0.00	0.00	0.00
0.55	0.05	4.25	0.06	0.13	0.00	0.00	0.00	0.00
0.60	0.04	3.00	0.04	0.09	0.00	0.00	0.00	0.00
0.65	0.03	2.25	0.03	0.06	0.00	0.00	0.00	0.00
0.70	0.03	1.50	0.01	0.03	0.00	0.00	0.00	0.00
0.75	0.02	0.98	0.00	0.00	0.00	0.00	0.00	0.00
0.80	0.02	0.59	0.00	0.00	0.00	0.00	0.00	0.00
0.85	0.01	0.25	0.00	0.00	0.00	0.00	0.00	0.00
0.90	0.01	0.06	0.00	0.00	0.00	0.00	0.00	0.00

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Table A1 – continued from previous page

$\overline{SR}$	MV	$MVTC$	HML	RB	DOL	$DDOL$	VAL	MOM
Panel B: Asset under Management in January 2024 (USD billions)								
0.00	0.83	>1000	1.65	3.04	101.46	4.16	4.93	0.76
0.05	0.82	>1000	1.62	2.93	45.05	3.59	4.54	0.69
0.10	0.81	>1000	1.58	2.85	0.00	2.96	4.27	0.61
0.15	0.80	>1000	1.54	2.75	0.00	2.33	3.86	0.51
0.20	0.79	228.72	1.49	2.65	0.00	1.60	3.47	0.40
0.25	0.78	147.20	1.43	2.53	0.00	0.77	3.03	0.27
0.30	0.76	114.08	1.37	2.39	0.00	0.00	2.54	0.10
0.35	0.75	97.25	1.29	2.24	0.00	0.00	1.99	0.00
0.40	0.72	80.14	1.20	2.06	0.00	0.00	1.36	0.00
0.45	0.70	55.80	1.09	1.87	0.00	0.00	0.65	0.00
0.50	0.67	45.07	0.97	1.65	0.00	0.00	0.00	0.00
0.55	0.64	36.61	0.83	1.40	0.00	0.00	0.00	0.00
0.60	0.60	29.79	0.67	1.12	0.00	0.00	0.00	0.00
0.65	0.56	25.14	0.46	0.79	0.00	0.00	0.00	0.00
0.70	0.52	19.81	0.24	0.43	0.00	0.00	0.00	0.00
0.75	0.45	15.29	0.00	0.02	0.00	0.00	0.00	0.00
0.80	0.39	10.93	0.00	0.00	0.00	0.00	0.00	0.00
0.85	0.32	5.75	0.00	0.00	0.00	0.00	0.00	0.00
0.90	0.30	1.76	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The table reports the maximum initial (panel A) and terminal (panel B) AUM (USD billions) of a fund such that its after cost Sharpe ratio is larger or equal than $\overline{SR} \in [0, 0.9]$. The strategies are described in Section 3. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

Table A2: **Trading at the Quarterly Frequency**

Strategies	Before TC SR	After TC SR	After TC ΔSR	Turnover	Costs (%)
PANEL A: NO PRICE IMPACT					
MV	0.90	0.86	-0.02	2.16	0.40
MVTC	0.91	0.87	-	1.72	0.30
HML	0.57	0.56	-0.31**	0.85	0.11
RB	0.60	0.58	-0.29**	0.71	0.12
DOL	0.08	0.08	-0.79***	0.06	0.02
DDOL	0.22	0.21	-0.66***	0.24	0.05
VAL	0.53	0.52	-0.35*	0.44	0.07
MOM	0.15	0.13	-0.75***	1.61	0.19
PANEL B: $AUM_0 = 100$ **million**					
MV	0.90	0.59	-0.21***	2.16	2.56
MVTC	0.86	0.80	-	1.10	0.44
HML	0.57	0.49	-0.31*	0.85	0.75
RB	0.60	0.55	-0.25	0.71	0.35
DOL	0.08	0.08	-0.72***	0.06	0.02
DDOL	0.22	0.21	-0.59***	0.24	0.10
VAL	0.53	0.49	-0.31*	0.44	0.31
MOM	0.15	0.06	-0.74***	1.61	0.82
PANEL C: $AUM_0 = 1$ **billion**					
MV	0.90	0.00	-0.69***	2.16	7.24
MVTC	0.77	0.69	-	0.59	0.53
HML	0.57	0.18	-0.51***	0.85	3.66
RB	0.60	0.36	-0.33**	0.71	1.85
DOL	0.08	0.08	-0.61***	0.06	0.05
DDOL	0.22	0.15	-0.54***	0.24	0.56
VAL	0.53	0.27	-0.42**	0.44	1.85
MOM	0.15	-0.26	-0.95***	1.61	3.69

The table summaries the performance of our FX market strategies when they are implemented at a quarterly frequency. The strategies are described in Section 3. Panel A summaries the performance when there are only proportional costs. Panel B and C report results when the initial AUM of a fund is USD 100 million respectively 1 billion and costs account for the price impact of trading. Column 2 and 3 report the annualized before (Before TC SR) and after cost (After TC SR) Sharpe ratios. ΔSR in column 4 is the difference in the after-cost Sharpe ratio of a strategy and that of $MVTC$. Standard errors of ΔSR are estimated using block bootstrapping with a block size of 5 observations to account for heteroskedasticity, cross- and auto-correlation (Ledoit and Wolf, 2008). ***, **, * indicate a statistical significance at the 1%, 5%, 10% level. Turnover in column 5 reports the average monthly turnover. Costs (%) in column 6 reports the annual transaction costs as a percentage of the AUM. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

Table A3: **Trading only Developed Currencies**

Strategies	Before TC SR	After TC SR	After TC ΔSR	Turnover	Costs (%)
		PANEL A: NO PRICE IMPACT			
MV	1.07	0.98	-0.04*	2.02	0.60
MVTC	1.08	1.02	-	1.47	0.39
HML	0.66	0.62	-0.40**	1.63	0.34
RB	0.64	0.59	-0.43***	1.40	0.36
DOL	0.03	0.03	-0.99***	0.02	0.01
DDOL	0.39	0.37	-0.64***	0.38	0.10
VAL	0.56	0.55	-0.47***	0.35	0.09
MOM	0.17	0.15	-0.87***	0.96	0.20
		PANEL B: $AUM_0 = 100$ **million**			
MV	1.07	0.33	-0.54***	2.02	4.51
MVTC	0.95	0.88	-	0.59	0.38
HML	0.66	0.22	-0.66***	1.63	3.94
RB	0.64	0.32	-0.55***	1.40	2.32
DOL	0.03	0.03	-0.85***	0.02	0.01
DDOL	0.39	0.35	-0.53***	0.38	0.30
VAL	0.56	0.50	-0.37	0.35	0.45
MOM	0.17	0.07	-0.81***	0.96	1.00
		PANEL C: $AUM_0 = 1$ **billion**			
MV	1.07	-0.41	-1.13***	2.02	9.90
MVTC	0.81	0.73	-	0.23	0.34
HML	0.66	-0.35	-1.08***	1.63	9.38
RB	0.64	-0.28	-1.01***	1.40	6.99
DOL	0.03	0.03	-0.70***	0.02	0.02
DDOL	0.39	0.18	-0.55**	0.38	1.63
VAL	0.56	0.24	-0.49*	0.35	2.48
MOM	0.17	-0.28	-1.00***	0.96	4.23

The table summaries the performance of our FX market strategies when they are constructed from only developed currencies. The strategies are described in Section 3. Panel A summaries the performance when there are only proportional costs. Panel B and C report results when the initial AUM of a fund is USD 100 million respectively 1 billion and costs account for the price impact of trading. Column 2 and 3 report the annualized before (Before TC SR) and after cost (After TC SR) Sharpe ratios. ΔSR in column 4 is the difference in the after-cost Sharpe ratio of a strategy and that of $MVTC$. Standard errors of ΔSR are estimated using block bootstrapping with a block size of 5 observations to account for heteroskedasticity, cross- and auto-correlation (Ledoit and Wolf, 2008). ***, **, * indicate a statistical significance at the 1%, 5%, 10% level. Turnover in column 5 reports the average monthly turnover. Costs (%) in column 6 reports the annual transaction costs as a percentage of the AUM. The sample includes 13 developed currencies against the USD for the period from February 1987 to January 2024.

Table A4: **Removing High Cost Currencies**

Drop # Top	Before TC SR			After TC SR		
TC Currencies	MV	MVTC	HML	MV	MVTC	HML
PANEL A: NO PRICE IMPACT						
keep all	1.12	1.08	0.79	0.99	1.01	0.74
drop 1	1.17	1.11	0.83	1.05	1.04	0.79
drop 2	1.03	0.99	0.76	0.92	0.92	0.72
drop 3	0.93	0.93	0.73	0.82	0.86	0.69
drop 4	0.79	0.79	0.65	0.69	0.72	0.61
drop 5	1.03	1	0.63	0.94	0.93	0.59
drop 6	0.74	0.66	0.63	0.67	0.61	0.59
drop 7	0.38	0.37	0.61	0.33	0.33	0.58
drop 8	0.34	0.32	0.54	0.3	0.29	0.51
drop 9	0.25	0.26	0.45	0.22	0.23	0.42
drop 10	0.3	0.3	0.45	0.27	0.27	0.43
PANEL B: $AUM_0 = 100$ **million**						
keep all	1.12	0.96	0.79	0.36	0.88	0.46
drop 1	1.17	0.98	0.83	0.33	0.89	0.47
drop 2	1.03	0.88	0.76	0.3	0.79	0.45
drop 3	0.93	0.81	0.73	0.22	0.71	0.41
drop 4	0.79	0.71	0.65	0.2	0.61	0.37
drop 5	1.03	0.7	0.63	0.3	0.61	0.35
drop 6	0.74	0.52	0.63	0.24	0.43	0.38
drop 7	0.38	0.48	0.61	0.13	0.39	0.37
drop 8	0.34	0.46	0.54	0.12	0.38	0.33
drop 9	0.25	0.31	0.45	0.06	0.23	0.28
drop 10	0.3	0.3	0.45	0.1	0.22	0.3

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Table A4 – continued from previous page

Drop # Top TC Currencies	Before TC SR MV	Before TC SR MVTC	Before TC SR HML	After TC SR MV	After TC SR MVTC	After TC SR HML
PANEL C: $AUM_0 = 1$ **billion**						
keep all	1.12	0.84	0.79	-0.27	0.75	-0.12
drop 1	1.17	0.82	0.83	-0.31	0.71	-0.12
drop 2	1.03	0.78	0.76	-0.32	0.67	-0.13
drop 3	0.93	0.66	0.73	-0.28	0.54	-0.14
drop 4	0.79	0.56	0.65	-0.31	0.43	-0.17
drop 5	1.03	0.57	0.63	-0.39	0.42	-0.17
drop 6	0.74	0.48	0.63	-0.32	0.34	-0.14
drop 7	0.38	0.58	0.61	-0.11	0.48	-0.15
drop 8	0.34	0.54	0.54	-0.11	0.44	-0.16
drop 9	$0.25^{\dagger}$	0.35	0.45	$-0.29^{\dagger}$	0.26	-0.16
drop 10	$0.3^{\dagger}$	0.31	0.45	$-0.25^{\dagger}$	0.23	-0.1

Notes: The table summaries the performance of the three FX market strategies MV, $MVTC$, and HML. The strategies are described in Section 3. Panel A summaries the performance when there are only proportional costs. Panel B and C report results when the initial AUM of a fund is USD 100 million respectively 1 billion and costs account for the price impact of trading. Annualized before (Before TC SR) and after cost (After TC SR) Sharpe ratios are reported in columns 2 to 4 respectively 5 to 7. † indicates that a strategy was wiped out at least once during the sample period. In such an event we replenish the strategy with the initial AUM right after it was wiped out. The top row includes all available currencies. In subsequent rows in every month t we remove one-by-one the currency with the highest median transaction cost over the previous 6 months. The sample (before removing expensive currencies) includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

E.1 Analyses of Sub-samples

Table A5: **Performance of FX Strategies: Sample Ending in December 2007**

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
				PANEL A: NO PRICE IMPACT				
Before cost SR	1.32	1.27	0.90	0.92	0.34	0.55	0.44	0.68
Before cost Mean (%)	12.36	11.63	7.10	5.90	2.35	3.76	3.05	6.21
Before cost Vol (%)	9.36	9.14	7.88	6.44	6.86	6.81	6.95	9.18
Mean Costs (%)	1.49	0.81	0.41	0.44	0.03	0.20	0.13	0.34
Turnover	2.81	1.73	0.99	0.84	0.04	0.35	0.24	0.84
Notional	4.00	3.80	2.00	2.00	1.00	1.00	2.00	2.00
SR	**1.16**	**1.19**	**0.85**	**0.85**	**0.34**	**0.52**	**0.42**	**0.64**
ΔSR	**-0.02**	-	**-0.34***	**-0.34***	**-0.85****	**-0.66****	**-0.77****	**-0.55**
Mean (%)	10.85	10.81	6.69	5.46	2.33	3.56	2.91	5.86
Vol (%)	9.34	9.12	7.88	6.44	6.86	6.82	6.94	9.17
Skew	-1.02	-0.93	-0.94	-0.74	-0.18	-0.49	-0.14	-0.26
MDD (%)	-26.42	-28.02	-32.28	-31.43	-32.02	-14.85	-22.39	-19.90
Total return	20.35	20.27	8.26	6.39	2.90	3.97	3.34	6.71
				PANEL B: $AUM_0 = 100$ **million**				
Before cost SR	1.32	1.21	0.90	0.92	0.34	0.55	0.44	0.68
Before cost Mean (%)	12.36	10.50	7.10	5.90	2.35	3.76	3.05	6.21
Before cost Vol (%)	9.36	8.69	7.88	6.44	6.86	6.81	6.95	9.18

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Table A5 – continued from previous page

	MV	$MVTC$	HML	RB	DOL	$DDOL$	VAL	MOM
Mean Costs (%)	7.31	0.82	1.57	0.90	0.03	0.31	0.27	1.14
Turnover	2.81	0.92	0.99	0.84	0.04	0.35	0.24	0.84
Notional	4.00	3.44	2.00	2.00	1.00	1.00	2.00	2.00
Avg USD Trade Size (millions)	64.19	29.17	39.33	18.24	0.43	6.46	6.60	26.97
Avg Relative Trade Size (%)	0.03	0.01	0.02	0.01	0.00	0.00	0.00	0.01
SR	**0.51**	**1.11**	**0.70**	**0.78**	**0.34**	**0.51**	**0.40**	**0.55**
ΔSR	**-0.61*****	-	**-0.41***	**-0.34**	**-0.78****	**-0.61***	**-0.71****	**-0.56***
Mean (%)	4.93	9.66	5.51	4.99	2.33	3.45	2.78	5.05
Vol (%)	9.73	8.67	7.87	6.44	6.86	6.82	6.94	9.17
Skew	-1.31	-1.14	-0.95	-0.72	-0.18	-0.49	-0.13	-0.26
MDD (%)	-35.91	-25.53	-33.24	-31.88	-32.05	-14.87	-22.55	-20.23
Total return	5.27	16.05	6.31	5.71	2.89	3.86	3.22	5.56
PANEL C: $AUM_0 = 1$ **billion**								
Before cost SR	1.32	1.06	0.90	0.92	0.34	0.55	0.44	0.68
Before cost Mean (%)	12.36	8.34	7.10	5.90	2.35	3.76	3.05	6.21
Before cost Vol (%)	9.36	7.89	7.88	6.44	6.86	6.81	6.95	9.18
Mean Costs (%)	16.55	0.87	6.74	3.80	0.06	1.19	1.33	5.32
Turnover	2.81	0.42	0.99	0.84	0.04	0.35	0.24	0.84
Notional	4.00	2.88	2.00	2.00	1.00	1.00	2.00	2.00
Avg USD Trade Size (millions)	206.42	92.00	239.11	136.94	4.28	59.63	60.60	190.69
Avg Relative Trade Size (%)	0.07	0.02	0.10	0.06	0.00	0.03	0.03	0.08

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Table A5 – continued from previous page

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
SR	**-0.36**	**0.94**	**0.03**	**0.32**	**0.33**	**0.37**	**0.24**	**0.09**
ΔSR	**-1.30*****	**-**	**-0.90*****	**-0.62*****	**-0.60***	**-0.57***	**-0.69****	**-0.85****
Mean (%)	-4.48	7.46	0.29	2.07	2.29	2.56	1.70	0.83
Vol (%)	12.48	7.96	8.28	6.52	6.87	6.89	6.95	9.36
Skew	-2.13	-1.07	-0.87	-0.61	-0.18	-0.47	-0.11	-0.25
MDD (%)	-143.63	-29.62	-41.02	-35.81	-32.37	-15.60	-23.90	-23.50
Total return	-0.17	9.96	1.49	2.68	2.87	3.04	2.37	1.79

Notes: The table reports summary statistics of monthly excess returns of our strategies in the FX market. The strategies are described in Section 3. Panel A summaries the performance when there are only proportional costs. Panel B and C report results when the initial AUM of a fund is USD 100 million respectively 1 billion and costs account for the price impact of trading. Before cost SR, Mean (%) and Vol (%) measure the annualized Sharpe ratio, and annualized average and volatility of the excess returns (reported in percentage points). Mean Costs (%) measures the average annualized trading costs as a percentage of the AUM. Turnover and Notional report the monthly turnover and the notional value as a fraction of the AUM. Avg Relative Trade Size (%) and Avg USD Trade Size (millions) measures the average amount traded per month (average across currency-month observations with non-trivial trade) as a percentage of the average daily trading volume in the market respectively in absolute terms as millions of USD. SR is the annualized after cost Sharpe ratio. ΔSR is the difference in the after-cost Sharpe ratio of a strategy and that of *MVTC*. Standard errors of ΔSR are estimated using block bootstrapping with a block size of 5 observations to account for heteroskedasticity, cross- and auto-correlation (Ledoit and Wolf, 2008). ***, **, * indicate a statistical significance at the 1%, 5%, 10% level. Mean (%) and Vol (%) are the annualized average and volatility of the after cost excess returns (reported in percentage points). Skew is the monthly skewness of the after cost excess returns, MDD (%) is the Maximum Draw Down (measured in percentage points). Total return is the return (including the risk-free rate) from February 1987 to December 2007. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to December 2007.

Table A6: **Performance of FX Strategies: Sample Starting in January 2008**

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
	PANEL A: NO PRICE IMPACT							
Before cost SR	0.91	0.86	0.88	0.86	-0.03	0.10	0.58	-0.22
Before cost Mean (%)	4.82	4.49	7.29	5.91	-0.25	0.83	3.96	-1.71
Before cost Vol (%)	5.30	5.20	8.29	6.90	8.34	8.21	6.80	7.63
Mean Costs (%)	0.48	0.27	0.24	0.31	0.01	0.16	0.07	0.23
Turnover	1.69	1.18	1.30	1.09	0.02	0.46	0.26	1.10
Notional	1.90	1.83	2.00	2.00	1.00	0.98	2.00	2.00
SR	**0.82**	**0.81**	**0.85**	**0.81**	**-0.03**	**0.08**	**0.57**	**-0.25**
ΔSR	**0.01**	-	**0.04**	**0.00**	**-0.84****	**-0.73****	**-0.24**	**-1.07*****
Mean (%)	4.33	4.22	7.04	5.60	-0.26	0.66	3.89	-1.94
Vol (%)	5.29	5.20	8.28	6.89	8.34	8.22	6.81	7.63
Skew	-0.38	-0.55	-0.51	-0.65	-0.19	-0.27	-0.34	-0.51
MDD (%)	-8.41	-9.15	-24.45	-17.73	-44.09	-18.30	-17.77	-53.71
Total return	1.10	1.07	2.07	1.51	0.05	0.17	0.96	-0.20
	PANEL B: $AUM_0 = 100$ **million**							
Before cost SR	0.91	0.82	0.88	0.86	-0.03	0.10	0.58	-0.22
Before cost Mean (%)	4.82	4.08	7.29	5.91	-0.25	0.83	3.96	-1.71
Before cost Vol (%)	5.30	5.00	8.29	6.90	8.34	8.21	6.80	7.63

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Table A6 – continued from previous page

	MV	$MVTC$	HML	RB	DOL	$DDOL$	VAL	MOM
Mean Costs (%)	1.22	0.28	0.99	0.64	0.01	0.23	0.20	0.50
Turnover	1.69	0.86	1.30	1.09	0.02	0.46	0.26	1.10
Notional	1.90	1.68	2.00	2.00	1.00	0.98	2.00	2.00
Avg USD Trade Size (millions)	12.34	6.38	20.58	9.49	0.13	2.73	3.66	7.52
Avg Relative Trade Size (%)	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
SR	**0.68**	**0.76**	**0.76**	**0.76**	**-0.03**	**0.07**	**0.55**	**-0.29**
ΔSR	**-0.08**	-	**0.00**	**0.01**	**-0.79****	**-0.69***	**-0.21**	**-1.05****
Mean (%)	3.59	3.79	6.29	5.26	-0.26	0.60	3.75	-2.21
Vol (%)	5.26	5.00	8.27	6.89	8.34	8.22	6.82	7.64
Skew	-0.48	-1.31	-0.51	-0.65	-0.19	-0.27	-0.35	-0.50
MDD (%)	-9.12	-9.82	-25.36	-18.13	-44.09	-18.45	-18.04	-57.23
Total return	0.88	0.94	1.74	1.39	0.05	0.16	0.92	-0.23

PANEL C: $AUM_0 = 1$ billion

	MV	$MVTC$	HML	RB	DOL	$DDOL$	VAL	MOM
Before cost SR	0.91	0.64	0.88	0.86	-0.03	0.10	0.58	-0.22
Before cost Mean (%)	4.82	2.86	7.29	5.91	-0.25	0.83	3.96	-1.71
Before cost Vol (%)	5.30	4.46	8.29	6.90	8.34	8.21	6.80	7.63
Mean Costs (%)	5.62	0.23	5.46	3.07	0.04	0.78	1.29	2.55
Turnover	1.69	0.44	1.30	1.09	0.02	0.46	0.26	1.10
Notional	1.90	1.39	2.00	2.00	1.00	0.98	2.00	2.00
Avg USD Trade Size (millions)	86.55	29.40	140.41	77.33	1.34	25.99	33.70	64.08
Avg Relative Trade Size (%)	0.05	0.01	0.07	0.04	0.00	0.01	0.02	0.03

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Table A6 – continued from previous page

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
SR	**-0.16**	**0.59**	**0.21**	**0.41**	**-0.03**	**0.01**	**0.38**	**-0.55**
ΔSR	**-0.75*****	**-**	**-0.37***	**-0.18**	**-0.62**	**-0.58**	**-0.20**	**-1.14*****
Mean (%)	-0.84	2.63	1.79	2.82	-0.28	0.05	2.67	-4.25
Vol (%)	5.33	4.46	8.33	6.88	8.35	8.26	6.94	7.74
Skew	-0.84	-1.67	-0.55	-0.65	-0.19	-0.28	-0.43	-0.48
MDD (%)	-32.59	-9.15	-36.30	-20.82	-44.11	-19.65	-20.41	-84.28
Total return	-0.03	0.63	0.40	0.66	0.04	0.07	0.64	-0.44

Notes: The table reports summary statistics of monthly excess returns of our strategies in the FX market. The strategies are described in Section 3. Panel A summaries the performance when there are only proportional costs. Panel B and C report results when the initial AUM of a fund is USD 100 million respectively 1 billion and costs account for the price impact of trading. Before cost SR, Mean (%) and Vol (%) measure the annualized Sharpe ratio, and annualized average and volatility of the excess returns (reported in percentage points). Mean Costs (%) measures the average annualized trading costs as a percentage of the AUM. Turnover and Notional report the monthly turnover and the notional value as a fraction of the AUM. Avg Relative Trade Size (%) and Avg USD Trade Size (millions) measures the average amount traded per month (average across currency-month observations with non-trivial trade) as a percentage of the average daily trading volume in the market respectively in absolute terms as millions of USD. SR is the annualized after cost Sharpe ratio. ΔSR is the difference in the after-cost Sharpe ratio of a strategy and that of *MVTC*. Standard errors of ΔSR are estimated using block bootstrapping with a block size of 5 observations to account for heteroskedasticity, cross- and auto-correlation (Ledoit and Wolf, 2008). ***, **, * indicate a statistical significance at the 1%, 5%, 10% level. Mean (%) and Vol (%) are the annualized average and volatility of the after cost excess returns (reported in percentage points). Skew is the monthly skewness of the after cost excess returns, MDD (%) is the Maximum Draw Down (measured in percentage points). Total return is the return (including the risk-free rate) from January 2008 to January 2024. The sample includes 13 developed and 13 emerging currencies against the USD for the period from January 2008 to January 2024.

Table A7: **Performance of FX Strategies: Sample Before the Introduction of the Euro (January 1999)**

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
	PANEL A: NO PRICE IMPACT							
Before cost SR	1.12	1.09	0.68	0.70	0.20	0.44	0.38	0.42
Before cost Mean (%)	11.76	11.16	5.84	5.09	1.48	3.19	3.00	3.92
Before cost Vol (%)	10.52	10.25	8.53	7.24	7.31	7.26	7.86	9.35
Mean Costs (%)	1.39	0.81	0.32	0.32	0.03	0.12	0.14	0.34
Turnover	2.76	1.69	0.76	0.62	0.04	0.22	0.27	0.88
Notional	4.35	4.17	2.00	2.00	1.00	1.00	2.00	2.00
SR	**0.98**	**1.01**	**0.65**	**0.66**	**0.20**	**0.42**	**0.36**	**0.38**
ΔSR	**-0.03**	-	**-0.36**	**-0.35**	**-0.81***	**-0.59**	**-0.65**	**-0.63**
Mean (%)	10.35	10.34	5.52	4.77	1.45	3.07	2.86	3.58
Vol (%)	10.52	10.23	8.53	7.26	7.31	7.27	7.86	9.34
Skew	-1.21	-1.14	-1.05	-0.74	-0.37	-0.57	-0.18	-0.57
MDD (%)	-26.42	-28.02	-32.28	-31.43	-21.40	-14.85	-22.39	-19.90
Total return	4.77	4.81	2.47	2.19	1.12	1.60	1.54	1.60
	PANEL B: $AUM_0 = 100$ **million**							
Before cost SR	1.12	1.01	0.68	0.70	0.20	0.44	0.38	0.42
Before cost Mean (%)	11.76	10.07	5.84	5.09	1.48	3.19	3.00	3.92
Before cost Vol (%)	10.52	9.95	8.53	7.24	7.31	7.26	7.86	9.35
Mean Costs (%)	4.97	0.98	0.62	0.46	0.03	0.14	0.23	0.58
Turnover	2.76	1.09	0.76	0.62	0.04	0.22	0.27	0.88
Notional	4.35	3.98	2.00	2.00	1.00	1.00	2.00	2.00
Avg USD Trade Size (millions)	46.28	19.92	18.08	7.71	0.40	2.44	5.75	17.84

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	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
Avg Relative Trade Size (%)	1.30	0.40	0.51	0.22	0.01	0.07	0.23	0.41
SR	**0.63**	**0.91**	**0.61**	**0.64**	**0.20**	**0.42**	**0.35**	**0.36**
ΔSR	**-0.28***	-	**-0.30**	**-0.28**	**-0.72**	**-0.49**	**-0.56**	**-0.56**
Mean (%)	6.70	9.07	5.22	4.63	1.44	3.06	2.77	3.34
Vol (%)	10.60	9.93	8.55	7.26	7.31	7.28	7.86	9.33
Skew	-1.38	-1.32	-1.04	-0.73	-0.37	-0.57	-0.18	-0.57
MDD (%)	-31.18	-25.53	-33.24	-31.88	-21.42	-14.87	-22.55	-20.23
Total return	2.77	4.06	2.35	2.14	1.12	1.60	1.52	1.53
PANEL C: $AUM_0 = 1$ **billion**								
Before cost SR	1.12	0.79	0.68	0.70	0.20	0.44	0.38	0.42
Before cost Mean (%)	11.76	7.21	5.84	5.09	1.48	3.19	3.00	3.92
Before cost Vol (%)	10.52	9.16	8.53	7.24	7.31	7.26	7.86	9.35
Mean Costs (%)	16.83	1.21	2.93	1.59	0.06	0.29	0.99	2.46
Turnover	2.76	0.52	0.76	0.62	0.04	0.22	0.27	0.88
Notional	4.35	3.53	2.00	2.00	1.00	1.00	2.00	2.00
Avg USD Trade Size (millions)	256.64	79.03	161.25	73.41	3.97	24.26	55.95	163.02
Avg Relative Trade Size (%)	6.76	1.40	4.44	2.04	0.13	0.66	2.27	3.74

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Table A7 – continued from previous page

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
SR	**-0.39**	**0.65**	**0.33**	**0.48**	**0.19**	**0.40**	**0.26**	**0.15**
ΔSR	**-1.04*****	**-**	**-0.31**	**-0.17**	**-0.45**	**-0.25**	**-0.39**	**-0.49**
Mean (%)	-5.42	5.99	2.90	3.49	1.41	2.90	2.01	1.44
Vol (%)	13.81	9.26	8.71	7.34	7.31	7.29	7.87	9.32
Skew	-1.71	-1.15	-0.99	-0.71	-0.37	-0.57	-0.19	-0.59
MDD (%)	-107.83	-29.62	-41.02	-35.81	-21.54	-15.12	-23.90	-23.49
Total return	-0.14	2.58	1.58	1.75	1.11	1.55	1.34	1.06

Notes: The table reports summary statistics of monthly excess returns of our strategies in the FX market. The strategies are described in Section 3. Panel A summaries the performance when there are only proportional costs. Panel B and C report results when the initial AUM of a fund is USD 100 million respectively 1 billion and costs account for the price impact of trading. Before cost SR, Mean (%) and Vol (%) measure the annualized Sharpe ratio, and annualized average and volatility of the excess returns (reported in percentage points). Mean Costs (%) measures the average annualized trading costs as a percentage of the AUM. Turnover and Notional report the monthly turnover and the notional value as a fraction of the AUM. Avg Relative Trade Size (%) and Avg USD Trade Size (millions) measures the average amount traded per month (average across currency-month observations with non-trivial trade) as a percentage of the average daily trading volume in the market respectively in absolute terms as millions of USD. SR is the annualized after cost Sharpe ratio. ΔSR is the difference in the after-cost Sharpe ratio of a strategy and that of *MVTC*. Standard errors of ΔSR are estimated using block bootstrapping with a block size of 5 observations to account for heteroskedasticity, cross- and auto-correlation (Ledoit and Wolf, 2008). ***, **, * indicate a statistical significance at the 1%, 5%, 10% level. Mean (%) and Vol (%) are the annualized average and volatility of the after cost excess returns (reported in percentage points). Skew is the monthly skewness of the after cost excess returns, MDD (%) is the Maximum Draw Down (measured in percentage points). Total return is the return (including the risk-free rate) from February 1987 to December 1998. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to December 1998.

Table A8: **Performance of FX Strategies: Sample After the Introduction of the Euro (January 1999)**

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
				PANEL A: NO PRICE IMPACT				
Before cost SR	1.18	1.14	0.81	0.85	0.07	0.24	0.60	0.33
Before cost Mean (%)	7.40	6.97	6.81	5.70	0.56	1.94	3.89	2.77
Before cost Vol (%)	6.26	6.13	8.40	6.68	8.20	8.10	6.50	8.31
Mean Costs (%)	0.80	0.42	0.35	0.40	0.01	0.20	0.10	0.27
Turnover	2.02	1.33	1.31	1.10	0.02	0.47	0.26	0.98
Notional	2.34	2.22	2.00	2.00	1.00	0.99	2.00	2.00
SR	**1.06**	**1.07**	**0.77**	**0.79**	**0.07**	**0.21**	**0.58**	**0.30**
ΔSR	**-0.01**	-	**-0.30**	**-0.28**	**-1.00*****	**-0.86*****	**-0.49****	**-0.77****
Mean (%)	6.59	6.54	6.46	5.30	0.54	1.74	3.79	2.51
Vol (%)	6.22	6.11	8.40	6.68	8.20	8.10	6.50	8.31
Skew	-0.02	-0.05	-0.61	-0.66	-0.43	-0.15	-0.22	-0.04
MDD (%)	-12.59	-11.99	-24.45	-17.73	-44.09	-18.30	-17.77	-54.73
Total return	5.71	5.64	5.27	3.92	0.57	1.04	2.46	1.45
				PANEL B: $AUM_0 = 100$ **million**				
Before cost SR	1.18	1.01	0.81	0.85	0.07	0.24	0.60	0.33
Before cost Mean (%)	7.40	5.92	6.81	5.70	0.56	1.94	3.89	2.77
Before cost Vol (%)	6.26	5.86	8.40	6.68	8.20	8.10	6.50	8.31

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	MV	$MVTC$	HML	RB	DOL	$DDOL$	VAL	MOM
Mean Costs (%)	2.81	0.41	1.53	0.91	0.02	0.31	0.31	1.01
Turnover	2.02	0.81	1.31	1.10	0.02	0.47	0.26	0.98
Notional	2.34	2.04	2.00	2.00	1.00	0.99	2.00	2.00
Avg USD Trade Size (millions)	29.10	13.19	30.82	14.81	0.20	4.51	5.43	18.89
Avg Relative Trade Size (%)	1.58	0.32	1.66	0.73	0.01	0.24	0.32	1.03
SR	**0.74**	**0.94**	**0.63**	**0.72**	**0.07**	**0.20**	**0.55**	**0.21**
ΔSR	**-0.20****	-	**-0.31**	**-0.23**	**-0.88*****	**-0.74****	**-0.39**	**-0.73****
Mean (%)	4.57	5.51	5.27	4.78	0.54	1.63	3.58	1.76
Vol (%)	6.14	5.86	8.40	6.69	8.20	8.11	6.52	8.32
Skew	-0.15	-0.47	-0.64	-0.67	-0.43	-0.15	-0.24	-0.04
MDD (%)	-14.56	-15.34	-26.05	-18.47	-44.09	-18.55	-18.24	-65.58
Total return	3.14	4.21	3.73	3.35	0.57	0.98	2.30	1.05

PANEL C: $AUM_0 = 1$ **billion**

	MV	$MVTC$	HML	RB	DOL	$DDOL$	VAL	MOM
Before cost SR	1.18	0.95	0.81	0.85	0.07	0.24	0.60	0.33
Before cost Mean (%)	7.40	4.82	6.81	5.70	0.56	1.94	3.89	2.77
Before cost Vol (%)	6.26	5.07	8.40	6.68	8.20	8.10	6.50	8.31
Mean Costs (%)	8.98	0.29	6.41	3.90	0.03	1.19	1.80	4.77
Turnover	2.02	0.37	1.31	1.10	0.02	0.47	0.26	0.98
Notional	2.34	1.70	2.00	2.00	1.00	0.99	2.00	2.00
Avg USD Trade Size (millions)	110.57	50.37	154.09	100.03	2.00	40.36	45.03	113.14
Avg Relative Trade Size (%)	5.91	0.85	8.21	4.91	0.11	2.18	2.67	6.15

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Table A8 – continued from previous page

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
SR	**-0.27**	**0.89**	**0.04**	**0.26**	**0.06**	**0.09**	**0.31**	**-0.24**
ΔSR	**-1.16*****	**-**	**-0.85*****	**-0.63*****	**-0.83****	**-0.80*****	**-0.58*****	**-1.13*****
Mean (%)	-1.70	4.52	0.36	1.78	0.53	0.76	2.09	-2.02
Vol (%)	6.28	5.06	8.62	6.82	8.20	8.21	6.71	8.41
Skew	-0.57	-0.12	-0.78	-0.77	-0.43	-0.21	-0.41	-0.05
MDD (%)	-56.41	-11.13	-50.65	-27.22	-44.11	-26.04	-21.76	-114.06
Total return	-0.08	3.15	0.46	1.12	0.56	0.61	1.33	-0.17

Notes: The table reports summary statistics of monthly excess returns of our strategies in the FX market. The strategies are described in Section 3. Panel A summaries the performance when there are only proportional costs. Panel B and C report results when the initial AUM of a fund is USD 100 million respectively 1 billion and costs account for the price impact of trading. Before cost SR, Mean (%) and Vol (%) measure the annualized Sharpe ratio, and annualized average and volatility of the excess returns (reported in percentage points). Mean Costs (%) measures the average annualized trading costs as a percentage of the AUM. Turnover and Notional report the monthly turnover and the notional value as a fraction of the AUM. Avg Relative Trade Size (%) and Avg USD Trade Size (millions) measures the average amount traded per month (average across currency-month observations with non-trivial trade) as a percentage of the average daily trading volume in the market respectively in absolute terms as millions of USD. SR is the annualized after cost Sharpe ratio. ΔSR is the difference in the after-cost Sharpe ratio of a strategy and that of *MVTC*. Standard errors of ΔSR are estimated using block bootstrapping with a block size of 5 observations to account for heteroskedasticity, cross- and auto-correlation (Ledoit and Wolf, 2008). ***, **, * indicate a statistical significance at the 1%, 5%, 10% level. Mean (%) and Vol (%) are the annualized average and volatility of the after cost excess returns (reported in percentage points). Skew is the monthly skewness of the after cost excess returns, MDD (%) is the Maximum Draw Down (measured in percentage points). Total return is the return (including the risk-free rate) from February 1999 to January 2024. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1999 to January 2024.

Table A9: **NBER Recessions**

Strategies	NBER Recessions			non-NBER Recessions		
	Before TC	After TC		Before TC	After TC	
	SR	SR	ΔSR	SR	SR	ΔSR
	PANEL A: NO PRICE IMPACT					
MV	0.58	0.38	0.00	1.14	1.02	-0.02
MVTC	0.50	0.38	-	1.10	1.04	-
HML	0.13	0.08	-0.30	0.86	0.82	-0.22
RB	0.57	0.50	0.11	0.82	0.77	-0.27
DOL	-0.21	-0.21	-0.60	0.13	0.13	-0.91***
DDOL	0.00	-0.04	-0.42	0.36	0.34	-0.70***
VAL	1.00	0.98	0.59	0.45	0.43	-0.60***
MOM	0.23	0.20	-0.18	0.38	0.34	-0.69***
	PANEL B: $AUM_0 = 100$ **million**					
MV	0.58	-0.29	-0.82**	1.14	0.39	-0.50***
MVTC	0.63	0.53	-	0.97	0.89	-
HML	0.13	-0.30	-0.84	0.86	0.56	-0.33**
RB	0.57	0.26	-0.27	0.82	0.62	-0.27*
DOL	-0.21	-0.21	-0.75	0.13	0.13	-0.77***
DDOL	0.00	-0.10	-0.63	0.36	0.31	-0.58**
VAL	1.00	0.88	0.34	0.45	0.39	-0.51**
MOM	0.23	0.04	-0.49	0.38	0.20	-0.70***
	PANEL C: $AUM_0 = 1$ **billion**					
MV	0.58	-0.99	-1.34***	1.14	-0.23	-0.99***
MVTC	0.42	0.35	-	0.85	0.76	-
HML	0.13	-1.06	-1.41**	0.86	0.02	-0.75***
RB	0.57	-0.57	-0.92	0.82	0.12	-0.64***
DOL	-0.21	-0.22	-0.57	0.13	0.13	-0.64***
DDOL	0.00	-0.48	-0.83	0.36	0.16	-0.60***
VAL	1.00	0.15	-0.20	0.45	0.14	-0.63***
MOM	0.23	-0.62	-0.97	0.38	-0.23	-1.00***

Notes: Columns 2 and 5 report Sharpe ratios before costs (Before TC SR). Columns 3 and 6 report Sharpe ratios after costs (After TC SR). Columns 4 and 7 report the difference between the Sharpe ratios after costs of the strategy on the current row and $MVTC$ (After TC ΔSR). Standard errors of ΔSR are estimated using block bootstrapping with a block size of 5 observations to account for heteroskedasticity, cross- and auto-correlation (Ledoit and Wolf, 2008). ***, **, * indicate a statistical significance at the 1%, 5%, 10% level. Columns 2 to 4 report results for the subsample of months during NBER recession, while columns 5 to 7 use the subsample of non-recession months. The strategies are described in Section 3. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

E.2 Alternative Estimates of the Price Impact

Table A10: **Performance of FX Strategies: Price Impact with Time-Invariant Amihud Measure**

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
PANEL B: $AUM_0 = 100$ **million**								
Before cost SR	1.12	0.93	0.79	0.81	0.09	0.32	0.51	0.36
Before cost Mean (%)	8.92	6.66	6.55	5.50	0.70	2.45	3.50	3.15
Before cost Vol (%)	7.95	7.14	8.34	6.80	7.83	7.74	6.92	8.67
Mean Costs (%)	5.80	0.56	2.36	1.32	0.02	0.36	0.40	1.42
Turnover	2.32	0.67	1.13	0.95	0.03	0.40	0.25	0.95
Notional	3.07	2.55	2.00	2.00	1.00	0.99	2.00	2.00
Avg USD Trade Size (millions)	62.93	31.90	67.61	33.29	0.39	9.58	10.97	37.55
Avg Relative Trade Size (%)	3.05	0.62	3.44	1.58	0.02	0.50	0.62	1.89
SR	**0.38**	**0.86**	**0.50**	**0.61**	**0.09**	**0.27**	**0.45**	**0.20**
ΔSR	**-0.48*****	**-**	**-0.36****	**-0.24**	**-0.77*****	**-0.59*****	**-0.41***	**-0.66*****
Mean (%)	3.05	6.09	4.18	4.17	0.68	2.09	3.10	1.73
Vol (%)	8.10	7.12	8.35	6.82	7.83	7.76	6.91	8.69
Skew	-1.20	-0.95	-0.80	-0.69	-0.41	-0.28	-0.20	-0.24
MDD (%)	-31.73	-26.68	-33.16	-31.85	-44.10	-18.91	-22.54	-76.37
Total return	6.77	23.40	10.76	11.27	2.37	4.51	7.36	3.72
PANEL C: $AUM_0 = 1$ **billion**								
Before cost SR	1.12	0.82	0.79	0.81	0.09	0.32	0.51	0.36
Before cost Mean (%)	8.92	4.79	6.55	5.50	0.70	2.45	3.50	3.15
Before cost Vol (%)	7.95	5.84	8.34	6.80	7.83	7.74	6.92	8.67

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Table A10 – continued from previous page

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
Mean Costs (%)	11.40	0.45	7.05	4.80	0.04	1.53	2.15	5.19
Turnover	2.32	0.28	1.13	0.95	0.03	0.40	0.25	0.95
Notional	3.07	2.05	2.00	2.00	1.00	0.99	2.00	2.00
Avg USD Trade Size (millions)	135.57	81.86	243.35	165.96	3.92	77.14	82.08	178.88
Avg Relative Trade Size (%)	5.51	1.26	11.27	7.62	0.19	3.96	4.51	8.20
SR	**-0.28**	**0.74**	**-0.07**	**0.10**	**0.08**	**0.12**	**0.19**	**-0.24**
ΔSR	**-1.02*****	**-**	**-0.80*****	**-0.64*****	**-0.65*****	**-0.62*****	**-0.55****	**-0.97*****
Mean (%)	-2.65	4.33	-0.56	0.68	0.66	0.91	1.34	-2.07
Vol (%)	9.40	5.87	8.56	6.95	7.83	7.86	7.04	8.79
Skew	-2.09	-0.70	-0.78	-0.67	-0.41	-0.30	-0.22	-0.24
MDD (%)	-132.56	-30.05	-95.94	-51.50	-44.13	-37.80	-23.82	-135.00
Total return	-0.09	12.17	1.04	2.37	2.34	2.57	3.44	0.16

Notes: The table reports summary statistics of monthly excess returns of our strategies in the FX market. The strategies are described in Section 3. Panel A is omitted as it is identical to panel A in table 3. Panel B and C report results when the initial AUM of a fund is USD 100 million respectively 1 billion and costs account for the price impact of trading. The price impact is based on the time-invariant Amihud measure as described in section B.3.1. Before cost SR, Mean (%) and Vol (%) measure the annualized Sharpe ratio, and annualized average and volatility of the excess returns (reported in percentage points). Mean Costs (%) measures the average annualized trading costs as a percentage of the AUM. Turnover and Notional report the monthly turnover and the notional value as a fraction of the AUM. Avg Relative Trade Size (%) and Avg USD Trade Size (millions) measures the average amount traded per month (average across currency-month observations with non-trivial trade) as a percentage of the average daily trading volume in the market respectively in absolute terms as millions of USD. SR is the annualized after cost Sharpe ratio. ΔSR is the difference in the after-cost Sharpe ratio of a strategy and that of *MVTC*. Standard errors of ΔSR are estimated using block bootstrapping with a block size of 5 observations to account for heteroskedasticity, cross- and auto-correlation (Ledoit and Wolf, 2008). ***, **, * indicate a statistical significance at the 1%, 5%, 10% level. Mean (%) and Vol (%) are the annualized average and volatility of the after cost excess returns (reported in percentage points). Skew is the monthly skewness of the after cost excess returns, MDD (%) is the Maximum Draw Down (measured in percentage points). Total return is the return (including the risk-free rate) from February 1987 to January 2024. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

Table A11: **Performance of FX Strategies: Time-Series Extrapolation of Volume Data**

	MV	$MVTC$	HML	RB	DOL	$DDOL$	VAL	MOM
PANEL B: $AUM_0 = 100$ **million**								
Before cost SR	1.12	0.97	0.79	0.81	0.09	0.32	0.51	0.36
Before cost Mean (%)	8.92	6.59	6.55	5.50	0.70	2.45	3.50	3.15
Before cost Vol (%)	7.95	6.83	8.34	6.80	7.83	7.74	6.92	8.67
Mean Costs (%)	6.68	0.52	3.04	1.68	0.02	0.51	0.61	1.95
Turnover	2.32	0.44	1.13	0.95	0.03	0.40	0.25	0.95
Notional	3.07	2.44	2.00	2.00	1.00	0.99	2.00	2.00
Avg USD Trade Size (millions)	41.69	22.84	51.63	29.20	0.39	9.23	10.30	31.75
Avg Relative Trade Size (%)	0.03	0.01	0.04	0.02	0.00	0.01	0.01	0.03
SR	**0.26**	**0.89**	**0.41**	**0.56**	**0.09**	**0.25**	**0.42**	**0.14**
ΔSR	**-0.63*****	-	**-0.48*****	**-0.33****	**-0.80*****	**-0.64*****	**-0.47****	**-0.75*****
Mean (%)	2.14	6.06	3.49	3.81	0.68	1.94	2.89	1.19
Vol (%)	8.16	6.80	8.44	6.83	7.83	7.78	6.92	8.69
Skew	-1.38	-0.83	-0.84	-0.71	-0.41	-0.30	-0.23	-0.24
MDD (%)	-46.99	-26.70	-35.75	-33.22	-44.10	-20.20	-22.77	-79.53
Total return	4.54	23.35	8.10	9.73	2.36	4.21	6.69	2.87
PANEL C: $AUM_0 = 1$ **billion**								
Before cost SR	1.12	0.77	0.79	0.81	0.09	0.32	0.51	0.36
Before cost Mean (%)	8.92	4.35	6.55	5.50	0.70	2.45	3.50	3.15
Before cost Vol (%)	7.95	5.68	8.34	6.80	7.83	7.74	6.92	8.67

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Table A11 – continued from previous page

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
Mean Costs (%)	12.34	0.49	8.13	5.69	0.07	2.38	3.12	6.34
Turnover	2.32	0.16	1.13	0.95	0.03	0.40	0.25	0.95
Notional	3.07	2.07	2.00	2.00	1.00	0.99	2.00	2.00
Avg USD Trade Size (millions)	78.24	46.17	137.06	107.56	3.90	61.65	59.55	111.42
Avg Relative Trade Size (%)	0.07	0.02	0.11	0.08	0.00	0.05	0.05	0.10
SR	**-0.35**	**0.67**	**-0.18**	**-0.03**	**0.08**	**0.01**	**0.05**	**-0.37**
ΔSR	**-1.02***	-	**-0.85***	**-0.70***	**-0.59**	**-0.66***	**-0.62***	**-1.04***
Mean (%)	-3.61	3.85	-1.64	-0.22	0.64	0.07	0.36	-3.23
Vol (%)	10.28	5.74	8.92	7.14	7.83	8.10	7.28	8.85
Skew	-2.63	-0.73	-0.87	-0.75	-0.41	-0.49	-0.45	-0.27
MDD (%)	-176.63	-32.37	-126.46	-79.11	-44.14	-54.16	-42.74	-149.58
Total return	-0.38	10.07	0.35	1.41	2.31	1.59	2.02	-0.25

Notes: The table reports summary statistics of monthly excess returns of our strategies in the FX market. The strategies are described in Section 3. Panel A is omitted as it is identical to panel A in table 3. Panel B and C report results when the initial AUM of a fund is USD 100 million respectively 1 billion and costs account for the price impact of trading. The price impact is based on the Amihud measure constructed from the extrapolated panel (cross-section and time-series) of CLS volume data as described in section B.3.2. Before cost SR, Mean (%) and Vol (%) measure the annualized Sharpe ratio, and annualized average and volatility of the excess returns (reported in percentage points). Mean Costs (%) measures the average annualized trading costs as a percentage of the AUM. Turnover and Notional report the monthly turnover and the notional value as a fraction of the AUM. Avg Relative Trade Size (%) and Avg USD Trade Size (millions) measures the average amount traded per month (average across currency-month observations with non-trivial trade) as a percentage of the average daily trading volume in the market respectively in absolute terms as millions of USD. SR is the annualized after cost Sharpe ratio. ΔSR is the difference in the after-cost Sharpe ratio of a strategy and that of *MVTC*. Standard errors of ΔSR are estimated using block bootstrapping with a block size of 5 observations to account for heteroskedasticity, cross- and auto-correlation (Ledoit and Wolf, 2008). ***, **, * indicate a statistical significance at the 1%, 5%, 10% level. Mean (%) and Vol (%) are the annualized average and volatility of the after cost excess returns (reported in percentage points). Skew is the monthly skewness of the after cost excess returns, MDD (%) is the Maximum Draw Down (measured in percentage points). Total return is the return (including the risk-free rate) from February 1987 to January 2024. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

Table A12: **Performance of FX Strategies: Price Impact based on BIS Triennial Survey Volume Data**

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
PANEL B: $AUM_0 = 100$ **million**								
Before cost SR	1.12	0.99	0.79	0.81	0.09	0.32	0.51	0.36
Before cost Mean (%)	8.92	7.14	6.55	5.50	0.70	2.45	3.50	3.15
Before cost Vol (%)	7.95	7.23	8.34	6.80	7.83	7.74	6.92	8.67
Mean Costs (%)	6.82	0.60	2.41	1.60	0.02	0.43	0.47	1.48
Turnover	2.32	0.86	1.13	0.95	0.03	0.40	0.25	0.95
Notional	3.07	2.65	2.00	2.00	1.00	0.99	2.00	2.00
Avg USD Trade Size (millions)	34.06	51.90	54.35	27.76	0.39	9.30	10.45	34.13
Avg Relative Trade Size (%)	0.03	0.01	0.03	0.02	0.00	0.01	0.01	0.02
SR	**0.21**	**0.90**	**0.49**	**0.57**	**0.09**	**0.26**	**0.44**	**0.19**
ΔSR	**-0.69*****	-	**-0.41****	**-0.33****	**-0.81*****	**-0.64*****	**-0.46****	**-0.71*****
Mean (%)	1.95	6.53	4.12	3.89	0.68	2.01	3.03	1.67
Vol (%)	9.19	7.25	8.41	6.83	7.83	7.77	6.91	8.68
Skew	-2.19	-1.12	-0.80	-0.70	-0.41	-0.30	-0.21	-0.25
MDD (%)	-75.56	-27.52	-34.85	-33.16	-44.09	-19.10	-23.17	-67.79
Total return	3.99	27.60	10.45	10.05	2.36	4.37	7.10	3.61
PANEL C: $AUM_0 = 1$ **billion**								
Before cost SR	1.12	0.80	0.79	0.81	0.09	0.32	0.51	0.36
Before cost Mean (%)	8.92	5.44	6.55	5.50	0.70	2.45	3.50	3.15
Before cost Vol (%)	7.95	6.79	8.34	6.80	7.83	7.74	6.92	8.67

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Table A12 – continued from previous page

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
Mean Costs (%)	11.84	0.62	7.12	5.49	0.06	1.97	2.52	5.33
Turnover	2.32	0.45	1.13	0.95	0.03	0.40	0.25	0.95
Notional	3.07	2.34	2.00	2.00	1.00	0.99	2.00	2.00
Avg USD Trade Size (millions)	62.31	168.43	139.57	91.33	3.89	63.52	61.18	128.72
Avg Relative Trade Size (%)	0.05	0.01	0.09	0.07	0.00	0.04	0.06	0.09
SR	**-0.23**	**0.70**	**-0.07**	**0.00**	**0.08**	**0.06**	**0.13**	**-0.24**
ΔSR	**-0.93*****	-	**-0.77*****	**-0.71*****	**-0.62****	**-0.64*****	**-0.57****	**-0.94*****
Mean (%)	-3.24	4.82	-0.63	-0.03	0.64	0.47	0.96	-2.21
Vol (%)	14.25	6.88	9.33	7.31	7.83	8.02	7.27	9.13
Skew	-7.58	-1.39	-0.98	-0.67	-0.41	-0.44	-0.37	-0.47
MDD (%)	-183.08	-39.36	-134.08	-103.57	-44.10	-39.02	-31.95	-118.21
Total return	-0.48	14.39	0.93	1.57	2.32	2.02	2.75	0.08

Notes: The table reports summary statistics of monthly excess returns of our strategies in the FX market. The strategies are described in Section 3. Panel A is omitted as it is identical to panel A in table 3. Panel B and C report results when the initial AUM of a fund is USD 100 million respectively 1 billion and costs account for the price impact of trading. The price impact is based on the Amihud measure constructed from the extrapolated panel (cross-section and time-series) of BIS Triennial Survey volume data as described in section B.3.3. Before cost SR, Mean (%) and Vol (%) measure the annualized Sharpe ratio, and annualized average and volatility of the excess returns (reported in percentage points). Mean Costs (%) measures the average annualized trading costs as a percentage of the AUM. Turnover and Notional report the monthly turnover and the notional value as a fraction of the AUM. Avg Relative Trade Size (%) and Avg USD Trade Size (millions) measures the average amount traded per month (average across currency-month observations with non-trivial trade) as a percentage of the average daily trading volume in the market respectively in absolute terms as millions of USD. SR is the annualized after cost Sharpe ratio. ΔSR is the difference in the after-cost Sharpe ratio of a strategy and that of *MVTC*. Standard errors of ΔSR are estimated using block bootstrapping with a block size of 5 observations to account for heteroskedasticity, cross- and auto-correlation (Ledoit and Wolf, 2008). ***, **, * indicate a statistical significance at the 1%, 5%, 10% level. Mean (%) and Vol (%) are the annualized average and volatility of the after cost excess returns (reported in percentage points). Skew is the monthly skewness of the after cost excess returns, MDD (%) is the Maximum Draw Down (measured in percentage points). Total return is the return (including the risk-free rate) from February 1987 to January 2024. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

Table A13: **Performance of FX Strategies: Cutting Costs in Half**

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
	PANEL A: NO PRICE IMPACT							
Before cost SR	1.12	1.09	0.79	0.81	0.09	0.32	0.51	0.36
Before cost Mean (%)	8.92	8.64	6.55	5.50	0.70	2.45	3.50	3.15
Before cost Vol (%)	7.95	7.94	8.34	6.80	7.83	7.74	6.92	8.67
Mean Costs (%)	0.53	0.37	0.17	0.19	0.01	0.10	0.05	0.15
Turnover	2.32	1.80	1.13	0.95	0.03	0.40	0.25	0.95
Notional	3.07	2.99	2.00	2.00	1.00	0.99	2.00	2.00
SR	**1.06**	**1.04**	**0.76**	**0.78**	**0.09**	**0.30**	**0.50**	**0.35**
ΔSR	**0.01**	-	**-0.28**	**-0.26**	**-0.95***	**-0.74***	**-0.54**	**-0.70***
Mean (%)	8.38	8.26	6.38	5.31	0.69	2.35	3.45	3.00
Vol (%)	7.93	7.93	8.34	6.80	7.83	7.75	6.92	8.67
Skew	-0.78	-0.86	-0.77	-0.69	-0.41	-0.28	-0.20	-0.25
MDD (%)	-24.72	-29.05	-31.80	-30.87	-44.07	-18.15	-22.26	-53.09
Total return	54.42	52.04	25.34	17.60	2.38	5.08	8.44	6.54
	PANEL B: $AUM_0 = 100$ **million**							
Before cost SR	1.12	0.99	0.79	0.81	0.09	0.32	0.51	0.36
Before cost Mean (%)	8.92	7.32	6.55	5.50	0.70	2.45	3.50	3.15
Before cost Vol (%)	7.95	7.43	8.34	6.80	7.83	7.74	6.92	8.67

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Table A13 – continued from previous page

	MV	$MVTC$	HML	RB	DOL	$DDOL$	VAL	MOM
Mean Costs (%)	4.24	0.50	1.61	0.81	0.01	0.21	0.24	0.89
Turnover	2.32	0.95	1.13	0.95	0.03	0.40	0.25	0.95
Notional	3.07	2.69	2.00	2.00	1.00	0.99	2.00	2.00
Avg USD Trade Size (millions)	96.32	52.79	79.00	37.04	0.40	9.90	11.29	41.76
Avg Relative Trade Size (%)	0.05	0.01	0.04	0.02	0.00	0.01	0.01	0.02
SR	**0.58**	**0.92**	**0.59**	**0.69**	**0.09**	**0.29**	**0.47**	**0.26**
ΔSR	**-0.34****	-	**-0.33***	**-0.23**	**-0.83*****	**-0.63*****	**-0.45****	**-0.66*****
Mean (%)	4.63	6.81	4.93	4.69	0.69	2.24	3.26	2.26
Vol (%)	7.99	7.41	8.36	6.81	7.83	7.76	6.92	8.68
Skew	-1.01	-0.97	-0.80	-0.70	-0.41	-0.29	-0.21	-0.25
MDD (%)	-27.29	-25.11	-32.29	-31.10	-44.07	-18.52	-22.33	-68.51
Total return	12.94	30.56	14.49	13.81	2.38	4.83	7.84	4.73

PANEL C: $AUM_0 = 1$ **billion**

	MV	$MVTC$	HML	RB	DOL	$DDOL$	VAL	MOM
Before cost SR	1.12	0.89	0.79	0.81	0.09	0.32	0.51	0.36
Before cost Mean (%)	8.92	6.08	6.55	5.50	0.70	2.45	3.50	3.15
Before cost Vol (%)	7.95	6.81	8.34	6.80	7.83	7.74	6.92	8.67
Mean Costs (%)	9.61	0.49	5.79	3.63	0.02	1.05	1.50	4.00
Turnover	2.32	0.43	1.13	0.95	0.03	0.40	0.25	0.95
Notional	3.07	2.34	2.00	2.00	1.00	0.99	2.00	2.00
Avg USD Trade Size (millions)	241.99	157.44	327.41	212.00	3.94	84.90	91.11	231.95
Avg Relative Trade Size (%)	0.10	0.03	0.16	0.10	0.00	0.04	0.05	0.11

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Table A13 – continued from previous page

	MV	*MVTC*	*HML*	*RB*	*DOL*	*DDOL*	*VAL*	*MOM*
SR	**-0.09**	**0.82**	**0.08**	**0.27**	**0.09**	**0.18**	**0.28**	**-0.10**
ΔSR	**-0.91*****	-	**-0.74*****	**-0.55*****	**-0.73*****	**-0.64*****	**-0.54****	**-0.92*****
Mean (%)	-0.84	5.58	0.73	1.85	0.68	1.40	2.00	-0.87
Vol (%)	9.33	6.80	8.63	6.97	7.83	7.86	7.03	8.78
Skew	-2.09	-1.11	-0.90	-0.78	-0.41	-0.35	-0.29	-0.23
MDD (%)	-104.72	-26.62	-72.15	-38.86	-44.09	-30.23	-23.02	-122.08
Total return	0.78	19.35	2.26	4.20	2.37	3.26	4.59	0.80

Notes: The table reports summary statistics of monthly excess returns of our strategies in the FX market. The strategies are described in Section 3. All trading costs are cut in half as described in section B.3.4. Panel A summaries the performance when there are only proportional costs. Panel B and C report results when the initial AUM of a fund is USD 100 million respectively 1 billion and costs account for the price impact of trading. Before cost SR, Mean (%) and Vol (%) measure the annualized Sharpe ratio, and annualized average and volatility of the excess returns (reported in percentage points). Mean Costs (%) measures the average annualized trading costs as a percentage of the AUM. Turnover and Notional report the monthly turnover and the notional value as a fraction of the AUM. Avg Relative Trade Size (%) and Avg USD Trade Size (millions) measures the average amount traded per month (average across currency-month observations with non-trivial trade) as a percentage of the average daily trading volume in the market respectively in absolute terms as millions of USD. SR is the annualized after cost Sharpe ratio. ΔSR is the difference in the after-cost Sharpe ratio of a strategy and that of $MVTC$. Standard errors of ΔSR are estimated using block bootstrapping with a block size of 5 observations to account for heteroskedasticity, cross- and auto-correlation (Ledoit and Wolf, 2008). ***, **, * indicate a statistical significance at the 1%, 5%, 10% level. Mean (%) and Vol (%) are the annualized average and volatility of the after cost excess returns (reported in percentage points). Skew is the monthly skewness of the after cost excess returns, MDD (%) is the Maximum Draw Down (measured in percentage points). Total return is the return (including the risk-free rate) from February 1987 to January 2024. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

E.3 Sensitivity Analyses of $MVTC$

Table A14: **Event Study of Crash Risks in Turbulent Times**

	Nature of the Event			No PI		$AUM_0 = 100$ mills		$AUM_0 = 1$ bill	
Date	Liquidity	Volatility	Crises	MVTC	BH	MVTC	BH	MVTC	BH
Sep-92	1	1	1	-12.15	-24.82	-8.28	-20.96	-11.23	-27.76
Mar-95	1	0	0	-2.61	-7.32	-4.57	-5.17	-10.50	-2.23
Jul-97	0	0	1	-13.09	-20.37	-12.81	-19.48	-14.50	-13.96
Sep-08	0	0	1	-1.03	-4.87	-0.49	-1.61	-0.86	-1.43
Oct-08	1	0	0	-1.03	-1.99	-0.49	-0.97	-0.86	-1.11
May-10	1	1	0	-2.36	-3.38	-2.10	-2.11	-1.32	-1.14
Sep-11	0	1	0	-2.63	-3.77	-2.26	-4.52	-2.51	-3.14
Mar-20	1	1	1	-0.46	-2.06	-1.60	-2.18	-2.32	-3.17
Mean				**-4.42**	**-8.57**	**-4.08**	**-7.12**	**-5.51**	**-6.74**

Notes: The table reports Maximum Draw Downs (MDD (%); measured in percentage points) for the time period starting 1 month before and ending 12 months after the turbulent month under investigation on each row. Turbulent months are defined as months with high volatility, illiquidity, or a known crisis as described in Figure A10. Each row corresponds to a separate turbulent month. The last row reports the average MDD across the different events (Mean). Column 1 identifies the date of the turbulent month. Column 2 to 4 indicates with 1 whether the turbulent month corresponds to a spike in volatility, illiquidity, or a crisis. Columns 5, 7 and 9 report the MDD from $MVTC$ and Columns 6, 8 and 10 the MDD of BH. $MVTC$ is the mean-variance-transaction-cost optimized portfolio described in section 3. BH is a buy and hold strategy that invests in the position of $MVTC$ at the beginning of the event sample and does not rebalance the initial position until the end of the event sample. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

Table A15: **Sensitivity to the Risk Aversion Coefficient λ**

Risk Aversion	Before TC SR		After TC SR			$MVTC$ After TC	
Coefficient λ	MV	$MVTC$	MV	$MVTC$	ΔSR	Vol (%)	MDD (%)
			PANEL A: NO PRICE IMPACT				
5	1.12	1.08	0.99	1	-0.01	38.41	-149.92
10	1.12	1.08	0.99	1.01	-0.02	19.26	-71.79
25	1.12	1.08	0.99	1.01	-0.02	7.73	-28.02
50	1.12	1.08	0.99	1.01	-0.02	3.87	-13.93
100	1.12	1.08	0.99	1.01	-0.02	1.94	-6.94
200	1.12	1.08	0.99	1.01	-0.02	0.97	-3.47
			PANEL B: $AUM_0 = 100$ **million**				
5	1.12	0.69	0.24	0.59	-0.35**	27.68	-171.95
10	1.12	0.84	0.12	0.77	-0.64***	15.68	-70.03
25	1.12	0.96	0.36	0.88	-0.52***	7.22	-25.53
50	1.12	1.01	0.71	0.94	-0.22***	3.74	-12.5
100	1.12	1.06	0.89	0.99	-0.1	1.89	-6.55
200	1.12	1.08	0.95	1	-0.05	0.96	-3.4
			PANEL C: $AUM_0 = 1$ **billion**				
5	1.12†	0.59	0.06†	0.43	-0.37**	23.17	-141.67
10	1.12	0.67	-0.13	0.54	-0.67***	13.67	-87.32
25	1.12	0.84	-0.27	0.75	-1.02***	6.44	-29.62
50	1.12	0.9	-0.19	0.83	-1.02***	3.52	-13.29
100	1.12	0.94	0.18	0.86	-0.68***	1.85	-6.49
200	1.12	0.99	0.58	0.91	-0.33***	0.94	-3.12

Notes: The table reports the performance of MV and $MVTC$ for different values $\lambda \in \{5, 10, 25, 50, 100, 200\}$. MV and $MVTC$ are the mean-variance respectively mean-variance-transaction-cost optimized portfolios. The strategies are described in section 3. Column 2 and 3 provide Sharpe ratios before transaction costs (Before TC SR), and columns 4 and 5 Sharpe ratios after costs (After TC SR). † indicates that a strategy was wiped out at least once during the sample period. In such an event we replenish the strategy with the initial AUM right after it was wiped out. Column 6 shows the difference in the after cost Sharpe ratios between MV and $MVTC$. Standard errors of ΔSR are estimated using block bootstrapping with a block size of 5 observations to account for heteroskedasticity, cross- and auto-correlation (Ledoit and Wolf, 2008). ***, **, * indicate a statistical significance at the 1%, 5%, 10% level. Column 7 and 8 report (in percentage points) the after cost volatility (Vol (%) and maximum draw-down (MDD (%)) for $MVTC$. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

Table A16: **Datastream Mnemonics for Exchange Rate Quotes against USD**

Currency	Spot Rate	Forward Rate
Australian dollar	BBAUDSP	BBAUD1F (USAUD1F)
Brazilian real	BRACRU$	USBRL1F
British pound	BBGBPSP	BBGBP1F
Canadian dollar	BBCADSP	BBCAD1F
Czech koruna	CZECHC$	USCZK1F
Euro	BBEURSP	BBEUR1F
French franc	BBFRFSP	BBFRF1F
German mark	BBDEMSP	BBDEM1F
Greek Drachma	GREDRA$	USGRD1F
Hungarian forint	HUNFOR$	USHUF1F
Irish punt	BBIEPSP	BBIEP1F
Italian lira	BBITLSP	BBITL1F
Japanese yen	BBJPYSP	BBJPY1F (USJPY1F)
Mexican peso	MEXPES$	USMXN1F
Netherland guilder	BBNLGSP	BBNLG1F
New Zealand dollar	BBNZDSP	BBNZD1F (USNZD1F)
Norwegian krone	BBNOKSP	BBNOK1F (USSEK1F)
Polish zloty	POLZLO$	USPLN1F
Portuguese escudo	PORTES$	USPTE1F
Singapore dollar	BBSGDSP	BBSGD1F
South Africa rand	BBZARSP	BBZAR1F
South Korean won	KORSWO$	USKRW1F
Spanish peseta	SPANPE$	USESP1F
Swedish krona	BBSEKSP	BBSEK1F (USSEK1F)
Swiss franc	BBCHFSP	BBCHF1F (USCHF1F)
Taiwan new dollar	TAIWDO$	USTWD1F

Notes: The table provides the Datastream mnemonics (data from Barclays and Reuters) for spot and forward exchange rate quotes against the USD. To obtain bid and ask exchange rates, the suffixes (EB) and (EO) are added to the corresponding mnemonics.

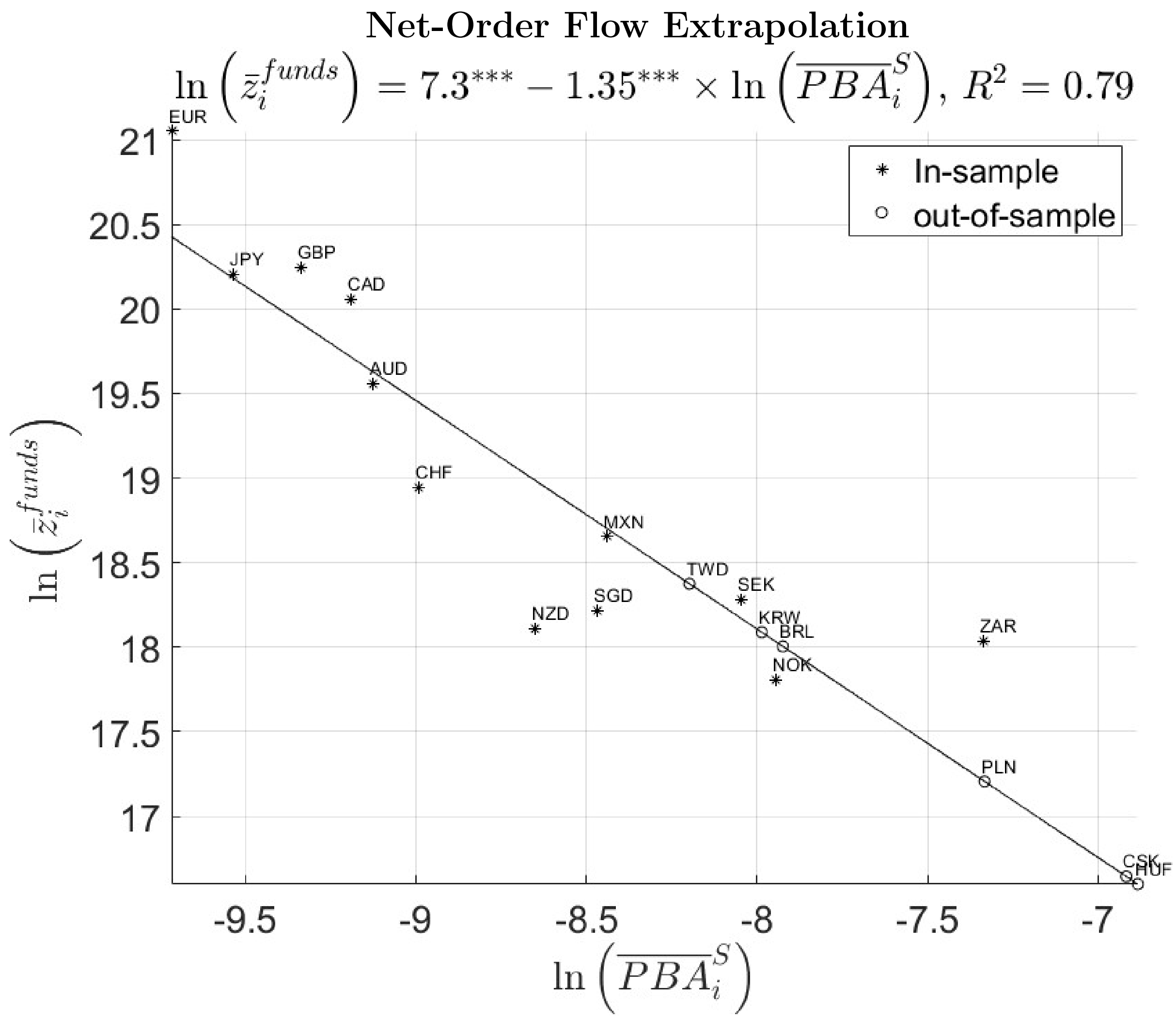

Figure A1: The asterisks in the figure plot the natural logarithm of the daily average of the absolute value of the net-order flow (daily buy minus sell orders) of funds $\ln\left(\bar{z}_i^{funds}\right)$ against the natural logarithm of the average proportional bid-ask spread $\ln\left(\overline{PBA}_i^S\right)$ for the 12 currencies $i \in \mathcal{I} = \{$AUD, EUR, GBP, NZD, CAD, CHF, JPY, NOK, SEK, MXN, SGD, ZAR$\}$. The linear line is the fitted regression $\ln\left(\bar{z}_i^{funds}\right) = 7.30 - 1.35 \ln\left(\overline{PBA}_i^S\right)$, and the circles on the line represent the fitted values $\ln\left(\bar{z}_i^{funds}\right)$ corresponding to $\ln\left(\overline{PBA}_i^S\right)$ for the 6 currencies BRL, CZK, HUF, KRW, PLN, and TWD (for which CLS order flow data is unavailable). The average is taken over the daily sample between September 3rd 2012 through September 24th 2021.

Country Specific Proportional Costs: Developed Countries

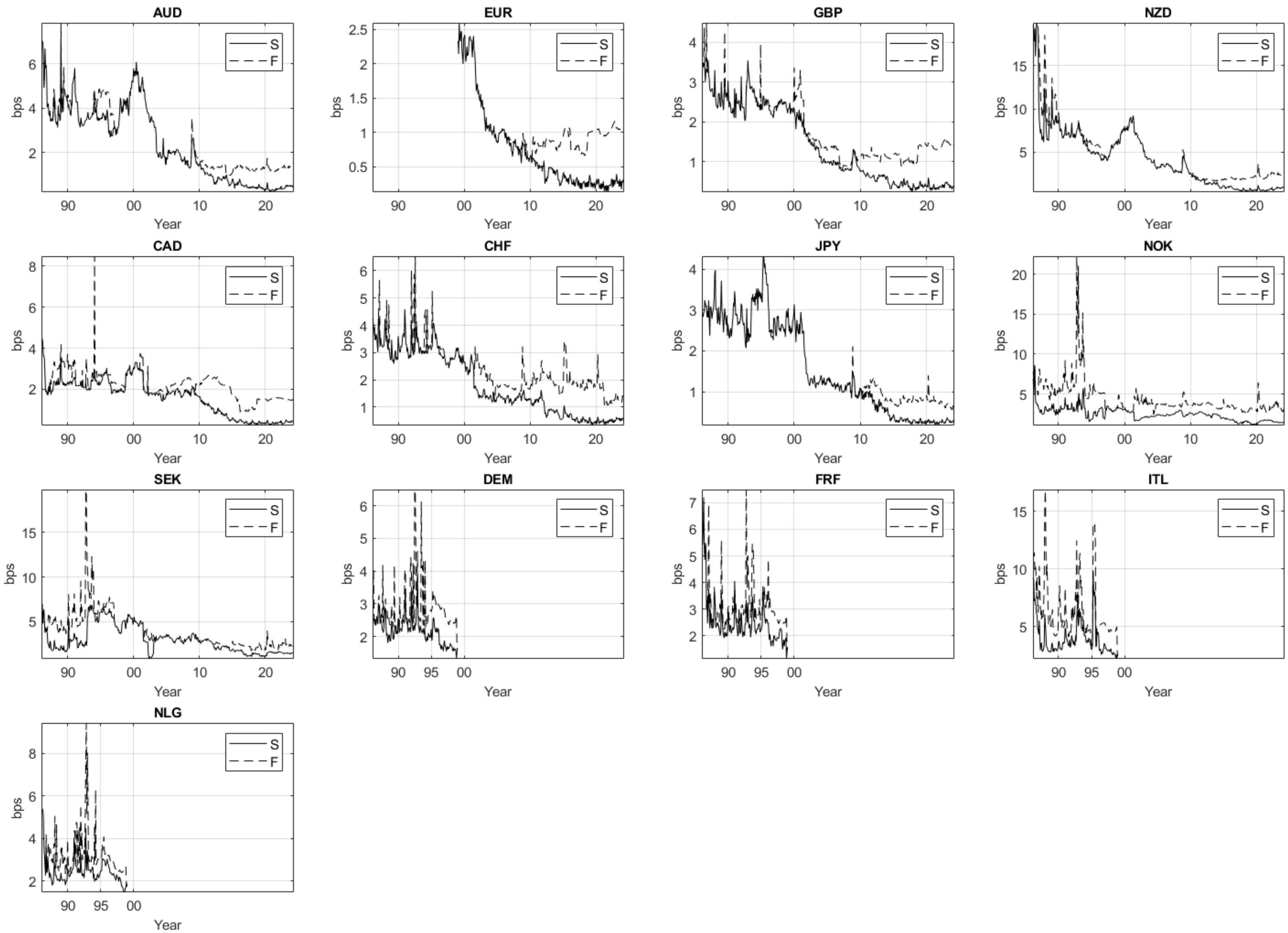

Figure A2: The figures plot the monthly average proportional costs for the spot market $0.5C^{S+}_{i,t} + 0.5C^{P-}_{i,t}$ (sold line), and for the forward market, $0.5C^{P+}_{i,t} + 0.5C^{S-}_{i,t}$ (dashed line). The sample are the 13 developed currencies from February 1986 to January 2024.

Country Specific Proportional Costs: Emerging Countries

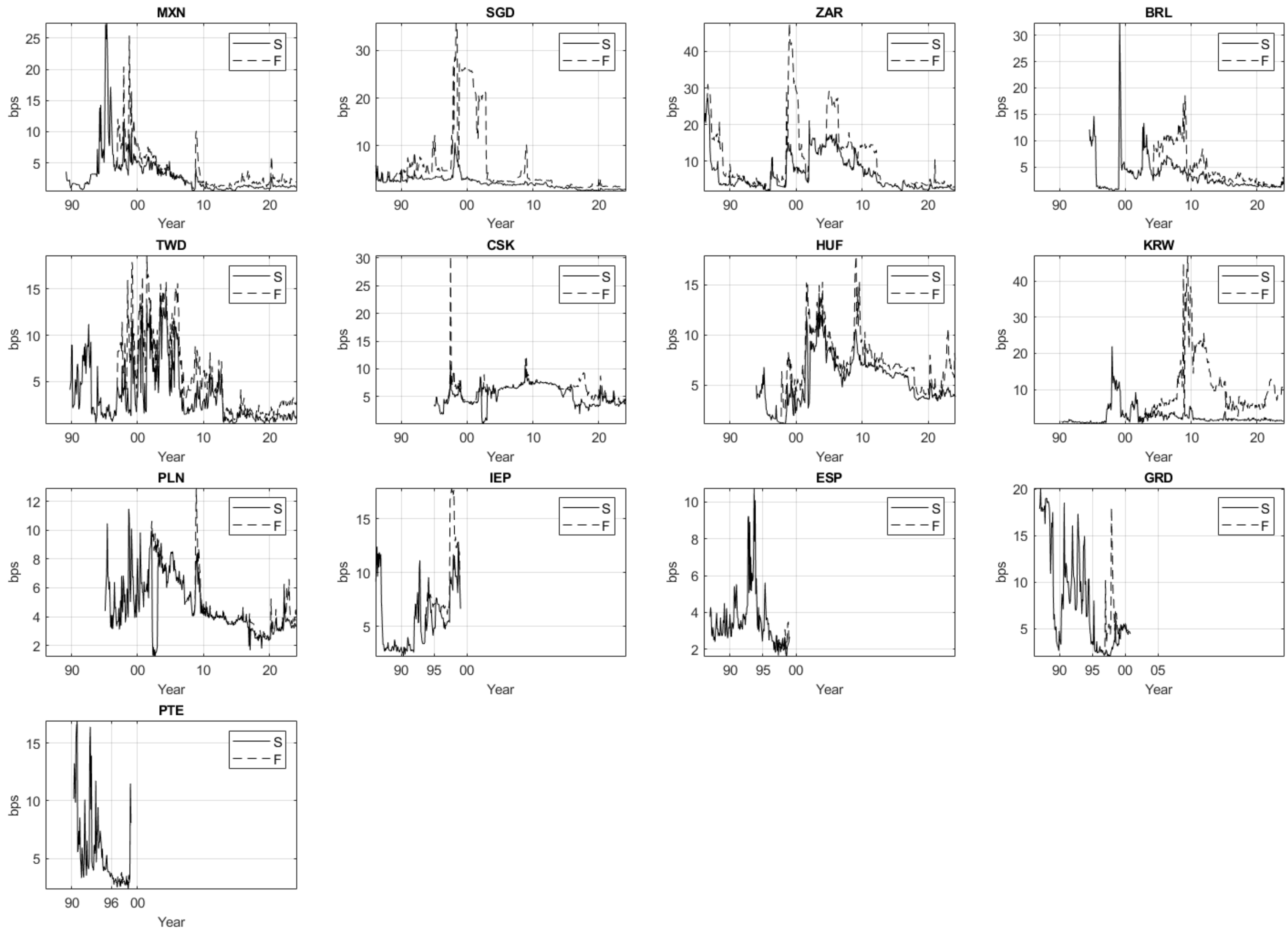

Figure A3: The figures plot the monthly average proportional costs for the spot market $0.5C_{i,t}^{S+} + 0.5C_{i,t}^{P-}$ (sold line), and for the forward market, $0.5C_{i,t}^{P+} + 0.5C_{i,t}^{S-}$ (dashed line). The sample are the 13 emerging currencies from February 1986 to January 2024.

Country Specific Price Impact: Developed Countries

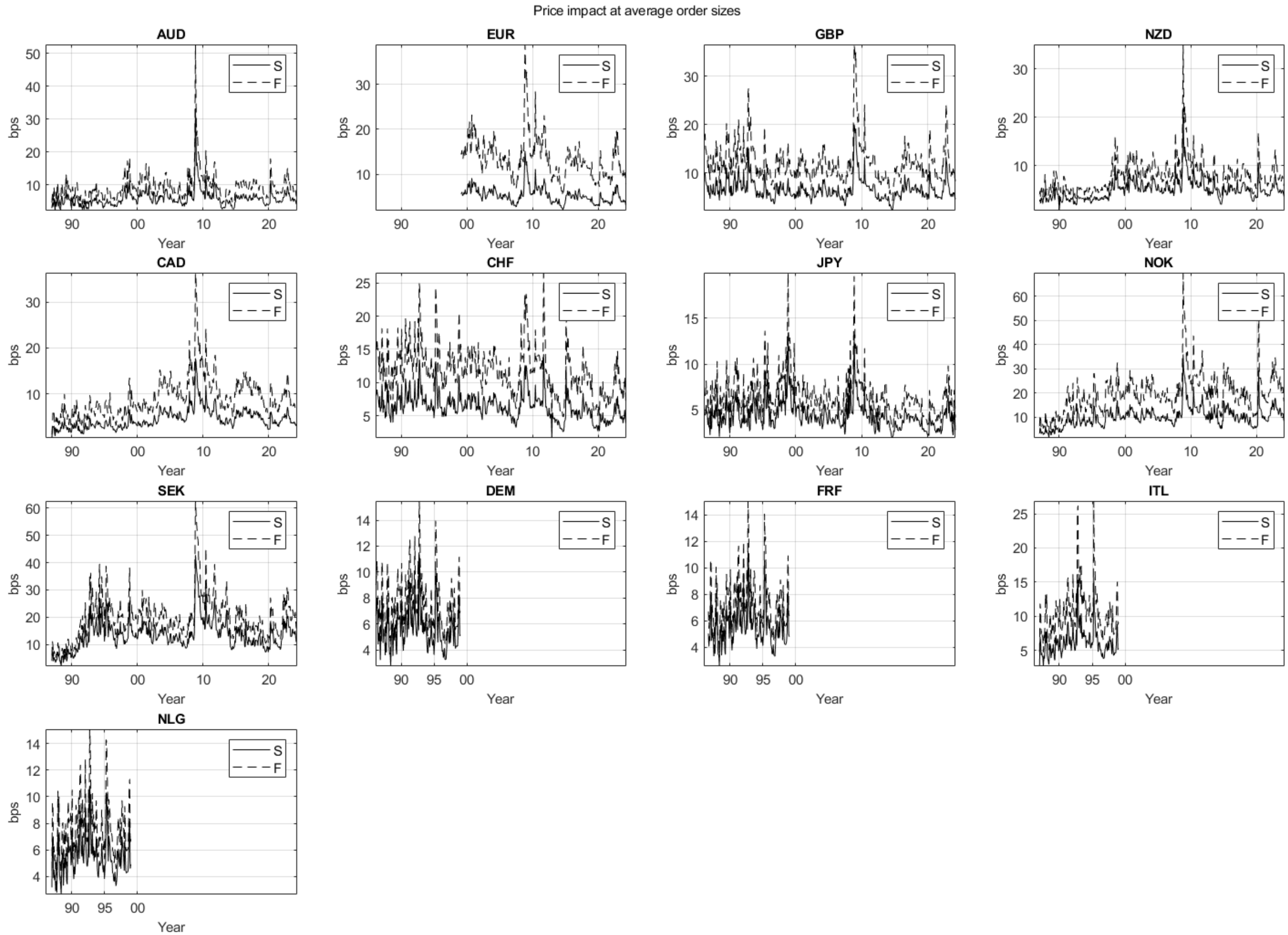

Figure A4: For each currency i the figures plot $A^S_{i,t}\bar{z}_i^{funds}$ for spot (solid line) and $A^F_{i,t}\bar{z}_i^{funds}$ for forwards (dashed line). $A^S_{i,t}$ and $A^F_{i,t}$ are the realized Amihud measures for spot and forwards. $\bar{z}_i^{funds}$ is the time-series average of the absolute value of the daily order flow imbalance of funds. The sample includes 13 developed currencies against the USD for the period from February 1986 to January 2024.

Country Specific Price Impact: Emerging Countries

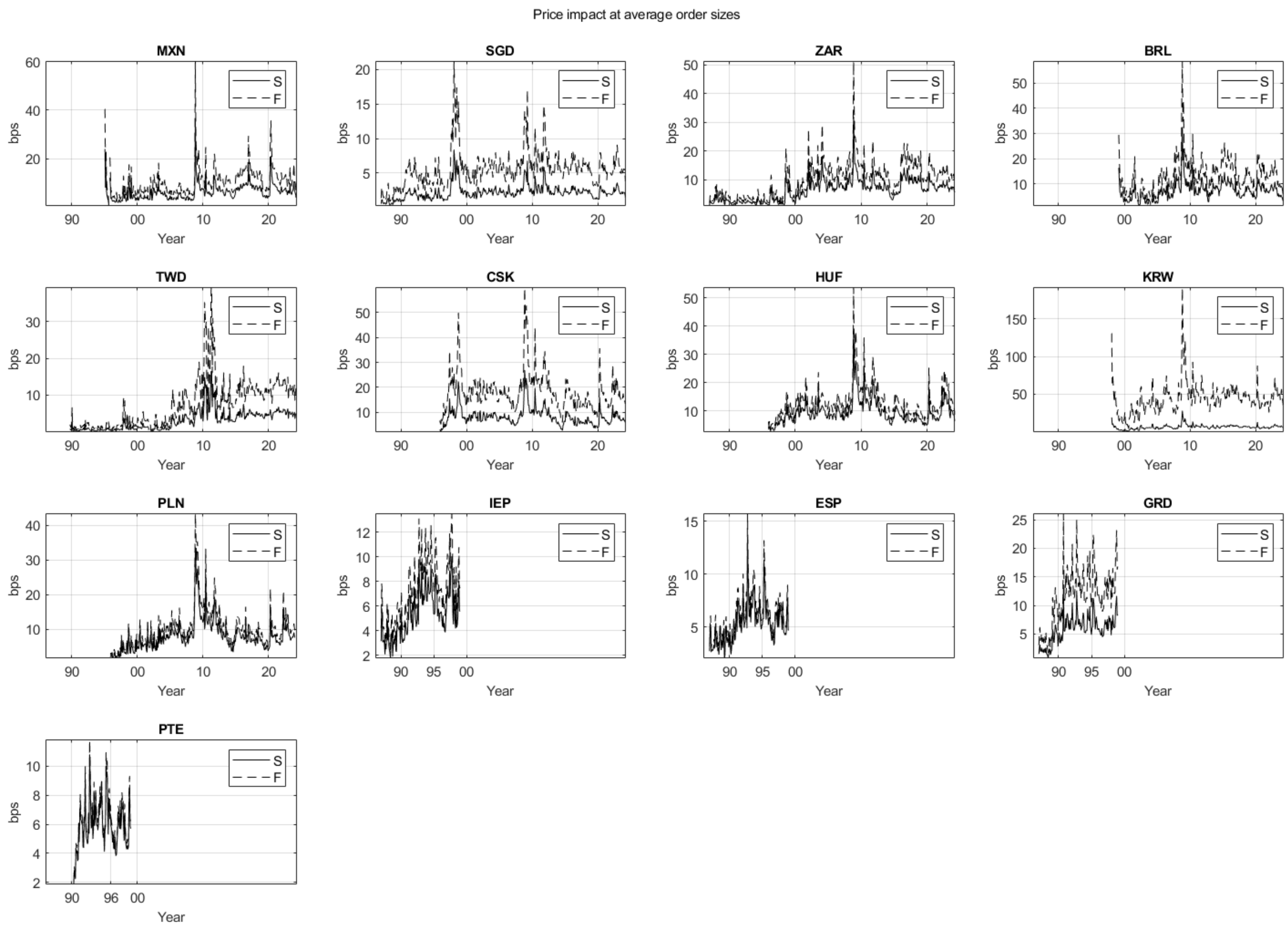

Figure A5: For each currency i the figures plot $A^S_{i,t}\bar{z}_i^{funds}$ for spot (solid line) and $A^F_{i,t}\bar{z}_i^{funds}$ for forwards (dashed line). $A^S_{i,t}$ and $A^F_{i,t}$ are the realized Amihud measures for spot and forwards. $\bar{z}_i^{funds}$ is the time-series average of the absolute value of the daily order flow imbalance of funds. The sample includes 13 emerging currencies against the USD for the period from February 1986 to January 2024.

Cumulative Before-Cost Excess Returns

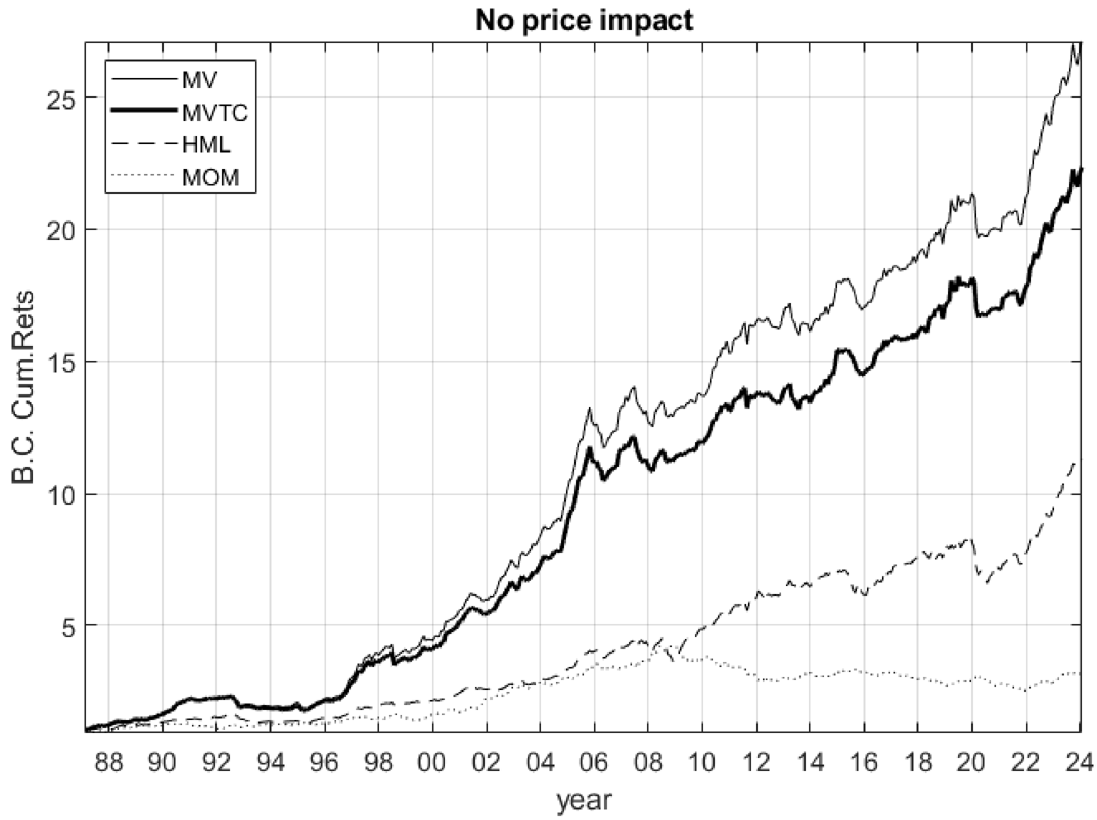

Figure A6: The figures plot the before-cost cumulative excess returns of MV (solid line), $MVTC$ (bold solid line), HML (dashed line), and MOM (dotted line). For the construction of $MVTC$ we set the price impact to zero. The strategies are described in Section 3. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

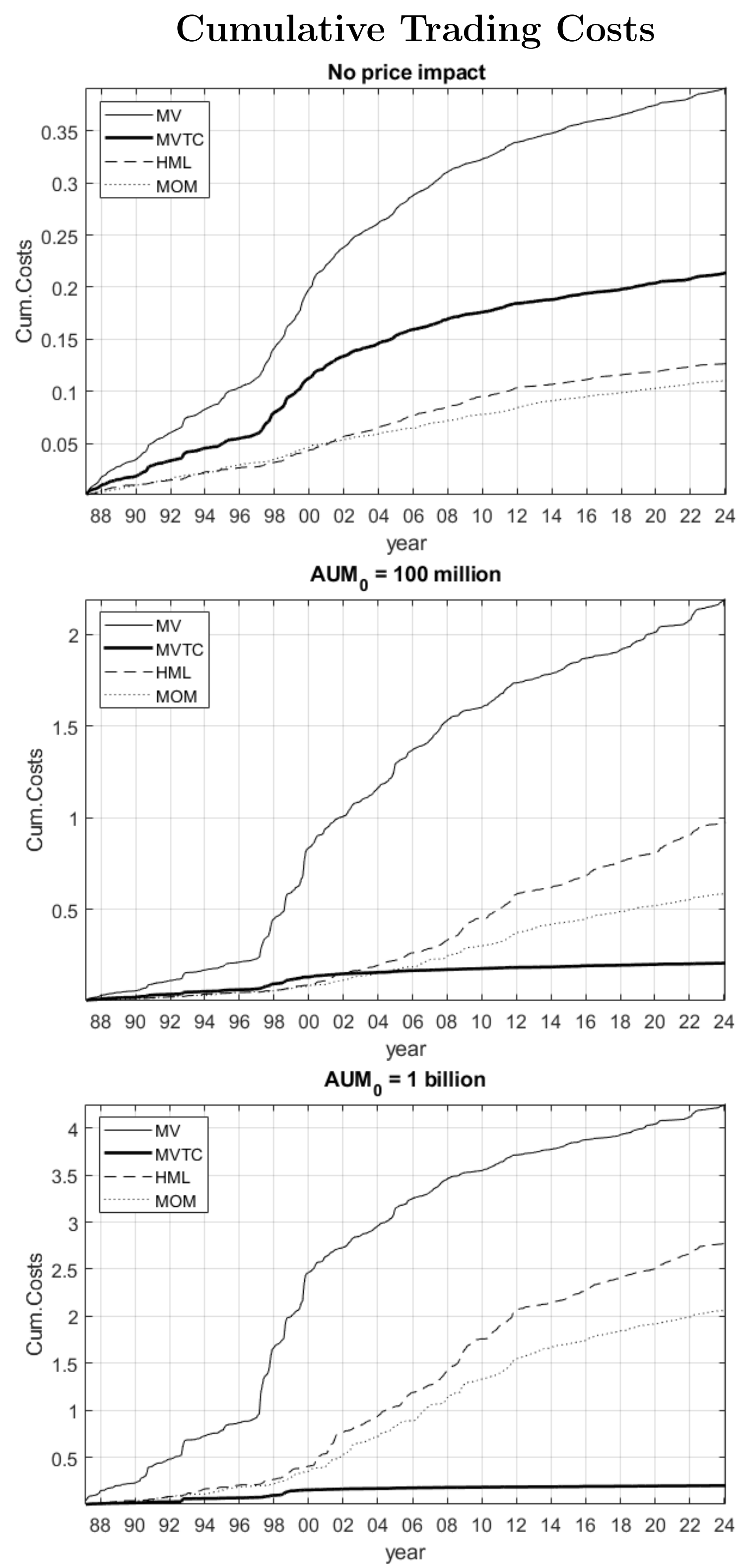

Figure A7: The figures plot the cumulative costs of MV (solid line), $MVTC$ (bold solid line), HML (dashed line), and MOM (dotted line). The strategies are described in Section 3. The top graph assumes no price impact, while the middle and bottom graphs assume an initial AUM of USD 100 million respectively 1 billion. The sample includes 13 developed and 13 emerging currencies against the USD for the period from February 1987 to January 2024.

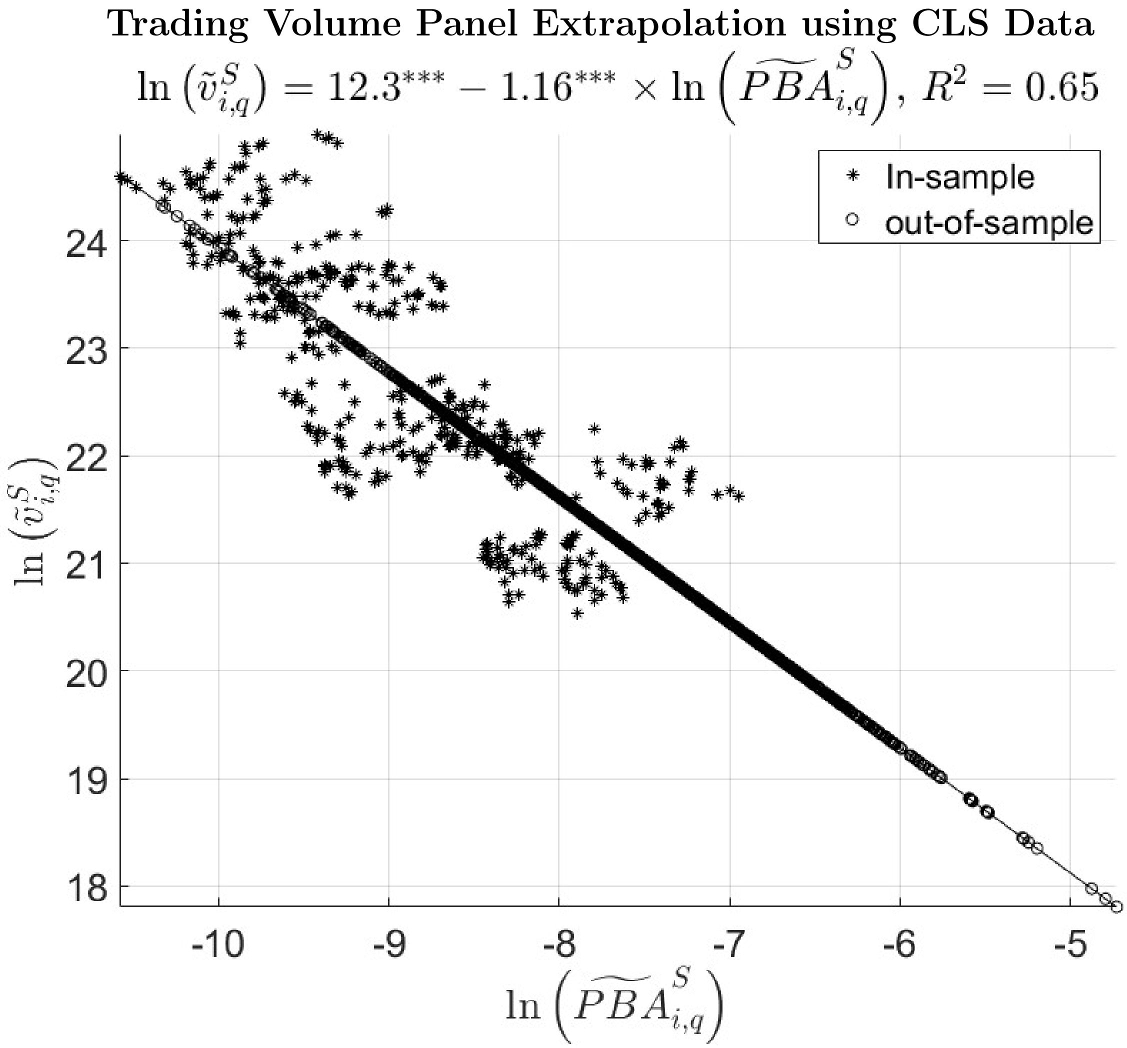

Figure A8: The asterisks in the figure plot the natural logarithm of the quarterly volume $\ln\left(\tilde{v}^S_{i,q}\right)$ against the natural logarithm of the quarterly proportional bid-ask spread $\ln\left(\widetilde{PBA}^S_{i,q}\right)$ for the 12 currencies $i \in \mathcal{I} =$ {AUD, EUR, GBP, NZD, CAD, CHF, JPY, NOK, SEK, MXN, SGD, ZAR} from September 2012 to September 2021. The linear line is the fitted regression $\ln\left(\tilde{v}^S_{i,q}\right) = 12.30 - 1.16 \ln\left(\widetilde{PBA}^S_{i,q}\right)$, and the circles on the line represent the fitted values $\ln\left(\tilde{v}^S_{i,q}\right)$ corresponding to $\ln\left(\widetilde{PBA}^S_{i,q}\right)$ for all currency-quarter observations for which we observe $\widetilde{PBA}^S_{i,q}$ but not $\tilde{v}^S_{i,q}$. Quarterly observations are constructed as daily averages within the quarter.

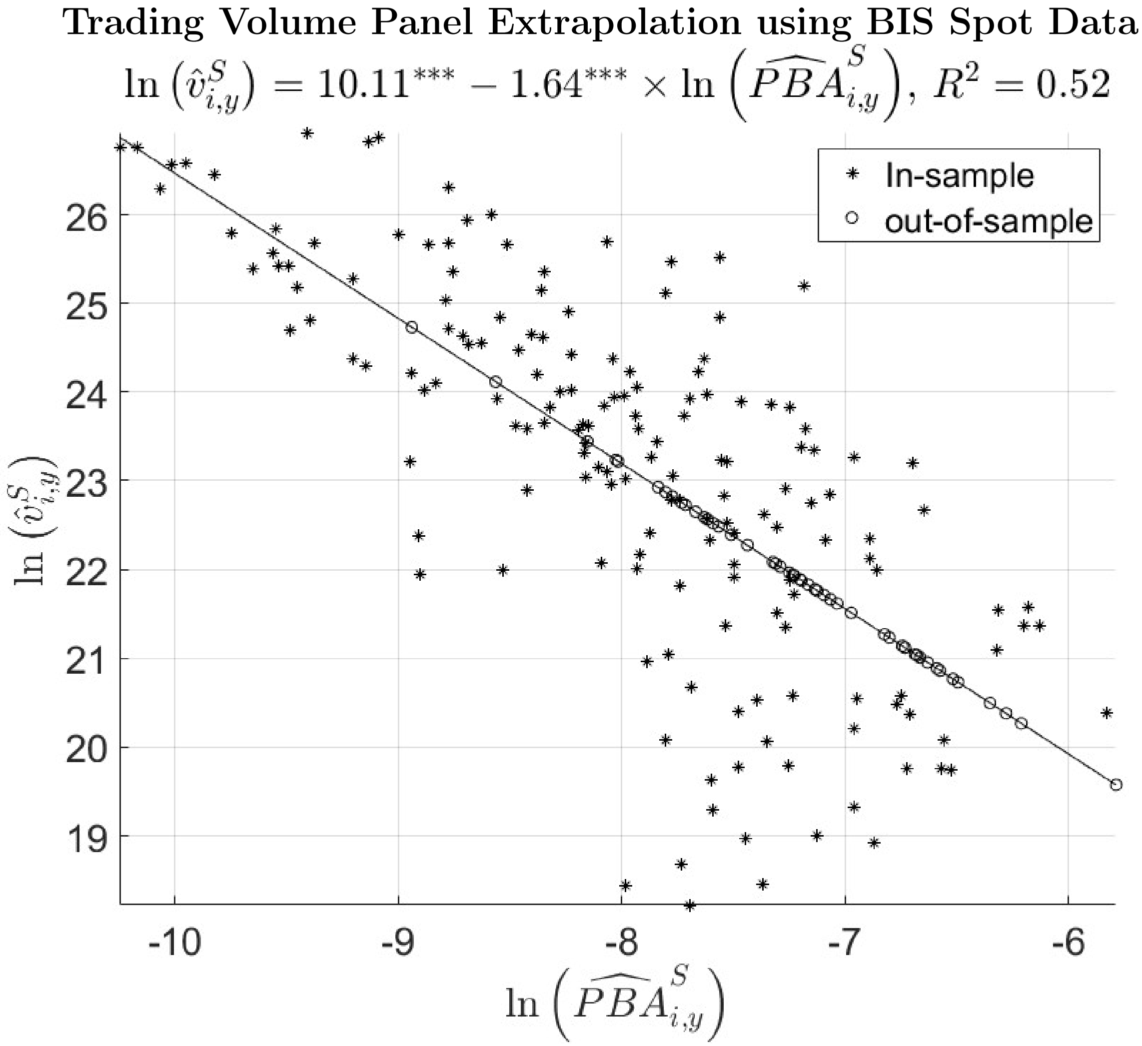

Figure A9: The asterisks in the figure plot the natural logarithm of the annual volume $\ln\left(\hat{v}^S_{i,y}\right)$ against the natural logarithm of the annual proportional bid-ask spread $\ln\left(\widehat{PBA}^S_{i,y}\right)$ for currency-year observations for which we have BIS Triennial volume survey data. The linear line is the fitted regression $\ln\left(\hat{v}^S_{i,y}\right) = 10.11 - 1.64 \ln\left(\widehat{PBA}^S_{i,y}\right)$, and the circles on the line represent the fitted values $\ln\left(\hat{v}^S_{i,y}\right)$ corresponding to $\ln\left(\widehat{PBA}^S_{i,y}\right)$ for all currency-year observations for which we observe $\widehat{PBA}^S_{i,y}$ but not $\hat{v}^S_{i,y}$. Annual observations of the bid-ask spread are constructed as daily averages within the year.

Turbulent Months

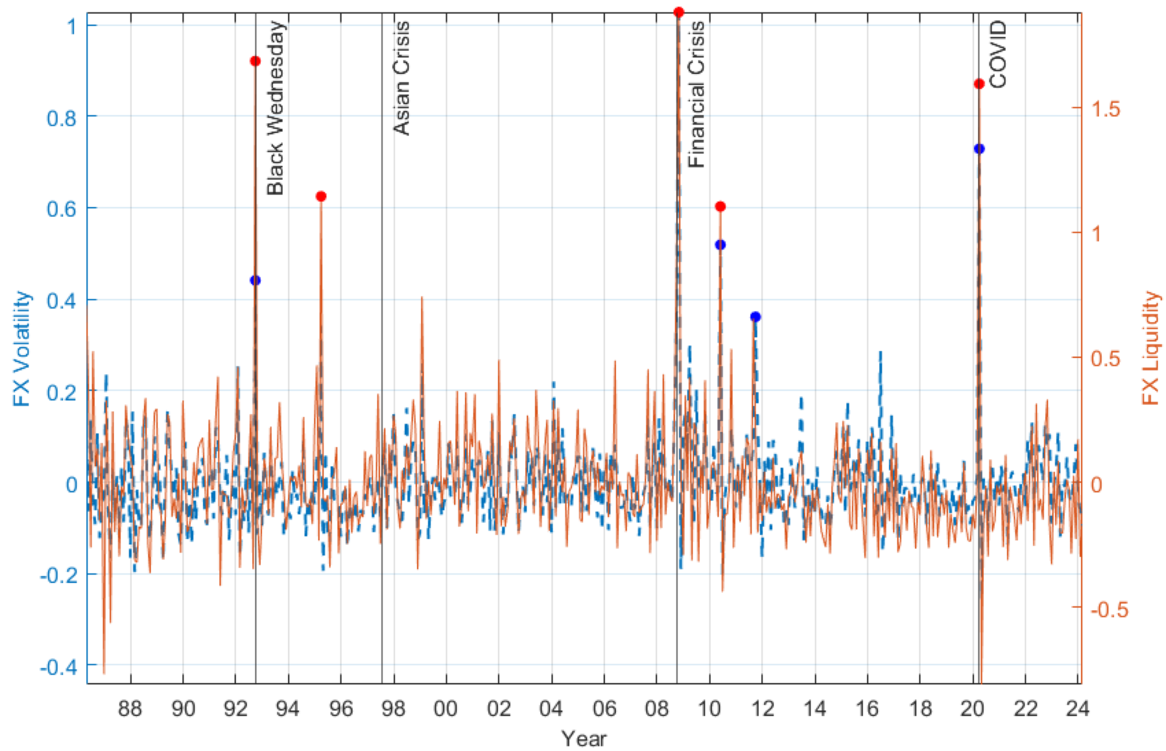

Figure A10: The plot shows the time series of the FX market volatility index following Menkhoff et al. (2012a) (dashed-blue), and the FX market illiquidity index following Karnaukh et al. (2015) (orange bold) over the sample period from February 1986 to January 2024. The blue and red dots represent the five highest non-consecutive peaks over a period of 13 months in these time series. Additionally, the vertical black lines report the dates of four known crises involving FX markets: the 1992 Black Wednesday (Sep-1992), the 1997 Asian Financial Crisis (Jul-1997), the 2008 Financial Crisis (Sep-2008), and the COVID crisis (Mar-2020).

Mean-Variance Problem with TC: Case of 2 Risky Assets

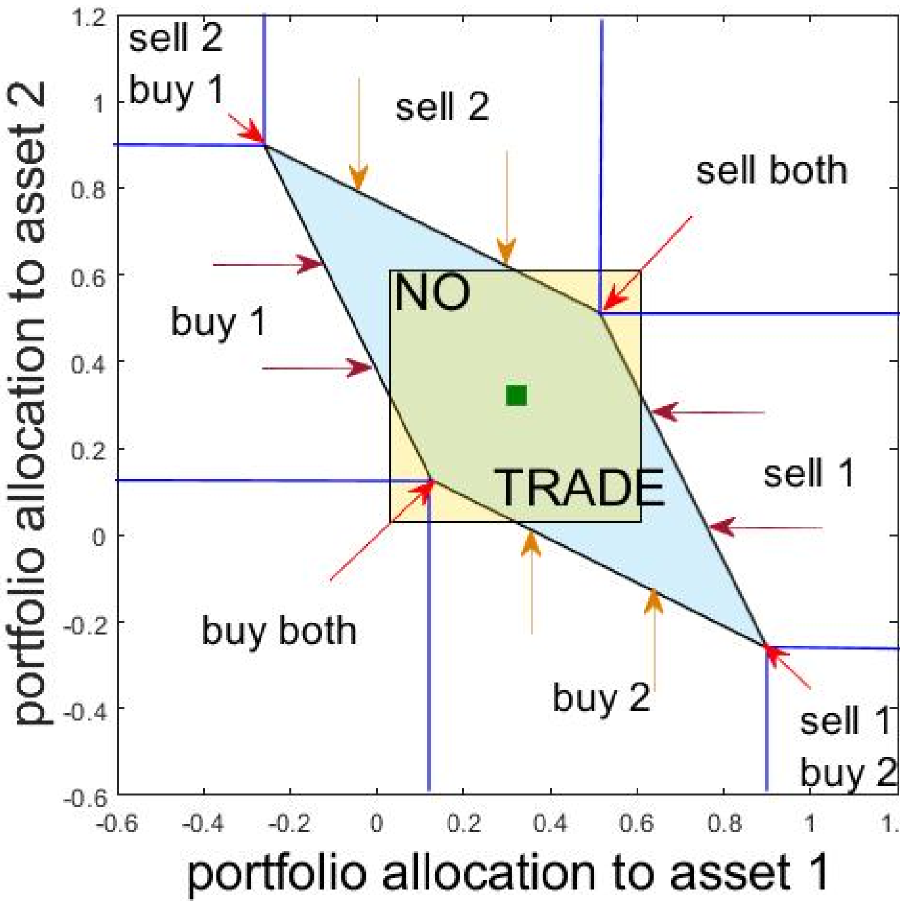

Figure A11: The investment opportunity set consists of two positively correlated risky assets. The horizontal axis measures the weight a portfolio places on asset 1 and the vertical axis the weight on asset 2. The green square is the optimal portfolio $\theta_{\mathbf{t}}^{\mathbf{MV}}$ if there are no transaction costs. The blue parallelogram illustrates the no trading region of $MVTC$, which optimizes over transaction costs. The yellow square determines the no trading region of a strategy that optimizes over transaction costs but assumes that the two assets are uncorrelated in the construction of the no trading region. If the initial position is within the no trading region, then the investor does not trade. If it is outside, then it is optimal to trade. In particular, when there are only proportional costs, the investor trades towards $\theta_{\mathbf{t}}^{\mathbf{MV}}$ until she reaches the boundary of the no trading region as indicated by the arrows. If we additionally model costs from a price impact, it is never optimal to trade all the way to the boundary of the no trading region. Purple, brown or red colors of the arrows indicate that only asset 1, 2 or both assets are traded.