# Essays on Frictional Financial Markets

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# Part I

# Introduction

## Summary of Research Results

This dissertation consists of three essays that uncover the origins of market frictions and their implications for the functioning of the global foreign exchange (FX) market.

The first research paper speaks to the hegemony of the US dollar in FX trading. Over 85% of all FX transactions involve the US dollar, despite the United States accounting for less than one quarter of global economic activity. I show both theoretically and empirically that the US dollar dominates FX volumes because FX market participants are strategic about their trading costs. Hence, they avoid directly transacting in non-dollar currency pairs if the expected trading cost is too large. Instead, market participants exchange non-dollar pairs indirectly by using the US dollar as a vehicle currency. That is, market participants first exchange a non-dollar currency into US dollars, and then trade those US dollars for their target currency. I derive a set of theoretical conditions for currency dominance in FX trading volume. To validate these conditions empirically, I use a granular and globally representative FX trade data set. My empirical findings are consistent with the predictions of my theoretical framework and corroborate the importance of strategic behaviour as a novel determinant of currency dominance. Using a novel identification strategy, I show that up to 36–40% of the daily volume in the most liquid dollar currency pairs are due to vehicle currency trading.

The second paper studies the information content of trades in the FX market. Specifically, we analyse a novel, comprehensive order flow data set, distinguishing among different groups of market participants and covering a large cross-section of currency pairs. We find compelling evidence that global FX order flows convey superior information heterogeneously across agents, time, and currency pairs. These findings are consistent with theories of asymmetric information and over-the-counter market fragmentation. A trading strategy based on exposure to asymmetric information risk generates high returns even after accounting for risk, transaction cost, and other common risk factors shown in the FX literature.

Finally, the third paper analyses the cross-sectional asset pricing implications of liquidity risk in the FX market. Precisely because of its sheer size and despite its decentralised nature, the FX market is commonly known as one of the most liquid and resilient trading venues. However, a clear understanding of whether FX liquidity matters for asset prices is still missing. This paper aims to fill this gap by providing the first systematic study of the pricing implications of FX liquidity risk. We show that, even in this market, exposure to liquidity risk commands a non-trivial risk premium of up to 4% percent per annum. In particular, systematic (marketwide) and idiosyncratic liquidity risk are not subsumed by existing FX risk factors and successfully price the cross-section of currency returns. However, we also find that liquidity and carry trade premia are significantly correlated. The carry trade is a simple trading strategy that aims to profit from the interest rate differential between high- and low-yielding currencies. The correlation between liquidity and carry trade premia lends support to a liquidity-based explanation of the infamous carry trade risk premium. To illustrate this point, we decompose carry trade returns and show that the commonality with liquidity risk stems from periods of high market stress and is confined to the static but not the dynamic carry trade.

## Zusammenfassung der Forschungsergebnisse

Diese Dissertation besteht aus drei Aufsätzen, die sich mit den Ursprünge von Marktfriktionen und ihren Auswirkungen auf die Funktionsweise des Devisenmarktes befassen.

Das erste Forschungspapier beleuchtet die Hegemonie des US-Dollars im globalen Devisenhandel. Über 85% aller Devisentransaktionen involvieren den US-Dollar, obwohl die Vereinigten Staaten weniger als ein Viertel der weltweiten Wirtschaftstätigkeit ausmachen. Ich zeige sowohl theoretisch als auch empirisch, dass der US-Dollar das Devisenhandelsvolumen dominiert, weil die Teilnehmer am Devisenmarkt strategisch auf ihre Handelskosten bedacht sind. Das heißt, die Marktteilnehmer tauschen zunächst eine Nicht-Dollar-Währung in US-Dollar um und wechseln dann diese US-Dollar gegen ihre Zielwährung. Ich leite eine Reihe von theoretischen Bedingungen für Währungsdominanz im Devisenhandelsvolumen her. Um diese Bedingungen empirisch zu überprüfen, verwende ich einen weltweit repräsentativen Devisenhandelsdatensatz. Meine empirischen Ergebnisse stimmen mit den Vorhersagen meines theoretischen Modells überein und bestätigen die Bedeutung des strategischen Verhaltens von Marktteilnehmern als neue Determinante von Währungsdominanz. Basierend auf einer neuen Identifikationsstrategie zeige ich, dass bis zu 36–40% des täglichen Handelsvolumens in den bedeutendsten Dollar-Währungspaaren auf die Verwendung des US-Dollar's als Zwischenwährung zurückzuführen ist.

Im zweiten Beitrag wird der Informationsgehalt von Transaktionen auf dem Devisenmarkt untersucht. Wir analysieren einen neuen, umfassenden Datensatz zu Devisenströmen, der zwischen verschiedenen Gruppen von Marktteilnehmern unterscheidet und eine große Anzahl an Währungspaaren abdeckt. Unsere Resultate bezeugen, dass die globalen Devisenauftragsströme asymmetrische Informationen über Akteure, die Zeit und Währungspaare hinweg heterogen vermitteln. Diese Ergebnisse stehen im Einklang mit Theorien über asymmetrische Informationen und mit der Fragmentierung des Freiverkehrsmarktes. Eine Handelsstrategie, die auf dem Risiko von asymmetrischer Information basiert, erzielt hohe Renditen, selbst wenn man Transaktionskosten und andere in der Literatur aufgezeigte Risikofaktoren berücksichtigt.

Im dritten Beitrag werden die Auswirkungen von Liquiditätsrisiken auf die Bestimmung von Wechselkursen analysiert. Gerade wegen seiner schieren Größe und trotz seines dezentralen Charakters ist der Devisenmarkt gemeinhin als einer der liquidesten und widerstandsfähigsten Handelsplätze bekannt. Es fehlt jedoch ein klares Verständnis dafür, ob FX-Liquiditätsrisiken einen Einfluss auf die Bestimmung von Wechselkursen haben. Die vorliegende Arbeit schließt diese Forschungslücke indem sie die erste systematische Studie über die Auswirkungen von FX-Liquiditätsrisiken auf die Bildung von Wechselkursen darstellt. Wir zeigen, dass selbst im Devisenmarkt Liquiditätsrisiken eine nicht-triviale Risikoprämie von bis zu 4% pro Jahr fordern. Darüber hinaus preisen das systematische und das idiosynkratische Liquiditätsrisiko erfolgreich den Querschnitt von Währungsrenditen. Wir stellen jedoch fest, dass Liquiditäts- und Carry-Trade-Prämien signifikant korreliert sind. Der Carry-Trade ist eine einfache Handelsstrategie, die darauf abzielt, von der Zinsdifferenz zwischen hoch- und niedrig-verzinslichen Währungen zu profitieren. Die Korrelation zwischen Liquiditäts- und Carry-Trade-Prämien spricht für eine liquiditätsbasierte Erklärung der weltbekannten Carry-Trade-Risikoprämie.

# Part II

# Research Papers

# Dollar Dominance in FX Trading

*Fabricius Somogyi*

**Abstract**

Over 85% of all foreign exchange (FX) transactions involve the US dollar, whereas the United States accounts for a much smaller fraction of global economic activity. My paper attributes the dominance of the US dollar in FX trading to strategic avoidance of price impact. Utilising a model of FX trading, I derive three conditions for dollar dominance. I then empirically test these conditions using a globally representative FX trade data set and provide evidence that is consistent with my model. I find that US dollar currency pairs enjoy a low-price-impact advantage, which favours their use as a vehicle currency to indirectly exchange two non-dollar currencies. Using a novel identification strategy, I show that up to 36–40% of the daily volume in dollar currency pairs are due to vehicle currency trading.

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# 1. Introduction

The US dollar dominates the international monetary and financial system (Gourinchas et al., 2019). This is particularly true for the foreign exchange (FX) market, which is the largest financial market in the world. Over 85% of all FX trades involve the US dollar, despite the United States only accounting for less than one quarter of global economic activity. From an economic and policymaking perspective, the dominance of the US dollar in FX transactions raises the following question: What conditions need to be satisfied for a currency, say the US dollar, to dominate global FX trading volumes?

I show both theoretically and empirically that the US dollar dominates FX trading volumes because FX market participants are strategic about their trading costs.[1] Hence, they avoid *directly* transacting in non-dollar currency pairs if the expected trading cost is too large. Instead, market participants exchange non-dollar currency pairs *indirectly* by using the US dollar as an intermediate vehicle currency. That is, market participants first exchange a non-dollar currency into US dollars, and then trade those US dollars for their target currency.

I show theoretically that dollar currency pairs enjoy a lower expected price impact than non-dollar pairs if two conditions are satisfied: First, dollar pairs exhibit more volatile fundamental trading demands than non-dollar pairs. Second, dollar exchange rates are less volatile than non-dollar rates. The lower price impact generates additional trading volume in dollar pairs beyond what the US share in global economic activity would suggest. Taken together, large fundamental trading demands coupled with significant vehicle currency trading demands due to strategic avoidance of price impact ensure that dollar pairs dominate FX volumes. To empirically validate these conditions, I use a globally representative FX trade data set and provide evidence that strongly supports the predictions of my model.

Understanding the origins of dollar dominance is relevant for at least two reasons: First, the concentration of FX trading volume in US dollar currency pairs entails both costs and benefits for the world economy.[2] Potential benefits stem from economies of scale and network effects reducing trading costs in dollar currency pairs, which in turn facilitates international trade and investment. But interconnectedness can also be a source of systemic risk and international spillover effects if it amplifies shocks from the US to other economies. Second, knowing the conditions for dollar dominance is key to both US and foreign policymakers. Central banks and governments may strengthen the importance of their own domestic currency by influencing these conditions through monetary policy.

The contribution of this paper is twofold. On the theory side, I introduce a market (micro)structure view of currency dominance in FX trading. Specifically, I identify strategic avoidance of price impact as a novel economic channel through which a currency can dominate FX volumes relative to its use in other areas of the global financial system (e.g., official FX reserves, trade invoicing, cross-border loans, and safe asset supply). My model provides a set

[1] Note that I do not focus on second-order costs of trading, such as brokerage fees or bid-ask spreads, but on the first-order effect: the price impact of trades (Frazzini et al., 2018).

[2] See "US dollar funding: an international perspective," CGFS Papers No 65, June 2020.

of equilibrium conditions for dollar dominance. These conditions can predict which non-dollar currency pairs are more likely to trade indirectly via the US dollar. Perhaps surprisingly, the conditions imply that even a symmetrical market with identical fundamental trading demand across currency pairs is prone to dollar dominance. This is the case if dollar pairs feature lower expected price impacts as they exhibit either more volatile fundamental trading demands or less volatile currency returns than non-dollar pairs.

On the empirical side, I make three key contributions: First, I provide evidence that around 33% of the variation in trading volume across time and currency pairs is explained by fundamental trading demands, whereas vehicle currency trading motives account for up to 26%. Second, I show that the model–based conditions for dollar dominance are economically significant predictors of the actual dollar dominance observed in the data. Third, I identify quasi-exogenous variation in vehicle currency demands and find that up to 36–40% of the daily trading volume in dollar pairs are due to vehicle currency trading activity.

This paper has two parts. The first part develops a model of FX trading that builds on the literature on imperfectly competitive markets (e.g., Kyle, 1989; Vayanos, 1999; Vives, 2011; Gârleanu and Pedersen, 2013; Rostek and Weretka, 2015; Malamud and Rostek, 2017). The modelling setup is closest to Rostek and Yoon (2021a). In general, my modelling approach reflects the key features of the FX market, which is a decentralised over-the-counter market that is organised via a network of limit order books. Traders in my model are strategic and consider their price impact when buying and selling one currency against another. Ideally, traders prefer not to trade more or less than their fundamental trading demand in a particular currency pair. However, they are willing to deviate from their fundamental trade interest and do the vehicle currency trade if they are sufficiently compensated by price.

In equilibrium, the optimal traded quantity increases both in traders' fundamental and vehicle currency trading demand, respectively. The latter is determined by the distribution of expected price impacts across currency pairs. The larger the expected price impact in a particular currency pair the lower the amount of vehicle currency trading activity. Price impact is endogenous in this model and depends on two exogenous drivers: i) covariance matrix of fundamental trading demands and ii) covariance matrix of currency returns. Using comparative statics analysis, I show that the equilibrium price impact decreases in the variance of fundamental trading demands but increases in the variance of currency returns.

Equipped with the intuition from the comparative statics, I derive a set of conditions for dollar dominance that I define as follows: A triplet of currency pairs is dominated by the US dollar if trading volume in US dollar currency pairs exceeds trading volume in non-dollar currency pairs within the same triplet. Based on this definition, the necessary and sufficient condition for dollar dominance is that at least one of the following three conditions is satisfied, while the other two remain equal: US dollar currency pairs exhibit i) larger average fundamental trading demands, ii) more volatile fundamental trading demands, or iii) less volatile exchange rate returns than non-dollar currency pairs.

The economic intuition behind these three conditions is as follows: The first condition emerges because fundamental trading demands have no direct effect on expected price impact but linearly increase the equilibrium trading volume. The second and third condition embrace the idea that, holding fundamental trading demands equal, dollar currency pairs dominate FX trading volumes if the expected price impact in dollar pairs is sufficiently low. Against this backdrop, the second condition arises because the decentralised market model implies that price impact decreases in the variance of fundamental trading demands. The last condition stems from the fact that expected price impact is increasing in the variance of currency returns capturing the fundamental riskiness of currency pairs.

The second part of this paper tests the predictions of my model using actual FX trade and quote data from two sources. First, I use spot FX volume and order flow data from CLS Group (CLS), which operates the world's largest multi-currency cash settlement system. Second, I pair the hourly FX volume and flow data with intraday spot rates from Olsen Data, which is the main source of academic research on intraday FX rates.

The key challenge for testing the model's predictions is that fundamental trading demands are unobservable as they correspond to intended rather than actual trades. I devise a suitable proxy for these demands by building on the fact that dealer banks provide immediacy to their customers by completing their trades with their own inventory. Dealers in turn rebalance their inventories by trading with other banks in the inter-dealer market. I leverage this institutional set-up by using data from CLS, which contains both customer- and inter-dealer trade data. Hence, customer-dealer trades across currency pairs can serve as a natural proxy for dealer banks' fundamental trading demands. The identifying assumption is that inter-bank trading activity is driven mainly by customer flows rather than by proprietary trading. This assumption is reasonable given that the sample covers the post-financial crisis period, which is characterised by a regulatory driven shift in the scope of banks' business models from proprietary trading to market-making (Moore et al., 2016).

The empirical evidence is presented in three parts. First, I use panel regressions to test whether the model–based drivers of trading volume and price impact are also economically relevant. Consistent with the comparative statics of the model, I find that inter-dealer volume significantly increases with larger and more volatile customer flows and currency returns, respectively. Specifically, changes in the variance of customer flows and currency returns account for 22% and 8%, respectively, of all the variation in inter-dealer volume, whereas customer flows account for roughly 33%. In light of my model, more volatile customer flows and currency returns, respectively, may lower the expected price impact resulting in more vehicle currency trading activity. Therefore, vehicle currency trading motives arising from strategic avoidance of price impact are almost equally important determinants of inter-dealer volumes as customer trading demands. Moreover, I estimate price impact as the ratio of intraday realised volatility and aggregate daily trading volume (Amihud, 2002). In line with my model, I find that price impact significantly decreases in the variance of customer flows but positively covaries with the realised variance of currency returns.

Second, I find strong evidence that the model–based conditions are both economically and statistically significant determinants of the time- and cross-sectional variation in my empirical measure of dollar dominance. My sample contains 15 triplets of currency pairs, which are all dominated by the US dollar except for three triplets involving the euro and the Danish, Norwegian or Swedish krone, respectively. In line with this observation, at least two out of three conditions for dollar dominance are satisfied for 12 currency pair triplets. Moreover, the model correctly predicts that the three aforementioned currency pair triplets are dominated by the euro rather than the US dollar as none of the conditions for dollar dominance is satisfied. Consistent with the evidence on trading volume, the first condition explains around 20% of the time series variation in dollar dominance, whereas the second and third condition jointly account for up to 13%. Thus, the time-varying degree of dollar dominance is driven by two forces: First, the dominance of the US dollar in fundamental trading demands. Second, the attractiveness of the US dollar for vehicle currency trading due to a lower expected price impact in dollar currency pairs relative to non-dollar pairs.

Lastly, I disentangle trading volume in dollar currency pairs due to fundamental trading motives from vehicle currency demands. For identification, I exploit the quasi-exogenous variation in vehicle currency trading demands associated with non-overlapping holidays. The intuition is as follows: Consider, for instance, the case where Australia is on holiday but neither Japan nor the United States are (e.g., ANZAC Day on 25 April). On such a day, hardly any of the inter-dealer volume in USDJPY is driven by vehicle currency trading motives stemming from indirectly exchanging Australian dollars to Japanese yen via the US dollar. This is because the number of counterparties with Australian dollars is much lower due to the public holiday. Eventually, my measure of vehicle currency trading activity is the difference between inter-dealer volume and my implied measure of fundamental demand based on non-overlapping holidays. Using an event study regression design, I find that vehicle currency demands for the largest and most liquid dollar currency pairs (e.g., USDEUR or USDJPY) account for up to 36–40% of aggregate daily inter-dealer trading volume in dollar pairs. These estimates are conservative since each non-overlapping holiday can only control for vehicle currency demands arising from one specific non-dollar pair (e.g., AUDJPY).

**Related literature.** This paper contributes to three strands of literature. First, I add to the monetary economics literature on vehicle currency trading. My main contribution is to derive explicit conditions for dollar dominance in FX trading volume. Methodologically, my model incorporates the market-size (e.g., Chrystal, 1977; Krugman, 1980; Rey, 2001; Devereux and Shi, 2013), risk-aversion (e.g., Black, 1991; Hartmann, 2004), and (asymmetric) information-driven (Lyons and Moore, 2009) approaches to international currencies. Consequently, FX trading volume in my model is a function of both fundamental and vehicle currency trading demand for a currency. Hence, in my model equilibrium is never "all or nothing" even if US dollar pairs theoretically enjoy a low-price-impact advantage. Moreover, the empirical evidence on vehicle currency trading is largely descriptive and lacks comprehensive results due to data scarcity. I fill this gap by employing a variety of different empirical tools, in order to test the predictions of my model using a granular FX trade data set.

Second, I contribute to the growing literature on the international role of the US dollar[3] and its omnipresence in the global financial system (Farhi and Maggiori, 2017; Gourinchas et al., 2019). My main contribution is to introduce a "market (micro)structure view" of dollar dominance in FX trading volume. I argue that dollar dominance emerges from strategic avoidance of price impact favouring the US dollar as a vehicle currency to indirectly exchange two non-dollar currencies. Current explanations can be classified into three categories. The first category is the "trade view," which argues that the reason for dollar dominance is trade invoicing in dollars (e.g., Portes and Rey, 1998; Goldberg and Tille, 2008; Bahaj and Reis, 2020; Gopinath et al., 2020; Gopinath and Stein, 2020; Tille et al., 2021). The second category is the "safe asset view," according to which dollar dominance arises both from its safe haven properties (e.g., Hassan, 2013; Maggiori, 2017; Farhi and Maggiori, 2017; He et al., 2019; Jiang et al., 2021) and from the growing demand for safe assets (e.g., Caballero et al., 2008, 2017, 2021). The third category is the "debt view" of dollar dominance (Eren and Malamud, 2022), which emphasises the role of firms' debt currency denomination. Maggiori et al. (2020) support this view by showing that global bond portfolios are mostly denominated in dollars.

Third, I expand on the literature on FX volume by underpinning the determinants of trading volume both theoretically and empirically. In contrast to the FX order flow literature (e.g., Evans, 2002; Evans and Lyons, 2002, 2005), the literature on trading volume is relatively scarce due to the lack of comprehensive data sets. Earlier research has focused largely on the inter-dealer segment, which is dominated by two platforms: Reuters (e.g., Evans, 2002; Payne, 2003) and EBS (e.g., Chaboud et al., 2008; Mancini et al., 2013). Alternative sources of spot FX trading volume are proprietary data sets from either specific bank holding companies (e.g., Bjønnes and Rime, 2005; Menkhoff et al., 2016) or central banks. Relatively recent public access to CLS data has enabled researchers to study global FX trading volume at higher frequencies (e.g., daily or even hourly). CLS is the only source of globally representative FX trade data that are not specific to a particular market segment or trading platform. Fischer and Ranaldo (2011) are the first to study FX volume from CLS around central bank decisions.[4] Hasbrouck and Levich (2018) and Ranaldo and Santucci de Magistris (2018) use CLS data to study commonality in FX volatility and trading volume. Cespa et al. (2021) introduce a momentum–based FX trading strategy that conditions on CLS volume.

**Roadmap.** The remainder of the paper is structured as follows. Section 2 describes the FX market structure and presents motivating evidence of dollar dominance. Section 3 outlines a simple model of FX trading and exchange rate determination. Section 4 tests the model using actual FX trade and quote data. Section 5 concludes with policy implications.

[3]See, for example, Matsuyama et al. (1993), Rey (2001), Caballero and Krishnamurthy (2003, 2009), Bruno and Shin (2017), Doepke and Schneider (2017), Bruno et al. (2018), Ilzetzki et al. (2019), Jiang et al. (2019), Chahrour and Valchev (2021), and Mukhin (2022).

[4]The authors use a different data set based on confidential *settlement* rather than actual FX *trade* data.

## 2. FX Market Structure and Dollar Dominance

This section has two purposes: First, to provide a schematic overview of the decentralised FX market structure and to introduce key trading platforms and players. Second, to supply *prima facie* evidence of dollar dominance in spot FX trading volume.

The FX market is organised as a two-tier over-the-counter (OTC) market that is intermediated by liquidity providers (e.g., Citigroup and UBS), so-called dealers (see King et al., 2012). On the one hand, there is a professional inter-bank OTC market, which is organised around electronic limit order books (e.g., EBS and Reuters). In recent years, this market has become less liquid and more concentrated due to the ongoing consolidation in the banking industry and the reduction of dealing rooms per financial institution (Schrimpf and Sushko, 2019). This tendency has supported the rise of non-bank liquidity providers (e.g., XTX Markets or Jump Trading). On the other hand, the second tier of the market covers dealer-customer currency transactions. Trades are submitted electronically to proprietary single- (e.g., Barclays' *BARX* or Deutsche Bank's *Autobahn*) and multi-dealer (e.g., Thomson Reuters' *FXall* or Deutsche Börse's *360T*) platforms. In sum, modern FX trading is organised as a network of central limit order books that transact independently from each other.[5]

Despite its OTC nature, the FX market has become significantly electronic over the past 10 years, with the market now dominated by execution algorithms. According to Rahmouni-Rousseau and Churm (2018), over 80% of total trading is executed electronically while roughly 70% of total FX spot volume on EBS are initiated by algorithms. As a result, search costs in today's market are negligible compared to 10 or 15 years ago when FX trading was mostly done via telephone. Moreover, at least 85% of all FX spot trades passing through CLS have a US dollar leg, which is fully consistent with what the Bank for International Settlements (BIS) reports in their triennial central bank surveys over the past 30 years. It is instructive to contrast this amount with the US share of global economic activity, which is around 35-51%. I use this share of global GDP, trade, stocks, and debt markets as a benchmark for the relative importance of the US dollar in FX trading volume.[6]

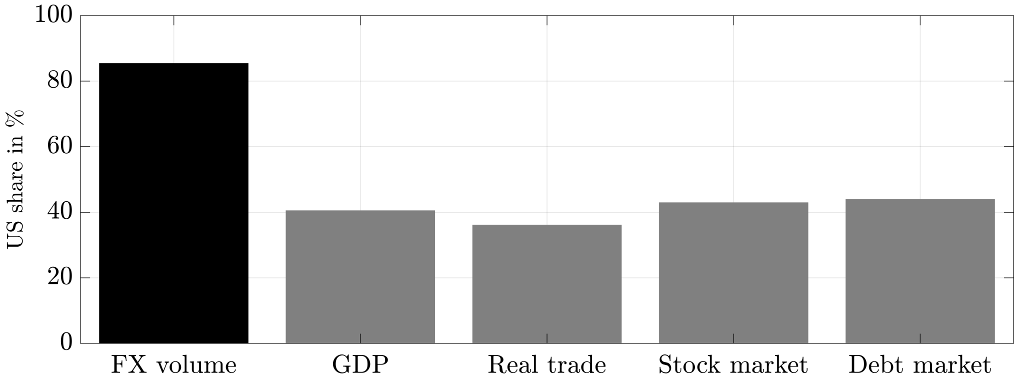
Figure 1 illustrates the pervasive dominance of the US dollar (USD) in FX trading volume. The underlying data come from five sources: First, spot FX trade data stem from CLS Group. Second, yearly GDP data by country and currency come from the World Bank and OECD national accounts data, respectively. Third, monthly imports and exports by country and currency stem from the World Trade Organisation. Trade is defined as the sum of imports

[5] In terms of FX spot trading volume, the market is roughly split into two equal halves: the inter-dealer and the dealer-to-customer segment (see "Triennial central bank survey — global foreign exchange market turnover in 2019," Bank for International Settlements, September 2019).

[6] Note that global GDP and world trade are computed based on countries whose national currency is settled via CLS. Thus, for instance, Chinese economic output does not show up in my estimates of global GDP and world trade. There are 16 national currencies in my sample: Australian dollar (AUD), Canadian dollar (CAD), Danish krone (DKK), euro (EUR), Hong Kong dollar (HKD), Israeli shekel (ILS), Japanese yen (JPY), Mexican peso (MXP), New Zealand dollar (NZD), Norwegian krone (NOK), pound sterling (GBP), Singapore dollar (SGD), South African rand (ZAR), Swedish krone (SEK), Swiss franc (CHF), and US dollar (USD).

and exports between two countries. The US share of world trade accounts for trades that are either invoiced in US dollars (Gopinath and Stein, 2020) or originated in countries where the US dollar is the official currency (e.g., Ecuador or Puerto Rico).[7] Fourth, the share of the US in global stock markets is from Bloomberg and based on the market value of all available equity securities. Fifth, the estimates of US dollar-denominated international debt securities are based on BIS locational banking statistics and comprise debt instruments that are issued outside the local market of the borrower's country (e.g., Eurobonds).

**Figure 1: Dollar Dominance in FX Trading**




*Note*: This figure compares the time series average of the relative share (in %) of the US dollar (USD) in FX trading to the share of the US economy in global GDP, real trade, stocks, and debt markets, respectively. The sample covers the period from 1 November 2011 to 29 September 2020.

What are the real economic consequences of dollar dominance? Who wins and who loses from FX liquidity being concentrated in dollar currency pair? Estimating the economic impact of dollar dominance in FX trading would likely require a heavy structural apparatus, which goes beyond the scope of this paper. Clearly, the fact that FX liquidity is clustered in dollar currency pairs primarily benefits US households, firms, and investors. However, universally lower transaction costs in dollar pairs create a win-win situation, allowing the rest of the world to enjoy almost the same benefits. This is because the average Amihud (2002) price impact in dollar pairs is just about 1.3 basis points per 10 million US dollars. Therefore, non-US currency traders are slightly worse off by a few basis points than their US counterparts as they incur price impact twice when using the dollar as a vehicle currency.

## 3. Theory of FX Trading

This section has two goals: First, I adapt Rostek and Yoon's (2021a) model to the FX market to formalise the trade-off faced by traders who wish to exchange one non-dollar currency for another non-dollar currency. Second, I use comparative statics analysis to derive a set of conditions for

[7]The stark discrepancy between trading volume and real economic activity persists even after accounting for any currencies that are pegged to the US dollar (i.e., Hong Kong and Singapore dollar).

dollar dominance in FX trading volume. To present the model in a concise manner, I relegate the detailed solution of the equilibrium to the Online Appendix.

### 3.1. Model Overview

Traders buy and sell currencies from each other in an OTC market setting. Some of these trades take place directly between two traders, whereas others occur between traders and dealers. The model does not explicitly distinguish trader types or dealers. Traders aim to satisfy their fundamental trading demand for a particular currency pair. When doing so, they consider their price impact.[8] Thus, traders are willing to deviate from their fundamental trading demand only if they are sufficiently compensated by price. Following this intuition, I show that in equilibrium such behaviour may result in a lower expected price impact and hence in greater trading volume for dollar pairs. Lastly, I use comparative statics to understand the drivers of FX volume and to derive equilibrium conditions for dollar dominance.

The left subfigure in Figure 2 provides evidence in favour of the idea that dollar pairs exhibit higher trading volumes and lower price impacts than non-dollar pairs. The y-axis shows the median Amihud (2002) price impact associated with buying or selling activity worth 10 million US dollars. The x-axis depicts the average daily trading volume settled by CLS. The average volume in dollar pairs is 8 times larger than in non-dollar pairs.

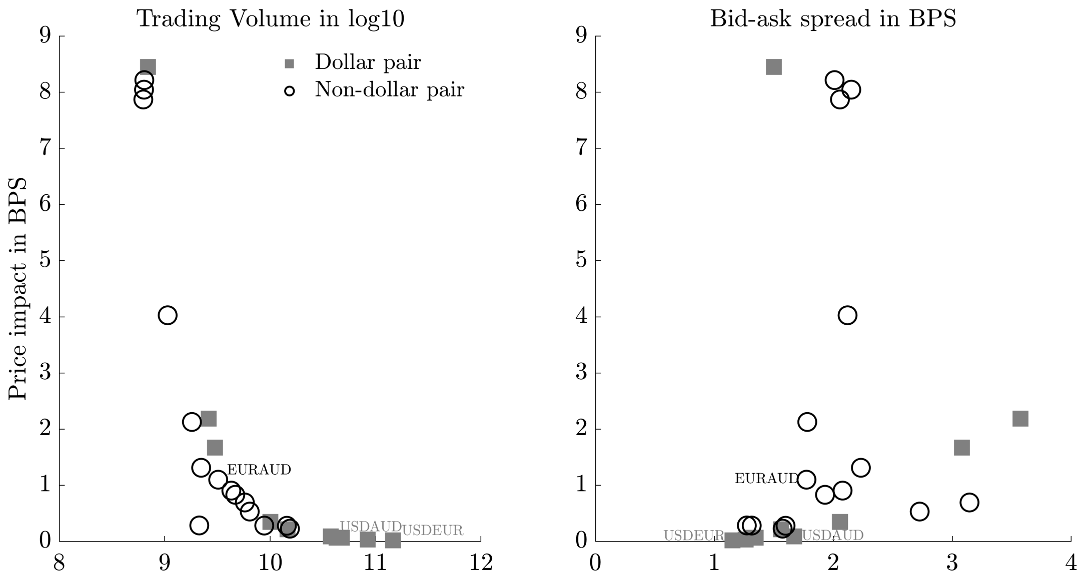
My model includes no traditional transaction costs in the form of relative bid-ask spreads. This is motivated by the observation that the average relative bid-ask spread in non-dollar currency pairs is only marginally higher than in dollar pairs. Contrarily, the median price impact in non-dollar currency pairs is on average 6 times larger than in dollar pairs.

The right subfigure in Figure 2 illustrates this point. The y-axis is the same as in the left subfigure and shows the median price impact for dollar and non-dollar currency pairs. The x-axis plots the average relative half bid-ask spread in basis points (BPS) based on indicative quotes from Olsen Data. These spreads presumably refer to the best deal a market-maker offers to some clients. However, the amount tradeable at these prices is unknown because of the OTC nature of the FX market, which has no central limit order book.

For instance, consider an FX trader who wishes to buy a certain amount of euros (EUR) and is endowed with Australian dollars (AUD). On a bid-ask spread basis, the trader would be better off exchanging AUD directly to EUR and on average incur the half spread of 1.8 BPS rather than first exchanging AUD to USD and then USD to EUR paying around 2.8 BPS in total. However, this intuition does not hold for price impact. On average, the same trade would incur an expected price impact of just about 0.1 BPS when executed via the US dollar and at least 1.1 BPS when completed directly.

[8]Studies on the market impact of trades include, for example, Glosten and Harris (1988), Stoll (1989), Foster and Viswanathan (1990), Hasbrouck (1991a,b) or Amihud (2002).

**Figure 2: Price Impact, Bid-ask Spread, and Trading Volume**




*Note*: The left subfigure shows the time series average of trading volume and the median Amihud (2002) price impact for 10 dollar and 15 non-dollar currency pairs, respectively. The y-axis depicts the median price impact in basis points (BPS) associated with trading activity worth 10 million US dollars. The x-axis plots the average daily trading volume (log10 scale) settled by CLS. The right subfigure covers the same 25 currency pairs and plots the time series average of relative half bid-ask spreads and the median price impact. Again, the y-axis shows the same as in the left subfigure, whereas the x-axis plots the average relative half bid-ask spread in BPS based on indicative quotes from Olsen Data. The sample covers the period from 1 September 2012 to 29 September 2020.

## 3.2. Set-up

I consider a market with $I \geq 3$ traders who trade $K \geq 3$ currency pairs in $N$ trading venues. In particular, I assume that all traders behave strategically in terms of game theory. Traders and currency pairs are indexed by $i$ and $k$, respectively. The payoffs of the $K$ currency pairs are exogenous and Gaussian $\mathbf{r} = r_k \sim N(\boldsymbol{\delta}, \boldsymbol{\Sigma})$ with a vector of payoffs $\boldsymbol{\delta} = \delta_k$ and a positive semi-definite covariance matrix $\boldsymbol{\Sigma}$. Throughout this paper, vectors and matrices are **boldface**, whereas scalars are in normal font. The *numéraire* is a riskless asset with zero interest rate. Further, I assume that each trader $i$ has quadratic mean-variance utility:

$$u^i(q^i) = \delta_k \cdot (\mathbf{q}^i + \mathbf{q}_0^i) - \frac{\gamma^i}{2}(\mathbf{q}^i + \mathbf{q}_0^i) \cdot \boldsymbol{\Sigma}(\mathbf{q}^i + \mathbf{q}_0^i), \tag{1}$$

where $\mathbf{q}^i = q_k^i$ is the (effectively) traded quantity, $\mathbf{q}_0^i = q_{0,k}^i$ represents every trader's *fundamental trading demand* in each currency pair, and $\gamma^i$ is trader $i$'s risk aversion.[9]

[9]Note that in a *contingent* market model linear-quadratic utility functions in terms of returns behave the same as utility functions with constant absolute risk aversion and normally distributed returns. This is often seen as unrealistic as it implies that risk aversion increases with wealth. However, this equivalence does not hold in *uncontingent* markets where equilibria also depend on the *distribution* of fundamental trading demands.

**Fundamental trading demand.** In the context of currency pairs, fundamental or initial trading demand may be seen as the amount of currency units in the base currency that a trader intends to buy or sell for the quote currency. The same logic applies to both customers and dealers, who execute their clients' trading demands and provide immediacy.[10] The trading demands (i.e., $\mathbf{q}_0^i$) at the beginning of every period are traders' private information and independent of the currency pairs' payoff vector $\mathbf{r}$. Traders derive their utility from the post-trade allocation defined by $\mathbf{q}^i + \mathbf{q}_0^i$ and choose $\mathbf{q}^i$ to maximise their expected payoff.

What determines fundamental trading demands across currency pairs? In principle, the motives for exchanging currencies may be divided into three categories: First, international trade related to imports and exports necessitates payments across borders. However, this accounts for less than 10% of global FX trading activity (e.g., Lyons and Moore, 2009; King et al., 2012). Second, cross-border purchases and sales of financial assets (e.g., stocks and bonds) are the single most important source of FX trading growth according to a recent BIS study.[11] Third, the demand for safe assets (e.g., He et al., 2019; Jiang et al., 2021) on the one hand and the need for credit (e.g., Ivashina et al., 2015; Eren and Malamud, 2022) on the other may fuel FX trades in periods of market stress. Against this backdrop, it is beyond the scope of this paper to provide a micro-foundation for fundamental trading demands that is able to encompass all of the above motives.

Following the closely related literature on imperfectly competitive markets (e.g., Rostek and Weretka, 2015; Kyle et al., 2017; Malamud and Rostek, 2017), traders' fundamental trading demand can be decomposed into a common ($\mathbf{q}_0^{cv} = q_{0,k}^{cv}$) and private value component ($\mathbf{q}_0^{i,pv} = q_{0,k}^{i,pv}$), respectively. For each currency pair $k$, fundamental trading demand $q_{0,k}^i$ is correlated among traders through $q_{0,k}^i \sim N(E[q_{0,k}^{cv}], \sigma_{cv}^2)$. I assume that for each trader $q_{0,k}^i = q_{0,k}^{cv} + q_{0,k}^{i,pv}$, where the private component is assumed to be normally distributed $q_{0,k}^{i,pv} \overset{iid}{\sim} N(E[q_{0,k}^{i,pv}], \sigma_{pv}^2)$. Importantly, trader $i$ knows their fundamental trading demand $\mathbf{q}_0^i$ but not its components $\mathbf{q}_0^{cv}$ or $\mathbf{q}_0^{i,pv}$. This ensures that the equilibrium exchange rate is random in the limit large market as the number of traders approaches infinity. Moreover, I denote the covariance matrix of fundamental trading demands $q_{0,k}^i$ (i.e., $Cov(q_{0,k}^i, q_{0,l\neq k}^i)$) by $\mathbf{\Omega}$.

**Demand schedules.** The exchange of currencies in this model is organised as a uniform-price double auction (Kyle, 1989; Vives, 2011) in which traders submit a package of limit orders (forming a demand schedule) to each trading venue.[12] For $q_{0,k}^i > 0$, trader $i$ is *long* in currency pair $k$ and *short* for $q_{0,k}^i < 0$. Being long in a currency pair is equivalent to buying the quote currency and selling the base currency, whereas the opposite holds for a trader who is short. To appropriately reflect the decentralised FX market structure (see Section 2), this model assumes

[10] FX dealers provide immediacy by selling the currency that the customer wants to buy in exchange for the currency that the customer wants to sell. Thus, the utility function in Eq. (1) embraces the decision problem of a risk-averse dealer who trades off the expected return against the variance of incoming customer order flows.

[11] See "BIS quarterly review — international banking and financial market developments," Bank for International Settlements, December 2019.

[12] See Foucault et al. (2013) for an overview of models based on limit-orders.

*uncontingent* demand schedules:

**Definition 1** (**Demand Schedule**). *In a double auction with* uncontingent *schedules, each trader $i$ submits $K$ demand functions $\mathbf{q}^i(\cdot) \equiv q_1^i(p_1), ..., q_K^i$, each $q_k^i(\cdot)$ specifies the quantity of currency pair $k$ demanded at a particular exchange rate $p_k$.*

The key property of *uncontingent* schedules is that orders placed at a given trading venue cannot be made contingent on the market clearing exchange rates at other venues.[13] As a result, the FX market in this model clears *exchange by exchange* rather than jointly as with *contingent* schedules.[14] Even if the FX market is possibly less decentralised from a large FX dealer's point of view it is still implausible to believe that market clearing exchange rates are determined jointly for all currency pairs. This is mainly because an OTC market lacks coordination in market clearing among both dealers and trading venues. Consistent with the notion of uncoordinated market clearing, Ranaldo and Santucci de Magistris (2018) document significant triangular no-arbitrage deviations over time and across currency pairs.

### 3.3. Equilibrium Characterisation

To derive the equilibrium exchange rates and quantities for a representative trader, I apply the solution concept of Bayesian Nash equilibria. Every trader $i$ submits their demand schedules $q_k^i$ at once across $N = K$ trading venues, each for one currency pair. The demand schedules are optimal if they maximise a trader's expected payoff for each currency pair $k$ subject to their residual supply function $S_l^i(\cdot) \equiv -\sum_{j \neq i} q_l^j(\cdot)$ for all currency pairs and their demand for other pairs $q_{l \neq k}^i(\cdot)$. The following definition formalises market equilibrium:

**Definition 2** (**Equilibrium**). *A profile of (net) demand schedules $q_k^i$ is a Bayesian Nash equilibrium if, for every trader $i$, $q_k^i$ maximises their expected payoff:*

$$max_{q_k^i(\cdot)} E[\boldsymbol{\delta} \cdot (\mathbf{q}^i + \mathbf{q}_0^i) - \frac{\gamma^i}{2}(\mathbf{q}^i + \mathbf{q}_0^i) \cdot \boldsymbol{\Sigma}(\mathbf{q}^i + \mathbf{q}_0^i) - \mathbf{p} \cdot \mathbf{q}^i | p_k, \mathbf{q}_0^i], \tag{2}$$

*given the demand schedules of other traders $q_k^{j \neq i}$ and market clearing $\sum_j q_k^j(\cdot) = 0$ for all currency pairs $k$.*

The trader's objective function with *uncontingent* demand schedules in Eq. (2) is similar to when all markets clear jointly (i.e., *contingent* demand schedules). The main difference is that the demand for currency pair $k$ is dependent on both the exchange rate $p_k$ and fundamental trading demand $\mathbf{q}_0^i$. As a result, the equilibrium characterisation is more challenging compared

[13] To my best knowledge, Wittwer (2021), Chen and Duffie (2021), and Rostek and Yoon (2021a) were the first to study markets with multiple heterogeneous assets and uncontingent demand schedules.

[14] Financial markets are often assumed to be competitive and centralised (e.g., Kyle, 1989; Vayanos, 1999). Two assumptions are implicit in the centralised market setting: First, there is complete participation of all traders across all assets. Second, traders can submit contingent schedules in which the quantity of each asset is a function of a price vector for all assets. The model only relaxes the latter assumption but not the former one.

to the contingent market since the requirements for *ex post* optimisation are not met.[15] That is, the best response quantities cannot be solved pointwise with respect to the exchange rate vector $\mathbf{p}$ since expected trade $E[q_l^i|p_k, q_0^i]$ depends on the functional form of $q_l^i(\cdot)$.

Given that best-response demands are not ex post and depend on the distribution of the conditioning variable $\mathbf{p}$, price impact $\mathbf{\Lambda}^i$ is *not* a sufficient statistic for a trader's residual supply. The solution to this issue is based on Rostek and Yoon (2021a) and involves transforming the fixed point problem for best-response schedules $q_k^i(\cdot)$ into one for demand coefficients, given residual supplies.[16] To keep matters interesting, I only consider markets that are not frictionless and hence only that case where the number of traders $I$ is finite.

**Equilibrium.** In equilibrium, the total residual supply $S_k^{-i}(p_k)$ must be zero, otherwise markets do not clear. This enables deriving the equilibrium exchange rate $\mathbf{p}^*$ as follows:

$$\mathbf{p}^* = \big(\boldsymbol{\delta} - (\gamma\mathbf{\Sigma} - \mathbf{C}^{-1}\mathbf{B})E[\bar{\mathbf{q}}_0]\big) - \mathbf{C}^{-1}\mathbf{B}\bar{\mathbf{q}}_0, \tag{3}$$

where demand coefficients $\mathbf{B}$ and $\mathbf{C}$ stem from conjecturing that trader $i$'s best-response for all other currency pairs $l \neq k$ is a linear function of the exchange rate $p_l$ and fundamental trading demand $\mathbf{q}_0^i$. In particular, I assume the following functional form:

$$q_l^i(p_l) \equiv a_l^i - \mathbf{b}_l\mathbf{q}_0^i - c_l p_l, \qquad \forall l \neq k \tag{4}$$

where $a_l^i \equiv \mathbf{a}^i$ is the vector of demand intercepts, $\mathbf{b}_l \equiv \mathbf{B}$ the matrix of demand coefficients, and $diag(c_k) \equiv \mathbf{C}$ the demand slope matrix on $p_l$. For simplicity's sake, I assume that all traders have identical risk preferences (i.e., $\gamma^i = \gamma$, $\forall i$). Hence, equilibrium quantity and price impact will not depend on risk aversion $\gamma$.

Substituting the equilibrium exchange rate $\mathbf{p}^*$ and demand coefficient $\mathbf{a}^i$ into traders' parametrised linear demand function yields the equilibrium quantity $\mathbf{q}^{i,*}$: for every $i$,

$$\mathbf{q}^{i,*} = (\mathbf{\Sigma} + \mathbf{\Lambda})^{-1}\mathbf{\Sigma}(E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i]), \tag{5}$$

where $\bar{\mathbf{q}}_0 \equiv \frac{1}{I}\sum_{j=1}^{I}\bar{\mathbf{q}}_0^j$ is the average fundamental trading demand across all traders. The equilibrium price impact matrix $\mathbf{\Lambda}$ is *endogenous* and characterised by the slope coefficients of the inverse residual supply function $\mathbf{C}^{-1}$:

$$\mathbf{\Lambda} = \frac{1}{I-1}\mathbf{C}^{-1} = \frac{1}{I-2}\Big[\mathbf{\Sigma}\underbrace{(\mathbf{B\Omega B'})\big[\mathbf{B\Omega B'}\big]_d^{-1}}_{\text{Inference coefficient}}\Big]_d, \tag{6}$$

where $[\cdot]_d$ is an operator such that for any matrix $M$, $[M]_d$ is a diagonal matrix. Note that $\mathbf{\Lambda}$ is a diagonal matrix because the cross-exchange price impact $\Lambda_{k,l}$ is zero since every currency pair clears independently when demand schedules are uncontingent.

[15]Equilibria are *ex post* if equilibrium demands $q_k^i(\cdot)$ are optimal for all $i$, given the demands of *all* other traders $j \neq i$.

[16]I am grateful to Marzena Rostek and Ji H. Yoon for providing access to their unpublished Online Appendix.

Given the expression for equilibrium volume $\mathbf{q}^{i,*}$ in Eq. (5), trading a non-zero amount is optimal only if there is dispersion in traders' fundamental trading demands, that is, if $E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i] \neq 0$. Trader $i$'s distance to the average trading demand $\bar{\mathbf{q}}_0$ determines whether they are a net-buyer or net-seller of the quote currency. Intuitively, a net-buyer's fundamental trading demand is below average (i.e., $\bar{q}_{0,k} > q_{0,k}^i$), whereas the opposite is true for a net-seller (i.e., $\bar{q}_{0,k} < q_{0,k}^i$). Below, I focus on the *absolute* value of $E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i]$ as buying and selling are symmetric in a linear equilibrium. Moreover, since price impact $\mathbf{\Lambda}$ is a positive definite matrix, trader $i$ optimally trades less relative to $E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i]$.[17]

**Price impact.** Equilibrium mapping of price impact and trading volume implies that, all else being equal, lower price impact currency pairs receive a larger weight in the equilibrium allocation. Hence, even a trader with zero fundamental trading demand in dollar currency pairs may find it optimal to trade a combination of dollar pairs and non-dollar pairs. In equilibrium, this can result in large trading volumes in dollar currency pairs even if little or even no fundamental trading demand exists for dollar pairs.

There are two key determinants of price impact in this model: First, the price impact of every trader emanates from the concavity of preferences of their residual market. In particular, price impact increases in traders' risk aversion and is concave in the variance of currency returns. Hence, the residual market is less elastic when currency pairs are either more risky or when other traders are more risk-averse. Thus, if the residual market is very inelastic, an additional trade has a larger price impact because of the greater price concession required to absorb the extra marginal unit such that markets clear (Rostek and Yoon, 2021b).

Second, since demand schedules are uncontingent, price impact also depends on the distribution of fundamental trading demands. Intuitively, this stems from the fact that each trader's demand for a particular currency pair depends on expected rather than on realised trades for all other currency pairs. This effect is captured by the inference coefficient $(\mathbf{B\Omega B'})\left[\mathbf{B\Omega B'}\right]_d^{-1}$ in Eq. (6), which increases in the variance fundamental trading demands $\mathbf{\Omega}$ for a given demand coefficient $\mathbf{B}$. As a result, a larger variance of fundamental trading demands in currency pair $k$ lowers the associated price impact $\lambda_k$.

**Summary.** The model presented here aims to epitomise the trade-off faced by traders when deciding how to satisfy their fundamental trading demands. So far, the key economic insight provided by the model is twofold: First, traders trade more in currency pairs where they face a lower expected price impact. Second, this effect is driven by the relative riskiness of a currency pair on the one hand and by the distribution of fundamental trading demands across currency pairs on the other. Hence, if each trader plays equilibrium, then avoidance of strategic complementarity in price impact creates a more liquid market for currency pairs that are either less risky or that exhibit more volatile fundamental trading demands.

[17] A growing body of literature shows that the traditional (theoretical) view of purely market rather than limit orders (i.e., demand schedules) having price impact does not hold up in the data across many asset classes, including FX: Roşu (2009), Hautsch and Huang (2012), Hoffmann (2014), Fleming et al. (2018), Brogaard et al. (2019), and Chaboud et al. (2021).

### 3.4. Comparative Statics

The equilibrium trading volume in Eq. (5) is characterised by three *exogenous* drivers: fundamental trading demand $\mathbf{q}_0^i$, covariance of fundamental trading demands $\mathbf{\Omega}$, and covariance of currency returns $\mathbf{\Sigma}$. I denote the $(k,l)^{th}$ element of a matrix (e.g., $\mathbf{\Sigma}$) by $\Sigma_{k,l}$. In particular, I am interested in the comparative statics of equilibrium volume with respect to $q_{0,k}^i$, $\Omega_{k,k}$, and $\Sigma_{k,k}$, respectively. For the sake of clarity, I assume that both the covariance matrix of fundamental trading demands $\mathbf{\Sigma}$ and the covariance matrix of currency returns $\mathbf{\Omega}$ are as follows: $\Sigma_{k,k} = \sigma^2$, $\forall k$ and $\Sigma_{k,l} = \sigma^2\rho$, $\forall l \neq k$ as well as $\Omega_{k,k} = \omega^2$, $\forall k$ and $\Omega_{k,l} = \omega^2\eta$, $\forall l \neq k$, where both $|\rho|$ and $|\eta|$ are less than 1. This implies that price impacts are identical across currency pairs (i.e., $\lambda_k = \lambda$, $\forall k$).[18] The partial derivatives are given by Theorem 1.

**Theorem 1** (**Comparative Statics**). *The comparative statics of equilibrium volume $\mathbf{q}^{i,*}$ with respect to fundamental trading demand $q_{0,k}^i$, variance of fundamental trading demands $\Omega_{k,k}$, and variance of currency returns $\Sigma_{k,k}$ are given by the following expressions: for every $k \neq l$*

$$\frac{\partial \mathbf{q}^{i,*}}{\partial q_{0,k}^i} =(\mathbf{\Sigma}+\mathbf{\Lambda})^{-1}\mathbf{\Sigma}\frac{\partial \mathbf{d}_0^i}{\partial d_{0,k}^i}, \text{ where } \mathbf{d}_0^i = |\bar{\mathbf{q}}_0 - \mathbf{q}_0^i| \text{ and } \frac{\partial q_k^{i,*}}{\partial d_{0,k}^i} > \frac{\partial q_l^{i,*}}{\partial d_{0,k}^i}, \text{ as } \frac{\partial d_{0,l}^i}{\partial d_{0,k}^i} = 0; \tag{7}$$

$$\frac{\partial \mathbf{q}^{i,*}}{\partial \Omega_{k,k}} = -(\mathbf{\Sigma}+\mathbf{\Lambda})^{-2}\mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Omega_{k,k}}(E[\bar{\mathbf{q}}_0]-E[\mathbf{q}_0^i]), \text{ where } \frac{\partial q_k^{i,*}}{\partial \Omega_{k,k}} > \frac{\partial q_l^{i,*}}{\partial \Omega_{k,k}} \text{ as } \frac{\partial \Lambda_{k,k}}{\partial \Omega_{k,k}} < \frac{\partial \Lambda_{l,l}}{\partial \Omega_{k,k}}; \tag{8}$$

$$\frac{\partial \mathbf{q}^{i,*}}{\partial \Sigma_{k,k}} =\Big((\mathbf{\Sigma}+\mathbf{\Lambda})^{-1}\frac{\partial \mathbf{\Sigma}}{\partial \Sigma_{k,k}} - (\mathbf{\Sigma}+\mathbf{\Lambda})^{-2}\mathbf{\Sigma}\Big(\frac{\partial \mathbf{\Sigma}}{\partial \Sigma_{k,k}}+\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k,k}}\Big)\Big)(E[\bar{\mathbf{q}}_0]-E[\mathbf{q}_0^i]), \tag{9}$$

$$\text{where } \frac{\partial q_k^{i,*}}{\partial \Sigma_{k,k}} < \frac{\partial q_l^{i,*}}{\partial \Sigma_{k,k}} \text{ iff } \Lambda_{k,k} - \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k,k}} < \Lambda_{l,l} - \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{l,l}}.$$

*See Online Appendix, Section Appendix B (Corollaries 1 to 3) for a formal derivation of these partial derivatives.*

The economic interpretation of the three partial derivatives in Theorem 1 is straightforward: For every additional marginal unit of $q_{0,k}^i$, $\Omega_{k,k}$, and $\Sigma_{k,k}$, holding all else equal, the equilibrium allocation in currency pair $k$ changes at the rate of the partial derivative. An increase in fundamental trading demand $q_{0,k}^i$ linearly increases the equilibrium quantity.

The effect of a change in the variance of fundamental trading demands $\Omega_{k,k}$ depends on the partial derivative with respect to price impact $\mathbf{\Lambda}$. An increase in the variance of fundamental trading demands reduces the expected price impact. The economic reason for this drop in price impact is the fact that the inference coefficient $(\mathbf{B\Omega B}')\big[\mathbf{B\Omega B}'\big]_d^{-1}$ decreases in $\Omega_{k,k}$. The lower price impact induces a surge in the equilibrium allocation.

On the contrary, an increase in the variance of currency returns affects the equilibrium allocation not only directly but also indirectly by inducing a change in price impact (i.e., $\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k,k}}$). The latter offsets the former if the increase in the variance of currency returns is sufficiently

[18] Note that $\mathbf{\Sigma}$ and $\mathbf{\Omega}$ only scale the level of price impact. Hence the sign of $\rho$ and $\eta$ has no effect on price impact ranking across currency pairs.

large such that price impact increases at a faster rate than the variance of currency returns.[19] Thus, equilibrium trading volume is non-monotonic in the variance of currency returns.

To illustrate the equilibrium dynamics, I simulate the model in Section Appendix B.2 of the Online Appendix. The simulation results support the idea that even a symmetrical market with identical net trading demands across currency pairs can become skewed towards a single currency (e.g., the US dollar) if a minor disparity exists in the variance of fundamental trading demands or in currency returns, respectively. The next section formalises this intuition in two steps: First, I introduce a formal definition of "dollar dominance." Second, I derive a set of sufficient conditions for dollar dominance based on the primitives of the model.

Next, I explore the role of strategic complementarity in FX trading by characterising the degree of amplification through the dominant vehicle currency associated with strategic avoidance of price impact. For this, I compare trading volume in dollar currency pairs in the above model with two benchmarks: i) competitive equilibrium where traders ignore their price impact and ii) contingent market equilibrium where the FX market clears jointly

**Proposition 1** (**Equilibrium Volume in Two Benchmark Models**).

1. *The competitive equilibrium is the limit case where* $I \to \infty$ *and hence* $\mathbf{\Lambda}^i = 0$, $\forall i$. *Thus, it is optimal for each trader to buy or sell their net trading demand* $E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i]$.
2. *The contingent market equilibrium implies that* $\mathbf{\Lambda}^i = \frac{1}{I-2}\mathbf{\Sigma}$, $\forall i$, *and hence the optimal traded quantity in Eq.* (5) *is independent of the demand coefficient* $\mathbf{B}$ *since there is no inference effect.*

*See Section Appendix A of the Online Appendix for a formal derivation of the contingent model.*

Proposition 1 allows for a direct comparison between the uncontingent equilibrium model and two benchmarks: First, in the competitive equilibrium there is no vehicle currency trading due to strategic avoidance of price impact because all traders ignore their price impact. As a result, trading volume in dollar currency pairs is determined solely by fundamental trading demands in dollar pairs. In particular, trading volume in dollar pairs in the uncontingent equilibrium exceeds that in the competitive equilibrium if price impact in dollar currency pairs is sufficiently low and hence it holds that $\sum_{l=1}^{L}(\mathbf{\Sigma}_{k,l} + \mathbf{\Lambda}_{k,l})^{-1}\mathbf{\Sigma}_{k,l} > 1$, $\forall k \in \$$.

Second, in the contingent equilibrium there is no scope for vehicle currency trading since the equilibrium is ex post. Hence, trader $i$'s conjectured demand in all other currency pairs is independent of the distribution of other traders' fundamental trading demand. Thus, price impact is proportional to the covariance matrix of currency returns. Note that trading volume in dollar pairs in the uncontingent market exceeds that in the contingent market if the inference effect in dollar pairs is small enough such that $\sum_{l=1}^{L}(\mathbf{\Sigma}_{k,l} + \mathbf{\Lambda}_{k,l})^{-1}\mathbf{\Sigma}_{k,l} > \frac{1}{2}$, $\forall k \in \$$.

In sum, the inference coefficient in the uncontingent market stems from two assumptions: First, trader $i$'s demand for a particular currency pair depends on *expected* trades in all other currency pairs. Second, all other traders $j \neq i$ are also strategic about their price impact.

[19] Mathematically, the partial derivative of price impact $\mathbf{\Lambda}$ with respect to the variance of currency returns $\Sigma_{k,k}$ in Eq. (9) must be such that $\mathbf{\Sigma}^{-1}\Lambda_{k,k} < \frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k,k}}$.

### 3.5. Dollar Dominance

Based on the above model, I define dollar dominance in terms of triplets of currency pairs. Every triplet comprises one non-dollar currency pair (e.g., GBPJPY) plus the two USD legs (e.g., USDGBP and USDJPY), which are required to indirectly trade the non-dollar currency pair by using the USD as a vehicle currency. Hence, I define dollar dominance as follows:

**Definition 3** (**Dollar Dominance**). *A triplet of currency pairs (i.e.,* \$/X, \$/Y, *and* X/Y*) is dominated by the US dollar (\$) if the trading volume in each of the two dollar currency pairs (i.e.,* \$/X *and* \$/Y*) exceeds the trading volume in the respective non-dollar pair (i.e.,* X/Y*) within the same triplet. Hence, for dollar dominance it must hold that* $min(q^{i,*}_{\$/X}, q^{i,*}_{\$/Y}) > q^{i,*}_{X/Y}$ *for every trader* $i$*.*

Consider, for example, the three currency pairs GBPJPY, USDGBP, and USDJPY (with associated volume of 90, 120, and 110 \$mn, respectively). Following Definition 3, the US dollar dominates because the minimum trading volume in dollar currency pairs ($min(110, 120)$ \$mn) exceeds trading volume in the direct non-dollar cross (90 \$mn). In other words, my definition of dollar dominance means that within a triplet of currency pairs the US dollar dominates all other currencies as a hub currency. This definition is appealing because it takes into account the possibility that trading volume is driven by fundamental *and* by vehicle currency demand. Moreover, given a measure for fundamental trading demands, it enables quantifying the amplification effect in volume, which stems from vehicle currency trading.

**Equilibrium conditions.** Next, I derive equilibrium conditions for dollar dominance based on the economic intuition gained from the comparative static results (summarised in Theorem 1). There are three exogenous determinants of equilibrium trading volume $\mathbf{q}^{i,*}$: fundamental trading demand $\mathbf{q}^i_0$, the covariance matrix of fundamental trading demands $\mathbf{\Omega}$, and the covariance matrix of currency returns $\mathbf{\Sigma}$. For the sake of clarity, I assume that both $\mathbf{\Sigma}$ and $\mathbf{\Omega}$ are such that the covariance terms are down-scaled versions of the variances (e.g., $\Sigma_{k,l} = \sigma^2\rho, \ \forall l \neq k$, where $|\rho| < 1$), which are assumed to be identical across all currency pairs (e.g., $\Sigma_{k,k} = \sigma^2, \ \forall k$). This is analytically convenient because it disciplines the influence of the covariance terms on equilibrium quantity.

**Theorem 2** (**Dollar Dominance: Equilibrium Conditions**). *Trading volume in a triplet of currency pairs (i.e.,* \$/X, \$/Y, *and* X/Y*) will be dominated by the dollar (\$) if the following three conditions are satisfied* simultaneously *for dollar currency pairs (i.e.,* \$/X *and* \$/Y*):*

*C1:* larger fundamental trading demands*,* $min(q^i_{\$/X,0}, q^i_{\$/Y,0}) > q^i_{X/Y,0}, \ \forall i$*;*

*C2:* more volatile trading demands*,* $min(\Omega_{\$/X,\$/X}, \Omega_{\$/Y,\$/Y}) > \Omega_{X/Y,X/Y}$*;*

*C3:* less volatile currency returns*,* $max(\Sigma_{\$/X,\$/X}, \Sigma_{\$/Y,\$/Y}) < \Sigma_{X/Y,X/Y}$*.*

*The last condition holds only if* $\Lambda_{k\in\$} - \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k\in\$}} < min(\Lambda_{k\in X} - \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k\in X}}, \Lambda_{k\in Y} - \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k\in Y}})$*. The proof of Theorem 2 follows from Corollaries 1 to 3 (see Online Appendix, Section Appendix B).*

Individually, each of the three conditions in Theorem 2 is sufficient if and only if the other two remain equal. Conversely, the necessary condition for dollar dominance is that at least one of the three conditions must hold. Thus, these three conditions are also useful for predicting which currency is unlikely to be dominant: A currency will *not* dominate trading volume within a currency pair triplet if none of the above conditions is satisfied. Moreover, when conditions two and three are both satisfied dollar currency pairs exhibit a lower price impact than non-dollar pairs. As a result, trading non-dollar pairs indirectly via the US dollar rather than directly becomes more attractive and should result in more dollar dominance.

The empirical part of this paper explores which of the three conditions are satisfied in the data. Such an empirical exercise can speak to two important questions: First, which conditions are close or far from being "necessary" for dollar dominance in trading volume. Second, how realistic are these equilibrium conditions for dollar dominance empirically.

### 3.6. Discussion

My model builds on several simplifying assumptions. First, the model is static and does not connect multiple periods. Specifically, I assume that a trader's fundamental trading demand is exogenous in every period and independent of prior trades. Hence, my model abstracts away from dynamic trading strategies, which stretch over multiple periods. I avoid this challenge because it would greatly increase the complexity of the model (see Chen and Duffie (2021) for a dynamic model with one asset) and thus obscure the main message: Strategic avoidance of price impact explains how a relatively minor dominance of the US dollar in real economic fundamentals can become heavily amplified in terms of FX volumes.

Second, I focus on linear Bayesian Nash equilibria in the uniform-price double auction. In principle, a trader's conjectured best response in all other currency pairs $l \neq k$ might be non-linear in the exchange rate $p_l$ as well as in the fundamental trading demand $\mathbf{q}_0^i$. Analysing the properties of price impact in non-linear equilibria is undoubtedly interesting but imposes mathematical challenges that lie beyond the scope of this paper.

Third, my model does not distinguish market and limit orders because I want to avoid the theoretical challenge of examining how traders optimally choose between order types. The microstructure literature (e.g., Foucault et al., 2013) stresses that the execution probabilities embedded in optimal order choice must be determined endogenously. I choose to avoid this challenge to keep the model tractable and also because its empirical relevance is unclear.

### 3.7. Testable Implications

My model serves two purposes: First, to describe a trading mechanism that hones economic intuition to the empirical observation that trading volume in the FX market is dominated by dollar currency pairs. Second, to deliver a set of empirically testable hypotheses that can be evaluated using actual FX trade and quote data.

The model's testable implications fall into three parts: First, it enables using panel regressions to test its empirical validity. Specifically, I am interested to what extent actual FX volume is driven by fundamental trading demands compared to vehicle currency trading motives stemming from strategic avoidance of price impact. Based on the comparative statics in Theorem 1, I expect that an increase (*a decrease*) in the variance of fundamental trading demands (*currency returns*) increases trading volume due to more vehicle currency trading. This is because price impact in my model decreases with the variance of fundamental trading demands but increases with more volatile exchange rate returns.

Second, my model enables evaluating the three conditions for dollar dominance in Theorem 2 for the cross-section of currency pair triplets. The aim is to understand whether the empirical counterparts of these conditions are on average over the full sample period consistent with the observed dollar dominance in the data. This is useful not only to determine which currency pair triplets will be dominated by the dollar, but also to identify which ones are on the verge of switching to another dominant currency. Moreover, this enables directly testing whether there is evidence of vehicle currency trading by comparing dollar dominance in trading volume with dollar dominance in fundamental trading demands.

Lastly, the model allows estimating the relative importance of the three model–based equilibrium conditions for explaining the time-variation of dollar dominance. To establish this, I first derive a time-varying empirical measure of dollar dominance. Second, I regress this proxy on the empirical counterparts of the three conditions to gauge the relative importance of each condition. Following my model, I presume that, holding all else equal, dollar dominance increases in the first and second condition but decreases in the third one. In particular, the first condition implies that fundamental trading demands in dollar currency pairs are larger than in non-dollar pairs. Furthermore, when conditions two and three are jointly satisfied dollar currency pairs exhibit lower expected price impacts relative to non-dollar pairs, which fosters vehicle currency trading via the US dollar.

## 4. Empirical Analysis

This section presents empirical evidence that is consistent with my model in four parts. First, I describe the data. Second, I use panel regression analysis to empirically test the model and to provide evidence that can substantiate the predictions of the comparative statics in Theorem 1. Third, I focus on the cross-section of currency pair triplets to evaluate which of the three equilibrium conditions in Theorem 2 are empirically supported. Lastly, I use non-overlapping holidays as a novel identification tool to estimate the share of vehicle currency trading volume in dollar currency pairs.

### 4.1. Data

The empirical analysis employs high-frequency trade and quote data from two publicly accessible sources. The data set on spot FX volume and order flow data comes directly from CLS Group (CLS). These data are also available from Quandl, a financial and economic data provider. CLS operates the world's largest multi-currency cash settlement system and handles over 40% of global spot FX transaction volume. At settlement, CLS alleviates principal and operational risk by simultaneously settling both sides of the trade. These data have been used previously, among others, by Hasbrouck and Levich (2018, 2021), Ranaldo and Santucci de Magistris (2018), Cespa et al. (2021), and Ranaldo and Somogyi (2021). These authors have comprehensively described both CLS volume and order flow data.

The CLS system is owned by its 72 settlement members, which are mostly large multinational banks. Hence, to protect member anonymity, CLS has been reluctant to disclose any transaction-level information about settlement activity. Therefore, the CLS data set only contains hourly aggregates of the trading activity in each currency pair and provides no information about counterparty identities or agreed transaction prices.

The volume and order flow data sets are interrelated. Volume data include the sum of all dealer-to-customer and inter-dealer trades, whereas order flow data contain separate entries for buying and selling activity but only for dealer-to-customer trades. CLS volume data are particularly well-suited to my analysis because they enable studying the properties of dollar dominance on a global scale rather than just for a specific market segment or trading platform. The buy and sell volume in a given hour and currency pair refers to how much of the base currency was bought and sold by customers from the market-makers (i.e., dealer banks).

Customers can be categorised into four customer groups: corporates, funds, non-bank financial firms, and non-dealer banks. The fund category may also include principal trading firms (PTFs) such as high-frequency trading firms and electronic non-bank market-makers (e.g., XTX Markets or Jump Trading). The majority of these PTFs relies on prime brokers to gain access to the FX market (Schrimpf and Sushko, 2019). Hence, if PTFs settle a trade via a prime broker who is a CLS member, then this trade would appear as a bank-to-bank transaction. However, inter-bank trades are excluded from the flow (but not from the volume) data set unless one of the counterparties is classified as a non-dealer bank. Section Appendix C in the Online Appendix provides further details on how CLS categorises market participants into customers, as well as into dealer and non-dealer banks, respectively. Furthermore, CLS provides no information on trade initiators since it solely observes the executed trade price used for settlement rather than the market behaviour of the bids and offers preceding execution.

Next, I pair the hourly FX volume and order flow data with intraday spot bid and ask quotes from Olsen Data, a market-leading provider of high-frequency data and time series management systems. Thus, FX trading volume, order flow, and exchange rate returns are measured hourly. By compiling historical tick-by-tick data from various trading platforms (e.g., IDC, Morningstar, and Reuters), these quote data are also representative of the entire FX spot market rather than merely of a specific segment (e.g., inter-dealer or customer-dealer). The full sample period spans 1 September 2012 to 29 September 2020 and includes data for 11 major currencies and

25 currency pairs.[20] To avoid ambiguity, I assume that for a US investor the quote currency is always the foreign currency (e.g., as in USDJPY).

## 4.2. Determinants of Trading Volume

According to the theoretical framework in Section 3, trading volume is driven by fundamental and vehicle currency trading demands, respectively. The latter is inversely related to price impact: the larger the expected price impact in a currency pair the lower the amount of vehicle currency trading. In my model, this reciprocity is governed by two primitives: i) the variance of fundamental trading demands and ii) the variance of exchange rate returns. This section has two goals: First, to derive an empirical counterpart for fundamental trading demands and the two theoretical determinants of price impact. Second, to use panel regressions to test whether the contemporaneous relation between trading volume, price impact, and their respective drivers is consistent with the comparative statics in Theorem 1.

**Identifying assumptions.** The main challenge for testing the model's predictions is to identify a meaningful empirical proxy for fundamental trading demands. The reason being that fundamental trading demands are unobservable. To overcome this challenge, I exploit a unique institutional feature of how large FX dealer banks operate in this market. In today's FX market, the vast majority of dealers engages in so called "principal trading." Dealers offer their clients immediacy by completing their trades with their own inventory. Some of these customer flows are netted internally, by offsetting flows from other customers or via dealers' existing trading demands, whereas others create an inventory imbalance. Since dealers have limited risk bearing capacity (Evans and Lyons, 2002), they try to flatten these open positions until the end of the FX trading day.[21] Thus, customer flows can be seen as a natural proxy for dealer banks' fundamental trading demands.

This measure has two potential limitations: First, it implicitly assumes that bank trading is driven mainly by customer flows rather than by proprietary bank trading demands. This assumption is reasonable given that my sample covers the post-financial crisis period where proprietary trading is much less prevalent. This is because banks have shifted the scope of their business models from proprietary trading to market-making (Moore et al., 2016) in response to post-crisis regulatory reforms (e.g., Dodd-Frank Act, EMIR, and MiFID II). Even if spot FX is formally excluded from the Volcker Rule it is indirectly affected by the consequences of regulation for FX derivatives (e.g., forwards and swaps).[22] The amount of proprietary trading

[20] In particular, the data set contains 15 non-dollar pairs (i.e., AUDJPY, AUDNZD, CADJPY, EURAUD, EURCAD, EURCHF, EURDKK, EURGBP, EURJPY, EURNOK, EURSEK, GBPAUD, GBPCAD, GBPCHF, and GBPJPY) and 10 dollar pairs (i.e., USDAUD, USDCAD, USDCHF, USDDKK, USDEUR, USDGBP, USDJPY, USDNOK, USDNZD, and USDSEK). These pairs are used to indirectly trade each of the non-dollar pairs.

[21] This usually takes place either bilaterally or on two major inter-bank trading platforms (i.e., EBS and Reuters). Whether these trades show up in the CLS volume data depends solely on the two counterparties being CLS members but not on the platform per se.

[22] This conclusion is also supported by my conversations with FX traders at several major FX dealer banks.

is unobservable in my data set and hence I cannot directly control for it. However, including currency pair and time series fixed effects in my panel regression set-up enables mitigating any bias stemming from proprietary trading activity, which is either constant over time or across currency pairs.

Second, some of the major FX dealer banks with large e-FX businesses can have internalisation ratios of up to 90% (Moore et al., 2016). Hence, customer order flows are likely to overestimate the true fundamental trading demand of an FX dealer. As a result, my estimates of the elasticity of trading volume with respect to fundamental trading demands can be interpreted as a lower bound, thus potentially underestimating the actual effect.

CLS volume and order flow data are ideal for my identification strategy for two reasons: First, by construction CLS order flow data only comprises transactions between customers and FX dealer banks but excludes any dealer-to-dealer trades.[23] Second, CLS volume is the sum of all customer-dealer and inter-dealer trades. Inter-bank trading accounts on average for 58% of CLS trading volume and is driven by two key factors: customer flows and inter-dealer "hot-potato" trading (Lyons, 1997). The latter refers to the idea that the order imbalance initiated by the customers of one bank is passed on to multiple other banks. This is particularly true for either exotic or illiquid currency pairs. Hence, the findings in this paper are unlikely to be driven by excessive hot-potato trading in dollar currency pairs, which are both highly liquid and less volatile than non-dollar pairs.

**Key variables.** With these assumptions in place, the mapping from the model to the data is straightforward. For every currency pair $k$ and every point in time $t$, I estimate fundamental trading demand $flow_{k,t}$ as the sum of customer buy and sell order volume measured in US dollars. Ideally, I would use the difference between buy and sell volume, which is commonly referred to as order flow. However, the CLS order flow data does not include any dealer-to-dealer trades, whereas inter-dealer volume is unsigned by definition. Thus, regressing inter-dealer volume on customer order flow rather than aggregate customer order volume (i.e., $flow_{k,t}$) would likely downward bias the regression coefficient due to the netting effect. CLS order flow data are available hourly, which enables proxying the variance of fundamental trading demands $var(flow)_{k,t}$ as the intraday realised variance of $flow_{k,t}$. Next, to measure the relative riskiness $volatility_{k,t}$ of every currency pair, I compute the daily realised variance $rv_{k,t}$ as the sum of squared intraday midquote returns (Barndorff-Nielsen and Shephard, 2002).

Table 1 summarises the key properties of hourly inter-dealer volume, customer flows, realised volatility, and relative bid-ask spreads for 15 non-dollar and 10 dollar currency pairs, respectively. Each row corresponds to the time series average of the variable except for the row headed "Volatility of customer flow in \$mn," which is the standard deviation of hourly customer flows across the full sample. The summary statistics table conveys three key messages: First, both inter-dealer and customer flows are heavily concentrated in five dollar currency pairs (i.e.,

[23] CLS maps all FX activity as a network. It classifies banks as either price takers or market-makers based on their trading behaviour. Transactions between two market-makers and two price takers are excluded by CLS so as to avoid double counting. Importantly, trades between price takers and market-maker banks are not excluded.

USDEUR, USDJPY, USDGBP, USDCAD, and USDAUD). Specifically, customer flows are on average 7 times higher in dollar pairs (532 $mn on average) than non-dollar pairs (73 $mn on average). Second, dollar and non-dollar currency pairs have similar risk characteristics. The average realised volatility is just about 0.5 BPS higher in dollar pairs (10.8 BPS on average) than non-dollar pairs (10.3 BPS on average). Third, relative bid-ask spreads are just marginally higher in non-dollar pairs (3.9 BPS on average) than dollar pairs (3.7 BPS on average). On the one hand, this deepens the puzzle about the concentration of trading volume in dollar pairs, but on the other provides evidence in favour of the notion that price impact rather than bid-ask spreads are the primary cost of trading.

**Table 1: Summary Statistics**

| | AUDJPY | AUDNZD | CADJPY | EURAUD | EURCAD |
|---|---|---|---|---|---|
| Dealer volume in $mn | 116.09 | 52.41 | 14.29 | 75.48 | 41.98 |
| Customer flow in $mn | 62.54 | 40.00 | 12.24 | 58.58 | 33.55 |
| Volatility of customer flow in $mn | 66.45 | 53.42 | 22.47 | 72.87 | 53.00 |
| Realized volatility in BPS | 14.35 | 9.33 | 12.65 | 11.54 | 10.13 |
| Relative bid-ask spread in BPS | 4.15 | 4.46 | 4.30 | 3.55 | 3.56 |
| | EURCHF | EURDKK | EURGBP | EURJPY | EURNOK |
| Dealer volume in $mn | 236.38 | 50.26 | 387.78 | 440.96 | 150.91 |
| Customer flow in $mn | 130.15 | 38.43 | 213.15 | 200.97 | 88.98 |
| Volatility of customer flow in $mn | 203.95 | 78.01 | 293.25 | 243.53 | 135.04 |
| Realized volatility in BPS | 6.37 | 1.83 | 9.51 | 11.40 | 11.05 |
| Relative bid-ask spread in BPS | 2.63 | 2.55 | 3.20 | 3.15 | 6.29 |
| | EURSEK | GBPAUD | GBPCAD | GBPCHF | GBPJPY |
| Dealer volume in $mn | 168.36 | 24.81 | 14.14 | 14.62 | 121.06 |
| Customer flow in $mn | 98.61 | 19.65 | 12.57 | 11.51 | 73.67 |
| Volatility of customer flow in $mn | 147.73 | 29.14 | 29.75 | 24.18 | 89.31 |
| Realized volatility in BPS | 9.20 | 12.51 | 10.83 | 10.67 | 12.75 |
| Relative bid-ask spread in BPS | 5.45 | 4.24 | 4.02 | 4.11 | 3.86 |
| | USDAUD | USDCAD | USDCHF | USDDKK | USDEUR |
| Dealer volume in $mn | 1092.58 | 1135.14 | 393.68 | 21.46 | 4142.23 |
| Customer flow in $mn | 476.42 | 644.59 | 217.25 | 7.47 | 1943.28 |
| Volatility of customer flow in $mn | 449.93 | 761.88 | 834.97 | 29.52 | 2196.16 |
| Realized volatility in BPS | 12.08 | 8.69 | 9.61 | 9.20 | 9.16 |
| Relative bid-ask spread in BPS | 3.34 | 2.69 | 3.12 | 3.00 | 2.30 |
| | USDGBP | USDJPY | USDNOK | USDNZD | USDSEK |
| Dealer volume in $mn | 1310.70 | 2403.16 | 62.99 | 280.04 | 70.21 |
| Customer flow in $mn | 690.60 | 1098.54 | 45.61 | 138.67 | 55.06 |
| Volatility of customer flow in $mn | 805.40 | 1049.86 | 78.79 | 143.28 | 89.16 |
| Realized volatility in BPS | 9.61 | 9.59 | 13.88 | 13.02 | 12.78 |
| Relative bid-ask spread in BPS | 2.66 | 2.53 | 7.15 | 4.11 | 6.16 |

*Note*: This table reports summary statistics for hourly inter-dealer volume, customer flow, realised volatility, and relative bid-ask spread for 15 non-dollar and 10 dollar currency pairs, respectively. Each row corresponds to the time series average of the variable except for the row headed "Volatility of customer flow in $mn," which is the standard deviation of hourly customer flows across the full sample. The sample is balanced (54292 hourly observations per currency pair) and covers the period from 1 September 2012 to 29 September 2020.

**Volume elasticity.** To empirically test the drivers of inter-dealer trading volume $volume_{k,t}$ I consider the following panel regression with fixed effects:

$$volume_{k,t} = \mu_t + \alpha_k + \beta' \mathbf{f}_{k,t} + \gamma' \mathbf{w}_{k,t} + \epsilon_{k,t}, \tag{10}$$

where $\mu_t$ are time series fixed effects, $\alpha_k$ denotes currency pair fixed effects, and $\mathbf{f}_{k,t}$ may include customer trading demands $flow_{k,t}$, variance of customer trading demands $var(flow)_{k,t}$, and realised variance $volatility_{k,t}$ as regressors. In some specifications, I also include the relative bid-ask spread $\textit{bid-ask spread}_{k,t}$, interest rate differential $\textit{interest rate}_{k,t}$, and cross-currency basis $\textit{cip-basis}_{k,t}$ as control variables in $\mathbf{w}_{k,t}$. Note that all three controls are given in absolute values because trading volume by definition is unsigned.

I construct these three control variables as follows: First, I compute the relative bid-ask spread as the ratio of the absolute bid-ask spread and midquote (average of bid and ask rates). Second, I approximate the daily interest rate differential between the base and quote currency country by the forward discount or premium, which I compute as the difference between the overnight forward rate $f_t$ and the spot midquote $s_t$.[24] Third, following Du et al. (2018), I estimate the cross-currency basis as the difference between the direct dollar interest rate in the base currency from the cash market and the synthetic interest rate obtained by swapping the quote currency into the base currency.[25]

The rationale for including each of these three variables as controls can be summarised in three points. First, the role of the relative bid-ask spread as a control is to address the concern that traditional transaction costs are an important determinant of trading volume. Second, the link between interest rate differentials and FX trading volume stems from the fact that carry trade speculators are long (*short*) in high (*low*) interest rate currencies (Lustig and Verdelhan, 2007). Hence, currency pairs exhibiting a larger interest rate differential in absolute terms are more likely to end up in the long or short leg of carry trade portfolios. Put differently, interest rate differentials aim to capture speculative trading motives as a potential driver of FX trading activity. Lastly, since the decentralised FX market heavily relies on intermediation by dealers, I expect dealer funding costs to significantly covary with dealer-intermediated volume. Following Andersen et al. (2019) and Rime et al. (2021), the cross-currency basis can be interpreted as a proxy for dealer funding costs.

The equilibrium expression for optimal trading volume in Eq. (5) is *linear* because traders' demand schedules are assumed to be linear in the exogenous determinants of the model (e.g., fundamental trading demands). However, any cross-sectional heterogeneity in fundamental trading demands is amplified by low-price-impact currency pairs frequently being used for vehicle currency trading. To take this into account, I allow for multiplicative effects across the key regressor in $\mathbf{f}_{k,t}$ by including interaction terms in some of the regression specifications. Moreover, to mitigate multicollinearity, I orthogonalise $flow_{k,t}$ against $var(flow)_{k,t}$ and $volatility_{k,t}$ when jointly including all three drivers as regressors.

[24] I obtain overnight forward points from Bloomberg using London closing rates.

[25] Daily LIBOR and interbank fixing rates are also obtained from Bloomberg.

Across all specifications, both dependent and independent variables are taken in logs and first differences. FX volume in levels is non-stationary and persistent, hence taking first differences is an effective remedy to render the time series stationary. In addition, I divide each time series by the standard deviation of the respective variable across all currency pairs. Thus, regression coefficients can be interpreted as percentage point (pp) changes measured in units of standard deviation. Notice that standardising changes neither the sign nor the significance of the regression estimates.

The frequency of these regressions is daily, hence preventing well-known intraday seasonalities (e.g., Ranaldo, 2009; Breedon and Ranaldo, 2013) from affecting my estimations. Robust standard errors are computed based on Driscoll and Kraay (1998), allowing for random clustering and serial correlation up to 7 lags. Optimal lag length is based on Newey and West's (1994) plug-in procedure for automatic lag selection.

Table 2 presents the results of running various specifications of Eq. (10) and provides strong empirical evidence in line with the comparative statics in Theorem 1: Changes in inter-dealer trading volume $volume_{k,t}$ positively covary with changes in customer trading demands $flow_{k,t}$, variance of customer trading demands $var(flow)_{k,t}$, and with realised variance of currency returns $volatility_{k,t}$. In light of the theory in Section 3, the latter result is intuitive as volatility carries information about dispersion in fundamental trading demands (i.e., investor disagreement), which induce trading volume.[26] This finding is particularly useful given that the sign of volume elasticity with respect to volatility is theoretically ambiguous.

In my model, trading volume is determined by fundamental trading demands on the one hand and vehicle currency trading due to strategic avoidance of price impact on the other. Specifically, the expected price impact in a currency pair hinges on the variance of trading demands and currency returns, respectively. The regression results in Table 2 show that fundamental customer trading demands $flow_{k,t}$ are the most important determinant of inter-dealer volume accounting for 33% of all the time series variation. Contrarily, changes in the realised variance of customer trading demands $var(flow)_{k,t}$ and currency returns $volatility_{k,t}$ account for 22% and 8% of the dispersion in inter-dealer volume. The fact that $var(flow)_{k,t}$ and $volatility_{k,t}$ are both economically and statistically significant provides compelling evidence in favour of the decentralised market model in Section 3 rather than a competitive or centralised market (see Proposition 1). This is because both variables stress the importance of vehicle currency trading motives stemming from strategic avoidance of price impact besides actual customer trading demands as a key driver of FX inter-dealer volume.

All regression results in Table 2 are qualitatively unchanged when including interaction terms besides the main effects (columns 7 and 8). Both interaction effects are statistically highly significant and similar in terms of economic magnitude. The regression coefficient on volatility is 0.04–0.05 standard deviations higher during periods of high volatility combined with large or more volatile fundamental trading demands. This result corroborates the idea

[26] This result is also consistent with the mixture-of-distribution hypothesis theory developed by Clark (1973) and by Tauchen and Pitts (1983).

that the multiplicative effect embedded in the model is also present in the data.

The three control variables are both economically and statistically significant across various specifications. Note that I neither include interest rate differentials $interest\,rate_{k,t}$ nor cross-currency bases $cip\text{-}basis_{k,t}$ in the same specification because they are by construction correlated. Three observations deserve to be highlighted: First, inter-dealer volume and relative bid-ask spreads $bid\text{-}ask\ spread_{k,t}$ are negatively correlated, which is consistent with theories of inventory and order processing costs (e.g., Glosten and Harris, 1988; Huang and Stoll, 1997). Second, the sign of the coefficient on interest rate differentials is negative (i.e., "the wrong sign"), suggesting that, on aggregate, investors might not be taking advantage of the increased efficacy of the carry trade. Third, the sign of the cross-currency basis is also negative, which I interpret as evidence that dealer funding costs play a significant role in determining dealer-intermediated FX trading volume.

**Price impact elasticity.** In my model, price impact is the key endogenous determinant of trading volume. The dimensions of price impact hinge on two model–based primitives: i) the variance of fundamental trading demands and ii) the variance of currency returns. Empirically, I am interested in whether price impact is driven purely by the relative riskiness of currency returns or to some extent also by the distribution of fundamental trading demands. To test this, I run the following panel regression with fixed effects:

$$\lambda_{k,t} = \mu_t + \alpha_k + \beta' \mathbf{f}_{k,t} + \epsilon_{k,t}, \tag{11}$$

where $\mu_t$ are time series fixed effects, $\alpha_k$ denotes currency pair fixed effects, and $\mathbf{f}_{k,t}$ may include the variance of customer trading demands $var(flow)_{k,t}$ and the realised variance of currency returns $volatility_{k,t}$ as regressors alongside the relative bid-ask spread $bid\text{-}ask\,spread_{k,t}$ as a control variable for transaction costs. The dependent variable is the Amihud price impact $\lambda_{k,t}$ in currency pair $k$ at time $t$ (Amihud, 2002). Following Ranaldo and Santucci de Magistris (2018), I estimate Amihud as the ratio between intraday realised volatility and aggregate daily trading volume.[27] Both dependent and independent variables are taken in logs and first differences and are measured in units of standard deviations.

Table 3 shows the results of estimating different variants of the panel regression set-up in Eq. (11). Three main results are worth highlighting: First, an increase in the variance of fundamental trading demands $var(flow)_{k,t}$ is associated with a decrease in price impact. This is consistent with the observation that the inference coefficient in my model (see Section 3) decreases in the variance of trading demands. Second, price impact positively covaries with the variance of currency returns $volatility_{k,t}$. Conceptually, this agrees with my model, where

[27] Note that my empirical results are robust to using alternative price impact measures including Kyle (1985), Hasbrouck (1991b), and Gabaix et al. (2006). The key advantage of the classic Amihud price impact measure is that unlike Kyle's (1985) lambda it does not require order flow data and is always positive by construction. On the other hand, the impulse response functions in Hasbrouck (1991b) are forward looking but sensitive to the forecast horizon. Gabaix et al. (2006) is identical to Kyle (1985) but assumes that prices react to large signed orders with a change proportional to the square root of the order size.

**Table 2: Economic Drivers of Trading Volume**

| | $\text{volume}_{k,t}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\text{flow}_{k,t}$ | ***0.58 | | | ***0.57 | | ***0.12 | ***0.53 | |
| | [44.85] | | | [43.13] | | [26.25] | [33.41] | |
| $\text{var(flow)}_{k,t}$ | | ***0.43 | | | ***0.38 | ***0.27 | | ***0.41 |
| | | [50.83] | | | [36.49] | [18.21] | | [47.16] |
| $\text{volatility}_{k,t}$ | | | ***0.30 | | ***0.20 | ***0.51 | ***0.16 | ***0.20 |
| | | | [28.13] | | [20.00] | [47.07] | [16.44] | [24.47] |
| $\text{bid-ask spread}_{k,t}$ | | | | ***−0.07 | ***−0.04 | **−0.01 | ***−0.06 | ***−0.05 |
| | | | | [11.36] | [4.57] | [2.34] | [6.04] | [6.81] |
| abs(interest $\text{rate}_{k,t}$) | | | | **−0.01 | | 0.00 | | ***−0.01 |
| | | | | [2.13] | | [1.42] | | [2.85] |
| abs(cip-$\text{basis}_{k,t}$) | | | | | ***−0.02 | | **−0.01 | |
| | | | | | [2.65] | | [2.07] | |
| $\text{flow}\times\text{volatility}_{k,t}$ | | | | | | | ***0.04 | |
| | | | | | | | [4.06] | |
| $\text{var(flow)}\times\text{volatility}_{k,t}$ | | | | | | | | ***0.05 |
| | | | | | | | | [6.53] |
| Adj. $R^2$ in % | 33.07 | 22.42 | 7.92 | 33.14 | 24.15 | 34.99 | 32.62 | 25.67 |
| Avg. #Time periods | 2069 | 2069 | 2069 | 2068 | 2065 | 2068 | 2065 | 2068 |
| #Exchange rates | 25 | 25 | 25 | 25 | 25 | 25 | 25 | 25 |
| Currency FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Time series FE | yes | yes | yes | yes | yes | yes | yes | yes |

*Note*: This table reports results from daily fixed effects panel regressions of the form $volume_{k,t} = \mu_t + \alpha_k + \beta' \mathbf{f}_{k,t} + \gamma' \mathbf{w}_{k,t} + \epsilon_{k,t}$, where $\mathbf{f}_{k,t}$ may include several regressors and $\mathbf{w}_{k,t}$ collects all control variables. The dependent variable is the daily inter-bank trading volume $volume_{k,t}$ measured in US dollars. $\mu_t$ and $\alpha_k$ denote time series and currency pair fixed effects, respectively. $flow_{k,t}$ is the aggregate daily customer order flow (buy plus sell volume) measured in US dollars. $var(flow)_{k,t}$ is the daily variance of hourly customer flows. $volatility_{k,t}$ is the daily realised variance of currency returns computed from one minute spot rates. $\textit{bid-ask spread}_{k,t}$ is the daily average relative bid-ask spread. $\textit{interest rate}_{k,t}$ is the interest rate differential computed as the difference between the overnight forward rate $f_t$ and the spot midquote $s_t$. $\textit{cip-basis}_{k,t}$ is the cross-currency basis following the methodology in Du et al. (2018). Both dependent and independent variables are taken in logs and first differences. The sample covers the period from 1 September 2012 to 29 September 2020. The test statistics based on Driscoll and Kraay's (1998) robust standard errors allowing for random clustering and serial correlation up to 7 lags are reported in brackets. The optimal lag length is based on Newey and West's (1994) plug-in procedure. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels.

Gaussian conditioning explains why price impact is concave in the variance of currency returns. Third, all findings are robust to including the relative bid-ask spread $\textit{bid-ask spread}_{k,t}$ as a control variable for general trading costs in columns 3, 4, and 6.

**Summary.** Two important findings emerge from this analysis: First, vehicle currency trading motives are almost equally important determinants of inter-dealer FX trading volume as customer trading demands. Second, price impact is contingent on both the relative riskiness of currency pairs and the distribution of fundamental trading demands. Taken together, the evidence in this section fully supports the decentralised market model in Section 3.

**Table 3: Economic Drivers of Price Impact**

| | $\lambda_{\rm k,t}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\text{var(flow)}_{\rm k,t}$ | ***−0.03 | | ***−0.04 | | ***−0.06 | ***−0.06 |
| | [5.01] | | [6.71] | | [10.55] | [10.30] |
| $\text{volatility}_{\rm k,t}$ | | ***0.14 | | ***0.17 | ***0.16 | ***0.19 |
| | | [19.74] | | [20.25] | [21.41] | [21.71] |
| $\text{bid-ask spread}_{\rm k,t}$ | | | ***0.08 | ***−0.05 | | ***−0.05 |
| | | | [8.15] | [5.23] | | [4.87] |
| Adj. $R^2$ in % | 0.02 | 1.21 | 0.28 | 1.29 | 1.49 | 1.55 |
| Avg. #Time periods | 2069 | 2069 | 2069 | 2069 | 2069 | 2069 |
| #Exchange rates | 25 | 25 | 25 | 25 | 25 | 25 |
| Currency FE | yes | yes | yes | yes | yes | yes |
| Time series FE | yes | yes | yes | yes | yes | yes |

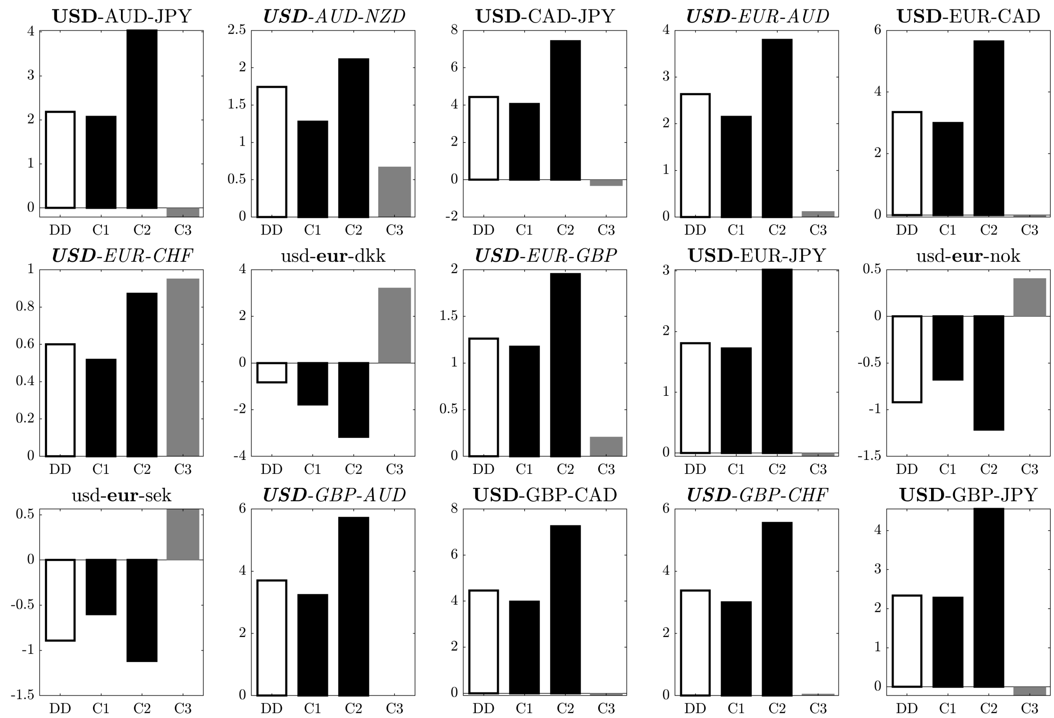
*Note*: This table reports results from daily fixed effects panel regressions of the form $\lambda_{k,t} = \mu_t + \alpha_k + \beta' \mathbf{f}_{k,t} + \epsilon_{k,t}$, where $\mathbf{f}_{k,t}$ may include several regressors. The dependent variable is the Amihud (2002) price impact $\lambda_{k,t}$ in currency pair $k$ at time $t$. $\mu_t$ and $\alpha_k$ denote time series and currency pair fixed effects, respectively. $var(flow)_{k,t}$ is the intraday realised variance of hourly customer flows. $volatility_{k,t}$ is the intraday realised variance of currency returns computed from one minute spot rates. $bid\text{-}ask\ spread_{k,t}$ is the daily average relative bid-ask spread. All variables are taken in logs and first differences and I standardise each time series, that is, divide by the standard deviation of the respective variable across all currency pairs. The sample covers the period from 1 September 2012 to 29 September 2020. The test statistics based on Driscoll and Kraay's (1998) robust standard errors are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels.

## 4.3. Evidence of Dollar Dominance

What follows provides empirical evidence of dollar dominance that is consistent with the economic intuition of my model. Theoretically, a triplet of currency pairs (e.g., GBPJPY, USDGBP, and USDJPY) will be dominated by the dollar if at least one of the following three conditions is satisfied, while the other two remain equal: US dollar currency pairs exhibit i) larger average fundamental trading demands, ii) more volatile fundamental trading demands, or iii) less volatile currency returns than non-dollar currency pairs. The intuition for these conditions stems directly from the comparative statics of trading volume in Theorem 1. In sum, this section has three goals: First, to derive empirical counterparts for dollar dominance as well as each of the three equilibrium conditions. Second, to test if the conditions for dollar dominance can correctly predict the observed currency dominance across triplets of currency pairs. Lastly, to pin down the relative importance of the three conditions for explaining the time- and cross-sectional variation in dollar dominance.

**Equilibrium conditions.** Figure 3 summarises the empirical counterparts of the three equilibrium conditions. I plot four bars for every triplet of currency pairs. The first bar from the left (i.e, $DD$) corresponds to the time series average of my empirical measure of dollar dominance: A positive figure implies dollar dominance, whereas a negative one disproves such dominance. The three other bars (i.e, $C1$, $C2$, and $C3$) each represent the time series average for one of the conditions in Theorem 2. To derive an empirical measure of dollar dominance $DD$, I proceed in three steps: First, I focus on triplets of currency pairs (e.g., GBPJPY, USDGBP, and USDJPY). Second, at every point in time and for each currency pair triplet I compute the ratio of the minimum inter-dealer trading volume in dollar currency pairs (e.g., USDGBP and USDJPY) relative to direct trading in the non-dollar pair (e.g., GBPJPY). Third, I take the natural log of these ratios to support the interpretation as percentage differences. Thus, $DD$ captures the degree of dollar dominance (i.e., intensive margin) within every currency pair triplet and point in time rather than just the binary outcome of whether the dollar dominates or not (i.e., extensive margin). I proceed analogously for the three equilibrium conditions (i.e., $C1$, $C2$, and $C3$) based on fundamental customer trading demand $flow_{k,t}$, the volatility of customer trading demands $std(flow_{k,t})$, and the realised volatility $\sqrt{rv}_{k,t}$ of currency returns. Note that for the realised volatility of currency returns I compute the maximum across two dollar currency pairs. This is because the third condition implies that less volatile currency pairs exhibit lower price impacts and thus more trading volume.

**Figure 3: Equilibrium Conditions: Empirical Evidence**




*Note*: This figure shows the time series average of the empirical counterparts of the equilibrium conditions in Theorem 2 for 15 triplets of currency pairs. A triplet is defined as one non-dollar currency pair (e.g., GBPJPY) plus the two USD legs (e.g., USDGBP and USDJPY). The first bar (i.e., $DD$) corresponds to my empirical measure of dollar dominance: A positive figure implies dollar dominance, whereas a negative one disproves such dominance. The other three bars (i.e., $C1$, $C2$, and $C3$) each represent one of the conditions in Theorem 2. For each currency pair triplet the dominant currency is highlighted in **boldface** within the header, which indicates whether a triplet is in the region of dollar dominance (title in upper case), multiplicity (title in *italics*) or non-dollar dominance (title in lower case). The sample covers the period from 1 September 2012 to 29 September 2020.

Next, I compare my estimates of dollar dominance and the three equilibrium conditions focusing on two null hypotheses: First, dollar dominance $DD$ is equal to the first condition $C1$, implying that the inter-dealer market is Walrasian in the sense that dealers simply pass through what customers want to trade. Clearly, this would mean that there is no scope for vehicle currency trading. Second, conditions $C2$ and $C3$ are equal to zero, which would refute price impact being a relevant determinant of vehicle currency trading. The inference is based on Newey and West's (1994) covariance matrix with a bandwidth of 7 lags.

Two results stand out from this analysis: First, in line with the evidence shown in Figure 3, for 13 out of 15 triplets, $DD$ is significantly larger than $C1$.[28] Second, the conditions $C2$ and $C3$ both significantly differ from zero for all 15 triplets of currency pairs except USD-GBP-AUD. Therefore, I find circumstantial evidence that FX dealers in the inter-bank market strategically avoid transacting directly in illiquid non-dollar currency pairs by using the US dollar as an intermediate vehicle currency. Another way to see this is by comparing the ratio of inter-dealer trading volume to customer trading demand (i.e., $flow_{k,t}$) across dollar and non-dollar currency pairs, respectively. On average, this ratio is significantly higher by 25.7% for dollar currency pairs than non-dollar pairs ($t$-statistic of 27.4 based on Driscoll and Kraay's (1998) standard errors). Moreover, the economic significance of the second and third condition further supports the idea that cross-sectional heterogeneity in price impact can explain the concentration of trading volume in dollar currency pairs.

**Classification.** Based on the empirical estimates of dollar dominance $DD$, and on the three conditions $C1$, $C2$, and $C3$, I classify the 15 currency pair triplets in Figure 3 into three regions: i) dollar dominance (title in upper case), ii) multiplicity (title in italics), and iii) non-dollar dominance (title in lower case). First, a triplet of currency pairs lies in the region of dollar dominance if all three conditions are jointly satisfied. Second, the region of multiplicity characterises triplets for which only one or two out of three conditions are satisfied while the remainder creates a counterbalance. This supports the idea that the status-quo of dollar dominance can potentially be scrutinised in triplets currently within the region of multiplicity. Lastly, currency pair triplets lie in the region of non-dollar dominance (i.e., euro dominance) if all three conditions (see Theorem 2) are violated in the data.

Following this classification, 12 out of 15 triplets of currency pairs lie either in the region of multiplicity or in that of dollar dominance. Six currency pair triplets lie in the region of multiplicity because the third condition (i.e., $C3$) for realised volatility is not satisfied. Nevertheless, these triplets are still dominated by the dollar (i.e., positive $DD$). This is consistent with the evidence in Table 2, which implies that the volatility of currency returns is the least important determinant of trading volume. On the contrary, the first two conditions (i.e., $C1$ and $C2$) with respect to the mean and variance of customer trading demands are empirically "necessary" for dollar dominance. This insight stems from the observation that there is no evidence of dollar dominance unless these two conditions jointly hold.

In my sample, only the USD-EUR-DKK, USD-EUR-NOK, and USD-EUR-SEK triplets are *not* dominated by the dollar in terms of FX trading volume. This finding is also consistent

[28] To save space, I relegate the test statistics for both hypothesis tests to Table 6 in the Online Appendix.

with the idea that certain geographical regions adopt regionally dominant vehicle currencies for intra-regional trade (Devereux and Shi, 2013). Based on the evidence in Figure 3, the euro seems to enjoy regional dominance as a vehicle currency for exchanging Scandinavian currencies against the US dollar. In particular, the large trading volume in EURDKK relative to that in USDDKK is a potential artefact of Danmarks Nationalbank's fixed FX rate policy against the euro. In my model, the necessary open market operations for maintaining the peg directly influence the distribution of customer trading demands in the EURDKK.

**Relative importance.** Following the evidence in Figure 3, not all three conditions are equally important determinants of dollar dominance in FX trading. In particular, one might wonder about the relative importance of $C1$, which is based on fundamental trading demands, relative to $C2$ and $C3$, that foster vehicle currency trading due to strategic avoidance of price impact. To estimate the relative importance of each condition, I run the following panel regression with time series $\mu_t$ and currency pair triplet $\alpha_j$ fixed effects:

$$DD_{j,t} = \mu_t + \alpha_j + \beta_1 C1_{j,t} + \beta_2 C2_{j,t} + \beta_3 C3_{j,t} + \gamma' \mathbf{w}_{j,t} + \epsilon_{j,t}, \tag{12}$$

where the dependent variable $DD_{j,t}$ is my time-varying empirical measure of dollar dominance that is either based on trading volume (i.e., $doldom_{j,t}$) or on Amihud's (2002) price impact (i.e., $amihud_{j,t}$).[29] Section Appendix D in the Online Appendix documents the time- and cross-sectional variation in $doldom_{j,t}$ and $amihud_{j,t}$, respectively, for $j = 1, 2, ..., 15$ triplets of currency pairs. I define $amihud_{j,t}$ as the maximum Amihud price impact across two dollar currency pairs (e.g., USDGBP and USDJPY) relative to the price impact in the non-dollar pair (e.g., GBPJPY) within the same triplet. Thus, dollar currency pairs exhibit a lower price impact than non-dollar currency pairs if $amihud_{j,t}$ is less than one. In some specifications, I also add the average relative bid-ask spread $\textit{bid-ask spread}_{j,t}$ and cross-currency basis $\textit{cip-basis}_{j,t}$ across two dollar currency pairs as control variables in $\mathbf{w}_{j,t}$ to account for market and funding liquidity in dollar pairs. Both dependent and independent variables are taken in logs and first differences since dollar dominance and the three conditions are persistent in levels. Moreover, I divide each variable by its standard deviation across all triplets of currency pairs.

Following the intuition of my model, I conjecture that dollar dominance based on trading volume $doldom_{j,t}$ correlates positively with $C1$ and $C2$, whereas the effect of $C3$ is theoretically ambiguous. On the contrary, dollar dominance based on price impact $amihud_{j,t}$ is presumably negatively related to $C2$ but positively to $C3$. Hence, if $C2$ is greater than one, whereas $C3$ is smaller than one, then dollar currency pairs feature a lower expected price impact than non-dollar pairs. Table 4 provides evidence that is in line with my model and hence fully concurs with a market (micro)structure view of dollar dominance. To mitigate multicollinearity, I orthogonalise $C1$ against $C2$ and $C3$ in column 6 where I jointly include all three conditions

[29] Estimating Eq. (12) does not aim to identify the direction of causality as dollar dominance and the three conditions are all equilibrium outcomes. Section Appendix D in the Online Appendix aims to mitigate endogeneity issues by following Gabaix and Koijen (2020) to identify quasi-exogenous spikes in the equilibrium conditions.

as regressors. The inference is based on Driscoll and Kraay's (1998) robust covariance matrix with a bandwidth of 7 lags (Newey and West's (1994) plug-in procedure).

There are four takeaways from Table 4 with respect to the relative importance of the three conditions: First, as expected, condition $C1$ is the most important determinant of dollar dominance in trading volume and accounts on average for 20% of the time series variation in $doldom_{j,t}$. Second, changes in conditions $C2$ and $C3$ jointly account for 13% of the dispersion in $doldom_{j,t}$. Third, condition $C3$ individually explains less than 1% of the variation in both $doldom_{j,t}$ and $amihud_{j,t}$, respectively. Lastly, dollar dominance based on the Amihud price impact $amihud_{j,t}$ covaries significantly negatively (*positively*) with $C2$ ($C3$), albeit the explanatory power of the regression models in columns 7-9 is less than 1%.

**Table 4: Dollar Dominance and Equilibrium Conditions**

| | $\text{doldom}_{\text{j,t}}$ | | | | | | $\text{amihud}_{\text{j,t}}$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\text{C1}_{\text{j,t}}$ | ***0.46 | | | ***0.46 | | ***0.61 | | | |
| | [36.28] | | | [36.04] | | [21.55] | | | |
| $\text{C2}_{\text{j,t}}$ | | ***0.35 | | | ***0.35 | ***0.36 | ***−0.04 | | ***−0.05 |
| | | [35.58] | | | [35.46] | [33.00] | [4.76] | | [4.66] |
| $\text{C3}_{\text{j,t}}$ | | | ***0.06 | | ***0.04 | ***0.04 | | ***0.09 | ***0.09 |
| | | | [5.30] | | [3.80] | [3.40] | | [6.83] | [6.51] |
| bid-ask $\text{spread}_{\text{j,t}}$ | | | | ***−0.06 | ***−0.09 | ***−0.04 | | | 0.02 |
| | | | | [4.03] | [5.89] | [2.77] | | | [0.73] |
| $\text{cip-basis}_{\text{j,t}}$ | | | | | | 0.02 | | | *−0.03 |
| | | | | | | [1.22] | | | [1.94] |
| Adj. $R^2$ in % | 20.22 | 12.68 | 0.23 | 20.29 | 12.99 | 20.36 | 0.14 | 0.52 | 0.74 |
| Avg. #Time periods | 2069 | 2069 | 2069 | 2069 | 2069 | 2015 | 2069 | 2069 | 2015 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| Time series FE | yes | yes | yes | yes | yes | yes | yes | yes | yes |

*Note*: This table reports results from daily fixed effects panel regressions of the form $DD_{j,t} = \mu_t + \alpha_j + \beta_1 C1_{j,t} + \beta_2 C2_{j,t} + \beta_3 C3_{j,t} + \gamma' \mathbf{w}_{j,t} + \epsilon_{j,t}$, where $\mu_t$ and $\alpha_j$ denote time series and currency pair triplet fixed effects. The dependent variable $DD_{j,t}$ is a measure of dollar dominance that is either based on trading volume (i.e., $doldom_{j,t}$) or on Amihud's (2002) price impact (i.e., $amihud_{j,t}$). $C1$, $C2$, and $C3$ are the empirical counterparts of the three equilibrium conditions in Theorem 2. $\textit{bid-ask spread}_{j,t}$ is the daily average relative bid-ask spread. $\textit{cip-basis}_{j,t}$ is the (absolute) cross-currency basis following the methodology in Du et al. (2018). These control variables in $\mathbf{w}_{j,t}$ are computed separately within every currency pair triplet as the average across two dollar pairs. Both dependent and independent variables are taken in logs and first differences. The sample covers the period from 1 September 2012 to 29 September 2020. The test statistics based on Driscoll and Kraay's (1998) robust standard errors allowing for random clustering and serial correlation are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels.

**Robustness.** What follows summarises two additional robustness checks that support my empirical findings. Section Appendix D in the Online Appendix documents these additional analyses. First, to guard against the possibility that my results are driven by seasonalities I follow Fischer and Ranaldo (2011) and filter the deterministic effect by including the lagged dependent variable as a regressor. The regression results are robust to adding this additional control variable. Second, I use Cespa et al.'s (2021) approach to first de-trend trading volume and second to divide today's volume in each currency pair by a moving average over the previous

22 days' volume: $volume_{k,t}/(\frac{1}{22}\sum_{m=1}^{22} volume_{k,t-m})$. All results remain qualitatively unchanged when computing $doldom_{j,t}$ based on de-trended rather than actual volume.

**Summary.** This section provides evidence that dollar dominance in FX trading is tightly linked to the model–based equilibrium conditions. There are three novel insights to be highlighted: First, the predictions of my model and the data are fully consistent in that I observe dollar or euro dominance in currency pair triplets where the model predicts this but not otherwise. Second, the two conditions for fundamental trading demands (i.e., $C1$ and $C2$) are empirically not only sufficient but also necessary, whereas the third condition on the variance of currency returns (i.e., $C3$) does not seem to play a pivotal role for dollar dominance. Lastly, the first condition (i.e., $C1$) explains around 20% of the time-variation in dollar dominance, whereas the second and third condition (i.e., $C2$ and $C3$) jointly account for up to 13%.

## 4.4. Evidence of Vehicle Currency Trading

In this section, I use a novel identification method based on non-overlapping holidays to disentangle trading volume in dollar currency pairs due to fundamental trading motives from vehicle currency demands. To be specific, I leverage the quasi-exogenous variation in non-overlapping holidays as an identification tool for fundamental trading demands in dollar currency pairs. The intuition is as follows: consider, for instance, the case where Australia is on holiday but neither Japan nor the United States are (e.g., ANZAC Day on 25 April). On such a day, inter-dealer trading volume in USDJPY is presumably mainly driven by fundamental demand for USDJPY rather than vehicle currency trading motives arising from the need to exchange Australian dollars against Japanese yen. This is because the number of market participants who wish to indirectly exchange Australian dollars to Japanese yen via the US dollar is heavily reduced due to the public holiday in Australia. Eventually, my proxy for vehicle currency trading is the difference between inter-dealer trading volume and my implied measure of fundamental demand based on non-overlapping holidays.[30]

To come up with an estimate of vehicle currency trading volume in dollar currency pairs I conduct an event study by running the following regression:

$$volume_{k,t} = \mu_t + \alpha_k + \sum_{m=M^-}^{M^+} \beta_m D_{k,m} + \epsilon_{k,t}, \tag{13}$$

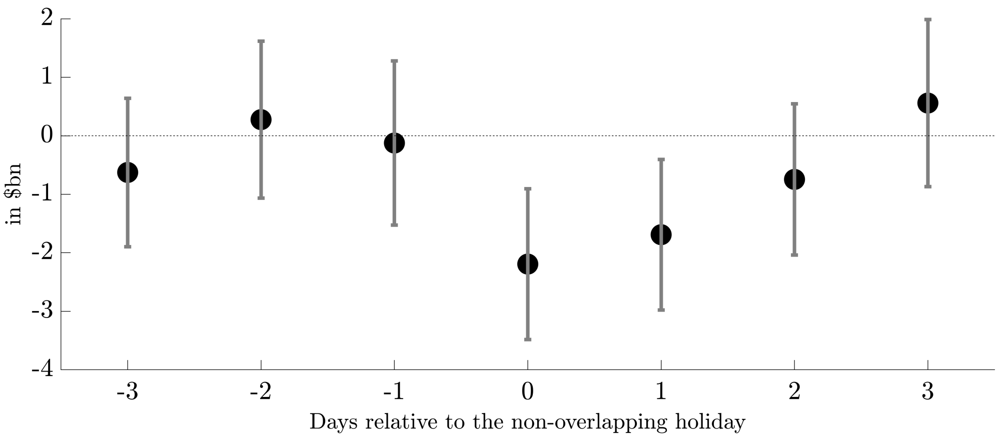
where the dependent variable is inter-dealer trading volume in dollar currency pair $k$ on day $t$. $\mu_t$ are time series fixed effects and $\alpha_k$ denotes currency pair fixed effects that control for any unobserved variation that is either constant across currency pairs or over time. The main regressor is $D_{k,m}$, which is an indicator variable equal to 1 $m$ days before and after there is a non-overlapping holiday on day $t$ and is 0 otherwise. The key parameters of interest (the $\beta$'s) are identified from how trading volume in dollar currency pairs changes before and after

[30] Non-overlapping holidays do not constitute a random experiment. Figure 13 in the Online Appendix provides evidence that the parallel trend assumption seems to hold for eight out of ten dollar currency pairs.

a non-overlapping holiday. Note that the number of non-overlapping holidays is different for each triplet of currency pairs and thus $D_{k,m}$ depends on which currency pair triplets the dollar currency pair $k$ is involved in.

Figure 4 shows that trading volume in dollar pairs is on average 2.3 \$bn lower on non-overlapping holidays than on all other days. Note that the average daily inter-dealer trading volume in dollar currency pairs is 24.2 \$bn. Put differently, on average at least 9.5% of the volume in dollar currency pairs on days that are *not* non-overlapping holidays are due to vehicle currency trading activity. This is a highly conservative estimate because a particular non-overlapping holiday can only capture vehicle currency trading motives in one specific triplet. For instance, on ANZAC Day it is plausible to assume that vehicle trading demand for USDJPY stemming from the need to exchange Australian dollars against Japanese yen is close to zero. However, this cannot control for the use of USDJPY as a vehicle currency to indirectly trade any other Japanese yen currency pair (e.g., CADJPY or GBPJPY).

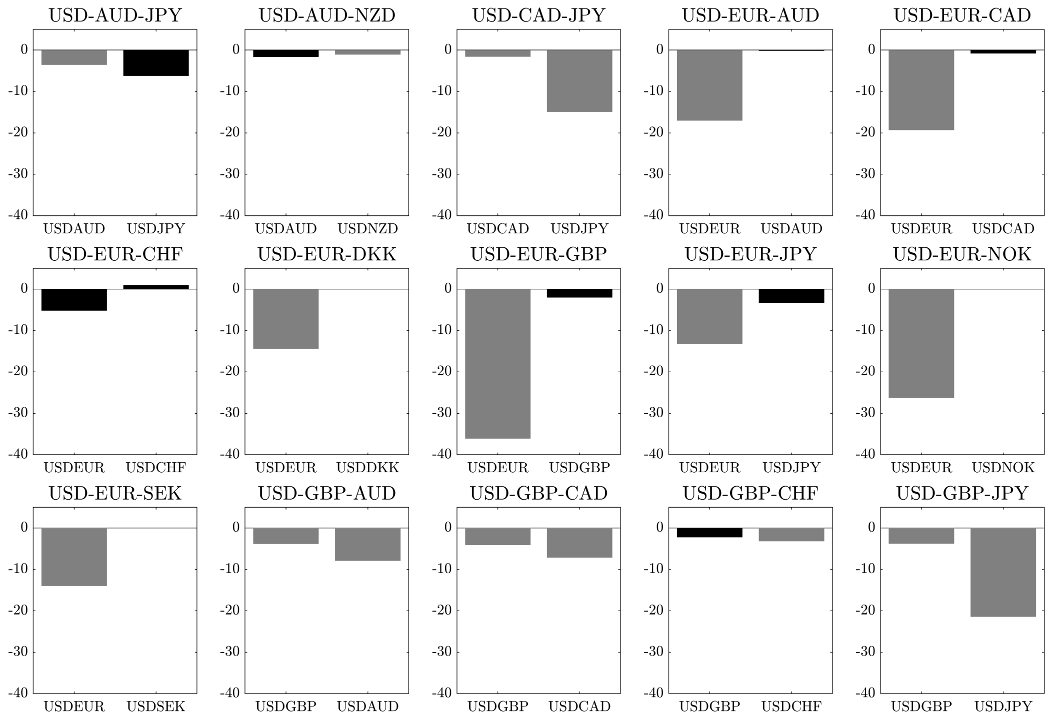
**Figure 4: Event Study: Evidence of Vehicle Currency Trading**




*Note*: This figure shows the $\beta_m$ estimates and the 95% confidence intervals of the event study regression of the form $volume_{k,t} = \mu_t + \alpha_k + \sum_{m=M^-}^{M^+} \beta_m D_{k,m} + \epsilon_{k,t}$ for 3 days before and after a non-overlapping holiday. $D_{k,m}$ is an indicator variable equal to 1 $m$ days before/after there is a non-overlapping holiday on day $t$. Each $\beta_m$ estimates by how much trading volume in dollar currency pairs differs $m$ days before/after a non-overlapping holiday relative to all other days. Standard errors are based on Driscoll and Kraay (1998) allowing for random clustering and serial correlation up to 7 lags following Newey and West's (1994) plug-in procedure. The sample covers the period from 1 September 2012 to 29 September 2020.

Figure 5 further illustrates the aforementioned caveat by showing estimates for the case $\beta$=$\beta_0$ separately for 15 triplets of currency pairs. The grey (*black*) bars correspond to significant (*insignificant*) coefficients at the 95% confidence level. For example, average vehicle trading volume in USDJPY amounts to almost 20 \$bn per day when estimated based on the USD-GBP-JPY currency pair triplet. On the contrary, vehicle trading volume in USDJPY is less than 5 \$bn when estimated from the USD-AUD-JPY currency pair triplet. Therefore, the event study regression above most probably underestimates the actual amount of vehicle currency trading volume since it averages across non-overlapping holidays based on different triplets of currency pairs. Note that my estimates for vehicle currency trading volume in USDDKK, USDNOK, and USDSEK are effectively zero. This is consistent with the empirical evidence for the equilibrium conditions suggesting that directly exchanging one of these three Nordic currencies against the euro is optimal in terms of expected price impact.

**Figure 5: Evidence of Vehicle Currency Trading in Dollar Currency Pairs**




*Note*: This figure shows individual estimates for $\beta{=}\beta_0$ in \$bn separately for 15 triplets of currency pairs from the regression $volume_t = \alpha + \beta D_t + \epsilon_t$, where $D_t$ is an indicator variable equal to 1 if day $t$ is a non-overlapping holiday in the given currency triplet. The grey (*black*) bars correspond to significant (*insignificant*) coefficients at the 5% level. The inference is based on robust standard errors allowing for heteroskedasticity and serial correlation up to 7 lags (Newey and West, 1994). The sample covers the period from 1 September 2012 to 29 September 2020.

Table 5 provides a detailed breakdown of my estimates of trading volume due to fundamental versus vehicle currency trading motives across 10 dollar currency pairs. The table is based on Figure 5 and reports the average, minimum, and maximum share of vehicle currency trading volume across currency pair triplets involving the same dollar currency pair (e.g., USDAUD). The last row headed "Mean" reports the volume weighted average fundamental and vehicle currency trading activity across dollar currency pairs.

There are three key takeaways from Table 5: First, the amount of vehicle currency trading is largest in the USDEUR, USDJPY, and USDCHF currency pairs ranging from 36–40%. Second, trading volume in USDDKK, USDNOK, and USDSEK is predominantly driven by fundamental trading motives resulting in zero estimates of vehicle currency trading demands. Third, the volume weighted average share of vehicle currency trading ranges from 5–33% suggesting that vehicle currency motives account for a significant share of inter-dealer trading activity. It is worth emphasising that even the 33% is still a conservative estimate that most likely underestimates the actual amount of vehicle currency trading volume in dollar pairs. This is because each non-overlapping holiday can only control for vehicle currency demands stemming from one particular non-dollar currency pair (e.g., AUDJPY).

**Table 5: Evidence of Vehicle Currency Trading in Dollar Currency Pairs**

| | Average | | | Minimum | | Maximum | |
|---|---|---|---|---|---|---|---|
| | non-VCT in $bn | VCT in $bn | VCT in % | VCT in $bn | VCT in % | VCT in $bn | VCT in % |
| USDAUD | 20.17 | 2.95 | 12.77 | 0.18 | 0.76 | 7.92 | 34.26 |
| USDCAD | 23.48 | 1.96 | 7.72 | 0.82 | 3.23 | 7.15 | 28.08 |
| USDCHF | 7.69 | 1.19 | 13.42 | 0.00 | 0.00 | 3.20 | 36.06 |
| USDDKK | 0.45 | 0.06 | 11.63 | 0.06 | 11.63 | 0.06 | 11.63 |
| USDEUR | 76.17 | 13.08 | 14.66 | 5.23 | 5.86 | 36.13 | 40.48 |
| USDGBP | 26.91 | 3.17 | 10.53 | 2.05 | 6.82 | 4.14 | 13.75 |
| USDJPY | 50.02 | 7.80 | 13.49 | 3.35 | 5.79 | 21.45 | 37.11 |
| USDNOK | 1.45 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| USDNZD | 5.46 | 1.10 | 16.80 | 1.10 | 16.80 | 1.10 | 16.80 |
| USDSEK | 1.62 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Mean | 47.23 | 7.46 | 12.71 | 3.04 | 5.19 | 20.12 | 32.96 |

*Note*: This table reports the breakdown of trading volume due to fundamental (non-VCT) versus vehicle currency trading (VCT) activity across 10 dollar currency pairs. These numbers are based on estimates of $\beta=\beta_0$ from the regression $volume_t = \alpha + \beta D_t + \epsilon_t$, where $D_t$ is an indicator variable equal to 1 if day $t$ is a non-overlapping holiday and is 0 otherwise. Note that if $\hat{\beta}$ is positive, that is, there is no evidence of VCT, I report zero in columns 3-8. The last row headed "Mean" shows the volume weighted average non-VCT and VCT trading activity across dollar currency pairs. The sample covers the period from 1 September 2012 to 29 September 2020.

**Summary.** The goal of this section is to supply direct evidence of vehicle currency trading activity in the FX market. For this, I exploit the quasi-exogenous variation in vehicle currency trading demands for dollar currency pairs associated with non-overlapping holidays. Using an event study regression design, I show that vehicle currency trading activity can account for up to 33% of aggregate daily inter-dealer trading volume in dollar pairs.

## 5. Conclusion and Policy Implications

This paper has studied the origins of dollar dominance in FX trading and contributes both theoretically and empirically to the existing literature. On the theory side, I propose a simple model that demonstrates how strategic avoidance of price impact can lead to dollar dominance in FX trading volume. The key economic insight of my model are three equilibrium conditions for dollar dominance that are capable of predicting which non-dollar currency pairs are more likely to trade indirectly via the US dollar.

On the empirical side, I apply my model to the data and document three novel empirical facts that corroborate my theoretical framework. First, I estimate the model in reduced form and find compelling empirical evidence that the three primitives of my model (i.e., the mean and variance of fundamental trading demands as well as the variance of currency returns) are also empirically relevant determinants of FX trading volume. Second, I confront the model–based conditions for dollar dominance with the data and find that they correctly predict the dollar as well as euro dominance observed in the data. Lastly, I use non-overlapping holidays as a novel identification tool to disentangle trading volume due to fundamental trading motives from vehicle currency demands.

My paper should be relevant for academics and policymakers alike. For academics, it provides a tractable theoretical framework for studying the emergence of a dominant currency. The key innovation of my model is that it bridges the gap between market-size (e.g., Krugman, 1980; Rey, 2001) and information-based theories (i.e., Lyons and Moore, 2009) of vehicle currency trading. A promising avenue for future research would be to explore the welfare consequences of dollar dominance. Demand submission games are particularly well-suited to welfare analysis since they do not rely on the presence of noise traders or not-fully-optimising traders (Rostek and Yoon, 2021b). For example, one might ask how the potential costs and benefits of being the dominant international currency are distributed between the hegemon (i.e., the United States) and the rest of the world.

For monetary policy analysis, my findings suggest that currency dominance depends on three factors: the mean and variance of fundamental trading demands as well as the variance of exchange rate returns. Thus, ousting the US dollar from its current dominant role would require a central bank or policymaker to influence at least one of these three levers. For instance, sterilised and non-sterilised currency interventions may directly affect both the size and variability of fundamental trading demands in currency pairs involving the domestic currency. Depending on the nature of these interventions, they may or may not dampen exchange rate fluctuations. To this end, pegging the domestic currency (e.g., the Chinese renminbi) against a basket of internationally dominant currencies may seem like a viable approach. However, it remains to be shown whether this establishes an international currency in its own right or merely mirrors existing ones.

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# Appendix A. Contingent Demands

In this section, I derive the optimal price and allocation with *contingent* demand schedules and contrast the equilibrium properties with the results derived in Section 3 for the *uncontingent* case.[31] Every trader $i$ submits their demand schedule $\mathbf{q}^{i,c}(\cdot)$ contingent on the exchange rates $\mathbf{p}$ of all other currency pairs in the economy. Within the context of contingent demand schedules it is convenient to approach the optimisation problem from the perspective of a (large) individual trader who optimises against the residual market $\mathbf{q}_k^j(\cdot)$, $\forall j \neq i$. The sufficient statistic for residual market supply is given by trader $i$'s own residual supply function $S_k^{-i} = -\sum_{j\neq i} q_k^j(\cdot)$ for all $k$, which is defined by aggregation and market clearing of other traders' demand schedules.[32]

Since maximising the expected payoff in Eq. (2) is identical to maximising the *ex-post* payoff pointwise for each currency pair $k$:

$$max_{q_k^i(\cdot)} \boldsymbol{\delta} \cdot (\mathbf{q}^{i,c} + \mathbf{q}_0^i) - \frac{\gamma^i}{2}(\mathbf{q}^{i,c} + \mathbf{q}_0^i) \cdot \boldsymbol{\Sigma}(\mathbf{q}^{i,c} + \mathbf{q}_0^i) - \mathbf{p} \cdot \mathbf{q}^{i,c}, \tag{14}$$

given trader $i$'s demand for other currency pairs $q_l^{i,c}$, $\forall l \neq k$ and the residual supply function $\mathbf{S}^{-i,c}$ for all currency pairs, which must be correct in equilibrium, that is, $\mathbf{S}^{-i,c}(\cdot) = -\sum_{j\neq i} \mathbf{q}^{j,c}(\cdot)$. This equivalence follows directly from the fact that the demand for each currency pair is measurable with respect to $\{\mathbf{p}, \mathbf{q}_0^i\}$ and as the price distribution has full support.

Pointwise optimisation of Eq. (14) creates an equilibrium characterisation in terms of two simple conditions that I derive in two simple steps. First, I take the first-order condition with respect to the demand for each currency pair $q_k^{i,c}$: for each $k$

$$\underbrace{\delta_k - \gamma^i(\sigma_{k,k}(q_k^{i,c} + q_{0,k}^i) + \sum_{l\neq k} \sigma_{k,l}(q_l^{i,c} + q_{0,l}^i))}_{\text{Marginal utility}} = \underbrace{p_k + \frac{\partial p_k}{\partial q_k^{i,c}} q_k^{i,c} + \sum_{l\neq k} \frac{\partial p_l}{\partial q_k^{i,c}} q_l^{i,c}}_{\text{Marginal cost}}. \tag{15}$$

Assuming that the best-responses of all other traders $j \neq i$ are linear it must hold that the price impact across currency pairs $\frac{\partial p_l}{\partial q_k^{i,c}} \equiv \lambda_{k,l}^{i,c}$ is a scalar for each $k$, $l$, and $i$. Rewriting the first-order condition in matrix form yields:

$$\boldsymbol{\delta} - \gamma^i \boldsymbol{\Sigma}(\mathbf{q}^{i,c} + \mathbf{q}_0^i) = \mathbf{p} + \boldsymbol{\Lambda}^{i,c}\mathbf{q}^{i,c}, \tag{16}$$

where $\boldsymbol{\Lambda}^{i,c} = \frac{\partial \mathbf{p}}{\partial \mathbf{q}_k^{i,c}}$ is a $K \times K$ Jacobian matrix characterising the price impact of trader $i$. The off-diagonal elements in $\boldsymbol{\Lambda}^{i,c}$ define the change in exchange rate $l$ following a demand change in currency pair $k$ by trader $i$. Re-arranging the first order condition in Eq. (16) yields the best-response demand of trader $i$:

$$\mathbf{q}^{i,c}(\mathbf{p}) = (\gamma^i \boldsymbol{\Sigma} + \boldsymbol{\Lambda}^{i,c})^{-1}(\boldsymbol{\delta} - \mathbf{p} - \gamma^i \boldsymbol{\Sigma} \mathbf{q}_0^i), \tag{17}$$

given their price impact $\boldsymbol{\Lambda}^{i,c}$, which is a sufficient statistic for trader $i$'s residual supply.

Second, I endogenise price impact by exploiting the fact that the price impact in the point-wise optimisation problem of trader $i$ must be correct in equilibrium. Put differently, the price impact must

[31] The derivations in this section are closely following Rostek and Yoon (2021a).

[32] The idea of considering the optimisation problem of an individual trader against their residual market dates back to the seminal work of Klemperer and Meyer (1989) and Kyle (1989). Rostek and Weretka (2015) show that there is equivalence between optimisation in demand schedules and pointwise optimisation in terms of the fixed point in price impacts. See Malamud and Rostek (2017) for an equilibrium characterisation of contingent demands with heterogeneous risk aversions.

be equal to the $K \times K$ Jacobian matrix of the inverse residual supply function of trader $i$. Applying market clearing conditions to the best-response demands in Eq. (17) for traders $j \neq i$ yields the residual supply function $\mathbf{S}^{-i,c}(\cdot)$ of trader $i$:

$$\mathbf{S}^{-i,c} = -\sum_{j\neq i}(\gamma^j \boldsymbol{\Sigma} + \boldsymbol{\Lambda}^{j,c})^{-1}(\boldsymbol{\delta} - \gamma^j \boldsymbol{\Sigma}\mathbf{q}_0^j) + \sum_{j\neq i}(\gamma^i \boldsymbol{\Sigma} + \boldsymbol{\Lambda}^{j,c})^{-1}\mathbf{p}, \tag{18}$$

where the price impact of trader $i$ is the transpose of the Jacobian of $(\mathbf{S}^{-i,c}(\cdot))^{-1}$, $\boldsymbol{\Lambda}^{i,c} \equiv \left(\frac{\partial p_l}{\partial q_k^{i,c}}\right)_{k,l} = \left(\left(\frac{\partial \mathbf{S}^{-i,c}(\cdot)}{\partial \mathbf{p}}\right)^{-1}\right)'$. The characterisation based on demand schedules is equivalent to traders optimising given their assumed price impact, which has to be correct in equilibrium.

**Theorem 3** (**Equilibrium: Contingent Trading**). *A profile of net demand schedules $\mathbf{q}^{i,c}$ is a linear Bayesian Nash equilibrium if and only if, for every trader i,*

1. *(Optimisations, given price impact) Demand schedules $\mathbf{q}^{i,c}(\cdot)$ are determined by pointwise equalisation of marginal utility and marginal payment in Eq.* (16)*, given their price impact $\boldsymbol{\Lambda}^{i,c}$;*
2. *(Correct price impact) The price impact of trader i equals the transpose of the Jacobian matrix of their inverse residual supply function:*

$$\boldsymbol{\Lambda}^{i,c} = ((\sum_{j\neq i}(\gamma^j \boldsymbol{\Sigma} + \boldsymbol{\Lambda}^{j,c})^{-1})^{-1})' \tag{19}$$

With contingent demands the fixed point for price impact matrices is defined by a system of $I$ equations in Eq. (19) and can be solved in closed form: for each trader $i$

$$\boldsymbol{\Lambda}^{i,c} = \beta^{i,c}\gamma^i \boldsymbol{\Sigma}, \tag{20}$$

where $\beta^{i,c} = \frac{2-\gamma^i b+\sqrt{(\gamma^i b)^2+4}}{2\gamma^i b}$ is the solution to the following quadratic equation:

$$\sum_j (\gamma_i b + 2 + \sqrt{(\gamma^j b)^2 + 4})^{-1} = 1/2. \tag{21}$$

For the case where risk aversions are symmetric, that is, $\gamma^i = \gamma,\ \forall i$ the price impact is simply proportional to fundamental risk: $\boldsymbol{\Lambda}^{i,c} = \frac{1}{I-2}\boldsymbol{\Sigma}$. As $I \to \infty$, then $\boldsymbol{\Lambda}^{i,c} \to 0$ for all $i$. Hence, the competitive limit case coincides with the inverse marginal utility, given the quasilinearity of the payoff function. With a positive price impact (i.e., $\boldsymbol{\Lambda}^{i,c} > 0$), trader $i$ demands (or sells) less than their competitive schedule.

Combining Eqs (17) and (20) yields the following expressions for demand coefficients $\mathbf{B}^c$, $\mathbf{C}^c$, and price impact $\boldsymbol{\Lambda}^c$, respectively:

$$\mathbf{B}^c = (\boldsymbol{\Sigma} + \boldsymbol{\Lambda}^c)^{-1}\boldsymbol{\Sigma} = \frac{I-2}{I-1} Id; \tag{22}$$

$$\mathbf{C}^c = (\boldsymbol{\Sigma} + \boldsymbol{\Lambda}^c)^{-1}; \tag{23}$$

$$\boldsymbol{\Lambda}^c = \frac{1}{I-2}\boldsymbol{\Sigma}, \tag{24}$$

where $Id$ is a $K \times K$ identity matrix. Contrarily to the uncontingent market, traders' demand coefficient $\mathbf{B}^c$, $\mathbf{C}^c$, and price impact $\boldsymbol{\Lambda}^c$ are independent of the *distribution* of traders' initial transaction demands, that is, $\sigma_0^2$ and $\boldsymbol{\Omega}$, respectively. What is more, in the contingent market, where $\mathbf{p} = \boldsymbol{\delta} - \gamma \boldsymbol{\Sigma}\bar{\mathbf{q}}_0$, the second moment of the distribution of equilibrium price $Var(\mathbf{p})$ is independent of the distribution of initial transaction demands and only depends on the *exogenous* covariance matrix $\mathbf{\Sigma}$. Thus, the equilibrium trading volume is: for each trader $i$

$$\mathbf{q}^{i,c,*} = (\mathbf{\Sigma} + \mathbf{\Lambda}^c)^{-1}\mathbf{\Sigma}(E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i]). \tag{25}$$

There are three properties of the contingent market that do *not* hold when traders submit uncontingent demand schedules. First, the price impact of every trader is proportional to the fundamental covariance matrix of currency returns $\mathbf{\Sigma}$ (see Eq. (19)). Rostek and Yoon (2021a) show that this proportionality has implications for market functioning that do not hold with limited demand conditioning. Second, a trader's own price impact $\mathbf{\Lambda}^c$ is a sufficient statistic for the residual supply function in the best-response problem. This holds due to the one-to-one mapping between the contingent variable (i.e., price vector $\mathbf{p}$) and the residual supply's intercept (i.e., the vector $s^{-i} \equiv -\sum_{j\neq i}(\gamma^j\mathbf{\Sigma} + \mathbf{\Lambda}^{j,c})^{-1}(\boldsymbol{\delta} - \gamma^j\mathbf{\Sigma}\mathbf{q}_0^j))$ for all currency pairs. Third, the equilibrium is *ex-post* given the one-to-one mapping described in the previous point.

# Appendix B. Uncontingent Demands

The purpose of this section is threefold: First, provide a detailed step-by-step derivation of the equilibrium exchange rate in Eq. (3) and quantity in Eq. (5) along the lines of Rostek and Yoon (2021a). Second, outline the partial equilibrium model that I use as a benchmark in Proposition 1. Third, collect the proofs of Theorems 1 and 2.

## Appendix B.1. Equilibrium

Every trader $i$ submits their *uncontingent* demand schedules $q_k^i$ simultaneously across $N = K$ exchanges, each for one currency pair, maximising their expected payoff for each $k$:

$$max_{q_k^i(\cdot)} E[\boldsymbol{\delta} \cdot (\mathbf{q}^i + \mathbf{q}_0^i) - \frac{\gamma^i}{2}(\mathbf{q}^i + \mathbf{q}_0^i) \cdot \mathbf{\Sigma}(\mathbf{q}^i + \mathbf{q}_0^i) - \mathbf{p} \cdot \mathbf{q}^i | p_k, q_0^i], \tag{26}$$

subject to their residual supply function $S_l^i(\cdot) \equiv -\sum_{j\neq i} q_l^j(\cdot)$ for all currency pairs and their demand for other currency pairs $q_{l\neq k}^i(\cdot)$. The trader's objective function is very similar to the case where all markets clear jointly, except that the demand for currency pair $k$ is contingent on both the exchange rate $p_k$ and initial transaction demands $q_0^i$.

Each trader maximises their expected payoff pointwise for each currency pair with respect to $p_k$ and given their demand for other currency pairs $q_l^i(\cdot)$. The first order condition is given by the following expression:

$$\delta_k - \gamma^i\mathbf{\Sigma}_n\mathbf{q}_{0,l}^i - \gamma^i\mathbf{\Sigma}_n \underbrace{E[\mathbf{q}^i|\mathbf{p}_n, \mathbf{q}_0^i]}_{\substack{\text{Expected trade of}\\ \text{currency pairs } l}} = \mathbf{p}_n + \underbrace{\mathbf{\Lambda}_n^i}_{\substack{\text{Zero cross-exchange}\\ \text{price impact}}}\mathbf{q}_n^i, \tag{27}$$

where the left hand side (LHS) is the *expected* marginal utility for trading currency pair $k$ and the right hand side (RHS) is the marginal cost (i.e., exchange rate $\mathbf{p}_n$ plus price impact $\mathbf{\Lambda}_n^i\mathbf{q}_n^i$ per unit of trade). The price impact $\mathbf{\Lambda}_n^i\mathbf{q}_k^i$ of every trader $i$ in exchange $n$ is a $K \times K$ Jacobian matrix that is constant in a linear equilibrium.[33] Moreover, the *cross-exchange* price impact is zero: $\lambda^i_{k,l} \equiv \frac{\partial p_k}{\partial q^i_k} = 0$ for all $p_{l \neq k}$. This is because with uncontingent demand schedules exchanges clear independently rather than jointly. As a result, the price impact matrices of all traders are diagonal matrices:

$$\Lambda^i \equiv \frac{\partial p_l}{\partial q^i_k} = diag(\lambda^i_k). \tag{28}$$

However, even if the cross-exchange price impact is zero, equilibrium outcomes of exchange rates and quantities are not independent across venues unless all currency pairs' payoffs are independent (i.e., $\sigma_{k,l} = 0,\ \forall l \neq k$). Thus, equilibrium in *uncontingent* markets can be characterised by two conditions: for each trader $i$

1. their demands are a best response, given $i$'s residual supply;
2. their residual supply function is correct.

The equilibrium characterisation is more challenging compared to the contingent market since the requirements for *ex post* optimisation are not met. That is, the best response quantities cannot be solved pointwise with respect to the exchange rate vector $\mathbf{p}$ since expected trade $E[q^i_l|p_k, q^i_0]$ depends on the functional form of $q^i_l(\cdot)$. Given that the best-response demands are not *ex post* and depend on the distribution of the conditioning variable $\mathbf{p}$, the price impact $\mathbf{\Lambda}^i$ itself is *not* a sufficient statistic for a trader's residual supply. More generally, the price impact between any two currency pairs depends on the covariance matrix of returns for all currency pairs. The solution to this predicament involves two steps:

1. endogenise all demand coefficients and conditional expectations $E[q^i_l|p_k, q^i_0]$ (step 1);
2. replace $p_k$ as a contingent variable by trader $i$'s residual supply intercept $s^{-i}_k$ (step 2).

The chief advantage of *step 2* is that unlike the distribution of $p_k$, that of $s^{-i}_k$ is only determined by the demand schedules of traders $j \neq i$ and is thus exogenous to the best-response problem of trader $i$.

To parametrise a trader's best-response schedules as a fixed point among the trader's demand coefficients I conjecture that trader $i$'s best response for currency pair $l \neq k$ is a linear function of $p_l$ and $\mathbf{q}^i_0$:

$$q^i_l(p_l) \equiv a^i_l - \mathbf{b}^i_l \mathbf{q}^i_0 - c^i_l p_l, \qquad \forall l \neq k \tag{29}$$

where $a^i_l$ is the demand intercept, $\mathbf{b}^i_l \mathbf{q}^i_0$ the demand coefficients, and $c^i_l$ the demand slope on $p_l$. To recap, parametrising the best-response demands for currency pairs $l \neq k$ and changing the contingent variable from $p_k$ to $s^{-i}_k$ gives me the license to fully endogenise expected trades in the demand for currency pair $k$. Thus, the fixed point problem for best-response schedules $q^i_k(\cdot)$ has been transformed to one for demand coefficients, given residual supplies. Rostek and Yoon (2021a) rigorously prove that the equilibrium fixed point in demand schedules is equivalent to a fixed point in price impact matrices.

For the ease of exposition, I assume that all traders have identical risk preferences (i.e., $\gamma^i = \gamma,\ \forall i$). This ensures that the best response fixed point has a unique solution and that equilibrium quantity and price impact do not depend on risk aversion $\gamma$. In order to derive the optimal exchange rates and quantities, I apply market clearing conditions to the best response schedules $q^{j \neq i}_k$ for each $k$:

$$S^{-i}_k(p_k) = -\sum_{j \neq i}(a^j_k - \mathbf{b}^j_k \mathbf{q}^j_0) + \sum_{j \neq i} c^j_k p_k = s^{-i}_k + \frac{p_k}{(\lambda^i_k)}, \tag{30}$$

[33] Rostek and Yoon (2021a) provide a rigorous proof that the equilibrium is unique for the case where $K = 2$ and indeed linear if traders' conjectured best responses are linear in price and quantity.

where $s_k^{-i}$ is the residual supply intercept and $(\lambda_k^i)^{-1}$ the slope coefficient. To derive the equilibrium exchange rate the total residual supply $S_k^{-i}(p_k)$ must be zero, otherwise markets do not clear. This allows me to derive $p_k$ as a function of demand coefficients $\mathbf{a}^i = a_k^i$, $\mathbf{B}^i = \mathbf{b}_k^i$, and $\mathbf{C}^i = diag(c_k^i)$:

$$\mathbf{p}^* = (\sum_i a^i - \sum_i B^i q_0^i) \cdot (\sum_i C^i)^{-1}. \tag{31}$$

**Theorem 4 (Equilibrium: Fixed Point in Demand Schedules).** *Consider a market with $N = K$ exchanges. In a sub-game perfect Nash equilibrium, the (net) demand schedules are defined by the following (matrix) coefficients $\mathbf{a}^i$, $\mathbf{B}$, and $\mathbf{C}$, as well as price impact $\mathbf{\Lambda} = \mathbf{\Lambda}^i$: for each trader i,*

1. *(Optimisation, given price impact) Given price impact matrices $\mathbf{\Lambda}$, net demand coefficients $\mathbf{a}^i$, $\mathbf{B}$, and $\mathbf{C}$ are characterised by:*

$$\mathbf{a}^i = \underbrace{\mathbf{C}(\boldsymbol{\delta} - (\gamma\mathbf{\Sigma} - \mathbf{C}^{-1}\boldsymbol{B})E[\bar{\mathbf{q}}_0]))}_{=\mathbf{p}-\mathbf{C}^{-1}\mathbf{B}\bar{\mathbf{q}}_0} + \underbrace{((\gamma\mathbf{\Sigma} + \mathbf{\Lambda})^{-1}\gamma\mathbf{\Sigma} - \mathbf{B})(E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i])}_{\textit{Adjustment due to cross-asset inference}}; \tag{32}$$

$$\mathbf{B} = \big((1-\sigma_0^2)(\gamma\mathbf{\Sigma} + \mathbf{\Lambda}) + \underbrace{\mathbf{C}^{-1}\sigma_0^2}_{\substack{\textit{Adjustment due to}\\ \textit{cross-asset inference}}}\big)^{-1}\gamma\mathbf{\Sigma}; \tag{33}$$

$$\mathbf{C} = \Big[(\mathbf{\Sigma} + \mathbf{\Lambda})\underbrace{(\mathbf{B\Omega B}')[\mathbf{B\Omega B}']_d^{-1}}_{\textit{Inference coefficient}}\Big]_d^{-1}, \tag{34}$$

*where $[\cdot]_d$ is an operator such that for any matrix $M$, $[M]_d$ is a diagonal matrix with all off-diagonal elements equal to zero, $\bar{\mathbf{q}}_0 \equiv \frac{1}{I}\sum_I \bar{\mathbf{q}}_0^j$ is the average initial trading demand across traders, $\sigma_0^2 \equiv \frac{\sigma_{cv}^2 + \frac{1}{I}\sigma_{pv}^2}{\sigma_{cv}^2 + \sigma_{pv}^2}$, and $\Omega = Cov(q_{0,k}^i, q_{0,l}^i)$ is a positive semi-definite covariance matrix of initial trading demands.*

2. *(Correct price impact) The parametric solutions to $\mathbf{a}^i$, $\mathbf{B}$, and $\mathbf{C}$ are based on the work by Rostek and Weretka (2015) and Rostek and Yoon (2021a) and imply that the price impact $\mathbf{\Lambda}$ is characterised by the slope of the inverse residual supply function:*

$$\mathbf{\Lambda} = \frac{1}{I-1}\mathbf{C}^{-1} = \frac{1}{I-2}\Big[\mathbf{\Sigma}\underbrace{(\mathbf{B\Omega B}')\big[\mathbf{B\Omega B}'\big]_d^{-1}}_{\textit{Inference coefficient}}\Big]_d, \tag{35}$$

*where $\mathbf{\Lambda}$ is a diagonal matrix because the cross-exchange price impact $\Lambda_{k,l}$ is zero since uncontingent demand schedules imply that exchanges clear independently.*

Building on Theorem 4 and plugging the demand intercept $\mathbf{a}^i$ into Eq. (31) yields the equilibrium exchange rate:

$$\mathbf{p}^* = \Big(\sum_i \mathbf{C}(\boldsymbol{\delta} - (\gamma\mathbf{\Sigma} - (\mathbf{C}^i)^{-1}\mathbf{B}^i)E[\bar{\mathbf{q}}_0])) - \sum_i \mathbf{B}^i q_0^i\Big) \cdot (\sum_i C^i)^{-1} \tag{36}$$

$$\mathbf{p}^* = \big(\boldsymbol{\delta} - (\gamma\mathbf{\Sigma} - (\mathbf{C})^{-1}\mathbf{B})E[\bar{\mathbf{q}}_0]\big) - \mathbf{C}^{-1}\mathbf{B}\bar{\mathbf{q}}_0 \tag{37}$$

Notice that $\sum_i \mathbf{a}^i = \sum_i \mathbf{C}(\boldsymbol{\delta} - (\gamma\mathbf{\Sigma} - \mathbf{C}^{-1}\mathbf{B})E[\bar{\mathbf{q}}_0]))$, since $((\gamma\mathbf{\Sigma} + \mathbf{\Lambda})^{-1}\gamma\mathbf{\Sigma} - \mathbf{B})\sum_i(E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i])$ is zero. In contrast to the contingent market, the second moment $Var(p)$ of the distribution of equilibrium prices depends on the distribution of initial transaction demands (through the endogenous demand coefficients $\mathbf{B}$ and $\mathbf{C}^{-1}$) rather than just on fundamental risk $\mathbf{\Sigma}$. Specifically, the price covariance of any two currency pairs depends on the second moment of the joint distribution of *all* currency pairs. Substituting exchange rate $\mathbf{p}^*$ and demand coefficient $\mathbf{a}^i$ into traders' parametrised demand function Eq. (29) yields the equilibrium quantity: for every $i$,

$$\mathbf{q}^{i,*} =((\mathbf{\Sigma}+\mathbf{\Lambda})^{-1}\mathbf{\Sigma}-\mathbf{B})(E[\bar{\mathbf{q}}_0]-E[\mathbf{q}_0^i])+\mathbf{B}(\bar{\mathbf{q}}_0-\mathbf{q}_0^i), \tag{38}$$

and adding $\mathbf{q}_0^i$ to both sides as well as collecting terms yields

$$\mathbf{q}^{i,*}+\mathbf{q}_0^i =((\mathbf{\Sigma}+\mathbf{\Lambda})^{-1}\mathbf{\Sigma}-\mathbf{B})(E[\bar{\mathbf{q}}_0]-E[\mathbf{q}_0^i])+\mathbf{B}\bar{\mathbf{q}}_0+(Id-\mathbf{B})\mathbf{q}_0^i, \tag{39}$$

where $Id$ is the identity matrix. Given $\mathbf{q}^{i,*}$ it is only optimal to trade a non-zero amount if and only if there is dispersion in traders' initial transaction demands, that is, if $E[\bar{\mathbf{q}}_0]-E[\mathbf{q}_0^i]\neq 0$ and $\bar{\mathbf{q}}_0-\mathbf{q}_0^i\neq 0$. Trader $i$'s distance to the average transaction demand $\bar{\mathbf{q}}_0$ determines whether she is a net-buyer or net-seller of the quote currency. Intuitively, net-buyers have initial transaction demands below the average (i.e., $\bar{q}_{0,k}>q_{0,k}^i$), whereas the opposite is true for net-sellers (i.e., $\bar{q}_{0,k}<q_{0,k}^i$).

## Appendix B.2. Simulation Exercise

To illustrate the equilibrium dynamics, I simulate the model for a simple market setting with $I$=15 market participants trading $K$=3 currency pairs (e.g., USDGBP, USDJPY, and GBPJPY). Trader $i$ has identical initial trading demands in each currency pair, that is, $\mathbf{q}_0^i=[100,100,100]^\top$ \$mn. For simplicity's sake, I set the average initial trading demand $\bar{\mathbf{q}}_0\equiv\frac{1}{I}\sum_{j=1}^{I}\bar{\mathbf{q}}_0^j$ equal to zero and hence $|\bar{\mathbf{q}}_0-\mathbf{q}_0^i|=\mathbf{q}_0^i$. Note that to facilitate comparison, I convert both initial trading demand $\mathbf{q}_0^i$ and equilibrium volume $\mathbf{q}^{i,*}$ into US dollars (\$) irrespective of the base and quote currency.[34]

To avoid ambiguity, I make two assumptions about the covariance matrix of initial trading demands $\mathbf{\Omega}$ and currency returns $\mathbf{\Sigma}$, respectively. First, the on-diagonal elements of $\mathbf{\Omega}$ and $\mathbf{\Sigma}$ are identical and equal to 50 and 0.2, respectively. Second, the off-diagonal elements of $\mathbf{\Omega}$ and $\mathbf{\Sigma}$ are also identical and equal to 17.5 and 0.19, respectively. Hence, while both covariance matrices are positive definite, I rule out the effect of heterogeneous covariance terms on equilibrium trading volume. Note that this simulation exercise takes into account that price impact $\mathbf{\Lambda}$, demand coefficients $\mathbf{B}$ and $\mathbf{C}^{-1}$, and trading volume $\mathbf{q}^{i,*}$ are endogenous and hence they must be determined simultaneously in equilibrium.

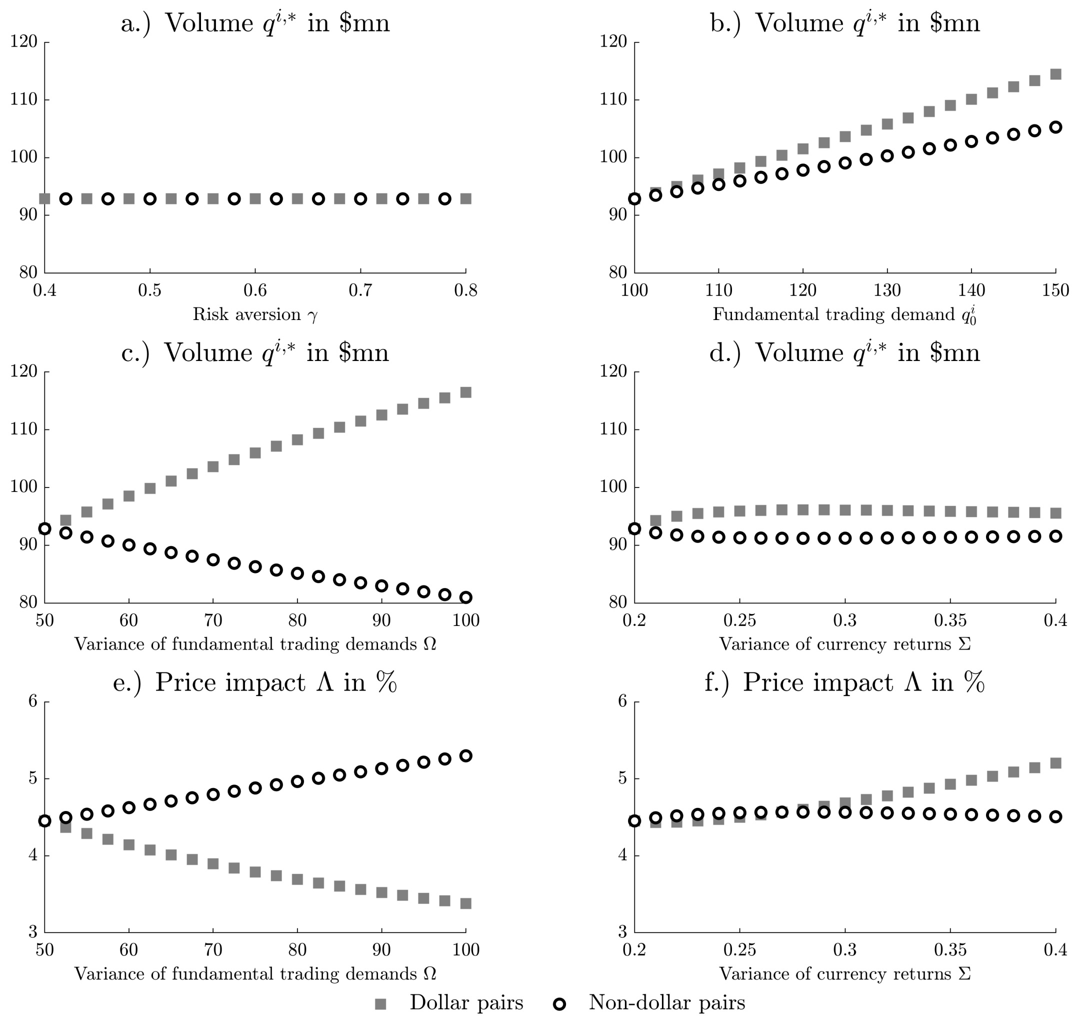
Figure 6 depicts the simulated comparative statics of equilibrium trading volume $\mathbf{q}^{i,*}$ with respect to the risk aversion coefficient $\gamma$, initial trading demand in US dollar pairs $q_{0,\$}^i$, the variance of initial trading demands in US dollar pairs $\Omega_{\$,\$}$, and the variance of currency returns in US dollar pairs $\Sigma_{\$,\$}$. In addition to these four first order effects, the bottom two subfigures show the *endogenous* change in the equilibrium price impact given the change in $\Omega_{\$,\$}$ and $\Sigma_{\$,\$}$, respectively. Notice that the equilibrium traded quantity (i.e., 93 \$mn) is less than the initial trading need (i.e., 100 \$mn) because price impact $\mathbf{\Lambda}$ is a positive definite matrix if the market is not perfectly competitive (i.e., $I$ is finite).[35]

There are four key takeaways from Figure 6: First, following subfigure a.), the optimal traded quantity in each currency pair is independent of risk aversion $\gamma$. This is because the equilibrium volume is a combination of fundamental trading demands and the covariance matrix of currency returns with weights that do not depend on risk aversion.

[34] For example, positive 100 \$mn in GBPJPY means that the representative trader would like to exchange the base currency (here GBP) equivalent of 100 \$mn to JPY.

[35] An increase in $I$ reduces the equilibrium price impact and hence the scale but not the shape of these simulated demand and price impact functions.

**Figure 6: Comparative Statics: Trading Volume and Price Impact**




*Note*: This figure plots the comparative statics of equilibrium trading volume $\mathbf{q}^{i,*}$ for a simple market setting with $I$=15 market participants trading $K$=3 currency pairs. The representative trader $i$ has identical initial trading demands in each currency pair, that is, $\mathbf{q}_0^i = [100, 100, 100]^\top$ \$mn. Subfigures a.) – d.) show how the *average* trading volume in dollar currency pairs (black dots) and non-dollar currency pairs (grey dots) changes given that one of the *exogenous* input factors on the x-axis changes: risk aversion coefficient $\gamma$, initial trading demand in dollar pairs $q_{0,\$}^i$, variance of initial trading demands in dollar pairs $\Omega_{\$,\$}$, and variance of currency returns in dollar pairs $\Sigma_{\$,\$}$. Subfigures e.) and f.) illustrate how the endogenous price impact $\mathbf{\Lambda}$ differs across dollar currency pairs (black dots) and non-dollar pairs (grey dots) given a change in $\Omega_{\$,\$}$ and $\Sigma_{\$,\$}$, respectively.

Second, following subfigure b.), an increase in fundamental trading demands in dollar currency pairs corresponds to a linear increase in the equilibrium allocation. However, given the positive correlation in trading demands across currency pairs, the trading volume in non-dollar pairs also increases, albeit at a slower rate. Notice that a change in the level of fundamental trading demands in dollar pairs has no effect on price impact in dollar pairs because the covariance matrix of fundamental trading demands is mean-invariant.

Third, subfigure c.) shows that a trader with identical fundamental trading demand in each currency pair on average ends up trading larger volumes in dollar currency pairs relative to non-dollar pairs as the variance of fundamental trading demands in dollar pairs increases. This wedge is driven by the assumption that traders are strategic about their price impact and thus find trading more via dollar currency pairs optimal if the expected price impact is lower due to the increasing variance of trading demands in dollar pairs $\Omega_{\$,\$}$. The economic reason for this drop in price impact (see subfigure e.)) is the fact that in decentralised markets the inference coefficient $(\mathbf{B\Omega B'})\big[\mathbf{B\Omega B'}\big]_d^{-1}$ decreases in $\Omega_{\$,\$}$.

Finally, subfigure d.) illustrates that an increasing variance of currency returns in dollar pairs increases the price impact in dollar currency pairs relative to non-dollar pairs if the variance of dollar pairs increases by more than 7 percentage points (pps). In contrast, an increase in the variance of currency returns in dollar pairs by less than 7 pps increases trading volume in dollar pairs. The increase is due to a drop in the expected price impact of dollar pairs. The non-linear effect in subfigure f.) stems from the variance of currency returns directly and also endogenously affecting trading volume via price impact.

**Summary.** Equilibrium trading volume is an increasing function of the mean and variance of fundamental trading demands but is non-monotonic in the variance of currency returns. The simulation results support the idea that even a symmetrical market with identical net trading demands across currency pairs can become skewed towards a single base-currency (e.g., the US dollar) if a minor disparity exists in the variance of fundamental trading demands or in currency returns, respectively.

## Appendix B.3. Proofs

**Notation.** I use the following notation: $\mathbf{v}$ is a vector in which the $k^{th}$ element is $x_k$ and $\mathbf{M}$ is a $k \times l$ matrix where the $(k,l)^{th}$ element is denoted by $M_{k,l}$. Note that vectors and matrices are **boldface** and in addition matrices are capitalised, whereas scalars are in normal font.

**Matrix properties.** This section collects the proofs of Theorems 1 and 2 for which it is useful to notice that $\mathbf{\Sigma}$, $\mathbf{\Omega}$, and $\mathbf{\Lambda}$ have the following properties:

- $\mathbf{\Sigma}$ is a $K \times K$ balanced covariance matrix (see Definition 4) of currency returns such that $\Sigma_{k,k} = \sigma^2$, $\forall k$ and $\Sigma_{k,l} = \sigma^2\rho$, $\forall l \neq k$, where $|\rho| < 1$;
- $\mathbf{\Omega}$ is a $K \times K$ balanced covariance matrix (see Definition 4) of fundamental trading demands with $\Omega_{k,k} = \omega^2$, $\forall k$ and $\Omega_{k,l} = \omega^2\eta$, $\forall l \neq k$, where $|\eta| < 1$;
- $\mathbf{\Lambda}$ is a $K \times K$ diagonal matrix of price impacts.

Given the properties of $\mathbf{\Sigma}$ and $\mathbf{\Omega}$ it must hold that $\lambda_k = \lambda$, $\forall k$. Clearly, the covariance matrices $\mathbf{\Sigma}$ and $\mathbf{\Omega}$ are by definition symmetric and positive semi-definite.[36] What is more, note that the partial derivatives $\frac{\partial \mathbf{q}^{i,*}}{\partial d^i_{0,k}}$, $\frac{\partial \mathbf{q}^{i,*}}{\partial \Omega_{k,k}}$, and $\frac{\partial \mathbf{q}^{i,*}}{\partial \Sigma_{k,k}}$ in Theorem 1 are $K \times 1$ vectors.

**Definition 4** (**Balanced matrix**). *A matrix* $\mathbf{M}$ *is called balanced if all on-diagonal elements are identical (i.e.,* $M_{k,k} = c^2$, $\forall k$*) and the off-diagonal elements are scaled versions of the on-diagonal elements (i.e.,* $M_{k,l} = c^2\rho$, $\forall l \neq k$, *where* $|\rho| < 1$*). Hence,* $\mathbf{M}$ *is symmetric and positive semi-definite.*

**Lemma 1.** $(\mathbf{\Sigma} + \mathbf{\Lambda})^{-1}\mathbf{\Sigma}$ *is a positive semi-definite matrix if markets are uncontingent and hence* $\mathbf{\Lambda}$ *is a positive definite diagonal matrix. This follows directly from the properties of* $\mathbf{\Sigma}$ *and* $\mathbf{\Lambda}$ *and by standard matrix algebra.*

[36] The sum of two positive semi-definite matrices $\mathbf{A}$ and $\mathbf{B}$ is always positive semi-definite and the product $\mathbf{AB}$ is also semi-definite if the matrices are *symmetric*. Moreover, the inverse of a positive definite matrix is also positive semi-definite because the eigenvalues of the inverse are inverses of the eigenvalues.

**Corollary 1** (Proof of Eq. (7))**.** *Note that* $\mathbf{d}_0^i = |\bar{\mathbf{q}}_0 - \mathbf{q}_0^i|$ *and the partial derivative* $\frac{\partial \mathbf{d}_0^i}{\partial d_{0,k}^i}$ *is a* $K \times 1$ *vector where element* $k$ *is equal to 1 and all other elements are equal to 0 (i.e.,* $\frac{\partial q_l^{i,*}}{\partial d_{0,k}^i} = 0,\ \forall l \neq k$*). In conjunction with Lemma 1 it follows directly that* $\frac{\partial q_k^{i,*}}{\partial d_{0,k}^i} > \frac{\partial q_l^{i,*}}{\partial d_{0,k}^i},\ \forall l \neq k$*. Specifically, as long as* $\mathbf{\Sigma}$*,* $\mathbf{\Omega}$*, and* $\mathbf{\Lambda}$ *are positive (semi-)definite matrices and exchange rate returns are not perfectly correlated the off-diagonal elements of these matrices will be strictly smaller than the on-diagonal elements, which implies that a marginal increase in* $d_{0,k}^i$ *benefits trading volume in currency pair* $k$ *the most.*

**Corollary 2** (Proof of Eq. (8))**.** *From Lemma 1 it follows directly that* $(\mathbf{\Sigma} + \mathbf{\Lambda})^{-2}\mathbf{\Sigma}$ *is a positive semi-definite matrix. Hence, all else equal,* $\frac{\partial \Lambda_{k,k}}{\partial \Omega_{k,k}} < \frac{\partial \Lambda_{l,l}}{\partial \Omega_{k,k}},\ \forall l \neq k$*, since* $(\mathbf{B\Omega B}')\big[\mathbf{B\Omega B}'\big]_d^{-1}$ *is a symmetric positive semi-definite matrix with all on-diagonal elements equal to 1. This follows directly from the fact that* $\mathbf{B\Omega B}'$ *is symmetric and positive semi-definite since* $\mathbf{\Omega}$ *is positive semi-definite by the definition of a covariance matrix. Hence, the off-diagonal elements in column* $k$ *decrease relative to all other columns* $l \neq k$ *as* $\Omega_{k,k}$ *increases. Since* $\mathbf{\Lambda}$ *is symmetric and positive semi-definite it follows directly that* $\frac{\partial \Lambda_{k,k}}{\partial \Omega_{k,k}} < \frac{\partial \Lambda_{l,l}}{\partial \Omega_{k,k}},\ \forall l \neq k$*.*

**Corollary 3** (Proof of Eq. (9))**.** *Note that the partial derivative* $\frac{\partial \mathbf{\Sigma}}{\partial \Sigma_{k,k}}$ *is a* $K \times 1$ *vector where element* $k$ *is equal to 1 and all other elements are equal to 0. All else equal,* $\frac{\partial \Lambda_{k,k}}{\partial \Sigma_{k,k}} > \frac{\partial \Lambda_{l,l}}{\partial \Sigma_{k,k}},\ \forall l \neq k$ *because* $(\mathbf{B\Omega B}')\big[\mathbf{B\Omega B}'\big]_d^{-1}$ *is positive semi-definite and symmetric. In Eq.* (9)*, the positive effect of an increase in* $\Sigma_{k,k}$ *on* $q_k^{i,*}$ *such that* $\frac{\partial q_k^{i,*}}{\partial \Sigma_{k,k}} > \frac{\partial q_l^{i,*}}{\partial \Sigma_{k,k}},\ \forall l \neq k$ *is counterbalanced by the increase in* $\Lambda_{k,k}$*. The two counterbalancing effects exactly offset each other if* $\Lambda_{k,k} = \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k,k}}$ *(see the proof below). Therefore,* $\Lambda_{k,k} - \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k,k}} < \Lambda_{l,l} - \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{l,l}},\ \forall l \neq k$ *is a sufficient statistic for* $\frac{\partial q_k^{i,*}}{\partial \Sigma_{k,k}} < \frac{\partial q_l^{i,*}}{\partial \Sigma_{k,k}}$*.*

*Proof of Corollary 3.* Setting Eq. (9) equal to zero and rearranging yields:

$$(\mathbf{\Sigma} + \mathbf{\Lambda})\frac{\partial \Sigma}{\partial \Sigma_{k,k}} = \mathbf{\Sigma}\frac{\partial \Sigma}{\partial \Sigma_{k,k}} + \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k,k}}$$
$$\Lambda_{k,k} = \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k,k}},$$

thus, $\frac{\partial q_k^{i,*}}{\partial \Sigma_{k,k}} < \frac{\partial q_l^{i,*}}{\partial \Sigma_{k,k}}$ if and only if $\Lambda_{k,k} - \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k,k}} < \Lambda_{l,l} - \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{l,l}},\ \forall l \neq k$. □

*Proof of Theorem 1.* The proof follows directly from Corollaries 1 to 3. □

*Proof of Theorem 2.* The first condition follows directly from Corollary 1, which implies that $q_k^{i,*}$ is an increasing function of $q_{k,0}^i$. Hence, $min(q_{\$/X,0}^i, q_{\$/Y,0}^i) > q_{X/Y,0}^i,\ \forall i$ or equivalently $\sum_{k\in\$} q_{k,0}^i > max(\sum_{k\in X} q_{k,0}^i, \sum_{k\in Y} q_{k,0}^i),\ \forall i$ is, holding all else equal, a sufficient condition for Definition 3. The second condition is sufficient because of Corollary 2, which proves that $q_k^{i,*}$ is increasing in $\Omega_{k,k}$. Hence, keeping the off-diagonal covariance terms constant, $min(\Omega_{\$/X,\$/X}, \Omega_{\$/Y,\$/Y}) > \Omega_{X/Y,X/Y}$ or equivalently $\sum_{k\in\$} \Omega_{k,k} > max(\sum_{k\in X} \Omega_{k,k}, \sum_{k\in Y} \Omega_{k,k})$ implies more trading volume in dollar currency pairs than non-dollar currency pairs (i.e., Definition 3). The third condition follows directly from Corollary 3 that can be intuitively interpreted as follows: as long as the increase in $\Lambda_{k,k}$ is larger than the overall positive effect of $\Sigma_{k,k}$ on $q_{0,k}^{i,*}$ the latter will be a decreasing function of $\Sigma_{k,k}$. Mathematically, this condition is described by $\Lambda_{k\in\$} - \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k\in\$}} < min(\Lambda_{k\in X} - \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k\in X}}, \Lambda_{k\in Y} - \mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k\in Y}})$ (see Proof of Corollary 3). □

# Appendix C. Additional Information on Data

The goal of this section is to describe how CLS categorises market participants into price takers and market-makers and how this impacts the relative coverage of the order flow dataset. CLS uses two distinct methods of categorising market participants, namely, the identity-based and behaviour-based approaches. For the first, CLS classifies market participants into corporates, funds, non-bank financial firms, and banks based on static identity information. The fund category includes pension funds, hedge funds, and sovereign wealth funds, whereas non-bank financial are insurance companies, brokers, and clearing houses. The corporate category comprises any non-financial organisation. These labels refer to the identities of the entities trading and not to the behaviour they exhibit. This is because CLS is a payment-versus-payment platform that solely observes the executed trade price used for settlement and does not see the market behaviour of bids and offers that precede the execution or any other such details. Hence, assuming that all corporates, funds and non-bank financial firms act as price takers leads to three possible transactor parings between price takers and market-makers: corporate-to-bank, fund-to-bank, and non-bank-to-bank.[37]

The above pairings account for about 10–15% of the total activity in the FX market. Most activity in this market is bank-to-bank. Therefore, CLS carries out a second analysis focusing on bank-to-bank transactions for determining which banks are market-makers and which banks are price takers. CLS maps all FX activity as a network. Market participants are nodes, while FX transactions are edges. Nodes that are mutually tightly interlinked and maintain a consistently high coreness over time are considered market-makers, while all other nodes are considered price takers. Thus, the total buy-side activity considers the sum of the three categories above plus all trades between price taker banks and market-maker banks, reaching a total of "all buy-side activity" versus "all sell-side activity." Hence, by construction, the sell side includes only banks that were identified to be market-makers. To avoid double counting, transactions between two market-makers or two price takers were excluded.

Empirically, transactions between market-makers make up most of the activity in the FX market. Typically, a price taker does an initial trade with one market-maker, and that market-maker hedges the resulting risk by trading with other market-makers. A single initial trade can lead to a chain of downstream transactions where various market-makers pass the "hot potato" around or slice up the risk in various ways. Consequently, the activity among market-makers will be higher than that between price takers and market-makers. There are three further reasons why transactions between non-bank price takers and market-maker banks represent a relatively low share of total FX turnover settled by CLS. First, many hedge funds and proprietary trading firms settle through prime brokers. CLS does not have look-through on these trades, and hence, they appear as bank-to-bank transactions. If those prime brokers are also market-makers, the transactions would be excluded from the order flow dataset. Second, CLS has relatively low client penetration among corporates and real money funds that trade FX infrequently and do not need a dedicated third-party settlement service. Third, market-maker banks may engage in price taking activity but price taker banks are unlikely to ever engage in market-making activity.

[37] In this context, the term "price taker" is interchangeably used with the term "buy side," and the term "market-maker" is used interchangeably with the term "sell side."

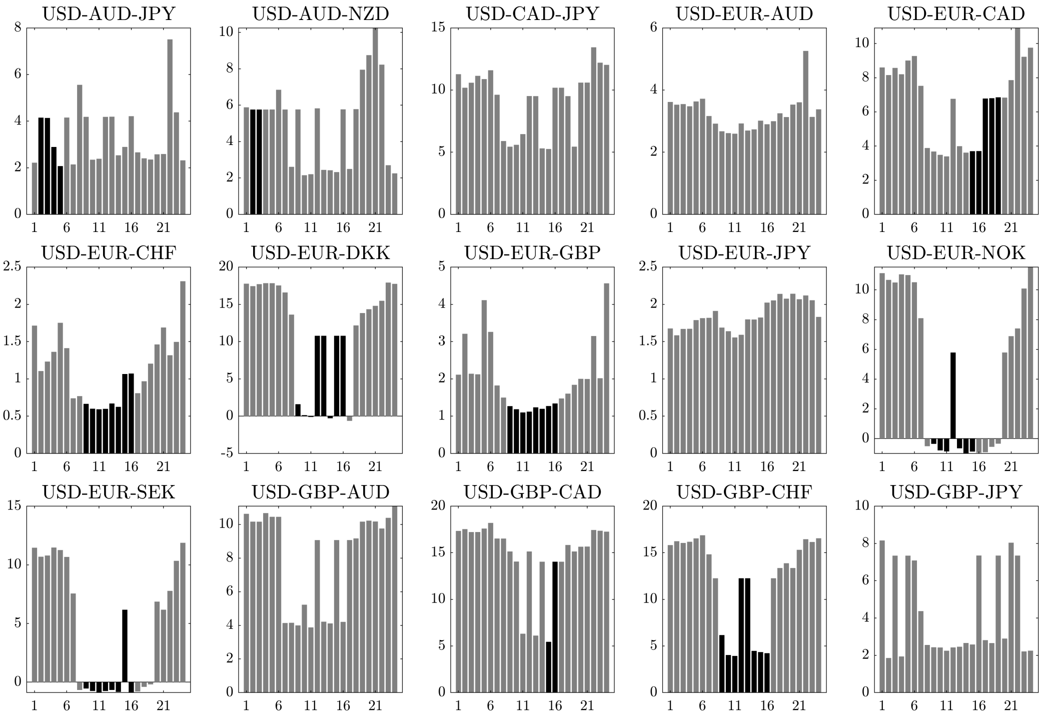
# Appendix D. Additional Empirical Results

**Table 6: Equilibrium Conditions: Hypothesis Tests**

| | DD | C1 | C2 | C3 | DD−C1 |
|---|---|---|---|---|---|
| USD-AUD-JPY | ***2.18 | ***2.07 | ***4.03 | ***−0.21 | ***0.12 |
| | [126.67] | [106.16] | [99.36] | [12.01] | [7.87] |
| USD-AUD-NZD | ***1.74 | ***1.28 | ***2.11 | ***0.67 | ***0.47 |
| | [137.00] | [89.34] | [60.57] | [48.17] | [37.93] |
| USD-CAD-JPY | ***4.43 | ***4.06 | ***7.42 | ***−0.34 | ***0.38 |
| | [189.35] | [162.54] | [153.86] | [23.17] | [22.17] |
| USD-EUR-AUD | ***2.64 | ***2.14 | ***3.80 | ***0.12 | ***0.49 |
| | [174.81] | [143.30] | [126.77] | [8.38] | [24.09] |
| USD-EUR-CAD | ***3.35 | ***2.99 | ***5.64 | ***−0.06 | ***0.35 |
| | [244.35] | [149.57] | [133.97] | [4.50] | [20.01] |
| USD-EUR-CHF | ***0.60 | ***0.52 | ***0.87 | ***0.95 | ***0.08 |
| | [47.36] | [33.06] | [25.40] | [23.39] | [6.71] |
| USD-EUR-DKK | ***−0.83 | ***−1.78 | ***−3.16 | ***3.23 | ***0.96 |
| | [34.12] | [60.84] | [49.00] | [80.93] | [25.60] |
| USD-EUR-GBP | ***1.26 | ***1.18 | ***1.95 | ***0.21 | ***0.09 |
| | [161.21] | [135.01] | [96.97] | [16.86] | [13.51] |
| USD-EUR-JPY | ***1.81 | ***1.72 | ***3.02 | ***−0.05 | ***0.09 |
| | [84.34] | [78.80] | [65.13] | [3.20] | [12.35] |
| USD-EUR-NOK | ***−0.92 | ***−0.68 | ***−1.21 | ***0.41 | ***−0.25 |
| | [63.47] | [50.57] | [37.51] | [25.57] | [15.32] |
| USD-EUR-SEK | ***−0.89 | ***−0.60 | ***−1.12 | ***0.56 | ***−0.29 |
| | [56.56] | [47.12] | [34.91] | [41.74] | [20.09] |
| USD-GBP-AUD | ***3.70 | ***3.23 | ***5.71 | 0.01 | ***0.47 |
| | [216.26] | [193.76] | [163.14] | [0.91] | [26.52] |
| USD-GBP-CAD | ***4.46 | ***3.97 | ***7.25 | ***−0.10 | ***0.49 |
| | [244.27] | [155.58] | [147.17] | [9.54] | [21.35] |
| USD-GBP-CHF | ***3.38 | ***3.00 | ***5.55 | ***0.06 | ***0.38 |
| | [195.08] | [134.83] | [126.43] | [5.33] | [14.95] |
| USD-GBP-JPY | ***2.33 | ***2.28 | ***4.55 | ***−0.22 | ***0.05 |
| | [118.21] | [111.99] | [110.70] | [19.31] | [3.52] |

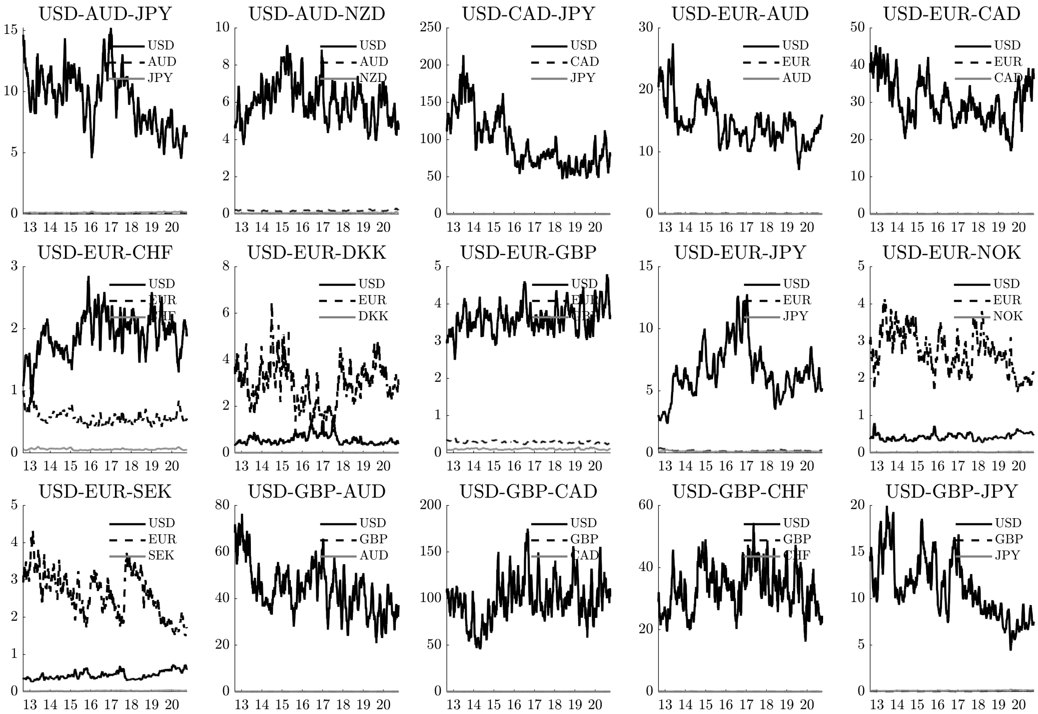
*Note*: This table summarises the empirical counterparts of the equilibrium conditions in Theorem 2 for 15 triplets of currency pairs. A triplet is defined as one non-dollar currency pair (e.g., GBPJPY as shown at the beginning of each row) plus the two USD legs (e.g., USDGBP and USDJPY). The first bar named $DD$ refers to my empirical measure of dollar dominance, whereas the next three columns labelled $C1$, $C2$, and $C3$ each correspond to one of the three conditions (in logs). The last column reports the difference between the columns labelled $DD$ and $C1$. The sample covers the period from 1 September 2012 to 29 September 2020. The test statistics based on Newey and West (1994) robust standard errors allowing for heteroskedasticity and serial correlation up to 7 lags are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels.

**Figure 7: Intraday Variation of Dollar Dominance**



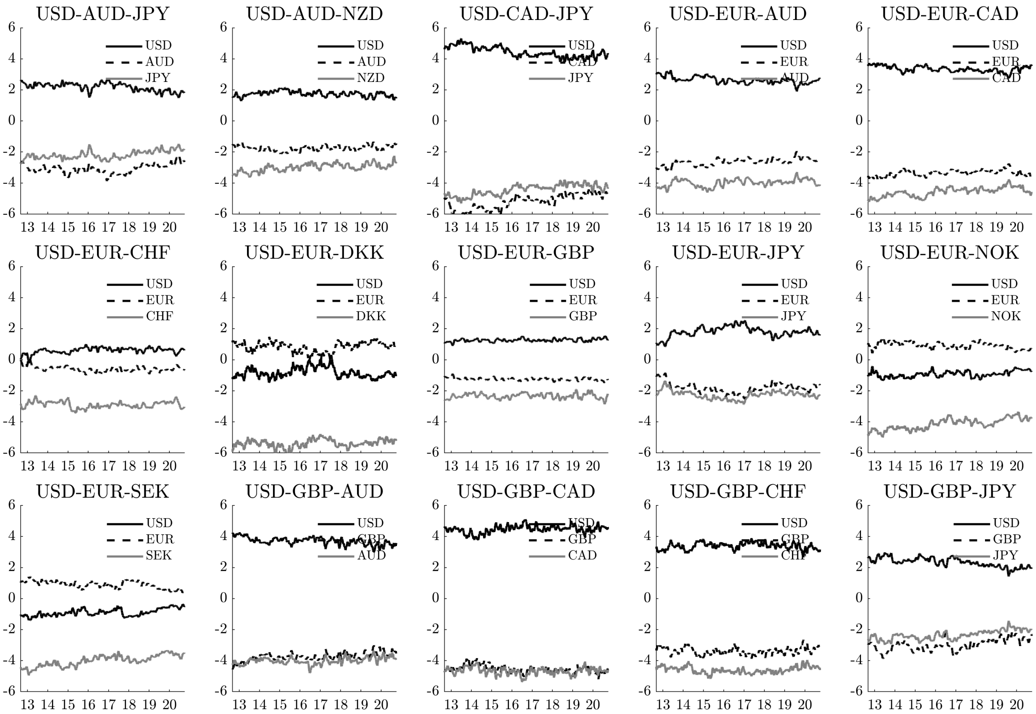

*Note*: This figure shows the intraday variation of log dollar dominance (i.e., $log(doldom)_{j,t}$) for 15 triplets of currency pairs. Dollar dominance is defined as the ratio of the minimum inter-dealer trading volume in dollar pairs (e.g., USDGBP and USDJPY) relative to the direct trading volume in non-dollar pairs (e.g., GBPJPY). Each bar corresponds to an average over the respective hour across all trading days. The black bars highlight times when both non-dollar countries' stock markets are open. The horizontal axis denotes the closing time, for instance, 16 refers to dollar dominance computed based on volume from 3-4 *pm* (London time, GMT). The sample covers the period from 1 September 2012 to 29 September 2020.

**Figure 8: Time-variation of Dollar Dominance in Volume (levels)**



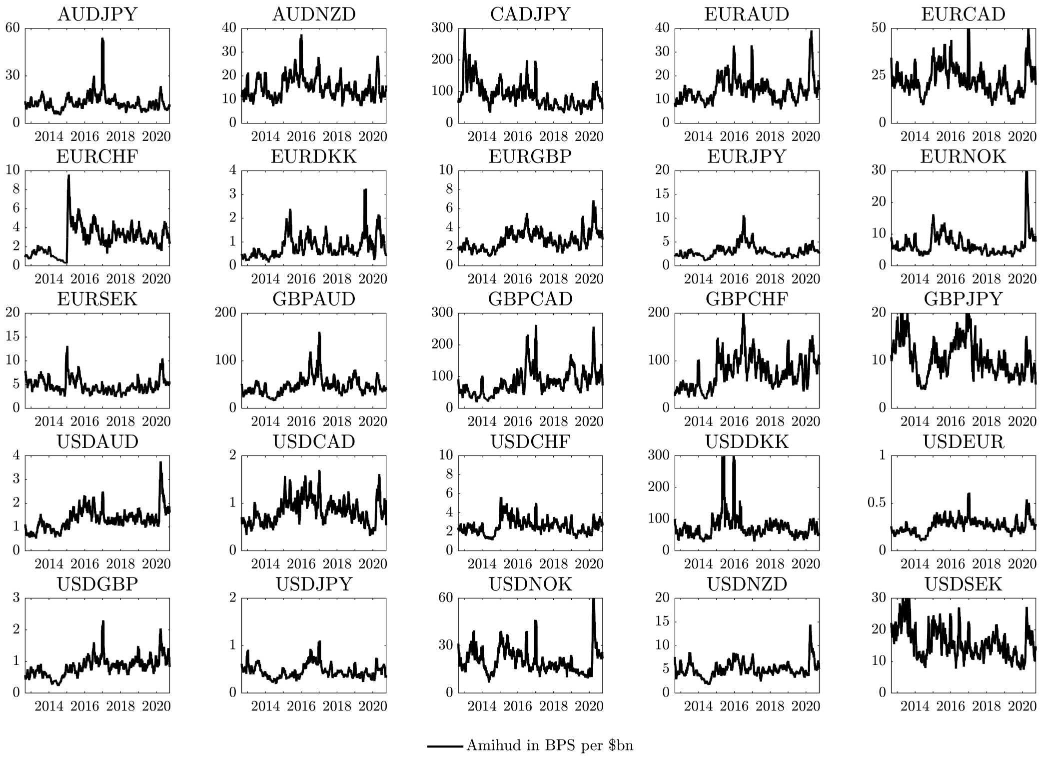

*Note*: This figure shows the time-variation of dominance scores based on trading volume for the US dollar (i.e., $doldom_{j,t}$, solid black lines) as well as two other non-dollar currencies (dashed black and solid grey lines) within each of the 15 triplets of currency pairs. Dollar dominance in trading volume is defined as the ratio of the minimum inter-dealer trading volume in dollar currency pairs (e.g., USDGBP and USDJPY) relative to the direct volume in non-dollar pairs (e.g., GBPJPY). The plotted time series correspond to a 22-day moving average of the raw data. The sample covers the period from 1 September 2012 to 29 September 2020.

**Figure 9: Time-variation of Dollar Dominance in Volume (logs)**



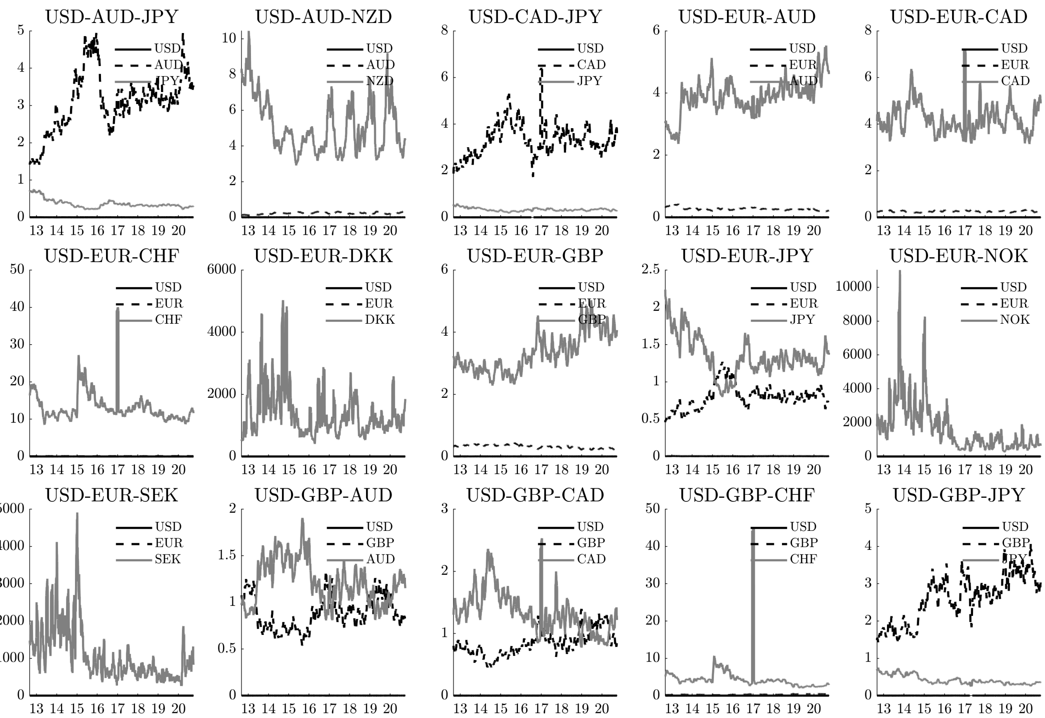

*Note*: This figure shows the time-variation of log dominance scores based on trading volume for the US dollar (i.e., $log(doldom)_{j,t}$, solid black lines) as well as two other non-dollar currencies (dashed black and solid grey lines) within each of the 15 triplets of currency pairs. Dollar dominance in trading volume is defined as the ratio of the minimum inter-dealer trading volume in dollar currency pairs (e.g., USDGBP and USDJPY) relative to the direct volume in non-dollar pairs (e.g., GBPJPY). The plotted time series correspond to a 22-day moving average of the raw data. The sample covers the period from 1 September 2012 to 29 September 2020.

**Figure 10: Time-variation of Amihud Price Impact**



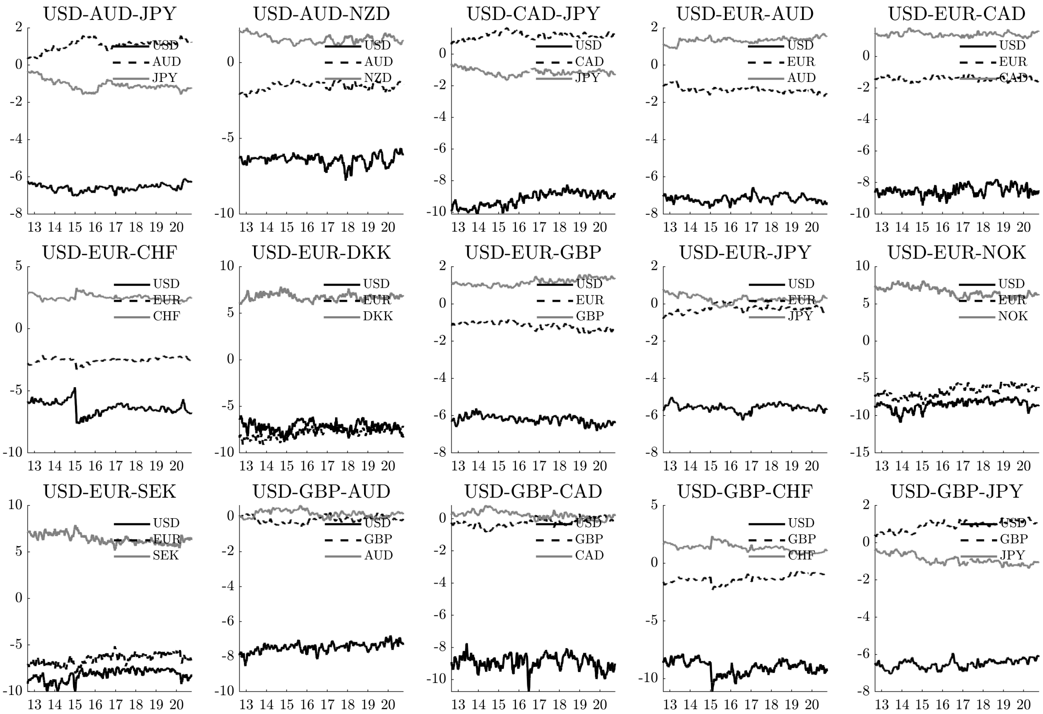

*Note*: This figure shows the time-variation of Amihud's (2002) price impact measure for 25 currency pairs. Following Ranaldo and Santucci de Magistris (2018), I estimate Amihud in BPS per $bn as the ratio between intraday realised volatility and aggregate daily trading volume. The plotted time series correspond to a 22-day moving average of the raw data. The sample covers the period from 1 September 2012 to 29 September 2020.

**Figure 11: Time-variation of Dollar Dominance in Price Impact (levels)**




*Note*: This figure shows the time-variation of dominance scores based on price impact for the US dollar (i.e., $amihud_{j,t}$, solid black lines) as well as two other non-dollar currencies (dashed black and solid grey lines) within each of the 15 triplets of currency pairs. Dollar dominance in price impact is defined as the ratio of the maximum Amihud price impact in dollar currency pairs (e.g., USDGBP and USDJPY) relative to the direct price impact in non-dollar pairs (e.g., GBPJPY). The plotted time series correspond to a 22-day moving average of the raw data. The sample covers the period from 1 September 2012 to 29 September 2020.

**Figure 12: Time-variation of Dollar Dominance in Price Impact (logs)**




*Note*: This figure shows the time-variation of log dominance scores based on price impact for the US dollar (i.e., $log(amihud)_{j,t}$, solid black lines) as well as two other non-dollar currencies (dashed black and solid grey lines) within each of the 15 triplets of currency pairs. Dollar dominance in price impact is defined as the ratio of the maximum Amihud price impact in dollar currency pairs (e.g., USDGBP and USDJPY) relative to the direct price impact in non-dollar pairs (e.g., GBPJPY). The plotted time series correspond to a 22-day moving average of the raw data. The sample covers the period from 1 September 2012 to 29 September 2020.

**Table 7: Dollar Dominance and Equilibrium Conditions (De-seasonalised)**

| | $\text{doldom}_{\text{j,t}}$ | | | | | | $\text{amihud}_{\text{j,t}}$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\text{C1}_{\text{j,t}}$ | ***0.39 | | | ***0.39 | | ***0.53 | | | |
| | [34.27] | | | [33.99] | | [21.16] | | | |
| $\text{C2}_{\text{j,t}}$ | | ***0.30 | | | ***0.29 | ***0.30 | ***−0.04 | | ***−0.04 |
| | | [33.89] | | | [33.54] | [30.73] | [5.15] | | [4.98] |
| $\text{C3}_{\text{j,t}}$ | | | ***0.04 | | ***0.03 | ***0.03 | | ***0.07 | ***0.07 |
| | | | [5.07] | | [3.49] | [3.20] | | [6.07] | [5.75] |
| bid-ask $\text{spread}_{\text{j,t}}$ | | | | ***−0.06 | ***−0.09 | ***−0.05 | | | 0.02 |
| | | | | [4.59] | [6.59] | [3.50] | | | [0.96] |
| $\text{cip-basis}_{\text{j,t}}$ | | | | | | 0.02 | | | **−0.02 |
| | | | | | | [1.57] | | | [2.15] |
| Lagged dep. | ***−0.38 | ***−0.40 | ***−0.44 | ***−0.38 | ***−0.40 | ***−0.37 | ***−0.50 | ***−0.50 | ***−0.50 |
| | [56.54] | [63.98] | [72.85] | [56.56] | [63.66] | [51.38] | [64.57] | [64.90] | [58.74] |
| $R^2$ in % | 33.94 | 28.36 | 19.92 | 34.01 | 28.62 | 33.92 | 25.63 | 25.85 | 25.86 |
| Adj. $R^2$ in % | 33.91 | 28.33 | 19.87 | 33.98 | 28.57 | 33.88 | 25.59 | 25.81 | 25.82 |
| Avg. #Time periods | 2068 | 2068 | 2068 | 2068 | 2068 | 2014 | 2068 | 2068 | 2014 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| Time series FE | yes | yes | yes | yes | yes | yes | yes | yes | yes |

*Note*: This table reports results from daily fixed effects panel regressions of the form $DD_{j,t} = \mu_t + \alpha_j + \beta_1 C1_{j,t} + \beta_2 C2_{j,t} + \beta_3 C3_{j,t} + \gamma' \mathbf{w}_{j,t} + \epsilon_{j,t}$, where $\mu_t$ and $\alpha_j$ denote time series and currency pair triplet fixed effects. The dependent variable $DD_{j,t}$ is a measure of dollar dominance that is either based on trading volume (i.e., $doldom_{j,t}$) or on Amihud's (2002) price impact (i.e., $amihud_{j,t}$). $C1$, $C2$, and $C3$ are the empirical counterparts of the three equilibrium conditions in Theorem 2. To mitigate multicollinearity, I orthogonalise $C1$ against $C2$ and $C3$ in column 6, where I jointly include all three conditions as regressors. *bid-ask spread*$_{j,t}$ is the daily average relative bid-ask spread. *cip-basis*$_{j,t}$ is the (absolute) cross-currency basis following the methodology in Du et al. (2018). These control variables in $\mathbf{w}_{j,t}$ are computed separately within every currency pair triplet as the average across two dollar pairs. Both dependent and independent variables are taken in logs and first differences. The sample covers the period from 1 September 2012 to 29 September 2020. The test statistics based on Driscoll and Kraay's (1998) robust standard errors allowing for random clustering and serial correlation are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels.

**Table 8: Dollar Dominance and Equilibrium Conditions (De-trended)**

| | $\text{doldom}_{j,t}$ | | | | | | $\text{amihud}_{j,t}$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\text{C1}_{j,t}$ | ***0.46 | | | ***0.45 | | ***0.60 | | | |
| | [36.21] | | | [35.96] | | [21.47] | | | |
| $\text{C2}_{j,t}$ | | ***0.35 | | | ***0.35 | ***0.36 | ***−0.04 | | ***−0.05 |
| | | [35.57] | | | [35.44] | [32.97] | [4.76] | | [4.66] |
| $\text{C3}_{j,t}$ | | | ***0.06 | | ***0.04 | ***0.04 | | ***0.09 | ***0.09 |
| | | | [5.29] | | [3.80] | [3.40] | | [6.83] | [6.51] |
| $\text{bid-ask spread}_{j,t}$ | | | | ***−0.06 | ***−0.09 | ***−0.04 | | | 0.02 |
| | | | | [3.97] | [5.81] | [2.72] | | | [0.73] |
| $\text{cip-basis}_{j,t}$ | | | | | | 0.02 | | | *−0.03 |
| | | | | | | [1.24] | | | [1.94] |
| $R^2$ in % | 20.20 | 12.72 | 0.28 | 20.27 | 13.04 | 20.34 | 0.19 | 0.57 | 0.80 |
| Adj. $R^2$ in % | 20.16 | 12.68 | 0.23 | 20.23 | 12.99 | 20.29 | 0.14 | 0.52 | 0.74 |
| Avg. #Time periods | 2068 | 2068 | 2068 | 2068 | 2068 | 2014 | 2069 | 2069 | 2015 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes | yes | yes | yes |
| Time series FE | yes | yes | yes | yes | yes | yes | yes | yes | yes |

*Note*: This table reports results from daily fixed effects panel regressions of the form $DD_{j,t} = \mu_t + \alpha_j + \beta_1 C1_{j,t} + \beta_2 C2_{j,t} + \beta_3 C3_{j,t} + \gamma' \mathbf{w}_{j,t} + \epsilon_{j,t}$, where $\mu_t$ and $\alpha_j$ denote time series and currency pair triplet fixed effects. The dependent variable $DD_{j,t}$ is a measure of dollar dominance that is either based on trading volume (i.e., $doldom_{j,t}$) or on Amihud's (2002) price impact (i.e., $amihud_{j,t}$). $doldom_{j,t}$ is computed based on de-trended trading volume that I define as today's volume divided by a moving average over the previous 22 days' trading volume: $volume_{k,t}/(\frac{1}{M}\sum_{m=1}^{M} volume_{k,t-m})$, setting $M$=22. $C1$, $C2$, and $C3$ are the empirical counterparts of the three equilibrium conditions in Theorem 2. To mitigate multicollinearity, I orthogonalise $C1$ against $C2$ and $C3$ in column 6, where I jointly include all three conditions as regressors. $bid\text{-}ask\ spread_{j,t}$ is the daily average relative bid-ask spread. $cip\text{-}basis_{j,t}$ is the (absolute) cross-currency basis following the methodology in Du et al. (2018). These control variables in $\mathbf{w}_{j,t}$ are computed separately within every currency pair triplet as the average across two dollar pairs. Both dependent and independent variables are taken in logs and first differences. The sample covers the period from 1 September 2012 to 29 September 2020. The test statistics based on Driscoll and Kraay's (1998) robust standard errors allowing for random clustering and serial correlation are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels.

**Endogeneity.** A causal interpretation of the regression results in Table 4 is not appropriate given that dollar dominance and the three equilibrium conditions are all determined simultaneously in equilibrium. Put differently, the regression set-up in Eq. (12) suffers from obvious reverse causality issues that may lead to biased estimates. To overcome this potential endogeneity issue, I need an instrument that directly affects my three model–based drivers but not the other way around. Ideally, one can point to a set of specific exogenous events that have affected the equilibrium conditions but not directly my measure of dollar dominance. Such events are, of course, hard to identify and therefore I take a more systematic approach.

In particular, I follow the granular instrumental variable (GIV) approach by Gabaix and Koijen (2020), which allows me to identify quasi-exogenous spikes in the three conditions based on the cross-sectional heterogeneity in the data. For each of the three conditions (i.e., $C1$, $C2$, and $C3$), I define the GIV as the difference between the size- and equal-weighted average of the daily conditions:

$$GIV_t^X = \sum_{j=1}^{15} S_{j,t-1} CX_{j,t} - \frac{1}{15} \sum_{j=1}^{15} CX_{j,t} \qquad \forall X = 1, 2, \text{ and } 3, \tag{40}$$

where $S_{j,t} = \frac{CX_{j,t}}{\sum_{j=1}^{15} CX_{j,t}}$ is the relative share of currency pair triplet $j$ at time $t$. The intuition is that by taking the difference between size and equal weighted averages the common component in the conditions is washed out across currency pair triplets and the residual corresponds to idiosyncratic shocks. Note that these idiosyncratic spikes are driven by triplets of currency pairs that are "large" in the sense that the equilibrium conditions are strongly satisfied. Given the interconnectedness of the global FX market these idiosyncratic shocks do not just affect the aggregate level of dollar dominance but also the extent to which individual currency pair triplets are dominated by the US dollar. Clearly, when there is not enough cross-sectional heterogeneity in the data, then this approach may not work. However, this does not concern this set-up since the three conditions strongly differ across currency pair triplets (see Figure 3). Note that it is not possible to include time-series fixed effects in Eq. (12) since the GIV is the same across all 15 triplets of currency pairs.

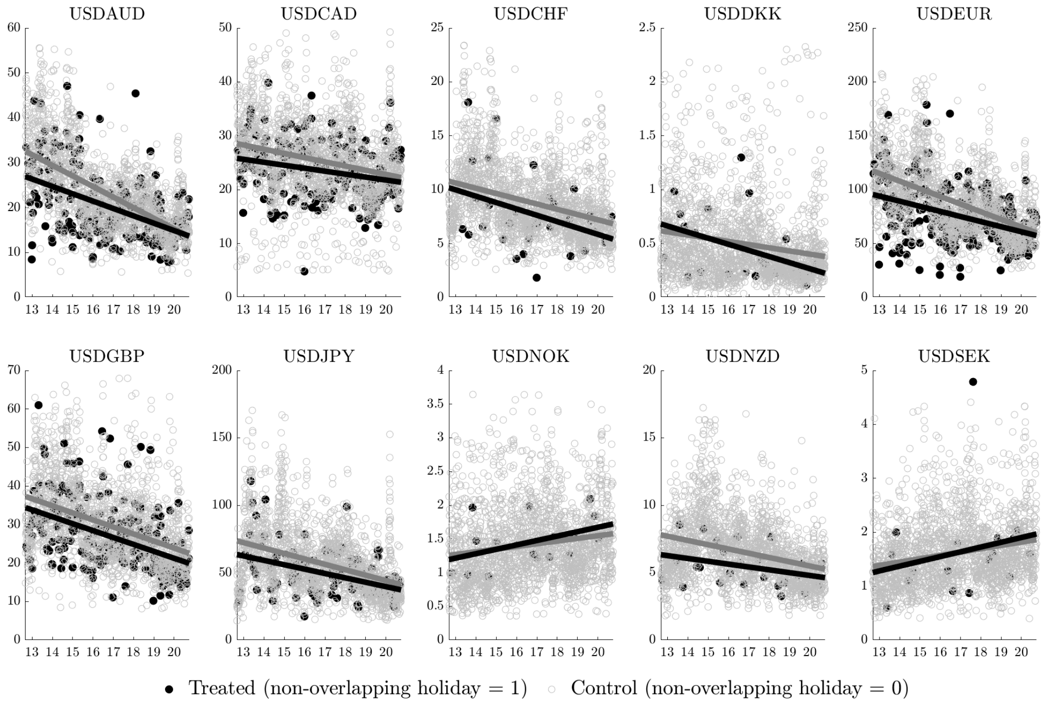
In Table 9, I compare the results from estimating Eq. (12) with ordinary least squares (OLS) and two-stage least squares (2SLS), respectively. Panel A presents the OLS estimates, while Panel B shows the first and second stage results of the IV regression. There are three key takeaways: First, the relevance of GIV as an instrument for each of the three model–based drivers is supported by the highly significant first stage $F$-statistics (Cragg and Donald, 1993). As a benchmark, an $F$-statistic of at least 10 indicates that the instruments are sufficiently correlated with the endogenous regressors (Staiger and Stock, 1997). Second, the 2SLS estimates are highly significant and consistent in terms of signs and magnitudes with OLS. However, the GIV correction matters for $C2$, since the Hausman test indicates that the difference between OLS and 2SLS estimates is significant. Third, controlling for changes in the average relative bid-ask spread and cross-currency basis in dollar currency pairs does not alter the economic nor the statistical significance of my estimates. Moreover, all results remain virtually unchanged when I include the S&P 500 index to control for confounding US specific state variables that are time-varying but constant across triplets of currency pairs.

**Table 9: Dollar Dominance and Equilibrium Conditions**

| | $\text{doldom}_{\text{j,t}}$ | | | | | | $\text{amihud}_{\text{j,t}}$ | | |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: OLS | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\text{C1}_{\text{j,t}}$ | ***0.45 | | | ***0.45 | | ***0.56 | | | |
| | [33.80] | | | [33.81] | | [18.29] | | | |
| $\text{C2}_{\text{j,t}}$ | | ***0.12 | | | ***0.12 | ***0.12 | ***−0.04 | | ***−0.05 |
| | | [35.85] | | | [35.66] | [33.44] | [6.15] | | [6.47] |
| $\text{C3}_{\text{j,t}}$ | | | ***0.12 | | ***0.09 | ***0.08 | | ***0.25 | ***0.24 |
| | | | [9.29] | | [7.60] | [6.24] | | [7.88] | [6.86] |
| bid-ask $\text{spread}_{\text{j,t}}$ | | | | 0.03 | ***−0.09 | −0.02 | | | **0.20 |
| | | | | [0.98] | [3.42] | [0.69] | | | [2.56] |
| $\text{cip-basis}_{\text{j,t}}$ | | | | | | ***0.01 | | | ***0.02 |
| | | | | | | [6.02] | | | [3.98] |
| S&P $500_{\text{t}}$ | | | | | | 0.31 | | | *1.30 |
| | | | | | | [1.04] | | | [1.73] |
| Adj. $R^2$ in % | 22.50 | 14.67 | 0.80 | 22.50 | 15.11 | 22.74 | 0.20 | 0.56 | 0.97 |
| Panel B: 2SLS | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\text{C1}_{\text{j,t}}$ | ***0.51 | | | ***0.51 | | *0.36 | | | |
| | [8.29] | | | [8.26] | | [1.88] | | | |
| $\text{C2}_{\text{j,t}}$ | | ***0.22 | | | ***0.22 | ***0.18 | *−0.06 | | **−0.10 |
| | | [11.92] | | | [11.43] | [7.90] | [1.75] | | [2.25] |
| $\text{C3}_{\text{j,t}}$ | | | ***0.18 | | ***0.13 | ***0.09 | | ***0.34 | ***0.21 |
| | | | [4.73] | | [3.98] | [2.70] | | [5.09] | [2.61] |
| bid-ask $\text{spread}_{\text{j,t}}$ | | | | −0.04 | ***−0.14 | ***−0.11 | | | ***0.30 |
| | | | | [1.38] | [4.23] | [3.38] | | | [3.62] |
| $\text{cip-basis}_{\text{j,t}}$ | | | | | | ***0.02 | | | ***0.02 |
| | | | | | | [8.26] | | | [3.99] |
| S&P $500_{\text{t}}$ | | | | | | 0.45 | | | *1.57 |
| | | | | | | [1.43] | | | [1.95] |
| Adj. $R^2$ in % | 22.05 | 4.20 | 0.94 | 22.04 | 5.48 | 18.74 | 0.11 | 0.31 | 0.32 |
| First-stage $F$-test | 2026.58 | 799.01 | 3743.16 | 2026.58 | 363.40 | 80.94 | 798.35 | 3743.50 | 329.33 |
| Hausman test | 1.06 | 30.81 | 1.25 | 1.01 | 35.57 | 9.87 | 0.44 | 3.62 | 1.88 |
| Avg. #Time periods | 2069 | 2069 | 2069 | 2069 | 2069 | 2015 | 2069 | 2069 | 2015 |
| #Currency triplets | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |
| Currency triplet FE | yes | yes | yes | yes | yes | yes | yes | yes | yes |

*Note*: This table reports results from daily fixed effects panel regressions of the form $DD_{j,t} = \alpha_j + \beta_1 C1_{j,t} + \beta_2 C2_{j,t} + \beta_3 C3_{j,t} + \gamma' \mathbf{w}_{j,t} + \epsilon_{j,t}$, where $\alpha_j$ denotes currency pair triplet fixed effects. The dependent variable $DD_{j,t}$ is a measure of dollar dominance that is either based on trading volume (i.e., $doldom_{j,t}$) or on Amihud's (2002) price impact (i.e., $amihud_{j,t}$). $C1$, $C2$, and $C3$ are the empirical counterparts of the three equilibrium conditions in Theorem 2. To mitigate multicollinearity, I orthogonalise $C1$ against $C2$ and $C3$ in column 6, where I jointly include all three conditions as regressors. *bid-ask* $spread_{j,t}$ is the daily average relative bid-ask spread. $cip\text{-}basis_{j,t}$ is the (absolute) cross-currency basis following the methodology in Du et al. (2018). These control variables in $\mathbf{w}_{j,t}$ are computed separately within every currency pair triplet as the average across two dollar pairs. The $S\&P\,500_t$ index tracks the performance of the 500 largest US stocks. Both dependent and independent variables are taken in logs and first differences. Panel A reports ordinary least squares (OLS) estimates. Panel B shows two-stage least squares estimates using a granular instrumental variable for $C1$, $C2$, and $C3$, respectively. The sample covers the period from 1 September 2012 to 29 September 2020. The test statistics based on Driscoll and Kraay's (1998) robust standard errors allowing for random clustering and serial correlation are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels.

**Figure 13: Common Trend Assumption: Non-overlapping Holidays**




*Note*: This figure provides evidence in favour of the internal validity of the parallel trend assumption. The treated period comprises non-overlapping holidays, whereas the control period consists of all other days. Every observation (black dots and grey circles) corresponds to the daily realisation of inter-dealer trading volume (measured in $bn). The bold black and grey lines are OLS regression lines of the treated and control period, respectively. The sample covers the period from 1 September 2012 to 29 September 2020.

# Asymmetric Information Risk in FX Markets

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**Abstract**

This work studies the information content of trades in the world's largest over-the-counter (OTC) market, the foreign exchange (FX) market. It analyzes a novel, comprehensive order flow data set, distinguishing among different groups of market participants and covering a large cross-section of currency pairs. We find compelling evidence of heterogeneous superior information across agents, time, and currency pairs, consistent with the asymmetric information theory and OTC market fragmentation. A trading strategy based on the permanent price impact, capturing asymmetric information risk, generates high returns even after accounting for risk, transaction cost, and other common risk factors shown in the FX literature.

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# 1. Introduction

One of the most important questions in financial economics is how security prices are determined. This is especially true for the foreign exchange (FX) market, which is the largest financial market in the world, with an average daily trading volume of $6.6 trillion.[1] Since it is almost entirely an over-the-counter (OTC) market, FX trading activity is relatively opaque and fragmented. Without a centralized trading mechanism, information is dispersed across various types of market participants such as commercial banks or asset managers, which maintain heterogeneous relationships with another. All these participants possess distinct information sets and contribute differently to FX determination.

The contribution of this paper is to uncover how different market participants determine currency values and to substantiate that asymmetric information risk is priced in the global FX market. To do this, we use a consistent methodology to analyze a novel, comprehensive data set that is representative of the global FX market rather than a specific segment (e.g., interdealer) or source (e.g., customers' trades of a given bank). The data set includes identity-based intraday order flow data broken down by types of market participants such as corporates, funds, nonbank financial firms, and banks acting as price takers. In this framework, we address the following two key questions: does order flow convey superior information across market participants, time, and currency pairs? Is asymmetric information risk priced in the FX market? We provide strong empirical evidence that asymmetric information risk in the FX market is systematic, time varying, and disseminated across groups of market participants as well as currency pairs. Consequently, we discover a new asset pricing factor capturing the economic value of asymmetric information risk and generating a both economically and statistically significant Sharpe ratio of 0.83.

The asymmetric information paradigm first formalized by Glosten and Milgrom (1985) and Kyle (1985) prescribes that when some agents[2] have superior information about the fundamental value of an asset, their trades covey information to the market. This body of the literature outlines two main empirical predictions: first, asymmetric information is positively related to the price impact of the trade. Second, the price impact tends to be persistent given the information content. Under asymmetric information, a representative agent faces the risk of being adversely selected (Easley, Hvidkjaer, and O'Hara, 2002). As a result, she demands an additional risk premium for trading against better informed investors (Wang, 1993, 1994). In addition to this, adverse selection also increases the required return through its allocation cost rather than through bid-ask spreads (Gârleanu and Pedersen, 2003). This paper provides empirical evidence supporting these theories and novel insights into price formation and asymmetric information

[1] See "Triennial central bank survey — global foreign exchange market turnover in 2019," Bank for International Settlements, September 2019.

[2] We use the terms "agents" and "market participants" interchangeably.

issues. Specifically, we dissect order flow into end-user segments of the global FX market and find that asymmetric information risk is priced.

What are the potential sources of asymmetric information risk in FX markets? To begin with, asymmetric information is inherent in FX trading due to its OTC nature that is characterized by distinct infrastructural features such as a decentralized network (Babus and Kondor, 2018) and dealership structure (Liu and Wang, 2016) giving rise to information dispersion.

In recent years, structural changes of the FX market, such as the rise of electronic and (high-frequency) automated trading and settlement, have exacerbated market fragmentation and asymmetric information issues across market participants.[3] Thus, individual investors have private information on currency values (Lyons, 1997; Evans and Lyons, 2006) or order flows that can also be exploited by dealers (Perraudin and Vitale, 1996). Furthermore, adverse selection in global FX markets can arise from information asymmetries in other asset classes (e.g., fixed income and equities) that are factored in FX trading via fundamental valuation, speculation, and portfolio rebalancing (Hau and Rey, 2004). Alternatively, asymmetric information premiums can stem from political uncertainty (Pástor and Veronesi, 2013), central bank decisions (Mueller, Tahbaz-Salehi, and Vedolin, 2017), or monetary policy interventions (Peiers, 1997) such that constrained global financial intermediaries require a compensation for adverse selection risk and uncertainty (Gabaix and Maggiori, 2015; He and Krishnamurthy, 2013).

This paper proceeds in two parts. In the first part, we empirically address the question of whether global FX order flows convey superior information heterogeneously across market participants, time, and currency pairs. To accomplish this, we estimate price impacts using a novel and unique data set from Continuous Linked Settlement Group (CLS) from 2012 to 2019. CLS operates the world's largest multi-currency cash settlement system, handling over 50% of the global spot, swap, and forward FX transaction volume. This data set includes hourly order flows divided into the following four types of market participants: corporates, funds, nonbank financial firms, and banks acting as price takers as well as the aggregate buy and sell side for 30 currency pairs. This data set has recently been introduced and made publicly accessible, thereby allowing the replicability and extensions of our study. By dissecting order flow into customer segments, we preserve the information diversity across market participants, which gets lost otherwise, when segments are aggregated.

Our empirical analysis builds on a vector autoregression (VAR) that decomposes the order flow price impact into transitory and permanent components. We extend the original VAR in Hasbrouck (1991a) by allowing for heterogeneous price impacts of different agents. We find clear evidence that order flow systematically impacts FX spot prices heterogeneously across three dimensions: agents, time, and currencies.

[3]See Imène Rahmouni-Rousseau and Rohan Churm, "Monitoring fast-paced electronic markets," Bank for International Settlements, September 2018.

Across agents, we find that some agents are always more informed than others, providing empirical evidence that asymmetric information and adverse selection are systematically present in the global FX market. For instance, corporates have, on average, a one–two basis point (BPS) lower permanent price impact across currency pairs than funds, nonbank financials or banks do, whose order flows are positively autocorrelated. This is consistent with the idea that sophisticated market participants have superior access to global FX markets, allowing them to engage in order splitting and price impact smoothing (Kervel and Menkveld, 2019). Moreover, the order flows of funds, nonbank financials, and banks are strongly linked to common FX trading strategies (i.e., carry (cf. Lustig, Roussanov, and Verdelhan, 2011) and value (cf. Menkhoff et al., 2017)). This behavior is in line with speculative trading motives and higher adverse selection risk when trading against such sophisticated speculators (Payne, 2003).

Across time, heterogeneity emerges as recurrent intraday patterns and time varying price impacts. From an intraday perspective, funds and nonbank financials transact around the clock, whereas corporates mostly trade during European stock market trading hours. This finding implies that in addition to banks, funds and nonbank financials gain more access to superior information by trading all around the clock and also squares well with the persistence of their (permanent) price impact. Rolling window regressions reveal that the order flow price impact is time varying and sensitive to market conditions (e.g., interest rate dynamics), which points toward temporal variation in asymmetric information risk.

Across currency pairs, we find that both the contemporary and permanent price impacts vary heavily across currencies, suggesting (time varying) asymmetric information and adverse selection cost in the cross-section of FX rates. Overall, the analysis of global FX order flow price impact substantiates that the information content of FX trading is heterogeneously disseminated across agents, time, and currency pairs. These findings corroborate the asymmetric information hypothesis and provide empirical evidence that the fragmented and opaque nature of the global FX market gives rise to asymmetric information risk and adverse selection issues.

In the second part of the paper, we analyze whether asymmetric information risk is priced in the FX market. To accomplish this, we introduce a novel long–short trading strategy that is consistent with the asymmetric information hypothesis: order flows of agents and currencies impounding a persistent price impact convey superior information. Put differently, holding currencies with higher informational asymmetries (i.e., a high average permanent price impact across agents) demands a positive risk premium for taking the risk of trading against informed investors. We provide empirical evidence that currency pairs with a large positive (small or negative) permanent price impact, that is, a high (small) informational advantage, gain positive (negative) excess returns. To be more precise, we take the perspective of a US investor and create an equally weighted dollar-neutral long–short portfolio that is rebalanced on a monthly basis. We dub our strategy $AIP_{HML}$. For every currency pair, the permanent price impact is averaged across agents to derive the systematic level of asymmetric information associated with this pair at a certain time. The $AIP_{HML}$ portfolio is long (short) currency pairs in the top (bottom) tertile that exhibit the highest (lowest) permanent price impact. Transaction cost are implemented using accurate quoted bid–ask rates for both forward contracts and spot transactions. $AIP_{HML}$ generates a both economically and statistically significant annualized return of 4.05% (3.16%) and a Sharpe ratio (SR) of 0.83 (0.65) before (after) transaction cost. Furthermore, we show that these returns cannot be explained by common FX risk factors, such as carry, momentum, value, and volatility.

We contribute to the microstructure and FX asset pricing literature in several ways. First, our analysis of heterogeneous FX order flows provides empirical evidence of information asymmetries across market participants.[4] Starting from the key contributions of Evans (2002) and Evans and Lyons (2002, 2005), several papers provide indirect evidence of information asymmetries by investigating how aggregate order flow determines FX rates.[5] The only few papers that study the order flow disaggregated by market participants focus on a specific market segment, such as a single interdealer trading platform or on customers' order flow for a specific bank.[6] However, these findings are not generalizable to the entire FX market.[7] This study represents the first analysis of order flow data representative for the entire global FX spot market with a large cross-section of FX rates and relatively long sample period. Building on the seminal work by Hasbrouck (1988, 1991a,b) and the notion of the permanent price impact, we propose a general model for detecting information asymmetries across agents. Thus, our findings provide direct empirical evidence of systematic information asymmetries in the world's largest OTC market. A battery of robustness checks suggests that this is a general result and does not hinge on specific assumptions such as risk neutrality that is assumed in many microstructure models with information asymmetry (e.g., Kyle, 1985; Glosten and Milgrom, 1985; Easley and O'Hara, 1987, 1991; Holden and Subrahmanyam, 1992).

Second, our paper contributes to the asset pricing literature by building a novel long–short trading strategy capturing asymmetric information risk. This is an effective method of extracting superior information inherent in order flow that can be applied to other asset classes beyond FX. In the FX asset pricing literature, Lustig and Verdelhan (2007), Lustig,

[4] For an excellent recent survey of this research, see Vayanos and Wang (2013).

[5] This vast literature on FX order flow includes, for example, Payne (2003); Bjønnes and Rime (2005); Evans and Lyons (2008); Breedon and Vitale (2010); Evans (2010); Menkhoff and Schmeling (2010), Rime, Sarno, and Sojli (2010), and Mancini, Ranaldo, and Wrampelmeyer (2013).

[6] For instance, some previous papers using a single interdealer trading platform are, for example, Moore and Payne (2011); Chaboud et al. (2014), and Breedon et al. (2018), while studies based on customers' order flow for a specific bank include, for example, Evans and Lyons (2006); Carpenter and Wang (2007); Breedon and Vitale (2010), Cerrato, Sarantis, and Saunders (2011); Osler, Mende, and Menkhoff (2011), Breedon and Ranaldo (2013), and Menkhoff et al. (2016).

[7] For instance, customer trading seems to have a greater price impact than interbank trading does (e.g., Bjønnes and Rime, 2000, 2005), and depending on their leverage, financial institutions have a different market impact in different currency markets (Lyons, 2006).

Roussanov, and Verdelhan (2011), Menkhoff et al. (2012a,b), and Asness, Moskowitz, and Pedersen (2013) identify common risk factors in currency markets based on the interest rate differential, real exchange rate, global FX volatility, and momentum. Other FX risk factors include macro-variables like global imbalances (e.g., Della Corte, Riddiough, and Sarno, 2016b) or volatility risk premiums (e.g., Della Corte, Ramadorai, and Sarno, 2016a). Using data from a specific dealer bank, Menkhoff et al. (2016) analyze whether that bank can extract valuable information from its disaggregated customer FX order flow data to predict the next day's FX rates. More specifically, they sort currency pairs into portfolios based on past order flows to assess the economic value as dealers' "smart money." To summarize, our paper makes two key contributions: first, we extend the methodology to isolate and analyze the information driven component of order flow with disaggregated customer flows. Second, we provide compelling empirical evidence that asymmetric information risk is priced in the global FX market.

The remainder of this paper is structured as follows. Section 2 describes our data set, Section 3 presents summary statistics, and Section 4 outlines the theoretical foundations. The market microstructure analysis is in Section 5, whereas the asset pricing analysis is in Section 6. Section 7 concludes. An Online Appendix provides additional results and robustness checks omitted in the paper.

## 2. Data

Our data set on spot FX order flow by market participant comes from CLS Group (CLS), which is publicly available directly from CLS or via Quandl.com, a financial and economic data provider.[8] CLS volume data (rather than order flow) have been used in prior research by Fischer and Ranaldo (2011); Hasbrouck and Levich (2018); Ranaldo and Santucci de Magistris (2019), and Cespa et al. (2020). To the best of our knowledge, this is the first paper to study CLS order flow data.

### 2.1. Heterogeneous FX Order Flow

Volume is recorded separately for buy and sell side market participants after instructions are received from both counterparties to the trade. Within the data set, CLS records the time of the transaction as if it had occurred at the first instruction being received. CLS receives confirmation for more than 90% of trade instructions from settlement members within two minutes of trade execution. Most of the 72 current settlement members are large multinational banks. Furthermore, there are over 25 000 "third party" clients of the settlement members, including other banks, funds, nonbank financial institutions, and corporations. At settlement,

[8]We are grateful to Tammer Kamel and his team at Quandl for granting us access to an initial sample of the order flow data set.

CLS mitigates principal and operational risk by simultaneously settling both sides of the FX transaction (Hasbrouck and Levich, 2018).

This data set has several features that make it suitable to investigating asymmetric information risk in FX trading. First, CLS records the buy and sell trading volume in the base currency as well as the number of transactions on an hourly basis from Sunday 9 pm to Friday 9 pm (London time, GMT), and thus it matches the whole FX trading week. Second, CLS sorts FX market participants into the following four distinct categories: corporates (CO), funds (FD), nonbank financial firms (NB), and banks (BA). These labels refer to the identities of the entities trading and not to the behavior they exhibit.[9] The fund category includes pension funds, hedge funds, and sovereign wealth funds, whereas nonbank financial are insurance companies, brokers, and clearing houses. The corporate category comprises any nonfinancial organization. Hence, there is substantial heterogeneity in the motives for market participation and in the access to price-relevant information across the end-user groups.

Corporates, funds, and nonbank financial firms are always considered to be price takers and are a subgroup of the total aggregate buy side. Banks acting as market makers are always reported on the sell side. In any given hour, CLS records the buy volume referring to how much of the base currency was purchased by the price takers from the market makers. The sell volume indicates the amount of base currency sold by the same price takers to the same market makers. The Online Appendix provides further institutional details and describes how CLS categorizes market participants into price takers and market makers.

Our full sample period spans from September 2, 2012 to December 31, 2019 and includes data for 16 major currencies and 30 currency pairs.[10] The order flow data set is limited to spot transactions. Three characteristics of the data set merit being discussed in more detail: first, it contains around seven years of hourly data, which is relatively long compared with previous studies on FX microstructure. Furthermore, using a high-frequency data set raises the statistical value of order flow in a time-series setting by mitigating potential reverse causality issues.

Second, despite being the most comprehensive time-series data set on FX order flow, it does not cover the full FX (spot) market. The Bank for International Settlements (BIS) triennial

[9] This is because CLS is a payment-versus-payment platform that solely observes the executed trade price used for settlement and does not see the market behavior of bids and offers that precede the execution or any other such details.

[10] The full data set contains data for 18 major currencies and 33 currency pairs. To maintain a balanced panel, we exclude the Hungarian forint (HUF), which enters the data set later, on November 7, 2015. Moreover, we discard the USDKRW due to insufficient amount of trades per price taker category. The remaining 30 currency pairs are AUDJPY, AUDNZD, AUDUSD, CADJPY, EURAUD, EURCAD, EURCHF, EURDKK, EURGBP, EURJPY, EURNOK, EURSEK, EURUSD, GBPAUD, GBPCAD, GBPCHF, GBPJPY, GBPUSD, NZDUSD, USDCAD, USDCHF, USDDKK, USDHKD, USDILS, USDJPY, USDMXN, USDNOK, USDSEK, USDSGD, and USDZAR.

survey reports an average daily trading volume of \$6.6 trillion.[11] Conversely, CLS settles approximately \$5.1 trillion per day, which translates to an average daily trading volume of \$1.9 trillion if one accounts for double-counting prime brokered trades. This is equivalent to covering 29% of the total FX volume based on the BIS triennial survey.[12] The reasons for this lack of coverage are manifold: first, FX options and nondeliverable forwards are not settled by CLS. Second, small banks with little FX turnover are seldom a settlement member. Third, CLS does not settle every currency for instance; the Chinese renminbi and Russian rubel are not yet eligible for settlement. Both Hasbrouck and Levich (2018) and Cespa et al. (2020) demonstrate that the CLS coverage is underestimated compared to the BIS survey, since a large fraction of the volume reported by the BIS is related to interbank trading across desks and double-counts prime-brokered "give-up" trades.[13] Adjusting for these facts shrinks total FX volume to \$3.8 trillion per day, and thus CLS covers at least 50% of it.[14]

Third, this data set does not cover all transactions originated by one of the three static price taker categories. More precisely, if a hedge fund settles a trade via a prime broker who is member of CLS, then this trade would show up as a bank/bank transaction.[15] This is because CLS does not observe the originator of such a trade but only the settlement itself. Consequently, such a transaction would either be excluded from the data set, if the prime broker is a market maker, or it would show up as a transaction originated by banks acting as price takers, if it behaves as a price taker.

Following the standard approach in the market microstructure literature, we measure order flow as net buying pressure $z_t$ against the base currency. Hence, we define order flow as the buy volume by price takers in the base currency minus the sell volume by market maker trades of the counter currency against the base currency,

$$T_t = \begin{cases} +1 & \text{if } z_t > 0 \\ 0 & \text{if } z_t = 0 \\ -1 & \text{if } z_t < 0 \end{cases}, \tag{1}$$

where a positive $T_t$ indicates the net buying pressure in the base currency against the counter currency.

[11]See "Triennial central bank survey — global foreign exchange market turnover in 2019," Bank for International Settlements, September 2019.

[12]See "Triennial central bank survey — Global foreign exchange market turnover in 2019," Bank for International Settlements, September 2019.

[13]In the 2019 BIS report (cf. p. 10), "related party trades" and "prime brokers" generated \$1.29 trillion and \$1.48 trillion in turnover, respectively.

[14]In their Online Appendix Cespa et al. (2020) further mitigate concerns about the representativeness of the sample by providing evidence that an almost perfect relation exists between the share of currency-pair volume in the BIS triennial surveys and the CLS data.

[15]This can be also true for algorithmic traders that are classified as funds when dealing with CLS.

### 2.2. Exchange Rate Returns

We pair the hourly FX volume data with intraday spot rates obtained from Olsen, a market-leading provider of high-frequency data and time-series management systems.[16] Thus, the FX order flow and exchange rate return are both measured hourly. The exchange rate return ($r_t$) is calculated as the log difference in the midquote FX rate over a trading hour:

$$r_t = \Delta s_t = s_t - s_{t-1}, \tag{2}$$

where natural logarithms are denoted by lowercase letters. Returns are always calculated from the perspective of the base currency.

## 3. Summary Statistics

In this section, we present summary statistics for our data on FX quotes and signed net volume, which is the buy minus sell volume (e.g., −USD100 mn or +EUR150 mn). In Table 1, we report the summary statistics for the quote in each currency pair. The first five rows report the sample mean and the standard deviation of the mean, minimum, and maximum hourly return as well as the average relative spread ($[ask - bid]/mid$) over the full sample. The last row reports the first-order autocorrelation.

There are three takeaways from the hourly spot returns summary statistics table, which are as follows: first, the average return over the hour is zero due to mean reversion (i.e., returns experience negative first-order autocorrelation). Second, the standard deviation of returns is in the range of 10–21 BPS. Third, the average relative spread varies in the cross-section due to variations in liquidity.

Table 2 reports detailed summary statistics for the hourly (absolute) net volume for the entire cross-section of currency pairs. Unsurprisingly, the currency pairs with the highest hourly volumes are the EURUSD ($433 mn), USDJPY ($237 mn), and USDCAD ($229 mn). Our ranking is largely in line with the BIS triennial survey and Cespa et al. (2020).[17] Funds and nonbank financials are the largest categories after price taker banks, while corporates form the smallest group.

Figure 1 fleshes out the idea that market participants behave heterogeneously during the day and provides prima facie evidence of market fragmentation. Notably, it shows that corporates trade at different times than funds or nonbank financials. For every market participant, we

[16] Olsen data are filtered in real time by assigning a credibility tick (ranging from 0–1), and they are directly available for all currency pairs. The number of ticks excluded from the supplied data due to credibility $< 0.5$ depends on the number of bad quotes but typically ranges from 0.5%–3.0% per day.

[17] See "Triennial central bank survey — Global foreign exchange market turnover in 2019," Bank for International Settlements, September 2019.

**Table 1: Summary Statistics for Hourly Spot Returns**

| *in BPS* | AUDJPY | AUDNZD | AUDUSD | CADJPY | EURAUD | EURCAD |
|---|---|---|---|---|---|---|
| Mean($\Delta_r$) | 0.00 | −0.04 | −0.08 | 0.02 | 0.07 | 0.04 |
| Std($\Delta_r$) | 15.38 | 9.34 | 12.53 | 14.11 | 12.16 | 11.14 |
| Min($\Delta_r$) | −540.61 | −120.73 | −228.41 | −407.53 | −140.71 | −146.40 |
| Max($\Delta_r$) | 175.69 | 162.48 | 137.07 | 159.59 | 184.65 | 169.51 |
| Avg. spread | 4.00 | 4.33 | 3.25 | 4.10 | 3.50 | 3.48 |
| AC(1) in % | 0.24 | −3.40 | −0.41 | 0.74 | 1.16 | 0.55 |
| *in BPS* | EURCHF | EURDKK | EURGBP | EURJPY | EURNOK | EURSEK |
| Mean($\Delta_r$) | −0.02 | 0.00 | 0.02 | 0.06 | 0.07 | 0.06 |
| Std($\Delta_r$) | 9.96 | 0.52 | 10.60 | 12.69 | 10.47 | 8.57 |
| Min($\Delta_r$) | −1,355.15 | −10.03 | −174.75 | −502.24 | −349.16 | −101.96 |
| Max($\Delta_r$) | 248.53 | 11.37 | 434.97 | 203.05 | 282.01 | 184.08 |
| Avg. spread | 2.71 | 2.61 | 3.24 | 3.10 | 6.00 | 5.30 |
| AC(1) in % | −3.36 | −19.32 | −1.07 | 0.98 | −1.42 | −2.43 |
| *in BPS* | EURUSD | GBPAUD | GBPCAD | GBPCHF | GBPJPY | GBPUSD |
| Mean($\Delta_r$) | −0.02 | 0.05 | 0.03 | −0.03 | 0.05 | −0.03 |
| Std($\Delta_r$) | 10.26 | 12.87 | 11.95 | 13.76 | 14.98 | 11.18 |
| Min($\Delta_r$) | −183.95 | −369.35 | −503.66 | −1,362.38 | −895.73 | −588.25 |
| Max($\Delta_r$) | 147.86 | 199.27 | 218.81 | 249.81 | 327.34 | 225.99 |
| Avg. spread | 2.27 | 4.16 | 3.96 | 4.15 | 3.79 | 2.66 |
| AC(1) in % | 1.43 | 0.52 | −0.93 | −3.13 | 1.77 | 1.72 |
| *in BPS* | NZDUSD | USDCAD | USDCHF | USDDKK | USDHKD | USDILS |
| Mean($\Delta_r$) | −0.03 | 0.07 | 0.01 | 0.03 | 0.00 | −0.03 |
| Std($\Delta_r$) | 13.71 | 9.64 | 12.72 | 10.25 | 0.84 | 9.54 |
| Min($\Delta_r$) | −204.26 | −142.93 | −1,377.04 | −145.23 | −30.93 | −178.48 |
| Max($\Delta_r$) | 174.39 | 187.09 | 250.23 | 182.45 | 16.35 | 187.19 |
| Avg. spread | 3.95 | 2.62 | 3.11 | 2.88 | 1.69 | 24.72 |
| AC(1) in % | −2.22 | −0.31 | −4.01 | 1.18 | −9.66 | −11.71 |
| *in BPS* | USDJPY | USDMXP | USDNOK | USDSEK | USDSGD | USDZAR |
| Mean($\Delta_r$) | 0.08 | 0.09 | 0.10 | 0.09 | 0.02 | 0.14 |
| Std($\Delta_r$) | 11.46 | 15.41 | 13.79 | 12.65 | 6.26 | 20.41 |
| Min($\Delta_r$) | −318.89 | −356.76 | −379.52 | −164.75 | −113.95 | −249.15 |
| Max($\Delta_r$) | 156.68 | 572.61 | 367.60 | 300.75 | 108.06 | 558.23 |
| Avg. Spread | 2.51 | 5.82 | 6.85 | 6.00 | 3.47 | 11.11 |
| AC(1) in % | 1.11 | 1.85 | −0.66 | −0.45 | −1.64 | −0.50 |

*Note*: This table presents summary statistics for average hourly returns of all 30 currency pairs in our sample. The first five rows report the sample mean (Mean($\Delta_r$)), standard deviation (Std($\Delta_r$)), minimum (Min($\Delta_r$)), and maximum (Max($\Delta_r$)) of the returns as well as the average relative spread (avg. spread = $[ask - bid]/mid$) over the full sample in basis points (BPS). The last row reports the first-order autocorrelation (AC(1)) for hourly returns in percent (%). The sample covers the period from September 2, 2012 to December 31, 2019.

report the average aggregate hourly volume for each hour of the trading day based on London time. Investigating at which hours market participants are most active helps to identify time fixed effects in the trading behavior of FX market participants. Volume levels are closely related to stock market opening hours around the world. Specifically, volume is lowest during the night when only the Australian market is open and is highest when both European and North American markets are operating in the afternoon. This pattern persists across market participants. Banks, nonbank financials, and funds all trade more around the clock. Banks are the largest subsection of the aggregate, with an average contribution of 30%–50%. They reduce

**Table 2: Summary Statistics for Hourly (Net) Volume**

| in USD mn | CO | FD | NB | BA | in USD mn | CO | FD | NB | BA |
|---|---|---|---|---|---|---|---|---|---|
| AUDJPY | 0.04 | 1.01 | 1.32 | 14.66 | GBPCHF | 0.02 | 1.56 | 0.73 | 5.75 |
| AUDNZD | 0.00 | 0.89 | 1.35 | 12.82 | GBPJPY | 0.09 | 1.80 | 2.55 | 16.45 |
| AUDUSD | 0.89 | 27.15 | 9.90 | 87.93 | GBPUSD | 4.06 | 47.29 | 15.20 | 131.13 |
| CADJPY | 0.02 | 0.31 | 0.57 | 5.06 | NZDUSD | 0.04 | 8.89 | 3.46 | 34.26 |
| EURAUD | 0.09 | 2.85 | 2.09 | 16.36 | USDCAD | 1.19 | 32.93 | 12.32 | 182.73 |
| EURCAD | 1.01 | 2.34 | 1.74 | 12.64 | USDCHF | 1.57 | 12.47 | 9.82 | 64.51 |
| EURCHF | 0.88 | 7.85 | 4.04 | 35.13 | USDDKK | 0.69 | 3.53 | 0.14 | 7.71 |
| EURDKK | 0.20 | 4.48 | 0.54 | 17.85 | USDHKD | 0.10 | 12.99 | 1.14 | 42.39 |
| EURGBP | 3.33 | 17.44 | 4.21 | 47.27 | USDILS | 0.04 | 1.16 | 0.22 | 10.63 |
| EURJPY | 1.39 | 7.08 | 7.22 | 38.67 | USDJPY | 3.70 | 50.49 | 18.57 | 164.32 |
| EURNOK | 0.95 | 5.20 | 2.31 | 19.50 | USDMXP | 0.31 | 10.29 | 2.36 | 31.44 |
| EURSEK | 2.30 | 8.22 | 2.45 | 23.81 | USDNOK | 0.21 | 5.18 | 1.53 | 18.53 |
| EURUSD | 19.32 | 121.36 | 27.37 | 264.84 | USDSEK | 0.59 | 7.83 | 1.68 | 22.35 |
| GBPAUD | 0.02 | 1.52 | 1.14 | 7.67 | USDSGD | 0.25 | 5.85 | 1.24 | 35.01 |
| GBPCAD | 0.21 | 0.97 | 0.83 | 6.13 | USDZAR | 0.07 | 5.62 | 1.32 | 21.53 |

*Note*: This table reports (absolute) net volume across 30 currency pairs and broken down by four categories of agents, namely, corporates (CO), funds (FD), nonbank financials (NB), and banks acting as price takers (BA). Net volume is defined as aggregate buy minus sell volume. All numbers are in USD million. The sample covers the period from September 2, 2012 to December 31, 2019.

their activity by about two-thirds outside of the London stock market trading hours[18] to limit inventory risk (Evans and Lyons, 2002).

To complete the descriptive analysis, the Online Appendix addresses two possible problematic issues on order flow data segregated by market participants groups: intratemporal and intertemporal dependence, respectively.

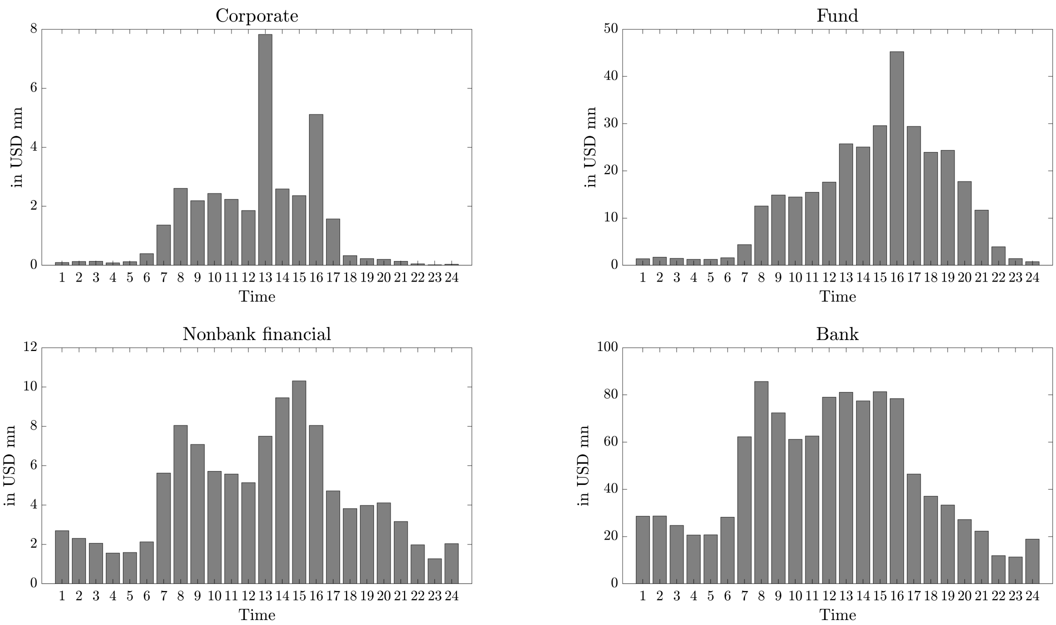
## 4. Methodology

In this section, we describe the methodology used for investigating whether market participants exhibit a heterogeneous price impact in the FX market. The approach builds on the framework developed by Hasbrouck (1988, 1991a), who introduces a VAR that makes almost no structural assumptions about the nature of information or order flow but instead infers the nature of information and trading from the observed sequence of quotes and trades.

Hasbrouck (1988) provides a useful model for separating the permanent (information) effects and temporary (inventory) effects of a trade but suffers from the limitation that order flow is assumed to evolve exogenously. However, prices can feed back to the order flow. To overcome this issue, Hasbrouck (1991a,b) proposes a bivariate VAR model that allows the price moves to be decomposed into trade-related and trade-unrelated components. Such a VAR model has two

[18]Rather than completely "closing their books" overnight, this result reflects the common practice of market makers to "pass on the book" from one regional banking hub to another.

**Figure 1: Distribution of (Net) Trading Volume Over a Day**




*Note*: This figure plots the average intraday hourly net volume (in USD mn). The average is computed across all 1885 trading days and 30 currency pairs. The horizontal axis denotes the closing time; for example, 17 refers to the volume between 4-5 pm (London time, GMT). The sample covers the period from September 2, 2012 to December 31, 2019.

important features that are key for our empirical analysis: first, it captures the persistent price impact of the trade innovation, which is a more precise and consistent estimate of processing superior fundamental information than the immediate price impact since the latter is contaminated by transient (liquidity) effects. Second, it is a model-free setting encompassing serial dependence of trades and returns, delays in the effect of a trade on the price, and nonlinear trade–price relations that can arise, for example, from inventory control, price pressure effects, and order fragmentation.

Consistent with this framework, we build an encompassing model that allows for heterogeneous order flows and controls for short-term mean reversion as well as hourly seasonalities. Especially, Eq. (4) describes the trade-by-trade evolution of the quote midpoint, while Eq. (5) refers to the persistent effect of order flow. We define $T_t$ to be the buy-sell indicator (+1 for buys, −1 for sells) for trade $t$ in a specific currency pair $k$.[19] Furthermore, we define $r_t$ as the log FX rate return based on the midquote. Easley and O'Hara (1987) present a theoretical asymmetric information model in which private information revealed by an order and the consequent change in quotes are positively related to order flow size. We account for these effects by intro-

[19] $T_t^{CO}$ for corporates, $T_t^{FD}$ for funds, $T_t^{NB}$ for nonbank financials, and $T_t^{BA}$ for banks acting as price takers, that is, the orthogonalized volume representing total buy side minus the aggregate (signed) net volume of every market participant.

ducing an order size variable (cf. Hasbrouck, 1988) into the VAR specifications. Logarithms of the signed net volume ($z_t$) are taken to control for the effect of presumed nonlinearities between order size and quote revisions:

$$v_t = \begin{cases} +log(z_t) & \text{if } z_t > 0 \\ 0 & \text{if } z_t = 0 \ . \\ -log(-z_t) & \text{if } z_t < 0 \end{cases} \tag{3}$$

To support the interpretation of the regression coefficients, $v_t$ is transformed by regressing it against the current and lagged values of the trade indicator variable $T_t$. As proposed in Hasbrouck (1988), we extract the residuals from this regression, denoted by $\tilde{S}_t$, which are by construction uncorrelated with the indicator variable $T_t$.[20] Hourly dummies are included to control for daily seasonalities affecting FX rates and order flows. More importantly, the VAR accommodates both lagged returns and order flow in both the return (i.e., Eq. (4)) and order flow equations (i.e., Eq. (5)), since many microstructure imperfections, such as price discreteness, inventory effects, lagged adjustment to information, noncompetitive behaviors, and order splitting, are thought to cause lagged effects. The number of lags is selected to be ten based on the Akaike/ Bayesian information criteria and the theoretical arguments in Hasbrouck (1991a,b):

$$r_t = \zeta_{1,l} D_{l,t} + \sum_{i=1}^{10} \rho_i r_{t-i} + \sum_{j \in C} \left( \sum_{i=0}^{10} \beta_i^j T_{t-i}^j + \sum_{i=0}^{10} \phi_i^j \tilde{S}_{t-i}^j \right) + \eta_1 \Delta s_{t;t-\tau} + \eta_2 \Delta s_{t;t-5\tau} + \epsilon_{r,t}, \tag{4}$$

$$T_t = \zeta_{2,l} D_{l,t} + \sum_{i=1}^{10} \gamma_i r_{t-i} + \sum_{j \in C} \left( \sum_{i=1}^{10} \delta_i^j T_{t-i}^j + \sum_{i=1}^{10} \omega_i^j \tilde{S}_{t-i}^j \right) + \epsilon_{T,t}, \tag{5}$$

where $D_{l,t}$ denotes a dummy variable matrix to account for time fixed effects with $l = 24$ columns and $t = n$ rows, in which element $l, t$ is 1 if there was a trade in that hour; and $C = \{CO, FD, NB, BA\}$ denotes disaggregated order flow categories. Moreover, the regression considers the lagged exchange rate changes over the previous day $\Delta s_{t;t-\tau}$ and over the prior week $\Delta s_{t;t-5\tau}$. Here, $\tau = 24$, and $t$ is measured hourly. For convenience of exposition, currency specific subscripts (i.e., $k$) have been suppressed in Eqs (4) and (5). The error terms $\epsilon_{r,t}$ and $\epsilon_{T,t}$ can be interpreted as the (unexpected) public and private information components (Hasbrouck, 1991a). This dichotomy ensures that the permanent price impact $\alpha_m^{j,k}$ in Eq. (7) can be interpreted as a measure of asymmetric/private information.[21] Since we include contemporaneous $T_t$ in Eq. (4) but not in Eq. (5), the system is exactly identified, and hence the error terms shall

[20] It is important to note that our main results remain qualitatively unchanged when excluding the order size variable from our baseline VAR model.

[21] Hasbrouck (1991a) thoroughly discusses some of the imperfections that might disturb this dichotomy in practice.

have a zero mean and be jointly and serially uncorrelated:

$$\begin{aligned} &E(\epsilon_{T,t}) = E(\epsilon_{r,t}) = 0 \\ &E(\epsilon_{T,t}\epsilon_{T,s}) = E(\epsilon_{r,t}\epsilon_{r,s}) = E(\epsilon_{T,t}\epsilon_{r,s}) = 0, \text{ for } s \neq t. \end{aligned} \tag{6}$$

A possible concern about our VAR setting is that some endogeneity originates from the contemporaneous returns having a simultaneous effect on order flows. One way of mitigating this issue empirically would be to use instrumental variables, as proposed in Daníelsson and Love (2006). However, two issues arose when implementing this approach: first, the instruments are too weak when applying the Daníelsson and Love (2006) methodology to frequencies greater than five minutes. Second, none of the instruments, such as the contemporaneous order flow of another currency pair, passed the Wald test for overidentification and exogeneity. Given the weakness of the instruments and limited data availability, the modified Hasbrouck (1991a,b) model remains the soundest method that can be applied in this setting.

**Permanent price impact.** We can derive the permanent price impact at the individual agent level as the sum of the asymmetric information coefficients from the VAR in Eq. (4). Following Hasbrouck (1988) and Payne (2003), the permanent price impact of agent $j \in C$, where $C = \{CO, FD, NB, BA\}$, within a particular currency pair $k$ can be calculated as follows:

$$\alpha_m^{j,k} = \sum_{t=0}^{m} \beta_t^{j,k}, \tag{7}$$

where $m$ indicates the number of lags, which is ten in our case. Since $\alpha_m^{j,k}$ is cumulative over several hours (even weak effects can add up), VAR estimates of a lower order ($m \leq 10$) are likely to overstate the long-run price impact.[22] In other words, such a model would catch the initial positive impact of a trade on the quote but will miss the subsequent long-run reversion. Using the VAR representation, the average permanent price impact across agents capturing the systematic level of superior information within currency pair $k$ is given by

$$\bar{\alpha}_m^k = \frac{1}{|C|} \sum_{j \in C} \sum_{t=0}^{m} \beta_t^{j,k} = \frac{1}{|C|} \sum_{j \in C} \alpha_m^{j,k}. \tag{8}$$

In this framework, the permanent price impact is a measure of asymmetric information and adverse selection that accounts for the persistence in order flow as well as for possible positive

[22] Note that the permanent price impact is not the same as the impulse response function of a VAR. The former estimates the informativeness of a trade by summing up the asymmetric information coefficients, whereas the latter measures the impact of a unit shock in order flow imbalance to the exchange rate (Hasbrouck, 1991a). As a robustness check, we estimate a five-variate structural VAR (SVAR) of disaggregated order flows to understand the lead-lag relation across price impacts of various customer segments. See the Online Appendix for further details.

or negative feedback trading. The $\bar{\alpha}_m^k$ lies at the heart of the subsequent asset pricing analysis and possesses a natural interpretation as the information content of a trade net of transient effects inherent in global FX trading.

It is worth noting that in microstructure models (e.g., Kyle, 1985) with asymmetric information, it is standard to assume risk neutral agents. However, risk aversion of both informed traders and market markets increases the price impact (Subrahmanyam, 1991) and reduces price efficiency, especially with imperfect competition (Kyle, 1989). For this reason, we account for the effect of risk aversion on cross-sectional and temporal variation of price impacts in our robustness tests.

## 5. Heterogeneous Asymmetric Information

In this section, we analyze whether the price impact in the global FX spot market systematically varies across market participants, currency pairs, and time. All the coefficients are reported using the notation introduced in Eqs (4) and (5).

### 5.1. Estimation Method and the Contemporaneous Price Impact

First, we estimate Eqs (4) and (5) using standard ordinary least squares (OLS) on the full sample, controlling for seasonal time-of-the day effects, lagged returns, and order size.[23] Second, we apply a 12-month rolling window for measuring the time variation of both the contemporary $\beta_0^j$ and permanent price impact $\alpha_m^j$, respectively. The main advantage of the VAR approach lies in its potential for generalization to gain a more nuanced view of the trade–quote interactions.[24] For the sake of clarity, we only present the results for lagged return equation coefficients $\rho_1$ and $\gamma_1$, the contemporary price impact $\beta_0^j$ and lagged order flow $\delta_1^j$, where $j \in C$ denotes one group of market participants. Table 3 shows the regression coefficients of the bivariate VAR estimated through ten lags. The most important ones are those of $T_0^j$ in Eq. (4) that measure the contemporary price impact of a trade.

For the great majority of currency pairs, regression coefficients bear the expected signs summarized in Table 3: here, $\rho_1$ coefficients are negative and entail short-term mean reversion, while $\beta_0^j$ coefficients are positive and in line with market microstructure theory (e.g., Kyle, 1985; Glosten and Milgrom, 1985). This is especially true for the most liquid and frequently

[23] To avoid misspecification in our regression analysis and to check the validity of our assumptions in Eq. (6), we conduct a battery of diagnostic tests that are summarized in the Online Appendix.

[24] As in Hasbrouck (1991a,b), $T_t$ is defined as a limited dependent variable. If $T_t$ and $r_t$ are jointly covariance stationary and invertible, a VAR model as in Eqs (4) and (5) exists. However, while the error terms are serially uncorrelated, they are not serially independent in general. The disturbance properties in Eqs (4) and (5) further ensure that the coefficients are estimated consistently by OLS.

traded currency pairs.[25] The true beauty of the log-level model in Table 3 is its interpretability: coefficients can be interpreted as percentage changes in the dependent variable for a one-unit change of the independent variable.[26] The coefficients at longer lags (i.e., beyond lags seven and eight) frequently alternate in sign, are seldom significant, and quickly decay to zero. From these results, it is apparent that, on average, all agents except corporates have a significantly positive contemporary price impact.

For some currency pairs (e.g., EURGBP, EURNOK, EURUSD), corporates experience significantly negative contemporary price impact parameters. The negative $\beta_0^{CO}$ is consistent with earlier work by Bjønnes, Rime, and Solheim (2005), Lyons (2006); Carpenter and Wang (2007), Cerrato, Sarantis, and Saunders (2011), Evans and Lyons (2012), and Menkhoff et al. (2016) and indicates that corporates often buy (sell) in a falling (rising) market.[27] Rather than from informational motives, a negative relation between order flow and return arises from liquidity needs (Grossman and Miller, 1988) and dealers' inventory features (Stoll, 1978). Thus, corporate trading seems to be driven by risk sharing, hedging, and liquidity issues as well as by additional costs unrelated to adverse selection. This idea squares well with the different timing in their trading behavior (see Figure 1). Whereas banks and other financial institutions access a richer information set by trading around the clock, the trading activity of corporates is more segmented and limited within a few hours.[28]

The negative $\beta_0^{CO}$ is also consistent with risk-averse FX dealers offsetting order flows coming from potentially more informed agents (e.g., other banks and financial firms) with the noninformative one from corporates to reduce their exposure to asymmetric information risk (Liu and Wang, 2016). The negative correlations between corporates' order flow and that of other financial agents reported above are fully in line with this picture. The coefficients of the return over the previous day ($\eta_1$) is negative and highly significant for all currency pairs, while the return over the prior week ($\eta_2$) is negative but insignificant for the majority of currency pairs.

Table 4 summarizes the order flow equation coefficients, which also bear the expected signs: here, $\gamma_1$ is negative and highly significant, while $\delta_1^j$ coefficients are positively significant for most

[25]One notable exception are the fixed pairs, for example, the EURDKK and USDHKD, where contemporary price impacts are zero in economic terms.

[26]The results are extremely similar when we use (signed) net volume (without order size variable $\tilde{S}_t^{\,j}$), calculated as the net of buy volume by price takers minus the sell volume by market maker transactions, broken down into types of market participants instead of (binary) order flow and using transaction prices instead of midquotes for calculating $r_t$ in Eq. (4). See the Online Appendix for further results.

[27]By analyzing the price discovery process in the US Treasury bond market, Pasquariello and Vega (2007) find that negative price impact coefficients are driven by transitory inventory effects.

[28]Alternatively, the negative coefficient for the contemporaneous price impact of corporate order flow can arise as market makers unwind their inventories onto nonfinancial customers (i.e., Lyons, 1997; Bjønnes and Rime, 2005). Moreover, Breedon and Vitale (2010) argue that, while the liquidity effects of order flow are transient, a trade imbalance could have a long-lived impact via a portfolio-balance effect. This could also hold true even if the order flow is not information driven.

## Table 3: Return Equation Coefficients

| Eq. (4) | $\rho_1$ | $\beta_0^{CO}$ | $\beta_0^{FD}$ | $\beta_0^{NB}$ | $\beta_0^{BA}$ | $\bar{R}^2$ in % | Eq. (4) | $\rho_1$ | $\beta_0^{CO}$ | $\beta_0^{FD}$ | $\beta_0^{NB}$ | $\beta_0^{BA}$ | $\bar{R}^2$ in % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AUDJPY | ***−8.597 | −0.018 | ***0.009 | ***0.007 | ***0.014 | 9.517 | GBPCHF | ***−11.915 | **−0.033 | −0.002 | ***0.008 | ***−0.004 | 9.915 |
| | [7.005] | [1.621] | [3.213] | [5.251] | [17.868] | | | [4.078] | [2.533] | [1.031] | [3.396] | [5.937] | |
| AUDNZD | ***−11.602 | −0.006 | −0.002 | ***−0.003 | ***−0.002 | 8.588 | GBPJPY | ***−7.688 | −0.008 | **0.003 | ***0.004 | ***0.010 | 9.793 |
| | [17.792] | [0.276] | [0.933] | [4.666] | [5.176] | | | [4.117] | [0.915] | [2.050] | [4.034] | [10.430] | |
| AUDUSD | ***−8.202 | ***−0.013 | ***0.004 | ***0.010 | ***0.003 | 9.358 | GBPUSD | ***−6.598 | ***−0.014 | ***0.004 | ***0.007 | ***0.005 | 9.485 |
| | [11.634] | [2.602] | [5.377] | [16.976] | [5.513] | | | [5.484] | [5.155] | [5.168] | [11.177] | [9.580] | |
| CADJPY | ***−7.497 | 0.002 | −0.001 | 0.002 | ***0.004 | 8.353 | NZDUSD | ***−9.579 | **−0.039 | ***0.007 | ***0.006 | ***0.006 | 8.601 |
| | [6.129] | [0.129] | [0.435] | [1.506] | [5.515] | | | [14.234] | [2.544] | [6.788] | [8.402] | [8.771] | |
| EURAUD | ***−6.910 | **−0.015 | **0.002 | **0.002 | ***0.003 | 8.280 | USDCAD | ***−8.680 | ***−0.024 | ***0.003 | ***0.004 | ***0.002 | 9.213 |
| | [6.617] | [2.358] | [2.180] | [2.386] | [6.023] | | | [10.932] | [5.493] | [4.152] | [8.924] | [5.230] | |
| EURCAD | ***−7.980 | ***−0.028 | 0.001 | ***0.005 | ***−0.002 | 8.883 | USDCHF | ***−12.859 | ***−0.012 | **0.002 | ***0.010 | **0.001 | 10.595 |
| | [7.430] | [6.152] | [0.961] | [5.581] | [3.641] | | | [3.532] | [4.120] | [1.999] | [14.811] | [2.374] | |
| EURCHF | ***−11.741 | ***−0.012 | 0.002 | 0.000 | ***−0.005 | 10.359 | USDDKK | ***−6.728 | ***−0.042 | −0.001 | ***0.007 | ***−0.002 | 8.248 |
| | [2.939] | [5.023] | [1.542] | [0.477] | [6.002] | | | [7.463] | [5.676] | [1.205] | [2.643] | [2.896] | |
| EURDKK | ***−28.951 | 0.000 | ***0.000 | 0.000 | ***0.000 | 15.163 | USDHKD | ***−20.058 | 0.000 | ***0.000 | 0.000 | ***0.000 | 12.558 |
| | [18.486] | [1.306] | [3.646] | [0.865] | [4.289] | | | [11.718] | [0.279] | [5.398] | [0.948] | [3.540] | |
| EURGBP | ***−9.385 | ***−0.012 | **0.002 | ***0.002 | ***−0.003 | 8.682 | USDILS | ***−21.784 | −0.001 | ***0.003 | ***−0.010 | ***0.002 | 12.746 |
| | [12.004] | [5.639] | [2.565] | [3.345] | [5.942] | | | [26.444] | [0.128] | [2.882] | [7.185] | [3.878] | |
| EURJPY | ***−7.433 | ***−0.019 | **−0.002 | ***0.004 | **−0.001 | 8.816 | USDJPY | ***−7.362 | ***−0.006 | ***0.005 | ***0.008 | ***0.005 | 9.457 |
| | [5.935] | [6.317] | [1.960] | [6.144] | [2.390] | | | [7.059] | [3.346] | [6.709] | [14.995] | [8.725] | |
| EURNOK | ***−9.768 | ***−0.019 | ***0.008 | 0.002 | ***0.002 | 9.494 | USDMXP | **−6.609 | *−0.015 | 0.002 | ***−0.008 | 0.000 | 8.404 |
| | [10.742] | [5.174] | [6.775] | [1.570] | [4.211] | | | [2.278] | [1.826] | [1.528] | [6.410] | [0.141] | |
| EURSEK | ***−9.996 | ***−0.010 | ***0.004 | **0.002 | ***0.002 | 8.549 | USDNOK | ***−9.614 | ***−0.034 | ***0.004 | ***0.005 | ***0.004 | 9.271 |
| | [12.360] | [4.961] | [5.101] | [2.379] | [4.143] | | | [10.544] | [3.104] | [3.459] | [4.140] | [5.170] | |
| EURUSD | ***−6.685 | ***−0.015 | 0.000 | ***0.006 | −0.001 | 9.475 | USDSEK | ***−8.518 | ***−0.023 | ***0.004 | ***0.004 | ***0.003 | 8.471 |
| | [7.261] | [12.389] | [0.337] | [11.522] | [1.342] | | | [10.176] | [4.560] | [4.353] | [3.637] | [5.206] | |
| GBPAUD | ***−7.873 | 0.026 | ***0.004 | 0.001 | ***0.003 | 8.624 | USDSGD | ***−10.698 | ***−0.013 | ***0.002 | ***0.002 | ***−0.001 | 9.577 |
| | [9.974] | [1.620] | [2.703] | [1.266] | [5.525] | | | [15.594] | [4.712] | [4.259] | [4.071] | [4.468] | |
| GBPCAD | ***−9.137 | **−0.035 | 0.001 | **0.003 | 0.000 | 8.392 | USDZAR | ***−9.591 | *−0.030 | ***0.006 | 0.003 | ***0.007 | 9.695 |
| | [11.353] | [2.436] | [0.594] | [2.500] | [0.780] | | | [10.749] | [1.934] | [3.417] | [1.433] | [6.707] | |
| Expected sign | - | + | + | + | + | | Expected sign | - | + | + | + | + | |

*Note*: This table reports estimates of the following regression model

$$r_t = \zeta_{1,l} D_{l,t} + \sum_{i=1}^{10} \rho_i r_{t-i} + \sum_{j \in C} \left( \sum_{i=0}^{10} \beta_i^j T_{t-i}^j + \sum_{i=0}^{10} \phi_i^j \tilde{S}_{t-i}^j \right) + \eta_1 \Delta s_{k,t;t-\tau} + \eta_2 \Delta s_{k,t;t-5\tau} + \epsilon_{r,t},$$

where agents are abbreviated as follows: corporates (CO), funds (FD), nonbank financials (NB), and banks acting as price takers (BA). $D_{l,t}$ denotes a dummy variable matrix to account for time fixed effects. In addition, $\Delta s_{k,t;t-\tau}$ and $\Delta s_{k,t;t-5\tau}$ account for the return over the prior day and week. Here, $\tau = 24$ and $t$ is measured at hourly frequency and $C = \{CO, FD, NB, BA\}$. Transactions are indexed by $t$, and $r_t$ refers to the log-return in the midquote. $\tilde{S}_t^j$ controls for order size and refers to the residuals of regressing signed log volume against current and lagged values of the trade indicator variable $T_t$ (+1 for a buy order and −1 for a sell order). The linear regression coefficients are estimated by ordinary least squares on the full sample. The sample covers the period from September 2, 2012 to December 31, 2019. All coefficients are in %. The $t$-stats in square brackets are based on heteroskedasticity- and autocorrelation-consistent errors (Newey and West, 1987), and asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively.

currency pairs and reflect the positive autocorrelation in trades. This is consistent with the findings in the stock market literature, for example, Hasbrouck and Ho (1987); Hasbrouck (1988), and Madhavan, Richardson, and Roomans (1997), and it shows that purchases tend to follow purchases and similarly for sales. Rather than with inventory control mechanisms, the short-run predominance of positive autocorrelation can be reconciled with delayed price adjustments to new information. Again, $\gamma_1$ implies negative autocorrelation in the quote revisions. In the order flow equation estimation, this implies Granger–Sims causality running from quote revisions to trades. This causality is in line with microstructure theory, where a negative relation between trades and lagged quote revisions is consistent with inventory control effects and/or the price experimentation hypothesis formulated by Leach and Madhavan (1992), in which the market maker sets quotes to extract information optimally from traders.

**Table 4: Order Flow Equation Coefficients**

| Eq. (5) | $\gamma_1$ | $\delta_1^{CO}$ | $\delta_1^{FD}$ | $\delta_1^{NB}$ | $\delta_1^{BA}$ | $\bar{R}^2$ in % | Eq. (5) | $\gamma_1$ | $\delta_1^{CO}$ | $\delta_1^{FD}$ | $\delta_1^{NB}$ | $\delta_1^{BA}$ | $\bar{R}^2$ in % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AUDJPY | ***34.453 | −0.014 | ***0.041 | 0.001 | ***0.061 | 1.672 | GBPCHF | ***−28.160 | **0.145 | 0.001 | 0.006 | ***0.023 | 0.377 |
| | [8.661] | [0.208] | [2.694] | [0.107] | [12.407] | | | [4.300] | [2.029] | [0.121] | [0.612] | [4.671] | |
| AUDNZD | ***−35.226 | 0.124 | 0.009 | 0.001 | ***0.051 | 0.585 | GBPJPY | ***42.777 | −0.001 | ***0.029 | 0.006 | ***0.054 | 1.389 |
| | [6.714] | [0.690] | [0.490] | [0.216] | [10.712] | | | [6.283] | [0.024] | [2.679] | [0.891] | [10.653] | |
| AUDUSD | **−8.763 | 0.010 | 0.008 | ***0.020 | ***0.039 | 0.507 | GBPUSD | **−10.448 | 0.018 | 0.008 | 0.005 | ***0.048 | 0.836 |
| | [2.276] | [0.328] | [1.426] | [4.102] | [8.036] | | | [2.525] | [1.142] | [1.350] | [0.894] | [9.976] | |
| CADJPY | −2.469 | 0.036 | 0.007 | 0.008 | ***0.030 | 0.209 | NZDUSD | ***−15.227 | −0.059 | **0.015 | 0.004 | ***0.056 | 0.694 |
| | [0.718] | [0.395] | [0.328] | [0.828] | [6.156] | | | [4.343] | [0.896] | [2.039] | [0.819] | [11.678] | |
| EURAUD | ***−14.415 | 0.023 | 0.003 | 0.003 | ***0.022 | 0.226 | USDCAD | 1.868 | 0.005 | 0.009 | 0.003 | ***0.054 | 1.117 |
| | [3.626] | [0.493] | [0.306] | [0.458] | [4.523] | | | [0.383] | [0.177] | [1.377] | [0.557] | [11.158] | |
| EURCAD | ***−27.702 | ***0.146 | −0.005 | **0.018 | ***0.037 | 0.620 | USDCHF | ***−15.953 | ***0.076 | ***0.025 | 0.001 | ***0.041 | 0.551 |
| | [6.512] | [4.850] | [0.578] | [2.464] | [7.529] | | | [3.741] | [3.205] | [3.730] | [0.161] | [8.454] | |
| EURCHF | *−41.130 | ***0.079 | ***0.028 | 0.004 | ***0.064 | 1.791 | USDDKK | **−8.360 | 0.008 | *0.014 | 0.004 | ***0.020 | 0.543 |
| | [1.739] | [3.636] | [3.609] | [0.537] | [12.341] | | | [1.967] | [0.199] | [1.669] | [0.196] | [3.528] | |
| EURDKK | 133.740 | −0.036 | ***0.026 | ***0.082 | ***0.074 | 1.070 | USDHKD | ***−301.884 | **0.232 | **0.015 | 0.021 | ***0.058 | 0.749 |
| | [1.578] | [0.946] | [2.641] | [2.812] | [13.460] | | | [4.764] | [2.228] | [2.461] | [1.215] | [11.823] | |
| EURGBP | ***−37.084 | **0.029 | ***0.022 | −0.004 | ***0.045 | 1.035 | USDILS | 4.110 | 0.165 | ***0.028 | 0.007 | ***0.075 | 1.369 |
| | [8.007] | [1.972] | [3.366] | [0.630] | [9.419] | | | [0.917] | [1.419] | [2.592] | [0.495] | [13.396] | |
| EURJPY | 0.970 | 0.004 | **0.018 | ***0.025 | ***0.039 | 0.993 | USDJPY | −2.790 | *0.023 | ***0.027 | ***0.016 | ***0.028 | 0.503 |
| | [0.261] | [0.190] | [2.178] | [4.777] | [8.076] | | | [0.681] | [1.698] | [4.699] | [3.235] | [5.819] | |
| EURNOK | ***−38.956 | ***0.053 | ***0.038 | ***0.034 | ***0.075 | 1.376 | USDMXP | ***−24.825 | *0.067 | 0.007 | **0.014 | ***0.048 | 0.530 |
| | [7.544] | [2.836] | [4.524] | [4.492] | [15.042] | | | [6.273] | [1.884] | [0.917] | [2.115] | [9.791] | |
| EURSEK | ***−44.468 | ***0.054 | ***0.035 | ***0.024 | ***0.081 | 1.392 | USDNOK | ***8.968 | 0.079 | ***0.021 | 0.005 | ***0.071 | 0.924 |
| | [8.165] | [3.875] | [4.707] | [3.149] | [16.525] | | | [2.670] | [1.541] | [2.663] | [0.616] | [14.005] | |
| EURUSD | ***−35.157 | 0.010 | ***0.030 | 0.001 | ***0.051 | 1.815 | USDSEK | **−7.691 | ***0.090 | ***0.026 | 0.006 | ***0.048 | 0.557 |
| | [7.576] | [1.179] | [5.421] | [0.270] | [10.439] | | | [2.080] | [3.351] | [3.648] | [0.822] | [9.833] | |
| GBPAUD | −5.831 | −0.191 | 0.016 | 0.012 | ***0.022 | 0.128 | USDSGD | ***−73.324 | −0.014 | 0.011 | −0.005 | ***0.049 | 0.705 |
| | [1.576] | [1.022] | [1.605] | [1.533] | [4.616] | | | [9.593] | [0.310] | [1.547] | [0.557] | [10.229] | |
| GBPCAD | ***13.404 | **0.224 | 0.008 | ***0.028 | ***0.034 | 0.258 | USDZAR | ***−16.545 | 0.032 | ***0.022 | **−0.016 | ***0.050 | 0.679 |
| | [3.102] | [2.123] | [0.739] | [3.211] | [6.852] | | | [6.707] | [0.785] | [2.828] | [2.171] | [10.238] | |
| Expected sign | - | + | + | + | + | | Expected sign | - | + | + | + | + | |

*Note*: This table reports estimates of the following regression model

$$T_t = \zeta_{2,l} D_{l,t} + \sum_{i=1}^{10} \gamma_i r_{t-i} + \sum_{j \in C} \left( \sum_{i=1}^{10} \delta_i^j T_{t-i}^j + \sum_{i=1}^{10} \omega_i^j \tilde{S}_{t-i}^j \right) + \epsilon_{T,t},$$

where agents are abbreviated as follows: corporates (CO), funds (FD), nonbank financials (NB), and banks acting as price takers (BA). $D_{l,t}$ denotes a dummy variable matrix to account for time fixed effects, and $C = \{CO, FD, NB, BA\}$. Transactions are indexed by $t$, and $r_t$ refers to the log-return in the midquote. $\tilde{S}_t^j$ controls for order size and refers to the residuals of regressing signed log volume against current and lagged values of the trade indicator variable $T_t$ (+1 for a buy order and −1 for a sell order). The linear regression coefficients are estimated by ordinary least squares on the full sample. The sample covers the period from September 2, 2012 to December 31, 2019. The $t$-stats in square brackets are based on heteroskedasticity- and autocorrelation-consistent errors (Newey and West, 1987), and asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively.

For both the return and order flow equation, hourly dummies ($\zeta_{1,l}$ and $\zeta_{2,l}$) are mostly significant and in line with well-known intraday patterns; i.e., significance surges at the opening/closing of major marketplaces. Order size coefficients ($\phi_i^j$ and $\omega_i^j$) are mostly positive and significant but are around a fraction of a BPS. Thus, larger trades subsequently lead to a larger price impact, increasing the level of asymmetric information and inventory risk (Glosten and Harris, 1988).

## 5.2. Analysis of the Permanent Price Impact

So far, we have centered our analysis on the contemporary price impact. We now turn to the permanent component. In the model of Hasbrouck (1991a), $\alpha_m^j$ can be interpreted as the measure of asymmetric/private information because trades are driven by a mixture of private (superior) information and liquidity needs rather than by public information. Therefore, any persistent impact of a trade on prices arises from asymmetric information signaled by that trade. This intuition is reflected in Eqs (4) and (5), which identifies all public information with the quote revision innovation ($\epsilon_{r,t}$) and all private information with the trade innovation ($\epsilon_{T,t}$). The dichotomy above ensures that $\epsilon_{T,t}$ reflects no public information, and hence the permanent price impact $\alpha_m^j$ can be interpreted as a measure of asymmetric/private information.

### 5.2.1 Heterogeneous Price Impact Across Agents

In Table 5 we summarize the estimates of the permanent price impact ($\alpha_m^j$) for every agent category and currency pair and draw three key considerations: first, across all currency pairs, there is always at least one category of agents with a significant $\alpha_m^j$, suggesting that some market participants always possess superior information. Second, the comparison of the permanent price impacts across traders' categories indicates that banks access superior information across almost all currencies, which is consistent with their privileged access to information that emanates from their central (network) role in the global FX market (Babus and Kondor, 2018; Perraudin and Vitale, 1996). Funds and nonbank financials also have superior information in many currency pairs, generalizing previous findings (Lyons, 1997; Evans and Lyons, 2006) at a global scale, suggesting that banks themselves are also exposed to asymmetric information risk. On the flip side, corporate trading is systematically not informationally driven. Third, for several currency pairs, banks appear to be the only category with superior information. This result goes beyond the "smart money" hypothesis in Menkhoff et al. (2016), in the sense that it provides evidence that dealers access superior information regardless of their customers' order flows being informative.

To assess whether the permanent price impact parameter $\alpha_m^j$ significantly differs across groups of agents, we test if all coefficients in Eq. (7) for a specific agent category $i$ are jointly significantly different from that of agent $j$. In line with asymmetric information theory (see Glosten and Milgrom, 1985; Grossman and Miller, 1988; Lyons, 2006), we find that order flows have a different effect on prices depending on the market participant behind them. For nearly

**Table 5: Permanent Price Impact Across Agents: Joint $F$-test**

| in BPS | $\alpha_m^{CO}$ | $\alpha_m^{FD}$ | $\alpha_m^{NB}$ | $\alpha_m^{BA}$ | in BPS | $\alpha_m^{CO}$ | $\alpha_m^{FD}$ | $\alpha_m^{NB}$ | $\alpha_m^{BA}$ |
|---|---|---|---|---|---|---|---|---|---|
| AUDJPY | −5.467 | 1.003 | ***0.472 | ***1.755 | GBPCHF | −1.312 | 0.861 | *0.740 | ***0.236 |
| | [1.216] | [1.889] | [4.114] | [31.727] | | [1.268] | [1.130] | [2.305] | [4.686] |
| AUDNZD | **1.919 | 1.536 | **−0.267 | ***0.465 | GBPJPY | −0.066 | 0.795 | ***−0.659 | ***1.431 |
| | [2.438] | [1.313] | [2.826] | [5.483] | | [0.770] | [1.447] | [3.618] | [19.415] |
| AUDUSD | 1.011 | ***0.500 | ***0.945 | ***0.848 | GBPUSD | ***−1.729 | ***0.515 | ***0.484 | ***1.630 |
| | [1.482] | [3.545] | [26.899] | [3.765] | | [3.262] | [3.379] | [12.913] | [12.300] |
| CADJPY | 2.708 | 0.688 | 0.204 | ***−0.135 | NZDUSD | −1.411 | ***0.749 | ***1.300 | ***0.931 |
| | [0.575] | [0.640] | [0.979] | [4.805] | | [1.926] | [4.378] | [8.118] | [7.616] |
| EURAUD | −1.868 | 0.577 | −0.214 | ***0.711 | USDCAD | ***−2.228 | ***0.447 | ***0.356 | ***0.576 |
| | [1.186] | [1.317] | [1.327] | [4.387] | | [3.680] | [2.878] | [8.262] | [3.536] |
| EURCAD | ***−0.867 | 0.555 | ***0.545 | ***0.425 | USDCHF | ***−1.054 | 0.686 | ***0.458 | 0.700 |
| | [4.268] | [0.976] | [4.000] | [3.469] | | [3.217] | [1.316] | [22.676] | [2.076] |
| EURCHF | ***−0.541 | 0.004 | −0.001 | ***0.084 | USDDKK | ***−2.216 | 0.113 | 0.635 | −0.247 |
| | [3.443] | [0.830] | [1.267] | [13.305] | | [4.832] | [1.916] | [1.684] | [1.910] |
| EURDKK | 0.068 | **0.040 | 0.092 | ***0.015 | USDHKD | −0.258 | ***0.036 | 0.028 | ***0.026 |
| | [1.690] | [2.553] | [1.989] | [3.238] | | [1.287] | [4.034] | [0.467] | [3.267] |
| EURGBP | ***−0.726 | 0.346 | ***0.047 | ***0.691 | USDILS | −0.015 | 0.905 | ***−1.310 | 0.507 |
| | [3.795] | [1.334] | [3.458] | [7.808] | | [1.224] | [1.997] | [5.934] | [1.905] |
| EURJPY | ***−0.384 | −0.682 | ***0.156 | 0.551 | USDJPY | 0.063 | ***0.513 | ***−0.135 | ***0.852 |
| | [4.483] | [1.248] | [6.206] | [1.997] | | [2.241] | [5.039] | [25.859] | [7.555] |
| EURNOK | ***−1.756 | ***0.928 | **0.149 | ***0.691 | USDMXP | 2.221 | −0.073 | ***−0.567 | 0.856 |
| | [3.167] | [6.124] | [2.512] | [3.562] | | [1.001] | [0.991] | [5.490] | [1.915] |
| EURSEK | ***−0.704 | ***1.130 | 0.538 | **0.601 | USDNOK | −0.981 | *1.086 | ***0.920 | ***0.143 |
| | [3.133] | [9.860] | [2.161] | [2.825] | | [1.725] | [2.309] | [3.220] | [4.145] |
| EURUSD | ***−1.096 | 0.507 | ***0.076 | ***0.977 | USDSEK | *−2.378 | ***1.770 | ***1.123 | ***0.364 |
| | [14.863] | [1.579] | [13.739] | [4.462] | | [2.307] | [4.952] | [3.382] | [3.598] |
| GBPAUD | 5.925 | 0.468 | 0.619 | ***1.341 | USDSGD | ***−0.600 | **0.119 | **0.302 | ***−0.078 |
| | [1.059] | [1.215] | [1.750] | [5.328] | | [3.193] | [2.829] | [2.838] | [3.049] |
| GBPCAD | *−0.119 | 0.702 | 1.436 | 0.427 | USDZAR | −7.323 | 0.562 | 0.738 | ***3.494 |
| | [2.397] | [1.110] | [1.563] | [0.747] | | [0.890] | [1.346] | [1.840] | [11.147] |

*Note*: This table reports estimates of the permanent price impact that are retrieved from estimating Eq. (7) on the full sample. All regression coefficients are in basis points (BPS). The numbers in brackets correspond to the test statistic for a heteroskedasticity-consistent joint $F$-test, where the parameters in Eq. (7) are jointly different from zero. The sample covers the period from September 2, 2012 to December 31, 2019. Asterisks *, **, and *** denote significance at the global 90%, 95%, and 99% levels ($\alpha_g$), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where $m$ is the number of multiple tests in the joint hypothesis. Agents are abbreviated as follows: corporates (CO), funds (FD), nonbank financials (NB), and banks acting as price takers (BA).

every pairwise combination of agents, the $F$-test clearly rejects the null hypothesis of equal price impacts.[29] All in all, we provide evidence that superior information is pervasive and systematically varies across market participants. For asset pricing, this also implies that each market participant is exposed to asymmetric information and adverse selection risk, which should be priced in FX rates.

### 5.2.2 Fragmentation in the FX Market Across Currencies

In traditional market microstructure models (e.g., Kyle, 1985), the price impact depends on the precision of the private signal, variation in liquidity trades, and risk aversion coefficients of informed traders and liquidity providers (Subrahmanyam, 1991). All these factors vary across currencies and time, creating systematically different price impacts across FX rates. Overall,

[29] The results here and in the next two sections are qualitatively similar for both the contemporary and permanent price impacts. Thus, the Online Appendix collects all the output tables and technical details.

currency pairs that are more affected by asymmetric information should reveal a larger permanent price impact. Table 5 shows that every currency pair is affected by multiple categories of agents' permanent price impact, suggesting that asymmetric information risk is pervasive across FX rates. This result holds for both the most (e.g., EURUSD and USDJPY) and least (e.g., EURCAD and USDSEK) liquid currency pairs. Generally, more (less) risk-averse investor should be more (less) reluctant to invest in illiquid assets. However, our estimates seem to have general validity and are not biased toward less liquid FX rates potentially being more affected by risk aversion. As an additional test, we reiterate our analysis by estimating the permanent price impact during the main stock markets trading hours (i.e., from 7 am London open to 9 pm New York close, GMT), that is, when risk aversion should be less pronounced. We find a similar picture reinforcing the idea that asymmetric information risk is ubiquitous across FX rates.

Empirically, we find the global FX market to be fragmented in the sense that a specific agent $i$ has a significantly different price impact parameter (both $\beta_0^j/\alpha_m^j$) across currency pairs. As before, we estimate Eq. (4) on the full sample and construct a pairwise $F$-test, where we test whether all the coefficients in Eq. (7) for a particular agent category $i \in C = \{CO, FD, NB, BA\}$ are jointly significantly different in currency pair $k$ compared with currency pair $q$.[30] The main result that emerges from this analysis is that corporates, funds, nonbank financials, and banks acting as price takers have a permanent price impact $\alpha_m^j$, which varies heavily across currencies. Overall, our empirical analysis extends earlier research on customer order flows (e.g., Evans and Lyons, 2006; Osler et al., 2011; Menkhoff et al., 2016) at a global scale. An avenue for future research would be to understand the effect of regulation on the local nature of FX price discovery.

To summarize, two main results have emerged from these two sections: first, order flow impacts FX prices heterogeneously across agents. Second, the FX spot market suffers from fragmentation in the sense that the same agent category has both a different contemporary and permanent price impact across currency pairs.

#### 5.2.3 Time Varying Information Flows

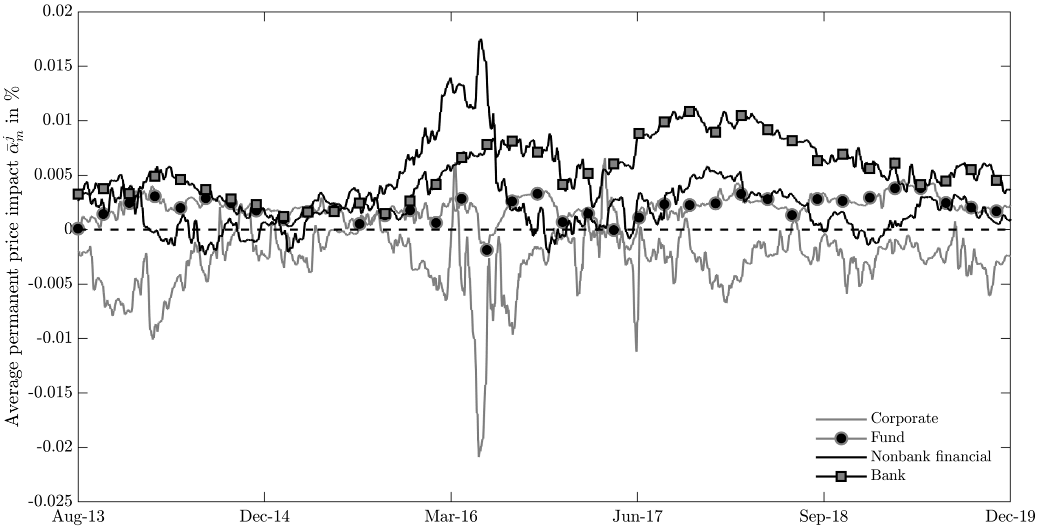
In this section, we introduce time as a third dimension of heterogeneity and study the systematic time variation of both the contemporary and permanent price impacts. Again we estimate Eq. (4) by OLS, but now we do so in a rolling window fashion instead of using the full sample. We choose a one-year rolling window, but our results are robust to shorter horizons.

In Figure 2, we plot the average permanent price impact ($\alpha_m^j$) across currency pairs over time. Importantly, the $\alpha_m^j$ is present at all times and does not cluster in distressed periods. Furthermore, the $\alpha_m^j$ appears to be larger and more dispersed across agents during the European

[30]For technical details and outputs, see the Online Appendix.

sovereign debt crisis (2010–2014), that is, when risk aversion was presumably high. Across agents, corporates seem to have the strongest time variation, consistent with the idea that their trades are driven by uninformative reasons (e.g., market risk, hedging, or liquidity shocks) rather than by a systematic processing of superior information.[31]

**Figure 2: Five-day Moving Average Permanent Price Impact ($\bar{\alpha}^j_m$)**




*Note*: This figure plots the average permanent price impact across 30 currency pairs for corporates, funds, nonbank financials, and banks after removing any permanent price impact estimates that are more than three scaled median absolute deviations away from the sample median. The currency pair specific permanent price impact coefficients are retrieved from estimating Eq. (7) in a twelve month rolling window fashion. The sample covers the period from August 26, 2013 to December 31, 2019.

The main difference across groups of market participants is that the permanent price impact of sophisticated agents, such as funds and banks, is rather stable on average across time, while financially less literate agents (i.e., corporates) experience stronger time variation in their permanent price impact. This is likely to reflect funds' and banks' superior financial sophistication for engaging in strategic and timely order submission behaviors, such as order splitting and price impact smoothing.[32] These results buttress our hypothesis that asymmetric information is time varying and heterogeneously disseminated across agents over time.

[31] We use the Brown–Forsythe test for formally testing whether corporates' price impact parameters exhibit a significantly higher variance than funds', nonbank financials', or banks' parameters do. For the great majority of currency pairs, we reject the null of homoskedasticity across agents' price impact parameters at conventional significance levels for all pairwise combinations.

[32] Some hedge funds use leverage to achieve greater market power. Due to high gearing, coupled with slack regulation in the FX market, these institutions can employ trading strategies to deliberately maximize their price impact in certain times.

## 5.3. Drivers of Customer Order Flows

To conclude our microstructure analysis, we analyze the key drivers of customer order flows. We focus on the following two aspects: first, we examine whether there are systematic spillover effects across some customer groups. Second, we study whether customers' flows relate heterogeneously to the performance of common FX trading strategies such as carry, value, volatility, and momentum (see Lustig et al., 2011; Menkhoff et al., 2012a,b, 2017; Asness et al., 2013). To answer these questions, we include further explanatory variables such as interest rate differentials ($f_{t-1,t} - s_t \approx i_t^* - i_t$), equity returns ($r_t^{equity}$), and changes in the ten-year government bond yield ($y_t^{bond}$). In particular, we estimate a fixed effects panel regression of the form

$$NV_{k,t}^{j} = \lambda_t + \alpha_k + \beta' f_{k,t} + \varepsilon_{k,t}, \tag{9}$$

where $NV_{k,t}^{j}$ is the daily standardized[33] net volume, $f_{k,t}$ collects contemporaneous and lagged standardized net volume, other economic factors, and the portfolio returns of common FX trading strategies; and $j \in C = \{CO, FD, NB, BA\}$ denotes one group of market participants. Our baseline model includes both cross-sectional ($\alpha_k$) and time fixed ($\lambda_t$) effects; hence the error term can be decomposed as $\epsilon_{k,t} = \lambda_t + \alpha_k + \varepsilon_{k,t}$. Standard errors are clustered by currency pair. We use country equity indices and ten-year government bond yields from Bloomberg at the daily frequency. To obtain economically meaningful results, we focus on all USD-based currency pairs.[34]

For every customer segment, the panel regression in Table 6 includes contemporary and lagged order flows plus economic variables as well as the portfolio returns of common FX trading strategies (e.g., value, carry, and momentum). There are three key findings: first, corporates, funds, and banks are significantly positively driven by their lagged flows, while nonbank financials trade rather independently of their past orders. The strong autocorrelation in order flows of funds and banks is consistent with the idea that sophisticated agents have superior access to FX markets, allowing them to engage in strategic order splitting and price impact smoothing (Kervel and Menkveld, 2019). Moreover, the banking sector trades against all other market participants, absorbing asymmetric information risk and being consistent with the two-tier market structure of FX markets. Second, all banks trade against the interest rate differential, which is in line with speculative activities. Albeit statistically not always significant, funds and nonbank financials buy more foreign currency when foreign equity markets are doing well and do the opposite for bond markets. This finding is in line with a general risk-taking attitude in upward markets inducing investments abroad (i.e., buy foreign currency and sell domestic currency) and an opposite pattern during flight-to-quality episodes (Ranaldo

[33] The standard deviation of flows is computed via a 60-day rolling window.

[34] To save space, we only report results for USD-based currency pairs, whereas results for EUR-based currency pairs are reported in the Online Appendix.

and Söderlind, 2010). Such a behavior is also in line with the role of financial intermediaries absorbing global imbalances in the FX markets (Gabaix and Maggiori, 2015).

Third, a general appreciation of the US dollar against all other currencies (higher $DOL$) is accompanied by a continuing buying pressure from corporates, funds, and banks, perhaps due to the US dollar being the predominant reserve and invoice currency. What is more, the time variation in order flows of funds, nonbank financials, and banks is closely tied to the performance of common FX trading strategies such as carry ($CAR_{HML}$) and value ($RER_{HML}$). This finding is in line with strategic behavior and higher adverse selection risk when trading against more sophisticated agents (Payne, 2003).

To summarize, our results are in line with Hau and Rey (2004) in the sense that investors rebalance their portfolios by buying a foreign currency in response to rising equity prices or falling bond yields in their home country. The results also show that the driving factors of customer order flows clearly differ across end-user groups and are a potential explanation for the observed heterogeneity in price impacts.

## 6. Asymmetric Information Risk Premium

In the foregoing sections, we have studied the systematic heterogeneity in asymmetric information across agents, time, and currency pairs. In particular, the analysis of the permanent price impact has provided compelling evidence of pervasive and persistent asymmetric information in FX markets. Furthermore, superior information is neither only confined to dealers nor to a few currencies but rather systematically varies across agents, time, and currency pairs. Hence, asset pricing theory would suggest that agents should demand a premium for potentially being adversely selected (Easley, Hvidkjaer, and O'Hara, 2002) when trading against better informed investors (Wang, 1993, 1994). Moreover, in addition to bid–ask spreads, the required return should increase with asymmetric information risk (Gârleanu and Pedersen, 2003). The remainder of this paper addresses if there is empirical support for this theoretical channel, that is, if asymmetric information risk is priced in the FX market.

### 6.1. Trading Strategy

From an asset pricing perspective, a coherent method to capture asymmetric information risk is to construct a long–short portfolio based on the systematic level of asymmetric information across currency pairs. In the context of global FX trading, we consistently apply this idea by introducing a novel and readily implementable trading strategy based on a simple idea: order flows of agents and currencies impounding a persistent price impact convey superior information. Put differently, holding currency pairs with higher informational asymmetries (i.e., high average permanent price impact) requires a positive risk premium for taking the risk of trading against

**Table 6: Economic Drivers of Net Order Volume (USD-based Currency Pairs)**

| | CO | FD | NB | BA |
|---|---|---|---|---|
| *Net order volume* | | | | |
| $CO_t$ | | −0.01 | *−0.02 | ***−0.05 |
| | | [1.30] | [1.67] | [3.94] |
| $FD_t$ | −0.01 | | *−0.02 | ***−0.21 |
| | [1.31] | | [1.79] | [6.42] |
| $NB_t$ | *−0.02 | *−0.01 | | ***−0.05 |
| | [1.67] | [1.80] | | [4.74] |
| $BA_t$ | ***−0.05 | ***−0.21 | ***−0.06 | |
| | [3.81] | [6.26] | [4.42] | |
| $CO_{t-1}$ | **0.03 | *−0.01 | 0.00 | 0.00 |
| | [2.13] | [1.72] | [0.46] | [0.07] |
| $FD_{t-1}$ | 0.00 | ***0.17 | *−0.02 | ***0.04 |
| | [0.40] | [5.07] | [1.91] | [2.81] |
| $NB_{t-1}$ | 0.01 | 0.01 | 0.03 | 0.00 |
| | [1.10] | [1.04] | [1.12] | [0.59] |
| $BA_{t-1}$ | 0.01 | 0.01 | **0.02 | ***0.15 |
| | [0.70] | [0.91] | [2.04] | [3.82] |
| *Market conditions* | | | | |
| $f_{t-1,t} - s_t$ | 0.02 | 0.00 | 0.00 | ***−0.07 |
| | [1.10] | [0.09] | [0.10] | [3.18] |
| $r_t^{equity}$ | 0.00 | ***−0.02 | −0.01 | 0.01 |
| | [0.46] | [2.93] | [1.36] | [0.88] |
| $y_t^{bond}$ | *0.01 | **0.01 | 0.00 | 0.00 |
| | [1.81] | [2.12] | [0.02] | [0.24] |
| *Trading strategies* | | | | |
| $\Delta DOL$ | ***0.03 | **0.02 | ***−0.04 | ***0.06 |
| | [3.48] | [2.46] | [3.46] | [5.66] |
| $\Delta RER_{HML}$ | *0.02 | *−0.01 | 0.00 | *0.01 |
| | [1.84] | [1.75] | [0.42] | [1.70] |
| $\Delta MOM_{HML}$ | 0.00 | 0.00 | −0.01 | 0.00 |
| | [0.34] | [0.39] | [1.17] | [0.38] |
| $\Delta CAR_{HML}$ | −0.01 | 0.00 | **0.02 | −0.01 |
| | [1.34] | [0.20] | [2.07] | [1.21] |
| $\Delta VOL_{LMH}$ | −0.01 | 0.00 | 0.00 | 0.00 |
| | [1.53] | [0.27] | [0.52] | [0.72] |
| $R^2$ in % | 0.57 | 7.41 | 0.87 | 8.64 |
| Adj. $R^2$ in % | 0.45 | 7.29 | 0.75 | 8.53 |
| Avg. #time periods | 1585 | 1585 | 1585 | 1585 |
| #Exchange rates | 15 | 15 | 15 | 15 |
| Currency FE | yes | yes | yes | yes |
| Time-series FE | yes | yes | yes | yes |

*Note*: This table collects results from fixed effects panel regressions of the form $NV_{k,t}^j = \lambda_t + \alpha_k + \beta' f_{k,t} + \varepsilon_{k,t}$, where $NV_{k,t}^j$ is daily standardized net volume, $f_{k,t}$ collects contemporaneous and lagged standardized net volume (the standard deviation of flows is computed via a 60-day rolling window), market conditions such as the interest rate differential ($f_{t-1,t} - s_t \approx i_t^* - i_t$), equity returns ($r_t^{equity}$) and changes in the ten-year government bond yield ($y_t^{bond}$), and the portfolio returns of common FX trading strategies. The superscript $j \in C = \{CO, FD, NB, BA\}$ denotes one of the market participants, namely, corporates (CO), funds (FD), nonbank financials (NB), and banks acting as price takers (BA). All specifications are based on standardized regressors and include both cross-sectional ($\alpha_k$) and time fixed ($\lambda_t$) effects; hence the error term can be decomposed as $\epsilon_{k,t} = \lambda_t + \alpha_k + \varepsilon_{k,t}$. $\Delta$ stands for relative changes. The test statistics based on cross-sectionally clustered White standard errors (White, 1980) are reported in brackets. The sample covers the period from November 26, 2012 to December 31, 2019. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels.

informed investors. Thus, if a currency's return responds permanently (weakly) to order flows in the same direction, it belongs to the long (short) basket.[35]

To be precise, the long–short strategy ($AIP_{HML}$) rests on the five following pillars: timing,

[35] As a result, the excess returns of this trading strategy are fueled by asymmetric information risk and are not driven by temporary liquidity effects.

weighting, signal extraction, rebalancing, and excess returns. Investment takes place immediately the day after the signal is extracted.[36] Throughout the investment period, the strategy exhibits equally weighted long and short legs, resulting in zero net exposure.[37] To make our results comparable to other common FX risk factors (e.g., Lustig et al., 2011; Menkhoff et al., 2017), we form tertile portfolios ($Q_1, Q_2, Q_3$) based on the uniform distribution, and we build cross-sections of currency portfolios.

Trading signals are generated from estimating Eq. (4) in a 12-month rolling window fashion at a daily frequency based on binary order flow and midquotes with the number of lags equal to ten days.[38] To avoid any look-ahead bias, we use yesterday's trading signals ($t-1$) to create portfolio weights today ($t$). The advantage of running this regression at daily rather than hourly frequency is twofold: first, it is computationally less expensive and hence is easily replicable in a real-world setting.[39] Second, forward rates are usually not available at an hourly frequency, and therefore using daily data ensure that signals are extracted at the same frequency as excess returns.

Hence, investment starts in September 2013 after one year of formation period. This leaves us more than six years for testing out-of-sample performance. For every rolling window index and currency pair $k$, we obtain the average permanent price impact $\bar{\alpha}_m^k$ (see Eq. (8)). Next, we sort currency pairs by $\bar{\alpha}_m^k$ in ascending order.[40] The $AIP_{HML}$ portfolio is long (short) currency pairs in the top (bottom) tertile that exhibit the highest (lowest) $\bar{\alpha}_m^k$. Portfolio rebalancing takes place at the beginning of every month.

Following the FX asset pricing literature (see, e.g., Lustig, Roussanov, and Verdelhan, 2011), the log excess return ($rx$) of buying a foreign currency in the forward market and selling it in the spot market in the next period is

$$rx_{t+1} = f_{t,t+1} - s_{t+1}, \tag{10}$$

where $f_{t,t+1}$ denotes the log-forward rate and $s_t$ the log-spot rate, in units of the foreign currency

[36] Results are robust to investing with a lag of one day up to a week.

[37] All our results are qualitatively unchanged when we use a rank- or value-based weighting scheme.

[38] The trading strategy is robust to our choice of model specification, that is, (signed) net volume instead of binary order flow and transaction prices instead of midquotes. Especially, it renders positive and significant returns for several different combinations of baseline VAR model, rolling window length, and number of lags. Note that by including the order size variable $\tilde{S}_t$ in Eq. (4), we do not have to weight the (permanent) price impact coefficients by their trading volume.

[39] The order flow data set is released hourly by CLS and is publicly accessible directly through CLS with a 15-minute lag. This release lag does not impact our trading strategy that only uses information up to yesterday ($t-1$). FX quotes by Olsen are readily available to investors at a one-minute frequency.

[40] Note that a trading strategy based on the permanent price impact derived from (unweighted) aggregate order flow (no disaggregation of customer flows) renders substantially lower returns and Sharpe ratios. This is because it implicitly assumes that each group of market participants conveys the same (superior) information set, which is clearly not the case.

per USD.

To account for the possibility of investing in a non-USD currency pair such as the *EURGBP*, we modify Eq. (10) such that, instead of one forward contract,[41] the US investor enters two forward contracts based on triangular no-arbitrage conditions:

$$rx_{t+1}^{X/Y} = f_{t,t+1}^{USD/Y} - s_{t+1}^{USD/Y} - (f_{t,t+1}^{USD/X} - s_{t+1}^{USD/X}), \tag{11}$$

where $X$ and $Y$ are the base and quote currency of a non-USD currency pair.[42] The main advantage of this approach is that we do not have to distinguish between different investors (e.g., European, Japanese), which would heavily reduce the cross-section of currency pairs, since all returns are dollar neutral.

Since we have bid ($b$) and ask ($a$) quotes for spot and forward contracts,[43] we can compute the investor's true realized excess return net of transaction cost. The net log currency excess return for an investor who goes long in foreign currency $y$ is

$$rx_{\mathrm{t+1}}^{\mathrm{X/Y}} = f_{t,t+1}^{\mathrm{USD/Y},b} - s_{t+1}^{\mathrm{USD/Y},a} - (f_{t,t+1}^{\mathrm{USD/X},a} - s_{t+1}^{\mathrm{USD/X},b}), \tag{12}$$

where the investor buys the foreign currency or equivalently sells the dollar forward at $f_{t,t+1}^{\mathrm{USD/Y},b} - f_{t,t+1}^{\mathrm{USD/X},a}$ in period $t$ and sells the foreign currencies or equivalently, buys USD at $s_{t+1}^{\mathrm{USD/Y},a} - s_{t+1}^{\mathrm{USD/X},b}$ in the spot market in period $t+1$. Similarly, for an investor being long the USD (hence, short the foreign currency), the net log excess return is

$$rx_{\mathrm{t+1}}^{\mathrm{X/Y}} = -f_{t,t+1}^{\mathrm{USD/Y},a} + s_{t+1}^{\mathrm{USD/Y},b} + (f_{t,t+1}^{\mathrm{USD/X},b} - s_{t+1}^{\mathrm{USD/X},a}), \tag{13}$$

and the (simple) portfolio return $RX^p$ is given by

$$RX_{t+1}^{p} = \sum_{k=1}^{K_t} w_{k,t} RX_{k,t+1}, \tag{14}$$

where $RX_{k,t+1}$ is a vector of simple excess returns based on Eq. (12) and Eq. (13), since log returns are not asset additive. Each tertile portfolio consists of ten currency pairs, where each of them receives an equal weight of $w_{k,t} = 10\%$.

[41] Daily, weekly, and monthly forward bid–ask points are obtained from Bloomberg. Forward rates can be expressed as the forward discount/premium (i.e., forward points) plus the midquote.

[42] For a detailed derivation and discussion of alternative methods, see the Online Appendix.

[43] To be conservative, unlike prior research (e.g., Goyal and Saretto, 2009; Menkhoff et al., 2016), we do not employ 50% of the quoted bid–ask spread as a proxy of the effective spread. Thus, from a real-world implementation point of view, our after transaction cost estimates constitute a lower bound.

## 6.2. Trading Performance

In Table 7, we present the annualized Sharpe ratio (SR); the annualized mean excess return (Mean); the maximum drawdown (MDD); and the $\Theta$ performance measure of Goetzmann et al. (2007), skewness, and excess kurtosis (Kurtosis-3) based on monthly rebalancing, respectively.[44] The $\Theta$ performance measure of Goetzmann et al. (2007) is only slightly lower than the mean return, indicating that neither outliers nor nonnormality are driving the superior performance.[45] Panel A and B of Table 7 tabulates the before and after transaction cost performances of the first ($Q_1$) and third ($Q_3$) tertile portfolios, where $AIP_{HML}$ is a linear combination of going short in $Q_1$ and long in $Q_3$. The same table also considers the performance of common FX trading strategies.[46]

From Table 7 three main results emerge, which are as follows: first, an economically and statistically high performance of the $AIP_{HML}$ strategy is observed both before and after transaction cost. Second, our strategy clearly outperforms common FX risk factor strategies based on the USD-based currency pairs basket (i.e., $DOL$),[47] the real exchange rate (i.e., $RER/RER_{HML}$),[48] momentum (i.e., $MOM_{HML}/CAR_{HML}$),[49] or volatility risk (i.e., $VOL_{LMH}$).[50] Third, $AIP_{HML}$ clearly outperforms $BMS$, which is a pure order flow-based strategy buttressing our proposition that order flow itself is not an accurate proxy of asymmetric information risk, as it can arise from both informational and noninformational motives (e.g., liquidity). Furthermore, it is also consistent with the idea that a dealer following a pure "smart money" strategy cannot extract all superior information disseminated in the global FX market.

Figure 3 depicts the cumulative (simple excess) returns of different rebalancing frequencies before and after transaction cost. Gross returns are based on midquotes for both the spot and forward rates. The investment period is the entire sample period (September 2012 to December

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[44] Before transaction cost, trading performance remains similar for weekly and daily returns, but it erodes significantly on a daily basis when transaction cost are taken into consideration.

[45] The SR doest not take into account the effect of nonnormalities, which could be important in a smaller sample setting. The $\Theta$ performance measure of Goetzmann et al. (2007) overcomes this issue by reestimating the sample mean but putting less weight on outlier returns.

[46] The summary statistics for these benchmark strategies differ from those in Cespa et al. (2020). Our correspondence with the authors revealed three potential reasons for the differences: first, different time period with only four overlapping years. Second, the authors use three-month averages to implement $CAR_{HML}$, $MOM_{HML}$, and $RER_{HML}$. Third, they only use a subsample of 15 USD-based currencies.

[47] The $DOL$ portfolio consists of equally weighted long USD currency pairs.

[48] The $RER$ and $RER_{HML}$ are constructed based on Menkhoff et al. (2017), where currency pairs are sorted based on their real exchange rate. $HML$ stands for "high-minus-low."

[49] The $MOM_{HML}$ strategy involves a currency sorting based on past excess returns (Asness, Moskowitz, and Pedersen, 2013). For $CAR_{HML}$ (Lustig, Roussanov, and Verdelhan, 2011), currency pairs are sorted based on the forward discount.

[50] The $VOL_{LMH}$ factor is constructed based on Menkhoff et al. (2012a), where currency pairs are sorted based on their exposure to innovations in global FX volatility.

## Table 7: Performance Benchmarking $AIP_{HML}$

| *Panel A: Gross returns* | $DOL$ | $RER_{HML}$ | $RER$ | $MOM_{HML}$ | $CAR_{HML}$ | $BMS$ | $VOL_{LMH}$ | $Q_1$ | $Q_3$ | $AIP_{HML}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| SR | −0.11 | −0.22 | −0.22 | −0.13 | 0.05 | 0.68 | −0.54 | *0.65 | 0.23 | **0.83 |
| | [0.33] | [0.53] | [0.58] | [0.32] | [0.16] | [1.49] | [1.25] | [1.84] | [0.59] | [2.35] |
| *Mean* in % | −0.33 | −1.08 | −0.71 | −0.91 | 0.39 | 2.79 | −3.20 | **3.01 | 1.04 | ***4.05 |
| | [0.33] | [0.52] | [0.58] | [0.31] | [0.16] | [1.48] | [1.24] | [1.97] | [0.58] | [3.01] |
| MDD in % | 6.48 | 14.26 | 10.14 | 28.56 | 19.31 | 8.30 | 29.30 | 8.05 | 11.24 | 7.19 |
| Scaled MDD | 7.40 | 9.40 | 10.22 | 12.19 | 8.34 | 6.71 | 15.00 | 5.78 | 8.23 | 4.95 |
| Θ in % | −0.41 | −1.32 | −0.81 | −1.41 | −0.14 | 2.62 | −3.55 | 2.79 | 0.84 | 3.81 |
| Skewness | 0.56 | 0.12 | −0.02 | −0.30 | −0.70 | 0.16 | 0.11 | −0.10 | 0.69 | 0.15 |
| Kurtosis-3 | 1.55 | −0.40 | 0.16 | 0.88 | 0.81 | −0.31 | −0.10 | 1.66 | 1.17 | 9.45 |
| *Panel B: Net returns* | $DOL$ | $RER_{HML}$ | $RER$ | $MOM_{HML}$ | $CAR_{HML}$ | $BMS$ | $VOL_{LMH}$ | $Q_1$ | $Q_3$ | $AIP_{HML}$ |
| SR | −0.24 | −0.38 | −0.38 | −0.24 | −0.07 | 0.47 | −0.69 | 0.55 | 0.13 | **0.65 |
| | [0.69] | [0.91] | [1.02] | [0.61] | [0.19] | [1.04] | [1.59] | [1.59] | [0.33] | [1.96] |
| *Mean* in % | −0.70 | −1.88 | −1.24 | −1.74 | −0.48 | 1.95 | −4.10 | *2.57 | 0.59 | **3.16 |
| | [0.70] | [0.92] | [1.02] | [0.60] | [0.19] | [1.03] | [1.58] | [1.69] | [0.33] | [2.35] |
| MDD in % | 7.67 | 17.51 | 12.01 | 31.57 | 21.24 | 10.19 | 35.65 | 8.58 | 12.35 | 7.57 |
| Scaled MDD | 8.71 | 11.38 | 12.03 | 13.29 | 9.07 | 8.20 | 17.83 | 6.13 | 9.01 | 5.18 |
| Θ in % | −0.78 | −2.12 | −1.34 | −2.24 | −1.01 | 1.78 | −4.45 | 2.36 | 0.39 | 2.92 |
| Skewness | 0.56 | 0.10 | −0.03 | −0.31 | −0.70 | 0.14 | 0.09 | −0.13 | 0.68 | 0.10 |
| Kurtosis-3 | 1.53 | −0.38 | 0.16 | 0.91 | 0.81 | −0.34 | −0.10 | 1.71 | 1.15 | 9.46 |

*Note*: This table presents the out-of-sample economic performance of the $AIP_{HML}$ trading strategy before and after transaction cost based on monthly rebalancing. Panel A reports the annualized Sharpe ratio (SR), annualized average (simple) gross excess return (*Mean*), skewness, excess kurtosis (Kurtosis-3), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and Θ performance measure of Goetzmann et al. (2007) for the tertile portfolios ($Q_1, Q_2, Q_3$) based on the uniform distribution. Panel B lists the same measures as Panel A but after transaction cost. $DOL$ is based on an equally weighted long portfolio of all USD currency pairs, $RER/RER_{HML}$ on the real exchange rate (cf. Menkhoff et al., 2017), $MOM_{HML}$ on $f_{t-1,t} - s_t$ (cf. Asness, Moskowitz, and Pedersen, 2013), and $CAR_{HML}$ on the forward discount/premium ($f_{t,t+1} - s_t$, cf. Lustig, Roussanov, and Verdelhan, 2011). $BMS$ is based on the lagged standardized order flow (cf. Menkhoff et al., 2016) and $VOL_{LMH}$ is based on currency pairs' exposure to the global volatility factor (cf. Menkhoff et al., 2012a). Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent errors correcting for serial correlation and the small sample size (using the plug-in procedure for automatic lag selection by Andrews and Monahan, 1992; Newey and West, 1994). The sample covers the period from September 9, 2013 to December 31, 2019.

2019) minus 12 months of the formation period to retrieve the first trading signal; thus, it spans from September 2013 to January 2019. Two merits arise from Figure 3: first, daily rebalancing is substantially less profitable than monthly rebalancing due to higher transaction cost, but it bears similar cumulative returns prior to transaction cost. Second, the equity curves steadily increase over time and do not experience any regime switches. Note that the cumulative returns are also increasing after October 2018 (i.e., the first dissemination of the working paper version), reinforcing the risk premium hypothesis rather than some unexploited trading opportunity or other forms of market inefficiency.

In addition to the cumulative returns, the maximum drawdown curves are constructed. This drawdown measure corresponds to the cumulative return of the $AIP_{HML}$ portfolio relative to the last peak. With monthly rebalancing, the $AIP_{HML}$ strategy beats itself over extended periods of time and exhibits a maximum drawdown of 7.19% (7.75%) prior (after) transaction cost.[51]

Analyzing the decomposition of the long and short legs of $AIP_{HML}$ delivers two main findings: first, our trading strategy exhibits a balanced exposure across currency pairs, where all the pairs receive an average absolute weight of 3%–5%. Second, we calculate the relative contribution of every agent category's $\alpha_m^{j,k}$ to the average permanent price impact $\bar{\alpha}_m^k$ per currency pair and then take the average across all currency pairs for $AIP_{HML}$ with monthly rebalancing. This calculation clearly shows that both the long and short legs appear to be equally balanced across agents, providing further evidence of asymmetric information across market participants.[52]

### 6.3. Exposure Regression

Here, we address the question of whether the returns of $AIP_{HML}$ are subsumed by any of the common FX risk factors presented in Lustig, Roussanov, and Verdelhan (2011), Menkhoff et al. (2012a), Asness, Moskowitz, and Pedersen (2013), and Menkhoff et al. (2016, 2017). In Table 8, we regress the monthly returns of the $AIP_{HML}$ strategy on those associated with common FX risk factors: $DOL$, $VOL_{LMH}$, $RER_{HML}$, $RER$, $MOM_{HML}$, $CAR_{HML}$, and $BMS$.

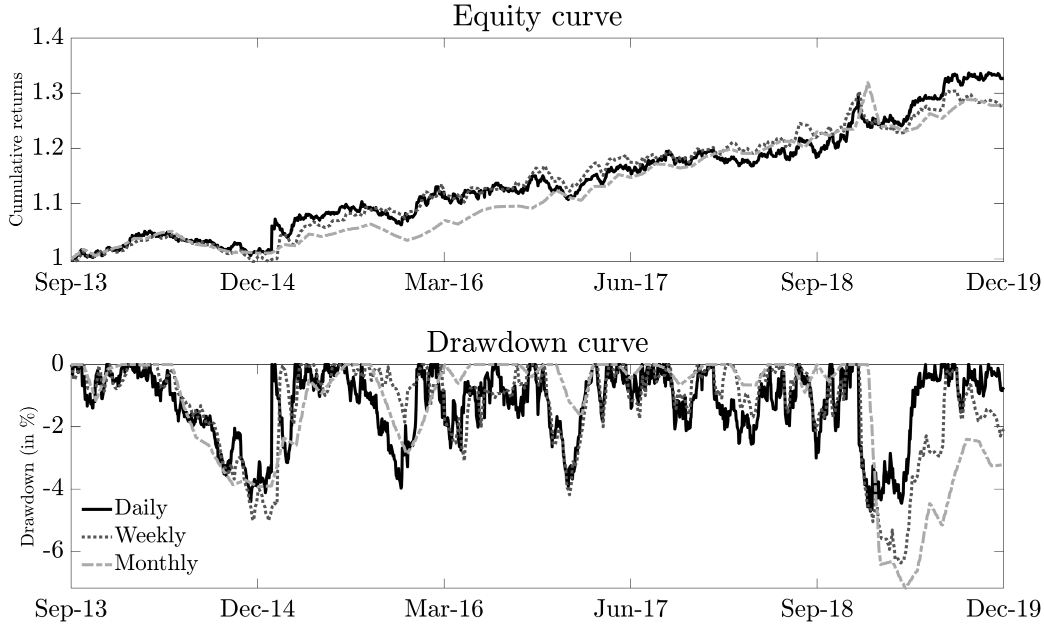
The low $R^2$ is a clear indication of the low explanatory power of these common FX risk factors. Especially, the variation in excess returns of $AIP_{HML}$ cannot be explained by traditional FX momentum ($MOM_{HML}$) and is negatively related to the carry trade ($CAR_{HML}$ à la Lustig, Roussanov, and Verdelhan, 2011). The trading strategy generates a significant Jensen's alpha ($\alpha$) of about 4.05%–4.66% per year and information ratios (IRs) of c. 24%–33%, where the IR is defined as $\alpha$ divided by the residual standard deviation.

Consistent with the asymmetric information hypothesis, $AIP_{HML}$ returns are more correlated (see Table 8) with factors related to (currency) fundamental values, that is, the real exchange rate ($RER_{HML}$) and carry ($CAR_{HML}$). As expected, $AIP_{HML}$ is unrelated to the standardized total order flow ($BMS$), global volatility ($VOL_{LMH}$), and momentum ($MOM_{HML}$). All these results hold after controlling for relative changes in the VIX index, JP Morgan Global FX Volatility index (VXY), the North American credit default swap index (CDX), and the TED spread, respectively. In addition, we decompose the VXY into an "uncertainty" and "risk

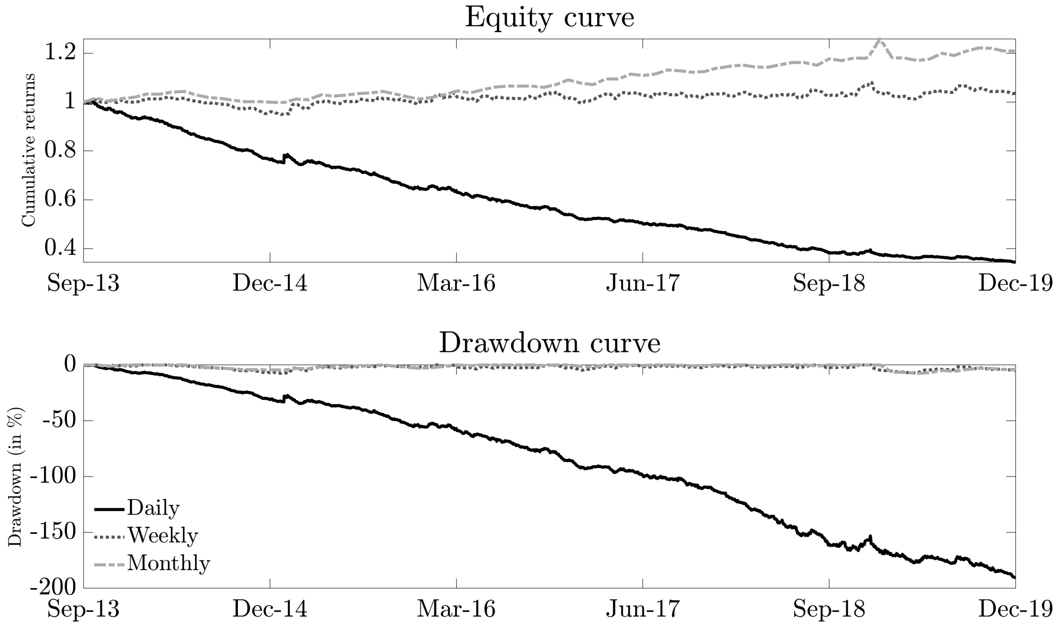
[51]To overcome the statistical limitations of a relatively short out-of-sample period, we use standard bootstrap techniques. The Online Appendix presents bootstrapped $p$-values for $AIP_{HML}$ before and after transaction cost, respectively. The bootstrapped $p$-values are fully in line with their asymptotic counterparts.

[52]See the Online Appendix for output tables and figures.

**Figure 3: Equity and Drawdown Curves $AIP_{HML}$**




**(a) Before transaction cost**




**(b) After transaction cost**

*Note*: Panel a) of this figure plots the before transaction cost cumulative equity curve of a one dollar investment into the $AIP_{HML}$ trading strategy as well as the drawdown curve in percent (%) for daily, weekly, and monthly rebalancing. Panel b) shows the same performance measures as Panel a) but after accounting for transaction cost. For nondaily rebalancing frequencies, missing data points are interpolated linearly. The sample covers the period from September 6, 2013 to December 31, 2019.

**Table 8: Exposure Regression Based on Monthly Gross Returns**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Intercept ($\alpha$) in % | ***4.05 | ***4.22 | **4.20 | ***4.14 | **4.29 | ***4.39 | **4.47 | **4.11 | ***4.66 |
| | [3.09] | [2.65] | [2.55] | [2.68] | [2.57] | [2.99] | [2.55] | [2.52] | [2.79] |
| $DOL$ | | −0.13 | −0.13 | 0.03 | −0.12 | −0.08 | −0.13 | 0.00 | 0.09 |
| | | [1.03] | [0.96] | [0.25] | [1.07] | [0.67] | [1.02] | [0.01] | [0.73] |
| $RER_{HML}$ | | | −0.02 | | | | | | |
| | | | [0.15] | | | | | | |
| $RER$ | | | | **−0.31 | | | | | **−0.33 |
| | | | | [2.27] | | | | | [2.41] |
| $MOM_{HML}$ | | | | | 0.16 | | | | |
| | | | | | [1.28] | | | | |
| $CAR_{HML}$ | | | | | | **−0.34 | | | **−0.35 |
| | | | | | | [1.96] | | | [2.11] |
| $BMS$ | | | | | | | −0.07 | | −0.10 |
| | | | | | | | [0.50] | | [0.81] |
| $VOL_{LMH}$ | | | | | | | | −0.15 | |
| | | | | | | | | [0.92] | |
| $\Delta RA$ | | −0.03 | −0.02 | 0.00 | −0.02 | ***−0.09 | −0.03 | −0.02 | **−0.06 |
| | | [1.04] | [0.83] | [0.17] | [0.81] | [2.90] | [1.02] | [0.85] | [2.14] |
| $\Delta UN$ | | *0.30 | *0.30 | *0.25 | *0.27 | 0.18 | *0.32 | *0.30 | 0.15 |
| | | [1.78] | [1.70] | [1.65] | [1.81] | [1.54] | [1.71] | [1.72] | [1.47] |
| $R^2$ in % | N/A | 12.97 | 12.99 | 19.35 | 15.46 | 22.47 | 13.41 | 13.50 | 29.90 |
| IR | 0.24 | 0.27 | 0.27 | 0.27 | 0.28 | 0.30 | 0.28 | 0.26 | 0.33 |
| #Obs | 75 | 75 | 75 | 75 | 75 | 75 | 75 | 75 | 75 |

*Note*: This table shows the results of regressing monthly gross excess returns by $AIP_{HML}$ on monthly excess returns associated with common risk factors, where $DOL$ is based on an equally weighted long portfolio of all USD currency pairs, $RER/RER_{HML}$ are based on the real exchange rate (cf. Menkhoff et al., 2017), $MOM_{HML}$ is based on $f_{t-1,t} - s_t$ (cf. Asness et al., 2013), $CAR_{HML}$ is based on the forward discount/premium ($f_{t,t+1} - s_t$, cf. Lustig et al., 2011), $BMS$ is based on the lagged standardized order flow (cf. Menkhoff et al., 2016), and $VOL_{LMH}$ is based on currency pairs' exposure to the global volatility factor (cf. Menkhoff et al., 2012a). $\Delta RA$ and $\Delta UN$ are relative changes in the risk-aversion and uncertainty component, respectively, of the JP Morgan Global FX Volatility index ($VXY$) based on Bekaert et al. (2013). All variables have been scaled by their standard deviations, except for the intercept ($\alpha$). The $\alpha$ is in units of excess returns expressed as percentage points and has been annualized ($\times 12$). The information ratio (IR) is defined as $\alpha$ divided by the residual standard deviation. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on heteroskedasticity- and autocorrelation-consistent errors correcting for serial correlation and the small sample size (using the plug-in procedure for automatic lag selection by Andrews and Monahan, 1992; Newey and West, 1994). The sample covers the period from October, 2013 to December, 2019.

aversion" component (Bekaert, Hoerova, and Duca, 2013). The regression coefficient of "risk aversion" bears the expected (negative) sign but is generally statistically insignificant and does not affect the abnormal returns ($\alpha$) generated by $AIP_{HML}$. This corroborates the overall validity of our results and highlights that they seem to hold in both a risk-neutral and risk-averse framework, respectively. Overall, none of the control variables has a material impact on our trading strategy's superior performance.[53]

[53]See the Online Appendix for tables showing these additional results.

## 6.4. Explaining the Asymmetric Information Risk Premium

The goal of this section is to explore how the asymmetric information premium ($AIP_{HML}$) relates to key economic variables that are known to be correlated with market-wide asymmetric information risk. To achieve this, we run daily multivariate regressions of gross $AIP_{HML}$ returns on its potential drivers:

$$AIP_{HML,t} = \alpha + \beta' f_t + \epsilon_t, \tag{15}$$

where, based on a loose classification à la Karnaukh, Ranaldo, and Söderlind (2015), $f_t$ refers to the following three broad categories: first, demand-side factors such as the VIX and the AAA–rated corporate bond yield. An increase of global uncertainty (measured by the former) and demand for safe assets (captured by the latter) prompt market participants to reassess the intrinsic value of financial instruments that have become information sensitive (Dang, Gorton, and Holmström, 2019), leading to possible currency devaluations via a reduction of the safety premium or liquidity services (Jiang, Krishnamurthy, and Lustig, 2018). Second, supply-side drivers such as an equally weighted stock return of the ten largest FX dealers and the North American CDX made up by 125 investment grade issuers of credit securities capture the equity capital and funding constraints of global FX dealers. A funding and capital erosion (i.e., increasing dealers' leverage and possibly funding needs) constrains global financial intermediaries, requiring a compensation for adverse selection risk and uncertainty (Gabaix and Maggiori, 2015; He and Krishnamurthy, 2013). Third, we include a set of market conditions such as the world equity and bond returns. The economic rationale is that higher risk factors (Christiansen, Ranaldo, and Söderlind, 2011) and information asymmetries in other asset classes such as stocks and bonds are conveyed in FX markets via fundamental valuations and portfolio rebalancing (Hau and Rey, 2004).

The regression specifications in Table 9 are chosen such that potential multicollinearity issues are mitigated. There are three key takeaways: first, $AIP_{HML}$ returns are increasing with the VIX, suggesting that general market uncertainty and flight-to-quality phenomena are associated with more asymmetric information risk in FX markets. Second, $AIP_{HML}$ returns are negatively related to the stock market performance of large FX dealers and positively related to changes in the CDX, supporting the idea that when asymmetric information increases, banks face more severe risk-bearing capacity constraints due to adverse selection issues. Third, $AIP_{HML}$ returns increase in downward (upward) equity (bond) markets, suggesting a cross-market transmission mechanism of risk factors and potentially asymmetric information via international portfolio rebalancing.

## 6.5. Robustness Tests and Limitations

We have performed a number of additional analyzes and robustness checks that we briefly summarize. To conserve space, we focus on four of them. More detailed results and additional tests are reported in the Online Appendix. First, we test whether cumulative returns are due to strong performance in some periods and poor performance in others. Second, we explore the performance of the strategy using various subsamples of currency pairs. Third, we check if our results are sensitive to including the contemporary price impact when deriving our trading signals. Fourth, we rebalance our trading strategy at different Bloomberg fixing times instead of using close prices. All these robustness checks corroborate our main results.

**Table 9: Economic Drivers of $AIP_{HML}$**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Intercept ($\alpha$) | ***0.05 | ***0.05 | **0.04 | ***0.05 |
| | [2.86] | [2.95] | [2.48] | [2.84] |
| VIX | ***0.01 | | | |
| | [8.58] | | | |
| AAA bond yields | | *−0.01 | | |
| | | [1.65] | | |
| Top FX dealers | | | ***−0.06 | |
| | | | [10.42] | |
| CDX | | | | ***0.03 |
| | | | | [11.95] |
| MSCI return | | ***−0.12 | | |
| | | [11.51] | | |
| BGBI return | **0.06 | **0.06 | **0.06 | ***0.07 |
| | [2.51] | [2.36] | [2.48] | [2.83] |
| $R^2$ in % | 4.78 | 9.03 | 6.77 | 8.78 |
| Adj. $R^2$ in % | 4.66 | 8.86 | 6.65 | 8.61 |
| #Obs | 1564 | 1564 | 1564 | 1564 |
| VIF | 1.05 | 1.14 | 1.07 | 1.10 |

*Note*: This table shows results from multivariate regressions of daily gross $AIP_{HML}$ returns on its potential drivers, $AIP_{HML,t} = \alpha + \beta' f_t + \epsilon_t$, where $f_t$ denotes demand- and supply-side sources as well as a set of market conditions. *VIX* is the Chicago Board Options Exchange's volatility index measuring the stock market's expectation of volatility based on S&P 500 index options. *AAA bond yields* is the bond yield on AAA–rated US corporate debt. *Top FX dealers* is an equally weighted equity portfolio consisting of the ten largest FX dealers' stocks, *CDX* is the North American credit default swap index made up by 125 issuers of credit securities, *MSCI return* is the return on the MSCI world equity index, and *BGBI return* is the return on the Barclays global-aggregate bond index. All variables enter the regressions contemporaneously as first differences, except for the *BGBI return*, which is lagged by one day. The intercept ($\alpha$) has been annualized ($\times 252$). All explanatory variables are in relative changes. The numbers in the brackets are the corresponding test statistics based on heteroskedasticity- and autocorrelation-consistent standard errors correcting for serial correlation and the small sample size (using the plug-in procedure for automatic lag selection by Andrews and Monahan, 1992; Newey and West, 1994). *VIF* is the maximum variance inflation factor. The sample covers the period from September 9, 2013 to December 31, 2019. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively.

# 7. Conclusion

In this paper, we study asymmetric information risk in global FX trading in an effort to improve our understanding of the world's largest OTC market, the FX market. We address the following two questions: first, does order flow convey superior information across market participants, time, and currency pairs? Second, is asymmetric information risk priced in the global FX market?

To answer these questions, we analyze a novel data set of global FX order flows disaggregated by groups of market participants. We find compelling evidence that order flow impacts FX spot prices heterogeneously across agents, time, and currency pairs, supporting the asymmetric information hypothesis. In particular, we demonstrate that some agents are always more informed than others, providing empirical substantiation that asymmetric information risk is systematically present in the FX market.

To assess the economic value of asymmetric information risk, we introduce a novel long–short trading strategy based on the permanent price impact. We provide empirical evidence that holding currencies with higher informational asymmetries requires a positive risk premium for taking the risk of trading against informed investors. Overall, the strategy generates significant returns that are neither subsumed by existing risk factors nor attenuated by a series of robustness checks.

Our paper should be relevant for both academics and policymakers. For academics, our method for detecting asymmetric information with permanent price impact estimates and building consistent long–short portfolios is generalizable and should find external validity in other asset classes. This is especially true if the assets are traded OTC (e.g., derivatives, government, and corporate bonds) and/or if order flow data are enriched by additional information about categories of market participants. For policymakers, our findings suggest that FX markets are still characterized by information asymmetries, heterogeneity, and fragmentation, despite the ongoing efforts to redesign and regulate OTC markets, including the Dodd–Frank Act, European Market Infrastructure Regulation (EMIR), and Markets in Financial Instruments Directive (MiFID) II. Future research should highlight whether the declared objectives (i.e., increase of transparency, price efficiency, and fairness) have yet to be achieved or have produced the suited effects in only some market segments.

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# FX Liquidity Risk and Carry Trade Premia

*Paul Söderlind and Fabricius Somogyi*

**Abstract**

The foreign exchange (FX) market is considered to be the largest and presumably most liquid financial market in the world. We show that even in this market exposure to liquidity risk commands a non-trivial risk premium of up to 3.6% per annum. In particular, systematic and idiosyncratic liquidity risk are not subsumed by existing risk factors and successfully price the cross-section of currency returns. However, we also find that liquidity and carry trade premia are significantly correlated. This lends support to a liquidity-based explanation of the carry trade risk premium. To illustrate this point, we decompose carry trade returns and show that the commonality with liquidity risk stems from periods of high market stress and is confined to the static but not the dynamic carry trade.

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# 1. Introduction

Trading volume in the foreign exchange (FX) market amounts to $6.6 trillion every day.[1] This makes the FX market the largest financial market in the world. Precisely because of its sheer size and despite its decentralised nature, the FX market is commonly known as one of the most liquid and resilient trading venues. However, a clear understanding of whether FX *liquidity risk* matters for asset prices is still missing. This paper aims to fill this void by providing the first systematic study of the pricing implications of FX liquidity risk.[2]

Starting from a simple liquidity adjusted capital asset pricing model (see Acharya and Pedersen, 2005), we derive four candidate sources of liquidity risks: commonality in liquidity with market liquidity, return sensitivity to systematic illiquidity (average liquidity across 15 exchange rates) liquidity sensitivity to market returns, and return sensitivity to idiosyncratic (currency pair specific) liquidity. We show that sorting currency pairs based on their exposure to systematic (market) and idiosyncratic illiquidity risk generates a non-trivial risk adjusted return. The correlation of these two factors with the infamous carry trade is relatively high and hence we delve deeper along two dimensions: First, we decompose carry trade returns and show that the correlation is only driven by the static and dollar component but not the dynamic part of the carry trade (Hassan and Mano, 2018). Second, we distinguish between normal times and periods of markets stress and find that the correlation is almost twice as large in periods of high uncertainty. In sum, our findings lend support to the idea of a liquidity-based explanation for the carry trade risk premium, albeit we cannot conclusively disprove potential alternative stories.

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

The contribution of this paper to the FX asset pricing and international finance literature

[1] See "Triennial central bank survey — global foreign exchange market turnover in 2019," Bank for International Settlements, September 2019.

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

is fourfold. First, it provides a methodological contribution to the identification of potential sources of FX liquidity risk. To be specific, we adapt the Acharya and Pedersen (2005) liquidity adjusted capital asset pricing model to the FX market context and use it to organise several theories about how liquidity risk might affect currency returns. This allows us to identify four potential sources of FX liquidity risk: i) commonality in currency liquidity and systematic liquidity (i.e., Mancini et al., 2013; Abankwa and Blenman, 2021), ii) return sensitivity to systematic (marketwide) liquidity (Pástor and Stambaugh, 2003), iii) commonality in currency liquidity and market returns, and iv) return sensitivity to idiosyncratic currency liquidity (e.g., Amihud, 2002; Chordia et al., 2001). In addition to this, we also identify empirical counterparts of systematic and currency specific FX liquidity.

The second contribution is to sort currency pairs into tradeable portfolios based on their exposure (i.e., 'betas') to the four above sources of FX liquidity risk. Note that we control for the correlation of currency specific illiquidity and volatility as well as systematic (market) illiquidity and global volatility by orthogonalising illiquidity and volatility measures. The main reason for doing this is that we want to capture the time series and cross-sectional variation in illiquidity that is not driven by volatility and hence should truly capture *liquidity*. To our best knowledge, we are the first to provide a systematic study of FX liquidity risk. The existing literature has only looked at one particular aspect of illiquidity risk at a time. For instance, Banti et al. (2012) study systematic illiquidity-based on order flow data, whereas Mancini et al. (2013) and Abankwa and Blenman (2021) examine commonality in liquidity. Evans (2020) investigates how the constituents of FX liquidity (e.g., depth, bid-ask spread, and volatility) rather than liquidity *risk* matter for currency risk premia.

Two clear results emerge from these portfolio sorts. First, all four liquidity beta based trading strategies, except for sorting on commonality in currency liquidity and market returns, generate significant risk-adjusted returns ranging from 2.3–3.6% per annum. In particular, the excess returns to commonality in illiquidity, systematic illiquidity, and idiosyncratic illiquidity risk are neither subsumed by the dollar base factor and carry factor (see Lustig and Verdelhan, 2007; Lustig et al., 2011), respectively, nor by the Menkhoff et al. (2012a) volatility risk factor. Second, all three liquidity factors significantly load on the dollar base factor, whereas only systematic and idiosyncratic illiquidity sorted portfolios are significantly exposed to carry trade returns.

The third contribution is to test if the liquidity-based risk factors can explain the cross-section of currency returns. To explore this, we run a horse race across different asset pricing models including traditional and liquidity-based risk factors. Our benchmark model is the same as in Verdelhan (2017) and therefore consists of two factors, namely, the dollar base and carry trade factor, respectively. There are two key takeaways from running these asset pricing tests. First, commonality in liquidity risk cannot explain any of the cross-sectional variation in expected returns but exhibits similar properties to the dollar base factor. Second, replacing the carry trade factor by systematic (market) and idiosyncratic liquidity risk factors yields a parsimonious asset pricing model that performs on par with the Verdelhan (2017) benchmark. These results lend support to the idea that exposures to liquidity risk can serve as an alternative explanation for the carry trade anomaly.

The fourth contribution is to explore whether the carry trade risk premium is, at least partially, a compensation for liquidity risk. This hypothesis is motivated by Burnside (2009) who suggests that liquidity frictions may explain the profitability of the carry trade since liquidity spirals can amplify currency crashes. Mancini et al. (2013) provide suggestive empirical evidence in favour of this statement over the short and unprecedented period of the global financial crisis 2007-09. Moreover, Brunnermeier et al. (2008) and Bakshi and Panayotov (2013) show that changes in US dollar funding liquidity can predict carry trade payoffs. Against this backdrop, our analysis proceeds in four steps. To begin with, we regress the carry factor on each of the four liquidity beta based risk factors. In line with expectations, we find that only systematic (market) and idiosyncratic liquidity risk are highly correlated with carry trade returns. Taken together, the two factors can explain up to 40% of the time series variation in carry trade premia.

In the second step, we compare the performance of the liquidity-based explanation of the carry trade to existing *risk based* theories.[3] In particular, we focus on the more recent literature that considers global imbalances (Della Corte et al., 2016), intermediary leverage (Fang, 2018), and network centrality (Richmond, 2019) as alternative explanations for carry trade premia. Our results show that a liquidity-based view outperforms the aforementioned interpretations of carry trade profitability based on simple statistical grounds such as coefficients of determination and pricing errors.

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

In the final step, we explore the possibility that the correlation of liquidity risk and carry trade returns is time-varying and state dependent. This analysis is motivated by Mancini

[3] Alternative sources of risk include innovations in currency volatility (Menkhoff et al., 2012a), skewness (Rafferty, 2012), correlation (Mueller et al., 2017), and commodity imports/ exports (Ready et al., 2017). Orlov (2016) compares liquidity in equities to the FX market and shows that the former is the dominant factor in determining carry trade returns. Chernov et al. (2020) use direct conditional projections of the stochastic discount factor to explain carry trade returns.

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

et al. (2013) who show that commonality in liquidity risk and carry trade returns increases in distressed markets. To explore this possibility, we regress the static and dynamic component of the carry trade on the systematic and idiosyncratic liquidity risk factors and include an interaction dummy capturing market stress. We define our stress factor as the average across the (standardised) AAA US corporate bond yield, TED spread, and global implied FX volatility. Commonality in liquidity and *static* carry premia is almost twice as large during periods of market stress as otherwise. On the other hand, we find no evidence of commonality in bad times for liquidity and *dynamic* carry trade returns.

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

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

## 2. Theoretical Background

Here, we introduce the basic idea of a liquidity adjusted capital asset pricing model that builds on the work by Acharya and Pedersen (2005). We use this approach to organise several theories about how liquidity might affect asset prices. Specifically, this framework can explain the empirical findings that commonality in liquidity, return sensitivity to market liquidity, and average liquidity are priced and that asset returns and liquidity comove. Furthermore, we identify empirical counterparts of systematic and currency pair specific liquidity risk.

## 2.1. Liquidity Adjusted Asset Pricing Model

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

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

where $r^i$ is the (gross) currency excess return on buying a foreign currency in the forward market and then selling it in the spot market after one month (i.e., 22 days), $\lambda = E[r^M - c^M]$ is the market risk premium net of the relative illiquidity cost $c^i$, $r^M$ is the currency market return following the two factor model by Verdelhan (2017), and $c^M$ is the global measure of FX illiquidity that is based on Karnaukh et al. (2015). Notice that throughout this paper we suppress the time and currency pair subscripts $t$ and $i$, respectively, unless they are needed for clarity. In the context of currencies one could also think of $rx^i$ as the after "illiquidity-cost" excess return that is, by construction of currency excess returns, net of the interest rate differential between the foreign and domestic risk-free rates. Since the covariance is a linear operator, we can rewrite the 'accounting identity' in Eq. (1) as follows:

$$E[r^i - c^i] = \lambda\beta^{M,i} + \lambda\beta^{1,i} - \lambda\beta^{2,i} - \lambda\beta^{3,i}. \tag{2}$$

This expression states that the net required excess return is simply given by an expression of four betas times the market risk premium. The first covariance is the standard market beta, whereas the three additional betas can be regarded as different forms of *systematic* liquidity risks.[5] The key empirical challenge is how to define $r^M$, $c^M$, $r^i$, and $c^i$ in the context of currency pairs. We tackle this empirical identification issue in the next sub-section.

Notice that many empirical liquidity estimates (especially those that can be applied to long samples) are measured on a different scale than $r^M$. The Amihud (2002) illiquidity measure is a notable exception to this but would require volume data for estimation. However, due to the decentralised nature of the FX market comprehensive volume data are unfortunately not available for a long enough sample period. Hence, in our setting, it is empirically not possible to directly recover $\lambda$ but rather a scaled version of it. In particular, we will assume that the observed illiquidity measure $c^i$ is a linear function of the "true" illiquidity measure $c^{i,*}$:

$$c^i = \alpha_c^i + \gamma_c^i \cdot c^{i,*}, \tag{3}$$

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

where $\alpha_c^i$ and $\gamma_c^i$ are parameter estimates. The impact of Eq. (3) on Eq. (1) is simply a scaling effect. Thus, we will not be able to directly estimate $\lambda$ but rather just the joint effect, that is, $\frac{\lambda}{\gamma_c^i}$. Clearly, this will not affect any of our asset pricing (see Section 4) results that are based on univariate portfolio sorts.

As mentioned above, Acharya and Pedersen (2005) provide a unified framework that can explain the empirical findings that commonality in liquidity (Mancini et al., 2013), return sensitivity to market liquidity (Pástor and Stambaugh, 2003), and average liquidity (Amihud and Mendelson, 1986; Amihud, 2002) are priced. These results are epitomised by the three liquidity betas (i.e., $\beta^{1,i}$, $\beta^{2,i}$, and $\beta^{3,i}$) in Eq. (2). In particular, the last point is subsumed by our approach in the sense that sorting on $\beta^{1,i}$ is essentially the same as sorting on one month (i.e., $\Delta = 22$ days) changes in the systematic level of illiquidity (i.e., $\Delta\tilde{c}^{i,SYS}$), which we define as the fitted value (without intercept) of the following regression:

$$\Delta\tilde{c}^i = \alpha^i + \underbrace{\beta^{1,i}\Delta\tilde{c}^M}_{\Delta\tilde{c}^{i,SYS}} + \epsilon. \tag{4}$$

Furthermore, the Acharya and Pedersen (2005) framework implies that *idiosyncratic* liquidity $c^i$ increases with current (gross) returns $r^i$ and predicts future returns (e.g., Amihud, 2002; Chordia et al., 2001). This directly stems from the fact that $r^i$ is linear in $c^i$ (this follows by inspection of Eq. (1) and by moving $c^i$ to the RHS). To take this into account, we consider the covariance between (gross) currency excess return $r^i$ and (idiosyncratic) currency pair specific illiquidity $c^i$ (i.e., $cov(r^i, c^i)$) as an additional source of liquidity risk.[6] Hence, we define a fourth liquidity beta (i.e., $\beta^{4,i}$) that we can use to sort currencies into long-short portfolios.

## 2.2. Four Covariances

The following points provide a brief summary of the economic intuition for the *systematic* (i.e., $\beta^1$, $\beta^2$, and $\beta^3$) and *idiosyncratic* (i.e., $\beta^4$) liquidity covariances:

1. **Commonality in illiquidity risk** $\beta_1 : cov(c^i, c^M)$, the required return increases with the covariance between the asset's illiquidity and the market illiquidity. This is because investors want to be compensated for holding a security that becomes illiquid when the market is illiquid. This is known as commonality in illiquidity (Mancini et al., 2013).

2. **Systematic illiquidity risk** $\beta_2 : cov(r^i, c^M)$, the required return increases as the covariance between the asset's return and the market illiquidity decreases. This is because investors require a higher return on an asset with a low return in times when the market becomes more illiquid in general (Pástor and Stambaugh, 2003).

[6] This approach is also motivated by the findings in Ang et al. (2006) showing that idiosyncratic volatility is priced in the cross-section of equity returns.

3. **Commonality in market risk** $\beta_3$ : $cov(c^i, r^M)$, the required return increases as the covariance between an asset's illiquidity and the market return decreases. This effect stems from the fact that investors are unwilling to accept a lower expected return on an asset that is illiquid in a down market. When the market declines, investors are poor and the ability to sell easily is especially valuable. Hence, an investor requires a higher return on financial assets with high illiquidity costs in states of poor market returns.

4. **Idiosyncratic illiquidity risk** $\beta_4$ : $cov(r^i, c^i)$, the required return increases as the covariance between the asset's return and its idiosyncratic illiquidity decreases. This is because investors require higher returns on an asset that yields lower returns in times when it is illiquid and thus perceived as more risky (Amihud, 2002; Chordia et al., 2001).

Our empirical approach is to sort currency pairs based on the four betas introduced in the previous section and described above in more detail. Specifically, we study the pricing of a *traded* liquidity risk factor that is not prone to any lookahead bias. To do this, the subsequent empirical part of this paper proceeds in three steps: First, we describe the data and identify empirical counterparts of $r^i$, $r^M$, $c^i$, and $c^M$ in the context of currency pairs. Second, we estimate the liquidity adjusted asset pricing model (see Eq. (2)) in a rolling window fashion. Third, we document the out-of-sample performance of sorting currency pairs based on each of the four liquidity betas. Note that we control for the correlation of illiquidity and volatility by orthogonalising illiquidity against global and currency specific volatility, respectively.

# 3. Data and Methodology

## 3.1. Data

We collect hourly nominal exchange rates against the US dollar (USD) for 15 major emerging and developed markets: Australia (AUD), Canada (CAD), Denmark (DKK), Euro area (EUR), Hong Kong (HKD), Israel (ILS), Japan (JPY), Mexico (MXP), New Zealand (NZD), Norway (NOK), Singapore (SGD), South Africa (ZAR), Sweden (SEK), Switzerland (CHF), and United Kingdom (GBP) for the period of 3 January 1994 to 30 December 2019 from Olsen Data, which is the standard source for academic research on high frequency FX rates. For the same set of currency pairs and time frame we retrieve 1-month forward rates from Bloomberg. The cross-sectional dimension of our data set is driven by two key considerations: First, we want to ensure a consistent data quality and availability across currency pairs for the entire sample period. Second, we want to study the asset pricing implications of FX liquidity risk by creating tradeable currency risk factors and hence, we focus on some of the most liquid currency pairs in terms of actual trading costs. Note that prior to 1999 we use the German mark instead of the EUR. For each hour of every trading day, the midquote, high and low bid ask quotes, and close bid and ask prices are used to construct liquidity measures and currency excess returns as we describe them below.

### 3.2. Methodology

Since our trading strategy builds on sorting currency pairs based on each of the four liquidity covariances (see Section 2.2) we first have to identify $r^i$, $r^M$, $c^i$, and $c^M$ in the context of currency pairs as follows:

1. $r^i$ is the gross asset returns. In line with the FX asset pricing literature (e.g., Lustig et al., 2011) it is useful to define the log excess return $r^i_{t+1}$ on currency $i$ as follows:

$$r^i_{t+1} = (f_{t-21,t+1} - s_{t+1})/22, \tag{5}$$

   where $f_{t,t+1}$ and $s_{t+1}$ are the daily 1-month log forward and spot rates quoted as foreign currency per unit of USD, e.g., 0.74 EUR per USD (i.e., *indirect* quotation).

2. $r^M$ is the gross market return that we define as the return on the tangency portfolio from a multi-factor asset pricing model given by:

$$r = \alpha + \beta\, DOL + \gamma\, CAR + \epsilon, \tag{6}$$

   where $DOL$ is the dollar factor and $CAR$ is the carry factor (see Lustig and Verdelhan, 2007; Lustig et al., 2011). Our choice of factors is motivated by Verdelhan (2017) who shows that the dollar and carry factor jointly account for up to 80% of the variation in monthly exchange rate movements. Hence, throughout this paper, we define the 'market model' to be the one in Eq. (6) and have that $M = \{DOL, CAR\}$. Note that conceptually the multi-factor model in Eq. (6) is the same as a one-factor model with the tangency portfolio being the single factor.

   In our base case we use the following tangency portfolio weights:

$$w_r = \frac{\Sigma^{-1}\mu}{\mathbb{1}'\Sigma^{-1}\mu}, \tag{7}$$

   where $\Sigma = cov(R)$ is the covariance matrix of market factors[7] and $\mu$ is the mean excess return. Based on full-sample estimates of $R$ we get the following weights for the dollar $DOL$ and carry factor $CAR$:

$$w_r = \{w_{DOL}, w_{CAR}\} = \{-0.25, 1.25\}. \tag{8}$$

[7] It is instructive to think of $R$ as being a matrix with $N$ columns, where every column represents one market factor, that is, $R = [DOL, CAR]_{\{T,N\}}$.

Weighting every market factor by its tangency portfolio weight $w_r$ is useful for two reasons: First, using a one factor model with tangency portfolio weights in Eq. (8) is equivalent to the two factor model in Eq. (6). Second, it ensures that the market structure $M$ can be easily linked to a classic mean-variance framework (Markowitz, 1952).[8]

3. $c^i$ is the currency pair specific measure of illiquidity estimated as a fraction of $r^i$. We define $c^i$ as follows:

$$c^i = \frac{1}{K} \sum_{k=1}^{K} \frac{z_k - \overline{z_k}}{std(z_k)}, \tag{9}$$

where in our base case $z_k \in \{BA, CS\}$ with $BA$ corresponding to the relative bid–ask spread and $CS$ to the spread measure by Corwin and Schultz (2012), respectively.[9] The $BA$ is the difference between the ask and bid price relative to the midquote. The $CS$ spread estimator is derived from high and low transaction prices over two consecutive trading days, assuming that the high price is buyer initiated and that the low price is seller initiated. The mean $\overline{z_k}$ and standard deviation $std(z_k)$ are estimated in a recursive fashion using an expanding window with an initial size of 252 days. This ensures that none of our liquidity betas in Eq. (2) suffers from any look-ahead bias. Given our choice of $z_k$, the currency specific liquidity $c^i$ is closest to Karnaukh et al. (2015) and most accurately proxies the effective cost of trading. Since higher values of this measure correspond to larger spreads, it is effectively a measure of *illiquidity* rather than *liquidity*. To obtain a daily measure of the relative bid–ask spread we take averages across hourly point estimates.

4. $c^M$ is the global measure of FX illiquidity that we define as follows:

$$c^M = \sum_{n=1}^{N} \sum_{i=1}^{K} w_c^n \varphi^i c^i, \tag{10}$$

where $\varphi^i$ is the relative weight associated with the illiquidity measure $c^i$ in currency pair $i$. To reflect our assumption about the 'market model' (i.e., $M = \{DOL, CAR\}$) we define the relative weights $\varphi^i$ as follows: we take the absolute value of the (long-short) portfolio weights associated with every market factor $R^n$ and recalibrate these weights to sum up to unity at every point in time. Eventually, we apply the same reasoning to the tangency portfolio weights associated with the $n$th market factor (i.e., $w_c$) and thus deal with the

[8] As a robustness check, we have also experimented with tangency portfolio weights ranging from $-1$ to 2 and found consistent results for all portfolio sorts in Section 4. See the online Appendix for these additional results.

[9] As a robustness check, in the online Appendix we document portfolio sorts that are based on either the bid–ask spread or the $CS$ spread as the sole liquidity measures. We find that the liquidity risk premium associated with $\beta^1$ is mainly driven by cross-sectional variation in the CS spread, whereas the risk factors based on $\beta^2$ and $\beta^4$ are mostly stemming from the variation in bid–ask spreads.

following modified tangency portfolio weights:

$$w_c = \{w^+_{DOL}, w^+_{CAR}\} = \{0.17, 0.83\}. \tag{11}$$

## 4. Portfolio Sorts

This section describes how we construct portfolio sorts based on the four liquidity covariances that we have outlined above in Section 2.2. We proceed in three steps: First, we describe how to orthogonalise global (marketwide) and currency specific measures of illiquidity risk against global and currency specific measures of volatility risk. This is motivated by the observation that global volatility (Menkhoff et al., 2012b) and global illiquidity are significantly correlated with each other. For our sample the correlation coefficient is around 51.5%. The resulting (residual) illiquidity measures capture the time series and cross-sectional variation in illiquidity that is presumably unrelated to volatility. Put differently, by performing various orthogonalisations we aim to derive clean liquidity measures that are independent from volatility.[10] Second, we outline how to estimate the time-varying systematic exposure (i.e., 'betas') with respect to global and currency specific factors, respectively. Third, we document the out-of-sample performance of sorting currency pairs based on the above four liquidity betas.

In the first step, we describe the methodology to orthogonalise systematic (market) illiquidity $c^M$ against global volatility $v^M$.[11] The same methodology can also be applied to orthogonalise currency specific illiquidity (i.e., $c^i$) against currency specific volatility (i.e., $v^i = |\Delta s^i|$). Our measure of global volatility $v^M$ is conceptually based on Menkhoff et al. (2012a) and corresponds to a weighted average of absolute log spot returns across $K$ exchange rates. Again, we assume that the 'market model' is $M = \{DOL, CAR\}$ and hence the weights are the same as in Eq. (10). Thus, we also use the same tangency portfolio weights as in Eq. (11) to aggregate across weighted averages of currency pair specific volatility measures.

Orthogonalising systematic illiquidity $c^M$ against global volatility $v^M$ is done by estimating the following regression equation using an expanding data window:

$$c^M = \alpha + \delta v^M + \tilde{v}^M \tag{12}$$

where the initial window length is equal to 252 days in our base-line scenario. We store $\tilde{v}^M$ in a vector called $\tilde{c}^M$. Note that all our portfolio sorts yield qualitatively similar results when using a rolling instead of an expanding window for the orthogonalisation. We also apply this

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

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

'recursive projection' to orthogonalise 22-day changes (denoted by $\Delta = 22$) in global illiquidity (i.e., $\Delta c^M$) against 22-day changes in global volatility (i.e., $\Delta v^M$). Note that following the Frisch-Waugh-Lovell theorem, orthogonalising $c^M$ against $v^M$ is equivalent to including $v^M$ as a control variable in the beta representation (see Eq. (2)). Analogously, we can use the same approach to orthogonalise idiosyncratic illiquidity $c^i$ against the currency specific volatility $v^i$.

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

$$\Delta\tilde{c}^i = \alpha + \beta^1 \Delta\tilde{c}^M + \varepsilon, \tag{13}$$

$$r^i = \alpha + \beta^2 \Delta\tilde{c}^M + \varepsilon, \tag{14}$$

$$\Delta\tilde{c}^i = \alpha + \beta^3 r^M + \varepsilon, \tag{15}$$

$$r^i = \alpha + \beta^4 \Delta\tilde{c}^i + \varepsilon. \tag{16}$$

where $\tilde{c}^i$ and $\tilde{c}^M$ have been orthogonalised (see Eq. (12)) against currency pair specific (i.e., $v^i$) and global volatility factors (i.e., $v^M$), respectively. Note that we consider 22-day changes in $\tilde{c}^i$ and $\tilde{c}^M$ as illiquidity is persistent (Acharya and Pedersen, 2005) and the autocorrelation of global illiquidity, for instance, is 78.1% at the daily frequency. Hence, also the exchange rate and market returns are measured over 22 days and are denoted by $r^i$ and $r^M$, respectively. These regressions are daily and we repeat them for every currency pair $i$.

Clearly, estimating betas and (scaled) covariances will yield identical results in terms of sorting if the regressors are the same for each currency pair. This applies to the first three regressions but not to the last one. As a robustness check we estimate (scaled) covariances instead of regression betas in Eq. (16) and find virtually identical results for the portfolio sorts. Furthermore, our results are robust to using an expanding window approach. However, the advantage of the rolling window estimation is twofold: First, the size of the information set is constant over time (i.e., the last $W$ periods) and hence the excess returns of the trading strategy at time $t$ are unaffected by the starting point. Second, the moving window approach allows for the possibility that the betas are time-varying. In each of these regressions in Eqs (13) to (16) we use a 252-day rolling window. All our results are qualitatively unchanged when using a longer or shorter estimation window.

In Table 1 we report the collinearity of measures of liquidity risk, bid-ask spreads, and volatility. Most correlations are economically insignificant with the notable exceptions of $corr(\beta^1, \beta^3)$ and $corr(\beta^2, \beta^4)$, respectively. Therefore, in practice, it should be possible to disentangle the effects of overall illiquidity and individual illiquidity betas despite of the mild collinearity issues. Not surprisingly, more illiquid currency pairs (i.e., higher bid-ask spread) also exhibit more volatile returns (i.e., higher volatility). Furthermore, we find that illiquid currency pairs also have high illiquidity *risk* as they tend to exhibit smaller values of $\beta^2$ and $\beta^4$, respectively. Thus, a currency pair that is illiquid in absolute terms (i.e., higher bid-ask spread), also tends to be more risky as it has a lower return sensitivity to systematic (i.e., $cov(r^i, c^M)$) and idiosyncratic (i.e., $cov(r^i, c^i)$) illiquidity. This result is reminiscent of the idea that 'liquidity begets liquidity' or put differently that there is 'flight to liquidity'.

**Table 1: Beta Correlations**

| | $\beta^1$ | $\beta^2$ | $\beta^3$ | $\beta^4$ | $bas$ |
|---|---|---|---|---|---|
| $\beta^2$ | 19.41 | | | | |
| $\beta^3$ | ***−84.59 | −25.51 | | | |
| $\beta^4$ | 10.01 | ***78.48 | 2.18 | | |
| $bas$ | −34.82 | *−50.47 | 43.30 | −13.96 | |
| $v$ | ***70.31 | −19.61 | **−56.64 | −9.50 | 28.59 |

*Note*: This table reports the cross-sectional correlations of the median $\beta^1$, $\beta^2$, $\beta^3$, and $\beta^4$ (based on 252-day rolling window estimates), median relative bid-ask spread $bas = (ask - bid)/mid$, and median volatility $v$ for 15 USD–based currency pairs. Significant correlations at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The sample covers the period from 21 February 1995 to 31 December 2019.

In the final step, we use each of the four rolling window liquidity betas (i.e., $\beta^q \ \forall q \in \{1, 2, 3, 4\}$) in Eqs (13) to (16) to form traditional tertile portfolios ($T_1, T_2$, and $T_3$). To minimise the impact of noise, we smooth the rolling window regression betas over a ten day moving window before translating them to trading signals. Moreover, we lag all trading signals by 22-days to ensure the implementability based on 1-month forward contracts. To be precise, we construct four dollar-neutral long–short portfolios by going long the currency pairs in the top tertile ($T_3$) and short the currency pairs in the bottom tertile ($T_1$). Each tertile portfolio consists of five currency pairs at most, where each of them receives an equal weight. Our findings are robust to using a rank or value based weighting scheme. We dub the four liquidity beta based trading strategies $\beta^q_{HML} \ \forall q \in \{1, 2, 3, 4\}$, where $HML$ stands for *high-minus-low.*

Table 2 reports summary statistics for these four liquidity beta based portfolios as well as four common FX risk factors, namely dollar $DOL$, carry $CAR$, volatility $VOL$, and tangency $TAN$. Specifically, $DOL$ is based on an equally weighted long portfolio of all USD currency pairs (Lustig et al., 2011), $CAR$ on the forward discount/ premium $f_{t,t+1} - s_t$ (Lustig and Verdelhan, 2007), $VOL$ is based on currency pairs' exposure to the global volatility factor $\beta^v$ (Menkhoff et al., 2012a), and $TAN$ is a strategy that sorts on exposures to the tangency portfolio $\beta^M$ (Markowitz, 1952). $IML$ is a trading strategy that sorts currencies into long-short portfolios based on the level of relative bid–ask spreads. To estimate a currency pair's sensitivity to global volatility $\beta^v$ and market risk $\beta^M$, respectively, we run regressions in a similar vein to Eqs (13) to (16). Three out of the four liquidity beta sorted trading strategies exhibit non-trivial mean excess returns, namely, commonality in illiquidity ($\beta^1_{HML}$), systematic (market) illiquidity ($\beta^2_{HML}$), and idiosyncratic illiquidity ($\beta^4_{HML}$). This result is in line with the equity market literature and in particular Amihud and Mendelson (1986), Chordia et al. (2001), Amihud (2002), Pástor and Stambaugh (2003), and Hameed et al. (2010). What is more, the liquidity risk premia $\beta^1_{HML}$, $\beta^2_{HML}$, and $\beta^4_{HML}$ are significantly larger than the liquidity premium on illiquid minus liquid currency pairs (i.e., $IML$).

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

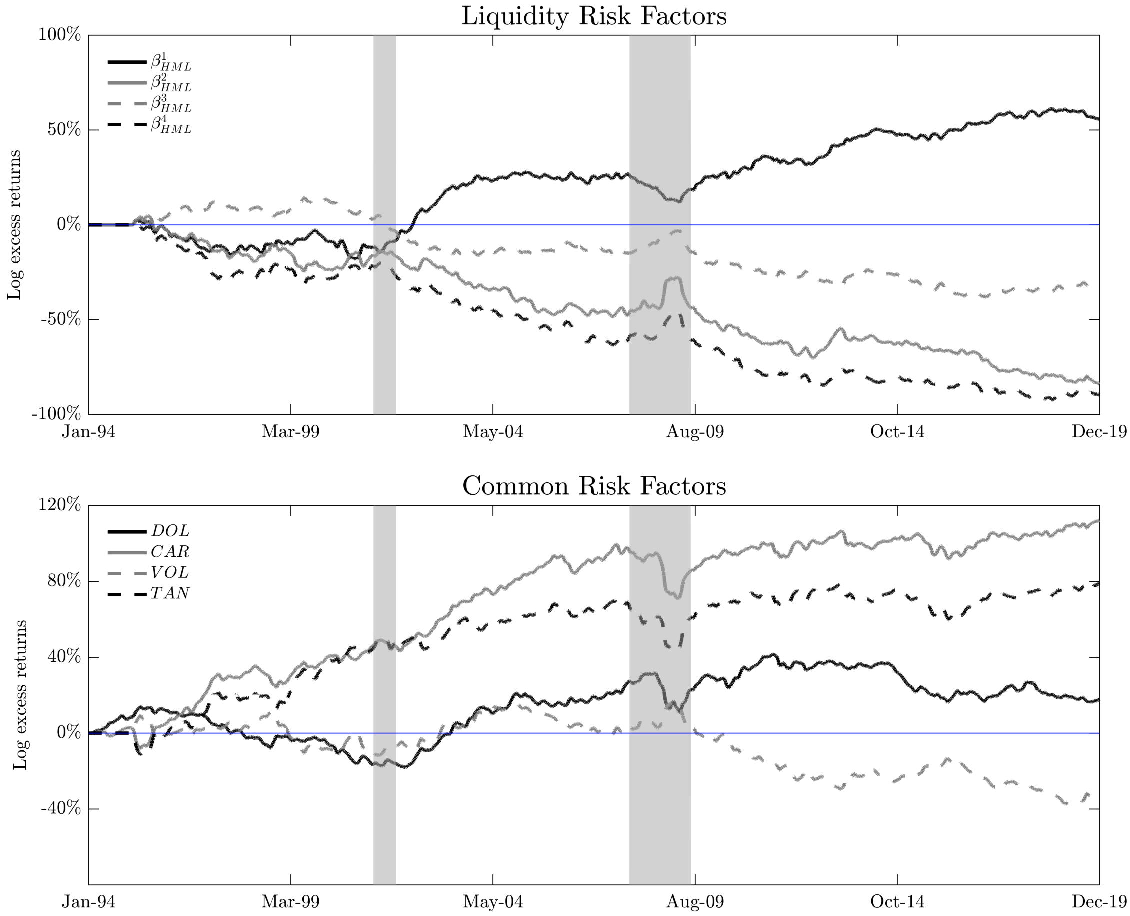
**Table 2: Summary Statistics Portfolio Sorts**

| | $DOL$ | $CAR$ | $VOL$ | $TAN$ | $IML$ | $\beta^1_{HML}$ | $\beta^2_{HML}$ | $\beta^3_{HML}$ | $\beta^4_{HML}$ |
|---|---|---|---|---|---|---|---|---|---|
| *Mean* in % | 0.39 | ***4.49 | −1.44 | **3.25 | *2.02 | **2.29 | ***−3.41 | −1.22 | ***−3.65 |
| | [0.34] | [3.33] | [1.19] | [2.32] | [1.90] | [2.24] | [2.81] | [1.38] | [3.31] |
| $\sigma$ | 1.44 | 1.73 | 1.57 | 1.81 | 1.40 | 1.36 | 1.59 | 1.21 | 1.46 |
| SR | 0.27 | ***2.60 | −0.92 | **1.79 | *1.44 | **1.69 | ***−2.14 | −1.01 | ***−2.51 |
| | [0.34] | [3.04] | [1.18] | [2.24] | [1.90] | [2.26] | [2.70] | [1.39] | [3.32] |
| Skewness | −0.15 | −0.87 | 0.07 | −0.49 | 0.10 | 0.21 | 0.33 | −0.13 | −0.14 |
| Kurtosis-3 | 2.10 | 4.71 | 1.52 | 2.68 | 1.16 | 0.72 | 4.25 | 1.00 | 1.28 |
| Min | −1.55 | −2.16 | −1.27 | −1.88 | −1.09 | −0.77 | −1.41 | −1.13 | −1.27 |
| Max | 0.91 | 1.68 | 1.53 | 1.55 | 1.05 | 1.04 | 1.92 | 0.68 | 1.02 |
| MDD in % | 31.97 | 28.60 | 28.03 | 25.57 | 19.70 | 20.41 | 20.74 | 14.49 | 17.28 |
| Scaled MDD | 22.28 | 16.53 | 17.85 | 14.11 | 14.03 | 15.05 | 13.04 | 11.94 | 11.87 |
| #Obs | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 |

*Note*: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., $\beta^1_{HML}$, $\beta^2_{HML}$, $\beta^3_{HML}$, and $\beta^4_{HML}$) as well as common FX risk factors such as dollar $DOL$, carry $CAR$, volatility $VOL$, and tangency $TAN$. $DOL$ is based on an equally weighted long portfolio of all USD currency pairs, $CAR$ on the forward discount/ premium $f_{t,t+1} - s_t$ (Lustig et al., 2011), $VOL$ is based on currency pairs' exposure to the global volatility factor $\beta^v$ (Menkhoff et al., 2012a), and $TAN$ is a strategy that sorts on exposures to the tangency portfolio $\beta^M$ (Markowitz, 1952). $IML$ is a trading strategy that sorts currencies into long-short portfolios based on the level of relative bid–ask spreads. Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*), annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

In Table 3 we test if any of the four liquidity beta based trading strategies (i.e., $\beta^1_{HML}$,

**Figure 1: Equity Curves for Liquidity and Common Risk Factors**




*Note*: These figures plot the cumulative gross (log) excess returns of the four liquidity beta sorted portfolios (i.e., $\beta^1_{HML}$, $\beta^2_{HML}$, $\beta^3_{HML}$, $\beta^4_{HML}$; top figure) as well as four common FX risk factors (i.e., $DOL$, $CAR$, $VOL$, and $TAN$; bottom figure). Grey shaded areas correspond to recession periods as they are defined by the National Bureau of Economic Research (NBER). The sample covers the period from 3 January 1994 to 31 December 2019.

$\beta^2_{HML}$, $\beta^3_{HML}$, and $\beta^4_{HML}$) is subsumed by existing FX risk factors. Specifically, we control for common FX risk factors based on the USD–based currency pairs basket (i.e., $DOL$), carry trade (i.e., $CAR$), and volatility risk (i.e., $VOL$). Except for $\beta^3_{HML}$, all other liquidity beta sorted trading strategies deliver statistically significant risk-adjusted returns (i.e., ‘alphas’). As expected, all four liquidity factors significantly load on $DOL$, whereas only the systematic (i.e., $\beta^2_{HML}$) and idiosyncratic liquidity risk (i.e., $\beta^4_{HML}$) factors are significantly exposed to $CAR$ and $VOL$. In particular, $CAR$ explains 37.9% of the variation in $\beta^2_{HML}$ and 26.4% of the variation in $\beta^4_{HML}$, respectively.

Note that as an alternative approach to sorting on recursive projections we also experi-

### Table 3: Exposure Regressions

| | $\beta^1_{HML}$ | | | | | $\beta^2_{HML}$ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| $\alpha$ in % | **2.291 | **2.086 | **2.164 | **2.237 | **2.555 | ***−3.412 | ***−3.314 | −0.871 | **−2.819 | −1.638 |
| | [2.243] | [2.447] | [2.072] | [2.196] | [2.492] | [2.807] | [2.798] | [0.834] | [2.534] | [1.633] |
| $DOL$ | | ***0.525 | | | | | ***−0.251 | | | |
| | | [13.747] | | | | | [2.847] | | | |
| $CAR$ | | | 0.028 | | | | | ***−0.566 | | |
| | | | [0.603] | | | | | [10.036] | | |
| $VOL$ | | | | −0.038 | | | | | ***0.412 | |
| | | | | [0.613] | | | | | [5.876] | |
| $TAN$ | | | | | −0.081 | | | | | ***−0.546 |
| | | | | | [1.601] | | | | | [9.955] |
| $\bar{R}^2$ in % | | 30.91 | 0.13 | 0.19 | 1.18 | | 5.12 | 37.85 | 16.53 | 38.68 |
| IR | 0.11 | 0.12 | 0.10 | 0.10 | 0.12 | −0.14 | −0.13 | −0.04 | −0.12 | −0.08 |
| #Obs | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 |
| | $\beta^3_{HML}$ | | | | | $\beta^4_{HML}$ | | | | |
| | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| $\alpha$ in % | −1.224 | −1.155 | −1.124 | −1.279 | −1.282 | ***−3.651 | ***−3.578 | *−1.709 | ***−3.243 | **−2.226 |
| | [1.381] | [1.328] | [1.266] | [1.464] | [1.452] | [3.314] | [3.306] | [1.728] | [3.116] | [2.371] |
| $DOL$ | | ***−0.176 | | | | | ***−0.187 | | | |
| | | [3.959] | | | | | [3.116] | | | |
| $CAR$ | | | −0.022 | | | | | ***−0.432 | | |
| | | | [0.460] | | | | | [9.801] | | |
| $VOL$ | | | | −0.038 | | | | | ***0.283 | |
| | | | | [0.701] | | | | | [5.282] | |
| $TAN$ | | | | | 0.018 | | | | | ***−0.439 |
| | | | | | [0.355] | | | | | [10.542] |
| $\bar{R}^2$ in % | | 4.34 | 0.10 | 0.24 | 0.07 | | 3.39 | 26.44 | 9.36 | 29.84 |
| IR | −0.06 | −0.06 | −0.06 | −0.07 | −0.07 | −0.16 | −0.16 | −0.09 | −0.15 | −0.12 |
| #Obs | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 |

*Note*: This table shows the results of regressing daily gross excess returns associated with the four liquidity beta based trading strategies (i.e., $\beta^1_{HML}$, $\beta^2_{HML}$, $\beta^3_{HML}$, and $\beta^4_{HML}$) on excess returns associated with common FX risk factors. $DOL$ is based on an equally weighted long portfolio of all USD currency pairs, $CAR$ is based on the forward discount/ premium $f_{t,t+1} - s_t$ (Lustig et al., 2011), $VOL$ is based on currency pairs' exposure to the global volatility factor $\beta^v$ (Menkhoff et al., 2012a), and $TAN$ is a strategy that sorts on exposures to the tangency portfolio $\beta^M$ (Markowitz, 1952). The intercept ($\alpha$) has been annualised ($\times 252$). The information ratio (IR) is defined as $\alpha$ divided by the residual standard deviation. The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for correlation up to 22 lags.

mented with a dependent *double-sort*: We first sort currency pairs into two groups[12] based on their volatility beta (i.e., $\beta^v$) and then conditionally into two subsets based on one of the liquidity betas (i.e., $\beta^1$, $\beta^2$, $\beta^3$, and $\beta^4$). Liquidity trading strategies are then formed by tak-

[12]We exclude any mid-ranked pairs such that the number of currency pairs in each of the two subgroups is divisible by two without remainder. For example, with 15 currency pairs we leave out the three mid-ranked ones.

ing long positions in high illiquidity beta currencies and short positions in low illiquidity beta currencies across the subsets of low and high volatility beta currencies. The resulting portfolio returns exhibit similar means and time series properties as the single-sorted liquidity factors. Specifically, all our findings in this and all subsequent sections remain qualitatively unchanged. See the online Appendix for the respective output tables and figures.

## 5. Cross-sectional Asset Pricing Tests

The goal of this section is to compare the empirical performance of a model with liquidity risk against the traditional FX 'market model' based on Lustig and Verdelhan (2007) and Lustig et al. (2011). Thus, the benchmark model is the same as in Eq. (6). The rationale for this model is the empirical observation that the first two principal components of the cross-section of currency returns are highly correlated with the dollar $DOL$ and carry factor $CAR$, respectively (see Lustig et al., 2011; Verdelhan, 2017). Specifically, the first principal component is a level factor that is essentially characterised by the average excess return on the dollar risk factor, whereas the second principal component is a slope factor whose weights decrease monotonically from high to low interest rate currency portfolios. We have also experimented with augmenting the two factor model by accounting for global volatility risk $VOL$ (Menkhoff et al., 2012a). However, the increase in the explanatory power of the augmented factor model is just marginal (see Figure 2) and hence we chose Eq. (6) as our baseline. This results is well expected since Menkhoff et al. (2012a) show that the cross-sectional variation in carry trade portfolios can be explained by their exposure to global volatility risk. Thus, $VOL$ is at least partially subsumed by $CAR$ and vice versa.

Next, we propose an alternative model that replaces the carry factor $CAR$ by one of the four liquidity risk factors. Since all our factors are tradeable, we can evaluate the performance of these competing factor models by comparing the actual versus model implied annualised ($\times 252$) mean currency excess return across factor models. In particular, we estimate the average fitted value of 15 individual time series regressions of the form:

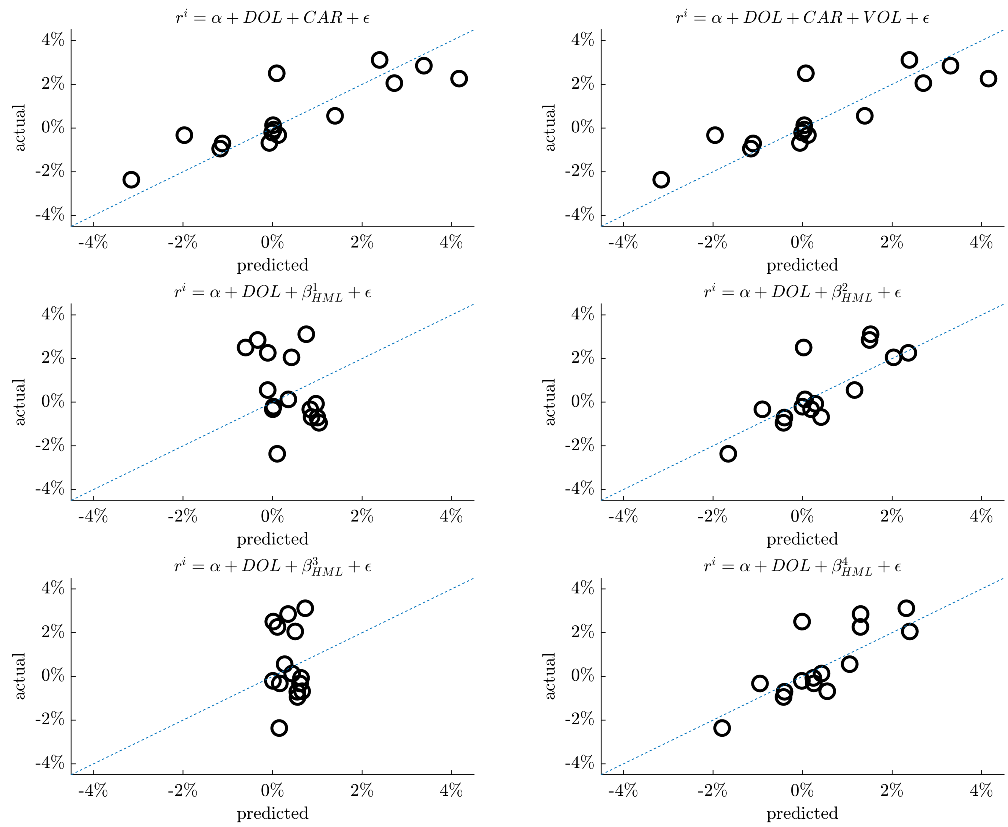
$$r^i = \alpha + \delta\, \mathbf{f} + \varepsilon, \tag{17}$$

where $\mathbf{f}$ may contain both 'traditional' and liquidity-based FX risk factors. The model is estimated using ordinary least squares (OLS) and standard errors are based on Newey and West (1987) heteroskedasticity- and autocorrelation-consistent standard errors correcting for serial correlation up to 22 lags.

Figure 2 plots the model implied versus actual annualised mean currency excess return for six factor models. There are two key takeaways: First, $\beta^1_{HML}$ and $\beta^3_{HML}$ do not explain any of the cross-sectional variation in expected returns. Second, replacing $CAR$ by systematic (i.e.,

$\beta^2_{HML}$) and idiosyncratic liquidity risk (i.e., $\beta^4_{HML}$) factors delivers an asset pricing model that performs similar to Eq. (6) in terms of pricing errors. These findings give rise to the idea that the carry factor and the liquidity beta based factors are interchangeable on statical grounds. Moreover, our results are also consistent with the idea that exposures to liquidity risk can explain carry trade returns. In particular, we conjecture that high (*low*) interest rate currencies earn higher (*lower*) expected returns due to being more exposed to liquidity risk. The next section will explore this possibility in more depth.

**Figure 2: Realised Versus Predicted Excess Return**




*Note*: These figures plot the actual versus model implied annualised ($\times 252$) mean currency excess return for six competing factor models of the form $r^i = \alpha + \delta\,\mathbf{f} + \varepsilon$, where $\mathbf{f}$ may contain both 'traditional' and liquidity-based FX risk factors. The model specifications are given in the titles of every subfigure. The sample covers the period from 13 February 1995 to 31 December 2019.

## 6. Liquidity Risk and Carry Trade Premia

In the previous section we have provided compelling evidence that an alternative asset pricing model using liquidity beta based factors performs at least as well as the 'standard' FX asset pricing model based on the dollar and carry factor (Verdelhan, 2017). Beyond doubt, the importance of the carry trade factor is empirically well established. However, there is still little consensus on how to interpret the carry trade risk premium.

For instance, Lustig and Verdelhan (2007) argue that high interest rate currencies are riskier because they are more exposed to consumption growth risk. The opposite holds for low interest rate currencies that offer a hedge against consumption growth risk because they appreciate in economic downturns. Burnside et al. (2011) suggest that risk alone does not account for carry trade excess returns and explore an alternative explanation based on price pressure in FX trading. Based on the more recent literature, other potential explanations for the carry trade are global imbalances (Della Corte et al., 2016), intermediary leverage (Fang, 2018), and network centrality (Richmond, 2019). The goal of this section is to provide empirical evidences in favour of an alternative view based on liquidity risk that works at least as well in explaining the carry trade premium as the aforementioned interpretations. The idea that liquidity risk matters for carry trade returns is not entirely new (e.g., Brunnermeier et al., 2008; Mancini et al., 2013). However, we are the first to systematically study *four* different sources of liquidity risk rather than just one and to highlight its explanatory power across different market states.

The first step in our analysis is to show which of the four liquidity risk factors (i.e., $\beta^1_{HML}$, $\beta^2_{HML}$, $\beta^3_{HML}$, $\beta^4_{HML}$) can be used to explain the conditional returns to the currency carry trade (i.e., $CAR$). If any of the four liquidity risk factors can explain carry trade returns, it should comove with and subsume the excess returns to the carry factor $CAR$. To test this hypothesis, we regress the carry factor on each of the four liquidity risk factors:

$$CAR = \alpha + \gamma\, \beta^q_{HML} + \epsilon \quad \forall q \in \{1, 2, 3, 4\}. \tag{18}$$

The results are presented in Table 4. We find that only $\beta^2_{HML}$ and $\beta^4_{HML}$ are highly correlated with $CAR$, with a statistically significant slope coefficient of $-0.67$ and $-0.61$ and an adjusted $R^2$ of 37.8% and 26.4%, respectively. The unexplained excess returns ($\alpha$) are statistically significant but small economically and range from 2.2% to 2.3% annually. The other two liquidity beta based risk factors, $\beta^1_{HML}$ and $\beta^3_{HML}$, have almost no explanatory power for carry trade returns and hence, we drop these two factors from all subsequent analyses. Since the four liquidity beta based risk factors are only mildly correlated, with an average correlation coefficient of around 25%, we propose an encompassing model in column 5. The adjusted $R^2$ of this model is 39.4%, which is remarkable given that the frequency of these regressions is daily.

Compared to the liquidity risk based specification in column 5, the three alternative explanations based on network centrality ($PMC$, Richmond, 2019), intermediary leverage ($UML$, Fang, 2018), and global imbalances ($IMB$, Della Corte et al., 2016) exhibit $R^2$s that are 0.1-17.3 percentage points lower and pricing errors ($\alpha$) that are 1.2-2.1 percentage points larger. What is more, individually, exposure to global illiquidity $\beta^2_{HML}$ and idiosyncratic liquidity risk $\beta^4_{HML}$ exhibit the lowest pricing errors ($\alpha$) across all 9 specifications. Note that the number

**Table 4: Explanatory Regressions for Carry Trade Returns**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Intercept ($\alpha$) in % | ***4.386 | **2.209 | ***4.436 | *2.259 | *2.099 | ***3.547 | **3.301 | ***4.168 | ***2.306 |
| | [3.220] | [2.002] | [3.288] | [1.889] | [1.944] | [3.262] | [2.531] | [3.266] | [2.840] |
| $\beta^1_{HML}$ | 0.046 | | | | *−0.120 | | | | ***−0.253 |
| | [0.587] | | | | [1.879] | | | | [5.010] |
| $\beta^2_{HML}$ | | ***−0.669 | | | ***−0.576 | | | | ***−0.192 |
| | | [10.971] | | | [6.686] | | | | [3.334] |
| $\beta^3_{HML}$ | | | −0.045 | | −0.087 | | | | ***−0.183 |
| | | | [0.460] | | [1.149] | | | | [3.640] |
| $\beta^4_{HML}$ | | | | ***−0.611 | **−0.163 | | | | **−0.124 |
| | | | | [9.363] | [2.508] | | | | [2.397] |
| $PMC$ | | | | | | ***0.744 | | | ***0.543 |
| | | | | | | [12.736] | | | [10.860] |
| $IMB$ | | | | | | | ***0.671 | | ***0.236 |
| | | | | | | | [9.177] | | [5.730] |
| $UML$ | | | | | | | | ***0.680 | ***0.401 |
| | | | | | | | | [10.079] | [8.962] |
| $\bar{R}^2$ in % | 0.12 | 37.84 | 0.08 | 26.43 | 39.43 | 39.29 | 22.09 | 29.07 | 70.13 |
| #Obs | 6179 | 6179 | 6179 | 6179 | 6179 | 5954 | 5706 | 5458 | 5458 |

*Note*: This table shows the results of regressing daily gross carry trade returns $CAR$ on four liquidity beta based risk factors (i.e., $\beta^1_{HML}$, $\beta^2_{HML}$, $\beta^3_{HML}$, and $\beta^4_{HML}$) as well as alternative carry trade determinants (i.e., $PMC$, $IMB$, and $UML$). $PMC$ is the peripheral minus central factor based on trade network analysis (Richmond, 2019), $IMB$ is the imbalanced minus balanced factor that is long the currencies of debtor nations with mainly foreign-currency-denominated external liabilities and short the currencies of creditor nations with mainly domestic-currency-denominated external liabilities (Della Corte et al., 2016), and $UML$ is the unlevered minus levered factor that is a long-short strategy that exploits cross-sectional variation in countries' bank leverage (Fang, 2018). The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

of observations is smaller for the $IMB$ and $UML$ factors because global imbalance measures and bank leverage ratios are not available after 2017 and 2016, respectively. All results are qualitatively unchanged when pruning our sample to the overlapping period (i.e., from 1994 to 2016). In sum, the specification in column 9 suggests that the liquidity risk based story provides additional explanatory power relative to the existing theories (i.e., $PMC$, $UML$, and $IMB$).

Given that the four liquidity risk factors explain an ample amount of carry trade returns, a risk-based interpretation implies that low interest rate currencies will have lower loadings on liquidity risk in absolute terms than high interest rate currencies. To test this hypothesis, we regress individual tertile portfolio excess returns (i.e., $T1$, $T2$, and $T3$) on the systematic (market) and idiosyncratic liquidity beta based risk factors (i.e., $\beta^2_{HML}$ and $\beta^4_{HML}$). In line with our conjecture, Table 5 documents that the carry trade tertile portfolios show a monotonically increasing factor loading from low to high interest rate portfolios and unexplained excess returns are insignificant. Hence, sorting on liquidity betas uncovers a novel source of heterogeneity in exposure to carry trade risk.

In a next step, we decompose the carry trade into the static, dynamic, and dollar trade

**Table 5: Time-Series Regressions of Carry Trade Portfolios on Liquidity Risk Factors**

| | $T1$ | $T2$ | $T3$ | $CAR$ |
|---|---|---|---|---|
| Intercept ($\alpha_i$) | $-0.015$ | $-0.001$ | 0.005 | *0.020 |
| | [1.210] | [0.046] | [0.381] | [1.829] |
| $\beta^2_{HML}$ | 0.067 | $-0.135$ | ***$-0.495$ | ***$-0.562$ |
| | [0.899] | [1.465] | [4.109] | [6.321] |
| $\beta^4_{HML}$ | 0.068 | $-0.057$ | $-0.090$ | **$-0.158$ |
| | [0.882] | [0.777] | [1.070] | [2.385] |
| $\bar{R}^2$ in % | 1.62 | 3.33 | 20.98 | 38.64 |
| #Obs | 6179 | 6179 | 6179 | 6179 |

*Note*: This table shows the results of regressing daily gross carry trade premia $CAR$ and individual carry trade tertile portfolios (i.e., $T1$, $T2$, and $T3$) on two liquidity beta based risk factors (i.e., $\beta^2_{HML}$ and $\beta^4_{HML}$). Note that by construction the return on the high-minus-low carry trade portfolio $CAR$ is given by the top tertile $T3$ minus the bottom tertile $T1$. The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

(Hassan and Mano, 2018). This is useful to shed light on which components are more related to liquidity risk than others. To make the carry trade from Hassan and Mano (2018) comparable to the traditional carry trade (e.g., Lustig and Verdelhan, 2007) we modify the original decomposition to accommodate traditional equally weighted long-short portfolios.[13] To be specific, we consider two types of 'carry' trades as outlined in Hassan and Mano (2018). One of them is the classic carry trade that exploits the correlation between currency returns and forward premia conditional on time fixed effects (e.g., Lustig and Verdelhan, 2007; Lustig et al., 2011). The other is the forward premium trade that weights each currency by the deviation of its current forward premium from its currency-specific mean (e.g., Cochrane, 2005; Bekaert and Hodrick, 2014). Hence, the the forward premium trade is not necessarily "dollar neutral" since the long and short leg may contain a different number of currencies.[14]

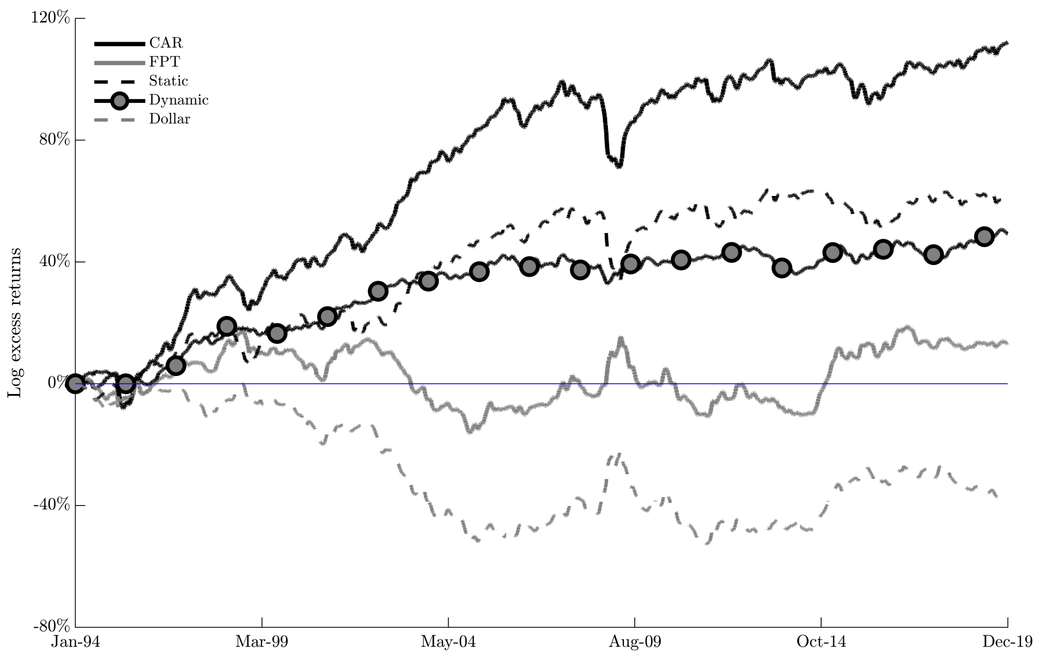
Figure 3 depicts the cumulative excess returns associated with the carry and forward premium trade as well as their three constituents, that is, the static, dynamic, and dollar trade, respectively. The forward premium trade and the carry trade are inversely related, whereas the carry and static trade as well as the forward premium and dollar trade exhibit correlated time-series patterns. The time variation in the dynamic trade shows a unique pattern that seems to

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

[14]The weights for the forward premium trade are given by the sum of the weights on the dollar (carry) trade (i.e., Lustig et al., 2014) plus the weights on the dynamic carry trade.

be unrelated to both the static as well as dollar trade. Note that the static and dynamic trade account for around 58% and 42% of total carry trade returns, respectively. To see this, compare across the elements of the last line in Table 6 that reports the annualised mean excess return associated with the carry and forward premium trade as well as their three constituents (i.e., static, dynamic, and dollar trade).

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




*Note*: This figure plots the cumulative gross (log) excess returns of the carry trade (CAR), forward premium trade (FPT), and the associated building blocks (i.e., static, dynamic, and dollar trade) following the Hassan and Mano (2018) decomposition. The sample covers the period from 3 January 1994 to 31 December 2019.

Table 6 shows results from regressing the carry trade (CAR), forward premium trade (FPT), and the associated building blocks (i.e., static, dynamic, and dollar trade) on our two liquidity risk factors, that is, $\beta^2_{HML}$ and $\beta^4_{HML}$, respectively. Notice that by construction the carry trade is equal to the sum of the dynamic and the static trade, whereas the forward premium trade is given by the sum of the dynamic and the dollar trade. The liquidity factors can explain an ample amount of the variation in the static and the dollar trade but largely fail to explain the dynamic trade. Thus, $\beta^2_{HML}$ and $\beta^4_{HML}$ can explain the average excess returns to both the carry and forward premium trade, respectively. Therefore, liquidity risk and carry trade premia are similar to each other on average because the carry trade returns are a combination of both dynamic and static components. This is in line with existing papers on the economics of the carry trade (e.g., Fang, 2018; Richmond, 2019) which both distinguish between unconditional and conditional forward discount sorted portfolios that are conceptually similar to the static and dynamic components in Hassan and Mano (2018). In sum, our findings suggest that a liquidity-based explanation only holds for the static carry trade, whereas the dynamic trade is a compensation for risks that are unrelated to liquidity.

**Table 6: Time series Regression: Carry Trade Decomposition**

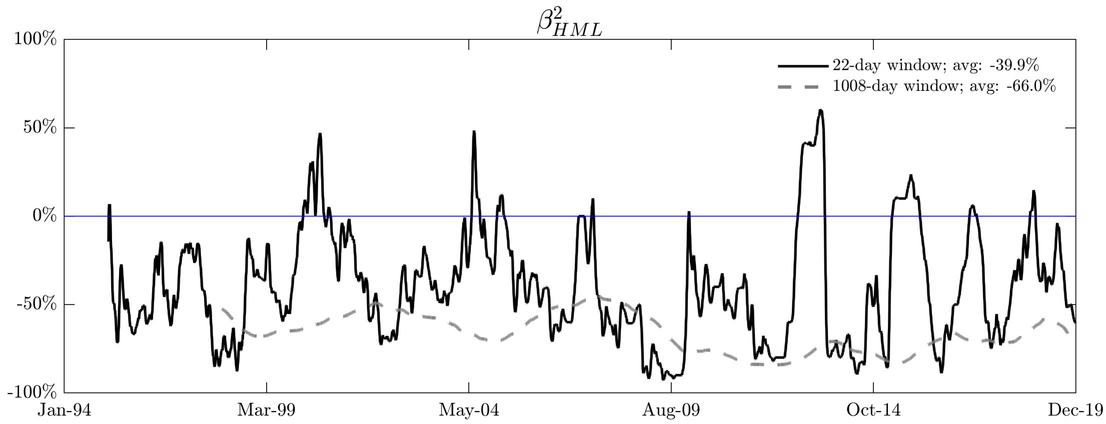
| | CAR | FPT | Static trade | Dynamic trade | Dollar trade |
|---|---|---|---|---|---|
| Intercept ($\alpha$) in % | *1.995 | 0.875 | 0.627 | **1.368 | −0.493 |
| | [1.829] | [0.740] | [0.661] | [2.222] | [0.430] |
| $\beta^2_{HML}$ | ***−0.562 | 0.096 | ***−0.454 | ***−0.109 | **0.205 |
| | [6.321] | [1.080] | [5.894] | [3.397] | [2.277] |
| $\beta^4_{HML}$ | **−0.158 | −0.035 | **−0.122 | −0.036 | 0.000 |
| | [2.385] | [0.495] | [2.184] | [1.045] | [0.004] |
| $\bar{R}^2$ in % | 38.64 | 0.58 | 35.25 | 6.57 | 5.03 |
| #Obs | 6179 | 6179 | 6179 | 6179 | 6179 |
| *Mean* in % | ***4.492 | 0.676 | **2.622 | ***1.869 | −1.193 |
| | [3.332] | [0.586] | [2.349] | [2.954] | [1.058] |

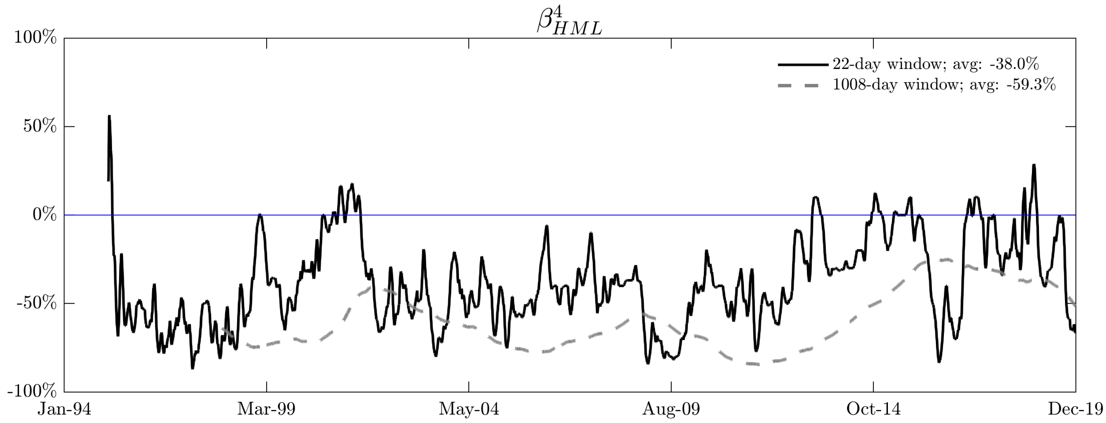
*Note*: This table reports the results from decomposing carry trade returns into the dynamic, static, and dollar trade (Hassan and Mano, 2018) and regressing the components on two liquidity risk factors, that is, $\beta^2_{HML}$ and $\beta^4_{HML}$, respectively. The last row reports the annualised mean excess returns of each carry trade component. The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

Figure 4 illustrates how the correlation between $CAR$ and $\beta^2_{HML}$ or $\beta^4_{HML}$ is driven by similarities in the portfolio weights associated with each currency pair. Specifically, the solid black and dashed grey lines depict the rolling window cross-correlation coefficient between the portfolio weights of the carry trade and liquidity risk factors based on 22-day and 1008-day moving averages, respectively. There are two observation that deserve to be highlighted: First, the average correlation coefficient over longer horizons (i.e., 1008 days) is almost twice as large as over shorter ones (i.e., 22 days). This is fully consistent with the fact that the static trade is based on average interest rate differentials, whereas the dynamic trade sorts currency pairs based on yesterday's realisations. Put differently, one can think of the moving window correlations based on 22 and 1008 days as being a proxy for the portfolio weights of the static and dynamic trade, respectively. Second, during times of market stress, such as the global financial crisis, the correlation between the portfolio weights increases for both liquidity risk factors (i.e., $\beta^2_{HML}$ and $\beta^4_{HML}$). Moreover, the 22-day moving window estimates temporarily (e.g., in August 2009) even exceed the ones based on 1008 days. These findings are also consistent with Mancini et al. (2013) showing that commonality in liquidity risk (i.e., $\beta^1_{HML}$) and carry trade returns are strongly correlated during the global financial crisis.

Lastly, motivated by the observation in Figure 4 that the correlation between the carry trade and our liquidity risk factors is time-varying we explore a state-dependent regression model. In

**Figure 4: Cross-sectional Correlation of Moving Average Weights in $CAR$ and $\beta^q_{HML}$**




*Note*: This figure plots the rolling window cross-sectional correlation coefficient between the portfolio weights of $CAR$ and $\beta^2_{HML}$ or $\beta^4_{HML}$ based on 22-day (solid black line) and 1008-day (dashed grey line) moving averages, respectively. The sample covers the period from 21 February 1995 to 31 December 2019.

particular, we regress the static ($CAR^S$) or the dynamic ($CAR^D$) component of the carry trade on our two liquidity risk factors (i.e., $\beta^2_{HML}$ and $\beta^4_{HML}$) and include an interaction dummy that is equal to 1 in periods of markets stress and zero otherwise. Our *stress factor* is simply the average across the bond yield on AAA-rated US corporate debt, the TED spread, and the VXY FX volatility index.[15] Each of these measures captures a different dimension of market stress: the AAA corporate bond yield measures the expected return on AAA prime rated companies; the TED spread captures the perceived credit risk in the general economy and is defined as the difference between the 3-month LIBOR rate and 3-month T-bill rate; the VXY is the JP Morgan Global FX Volatility index measuring the FX market's expectation of uncertainty based

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

on option prices. To be precise, we estimate a regression of the form:

$$CAR^p = \alpha_L + \alpha_H \cdot D + \delta DOL + \beta_L \beta^q_{HML} + \beta_H \beta^q_{HML} \cdot D + \epsilon \ \ \forall q \in \{2, 4\} \cup \forall p \in \{S, D\} \,. \quad (19)$$

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

Table 7 reports the results from estimating Eq. (19) for the static ($CAR^S$) and the dynamic ($CAR^D$) part of the carry trade, respectively. There are three key takeaways from these multiple regressions: First, the risk-adjusted excess returns ('alphas') are only significant for the dynamic trade in normal times but not during periods of market stress ($\alpha_L + \alpha_H$ is close to zero and statistically insignificant). Second, the correlation of the static trade with $\beta^2_{HML}$ and $\beta^4_{HML}$ is almost twice as large during periods of uncertainty as otherwise. We interpret this as evidence that carry and liquidity risk premia are prone to commonality in bad times. Third, the correlation between the dynamic component of the carry trade and our two liquidity factors is independent of market stress. Put differently, the dynamic component of the carry trade is a truly orthogonal risk factor to $\beta^2_{HML}$ and $\beta^4_{HML}$, respectively.

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

## 7. Conclusion

Using low-frequency measures of liquidity, this paper provides a comprehensive investigation of FX liquidity risk and carry trade returns. Our marginal contribution is threefold: First, we show that sorting currency pairs into portfolios based on their exposure to systematic (i.e., $\beta^2$) and idiosyncratic liquidity risk (i.e., $\beta^4$) yields non-trivial risk-adjusted returns. Second, we find that an asset pricing model that includes the dollar factor but replaces the carry factor by either of our two aforementioned liquidity factors performs on par in terms of pricing errors. Lastly, we provide compelling evidence in favour of a liquidity-based explanation of the carry trade premium. To do this, we decompose the carry trade into the static, dynamic, and dollar trade, respectively. We show that only the static and dollar trade are subsumed by systematic (market) and idiosyncratic liquidity risk, whereas the dynamic trade does not load significantly on either of the two liquidity risks. Moreover, we find that commonality in liquidity and static carry premia is almost twice as large during periods of markets stress.

**Table 7: Commonality in Carry Trade and Liquidity Premia in Distressed Markets**

| | Static trade, $CAR^S$ | | | Dynamic trade, $CAR^D$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Intercept LOW ($\alpha$) in % | 1.517 | *1.570 | 1.255 | ***1.832 | ***1.909 | ***1.774 |
| | [1.626] | [1.684] | [1.354] | [2.725] | [2.711] | [2.577] |
| Intercept HIGH ($\alpha$) in % | −0.591 | −0.729 | −0.330 | −1.476 | −1.567 | −1.414 |
| | [0.286] | [0.312] | [0.160] | [1.092] | [1.116] | [1.039] |
| DOL | ***0.237 | ***0.284 | ***0.234 | ***−0.088 | ***−0.076 | ***−0.088 |
| | [6.199] | [5.396] | [6.185] | [3.050] | [2.582] | [3.041] |
| $\beta^2_{HML}$ LOW | ***−0.374 | | ***−0.287 | ***−0.137 | | ***−0.117 |
| | [6.749] | | [4.065] | [4.173] | | [2.789] |
| $\beta^2_{HML}$ HIGH−LOW | ***−0.232 | | **−0.278 | −0.024 | | −0.014 |
| | [3.091] | | [2.367] | [0.572] | | [0.208] |
| $\beta^4_{HML}$ LOW | | ***−0.335 | **−0.136 | | ***−0.112 | −0.030 |
| | | [6.941] | [2.358] | | [3.498] | [0.741] |
| $\beta^4_{HML}$ HIGH−LOW | | **−0.232 | 0.074 | | −0.048 | −0.013 |
| | | [2.383] | [0.684] | | [1.041] | [0.187] |
| $\bar{R}^2$ in % | 41.98 | 33.38 | 42.57 | 8.72 | 6.46 | 8.86 |
| #Obs | 6083 | 6083 | 6083 | 6083 | 6083 | 6083 |

*Note*: This table reports the results from estimating a multiple linear regression of the form $CAR^p = \alpha_L + \alpha_H \cdot D + \delta DOL + \beta_L \beta^q_{HML} + \beta_H \beta^q_{HML} \cdot D + \epsilon \ \forall q \in \{2, 4\} \cup \forall p \in \{S, D\}$, where the dependent variable is either the static ($CAR^S$) or the dynamic ($CAR^D$) part of the carry trade and the regressors are the dollar factor $DOL$ and our liquidity factors $\beta^2_{HML}$ and $\beta^4_{HML}$, respectively. In addition, we include interaction terms based on a dummy $D$ that is equal to 1 if the stress factor is above its 75% quantile in period $t$. Our stress factor is defined as the average across the bond yield on AAA-rated US corporate debt, the TED spread, and the VXY FX volatility index, respectively. Note that we standardise each time-series by first subtracting the mean and then scaling by the standard deviation. The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

While we cannot conclusively disprove alternative explanations for the carry trade, the evidence in this paper suggests that exposures to liquidity risk play a significant role. A promising avenue for future research would be to test the liquidity-based explanation for different implementations of the carry trade (e.g., Bekaert and Panayotov, 2019). In particular, it would be interesting to contrast approaches with different samples of currencies, weighting schemes, and also distinguishing whether the long and short sides of the trade are equal.

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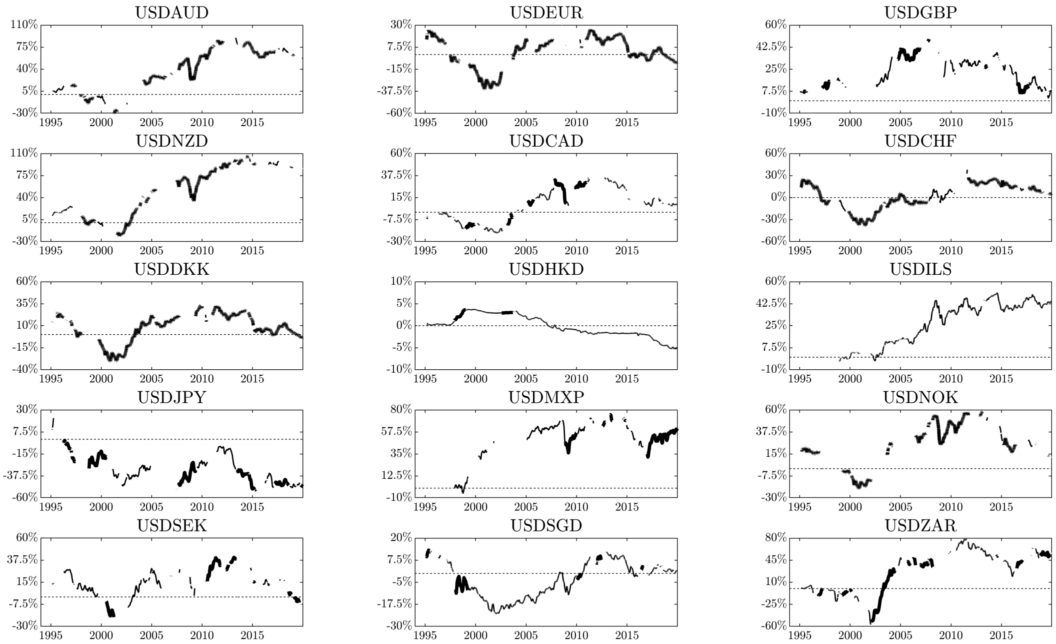
# Appendix A. Additional Empirical Results

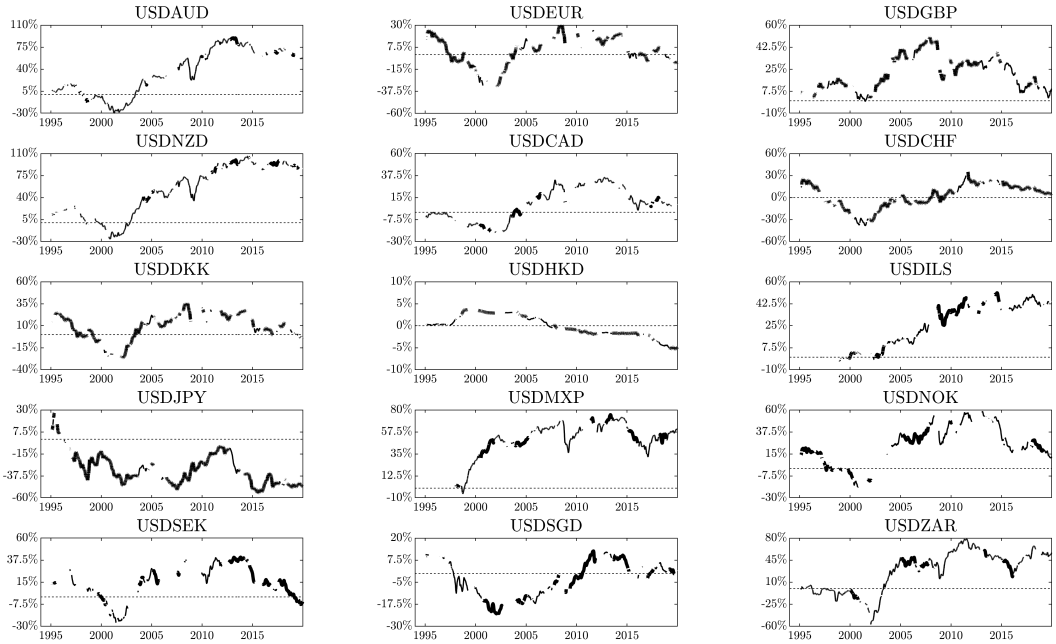
## Appendix A.1. Single Sorting

**Figure 5: Cumulative Excess Returns by Currency Pair ($\beta^1_{HML}$)**



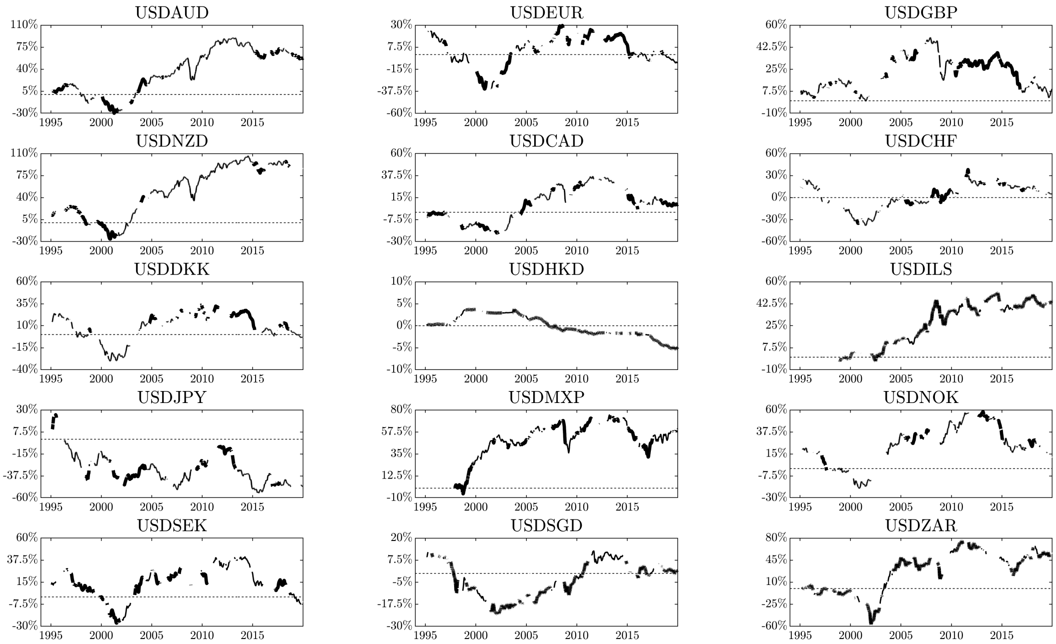

*Note*: This figure shows the cumulative daily excess returns from trading each currency against the US dollar (as shown at the top of the plot). The thin portions of each line correspond to periods when the respective foreign currency was held short in the $\beta^1_{HML}$ trade. Similarly, the thick portions correspond to periods when the foreign currency was held long in the trade. Empty gaps correspond to periods where the foreign currency was *not* invested at all and hence received a zero weight in the portfolio allocation. The sample covers the period from 3 January 1994 to 31 December 2019.

**Figure 6: Cumulative Excess Returns by Currency Pair ($\beta^2_{HML}$)**



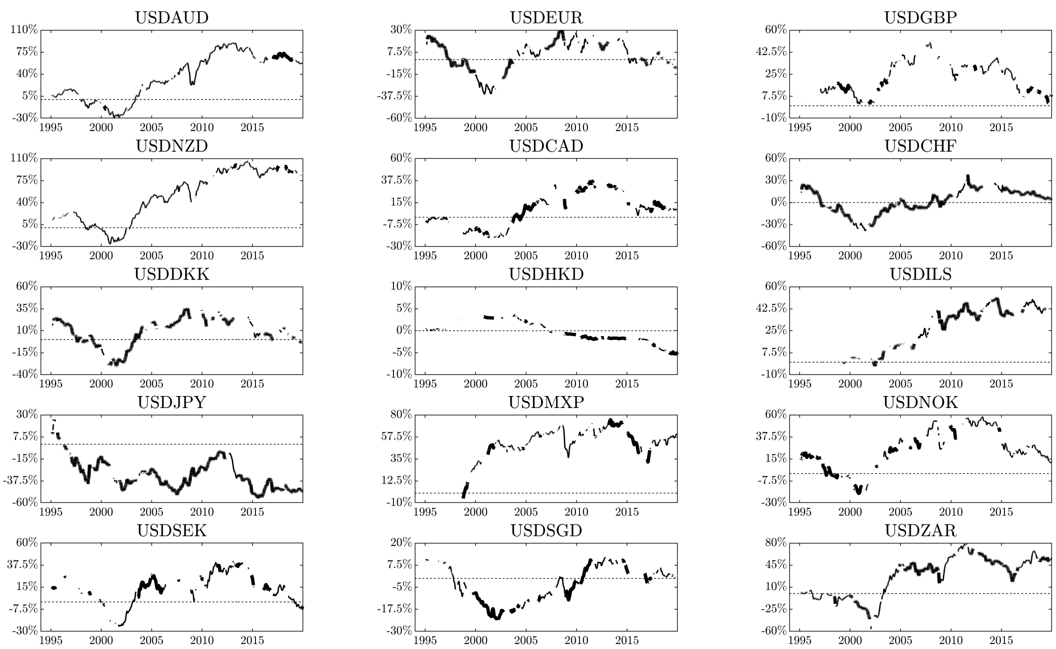

*Note*: This figure shows the cumulative daily excess returns from trading each currency against the US dollar (as shown at the top of the plot). The thin portions of each line correspond to periods when the respective foreign currency was held short in the $\beta^2_{HML}$ trade. Similarly, the thick portions correspond to periods when the foreign currency was held long in the trade. Empty gaps correspond to periods where the foreign currency was *not* invested at all and hence received a zero weight in the portfolio allocation. The sample covers the period from 3 January 1994 to 31 December 2019.

## Figure 7: Cumulative Excess Returns by Currency Pair ($\beta^3_{HML}$)



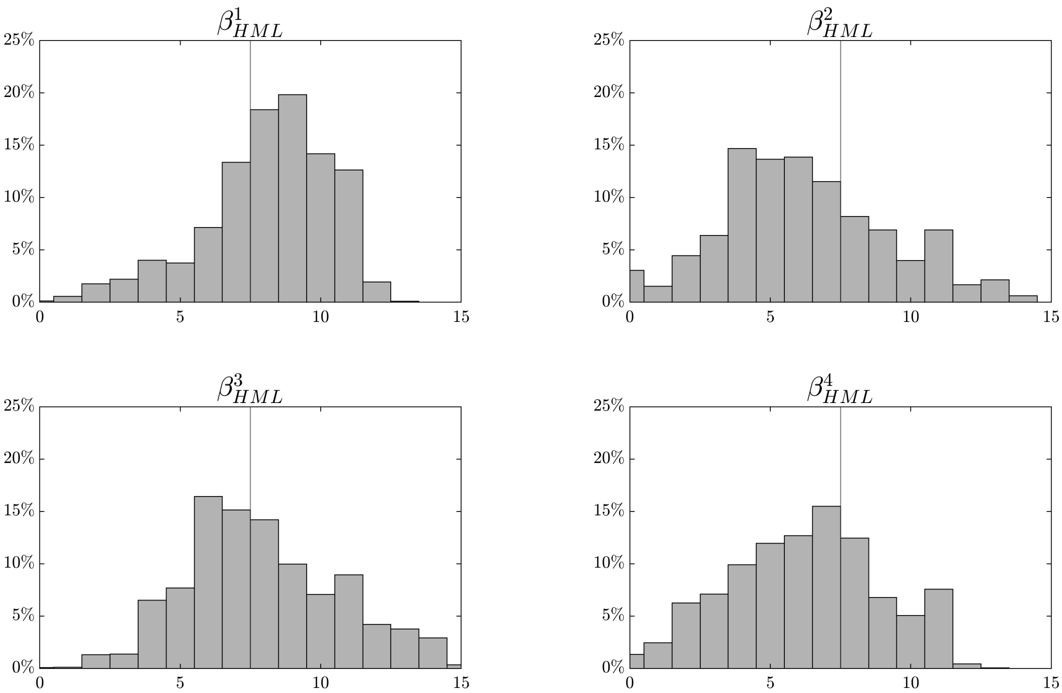

*Note*: This figure shows the cumulative daily excess returns from trading each currency against the US dollar (as shown at the top of the plot). The thin portions of each line correspond to periods when the respective foreign currency was held short in the $\beta^3_{HML}$ trade. Similarly, the thick portions correspond to periods when the foreign currency was held long in the trade. Empty gaps correspond to periods where the foreign currency was *not* invested at all and hence received a zero weight in the portfolio allocation. The sample covers the period from 3 January 1994 to 31 December 2019.

**Figure 8: Cumulative Excess Returns by Currency Pair ($\beta^4_{HML}$)**



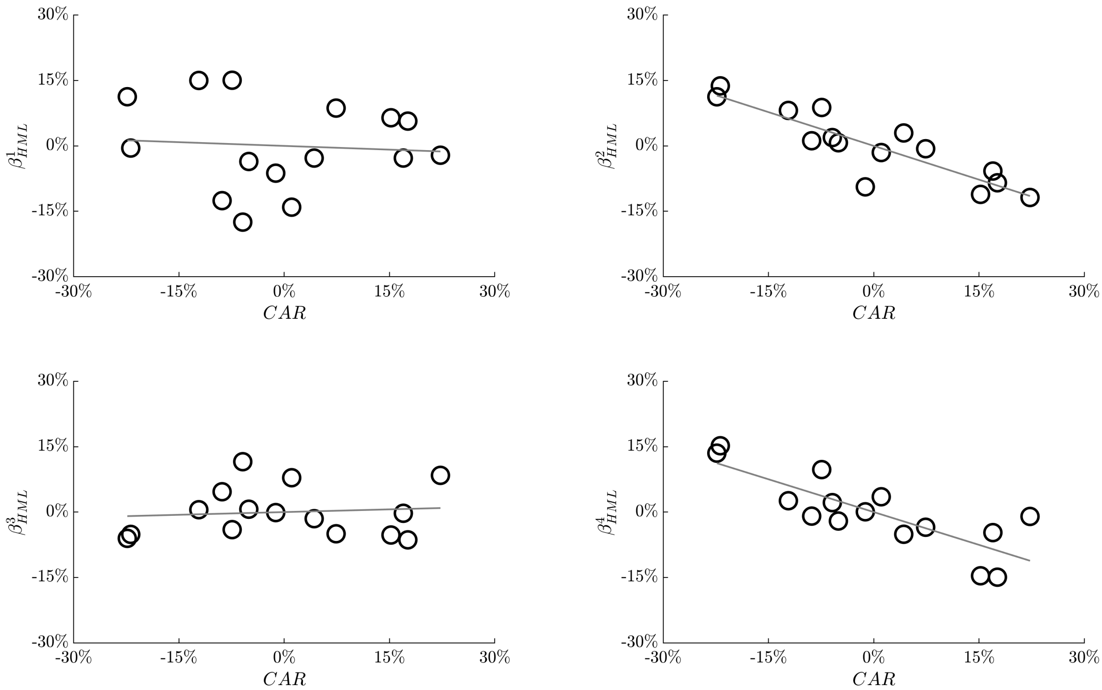

*Note*: This figure shows the cumulative daily excess returns from trading each currency against the US dollar (as shown at the top of the plot). The thin portions of each line correspond to periods when the respective foreign currency was held short in the $\beta^4_{HML}$ trade. Similarly, the thick portions correspond to periods when the foreign currency was held long in the trade. Empty gaps correspond to periods where the foreign currency was *not* invested at all and hence received a zero weight in the portfolio allocation. The sample covers the period from 3 January 1994 to 31 December 2019.

**Figure 9: Histogram of Overlapping Weights in $CAR$ and $\beta^q_{HML}$**




*Note*: The numbers on the x-axis refer to the total number of available currency pairs minus the number of currency pairs that either receive opposite weights in $CAR$ and $\beta^q_{HML} \forall q \in \{1, 2, 3, 4\}$ or are not invested at all. The percentages on the y-axis show the relative frequency of each possible combination of overlapping portfolio weights. The sample covers the period from 21 February 1995 to 31 December 2019.

**Figure 10: Average Weights in $CAR$ and $\beta^q_{HML}$**




*Note*: The numbers on the x-axis (*y-axis*) refer to the average portfolio weight in $CAR$ ($\beta^q_{HML} \forall q \in \{1,2,3,4\}$) associated with a particular currency pair (black circles). The sample covers the period from 21 February 1995 to 31 December 2019.

**Table 8: Sensitivity Table for Tangency Portfolio Weights**

| $w_{DOL}$ | $w_{CAR}$ | $w^+_{DOL}$ | $w^+_{CAR}$ | $\beta^1_{HML}$ | $\beta^2_{HML}$ | $\beta^3_{HML}$ | $\beta^4_{HML}$ |
|---|---|---|---|---|---|---|---|
| −1.00 | 2.00 | 0.33 | 0.67 | *1.84 | ***−3.39 | −0.87 | ***−3.65 |
| | | | | [1.80] | [2.81] | [0.95] | [3.31] |
| −0.75 | 1.75 | 0.30 | 0.70 | *1.92 | ***−3.38 | −0.90 | ***−3.65 |
| | | | | [1.87] | [2.80] | [0.98] | [3.31] |
| −0.50 | 1.50 | 0.25 | 0.75 | **2.02 | ***−3.41 | −0.94 | ***−3.65 |
| | | | | [1.97] | [2.82] | [1.03] | [3.31] |
| −0.25 | 1.25 | 0.17 | 0.83 | **2.31 | ***−3.42 | −1.25 | ***−3.65 |
| | | | | [2.26] | [2.81] | [1.41] | [3.31] |
| 0.00 | 1.00 | 0.00 | 1.00 | ***2.64 | ***−3.42 | −1.41 | ***−3.65 |
| | | | | [2.61] | [2.80] | [1.59] | [3.31] |
| 0.25 | 0.75 | 0.25 | 0.75 | **2.02 | ***−3.41 | **−1.89 | ***−3.65 |
| | | | | [1.97] | [2.82] | [2.12] | [3.31] |
| 0.50 | 0.50 | 0.50 | 0.50 | 1.60 | ***−3.34 | **−2.07 | ***−3.65 |
| | | | | [1.55] | [2.76] | [2.14] | [3.31] |
| 0.75 | 0.25 | 0.75 | 0.25 | 1.23 | ***−3.37 | −1.08 | ***−3.65 |
| | | | | [1.17] | [2.74] | [1.11] | [3.31] |
| 1.00 | 0.00 | 1.00 | 0.00 | 0.66 | ***−3.39 | −1.10 | ***−3.65 |
| | | | | [0.60] | [2.76] | [1.08] | [3.31] |
| 1.25 | −0.25 | 0.83 | 0.17 | 1.01 | ***−3.29 | −1.42 | ***−3.65 |
| | | | | [0.95] | [2.68] | [1.40] | [3.31] |
| 1.50 | −0.50 | 0.75 | 0.25 | 1.23 | ***−3.37 | −0.89 | ***−3.65 |
| | | | | [1.17] | [2.74] | [0.89] | [3.31] |
| 1.75 | −0.75 | 0.70 | 0.30 | 1.30 | ***−3.40 | −0.84 | ***−3.65 |
| | | | | [1.25] | [2.78] | [0.84] | [3.31] |
| 2.00 | −1.00 | 0.67 | 0.33 | 1.40 | ***−3.37 | −1.16 | ***−3.65 |
| | | | | [1.35] | [2.75] | [1.17] | [3.31] |

*Note*: This table presents the performance sensitivity of the portfolio sorts based on the four liquidity betas (i.e., $\beta^1_{HML}$, $\beta^2_{HML}$, $\beta^3_{HML}$, and $\beta^4_{HML}$) to the tangency portfolio weights associated with each market factor, that is, $w_{DOL}$ ($w^+_{DOL}$) and $w_{CAR}$ ($w^+_{CAR}$), respectively. Note that the modified portfolio weights $w_c$ in Eq. (11) are directly linked to the tangency portfolio weights $w_r$ in Eq. (7), since $w^n_c = |w^n_r| / \sum_{n=1}^{N} |w^n_r|$. The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return being equal to zero based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

**Table 9: Summary Statistics Portfolio Sorts - BA Spread**

| | $DOL$ | $CAR$ | $VOL$ | $TAN$ | $\beta^1_{HML}$ | $\beta^2_{HML}$ | $\beta^3_{HML}$ | $\beta^4_{HML}$ |
|---|---|---|---|---|---|---|---|---|
| *Mean* in % | 0.39 | ***4.49 | −1.44 | **3.25 | 0.52 | ***−3.53 | −0.40 | ***−4.04 |
| | [0.34] | [3.33] | [1.19] | [2.32] | [0.53] | [2.91] | [0.43] | [3.62] |
| $\sigma$ | 1.44 | 1.73 | 1.57 | 1.81 | 1.32 | 1.59 | 1.24 | 1.48 |
| SR | 0.27 | ***2.60 | −0.92 | **1.79 | 0.40 | ***−2.22 | −0.32 | ***−2.73 |
| | [0.34] | [3.04] | [1.18] | [2.24] | [0.53] | [2.77] | [0.43] | [3.67] |
| Skewness | −0.15 | −0.87 | 0.07 | −0.49 | 0.32 | 0.44 | 0.09 | −0.23 |
| Kurtosis-3 | 2.10 | 4.71 | 1.52 | 2.68 | 0.65 | 4.51 | 0.62 | 1.99 |
| Min | −1.55 | −2.16 | −1.27 | −1.88 | −0.69 | −1.41 | −0.75 | −1.41 |
| Max | 0.91 | 1.68 | 1.53 | 1.55 | 0.92 | 1.92 | 0.98 | 1.27 |
| MDD in % | 31.97 | 28.60 | 28.03 | 25.57 | 31.52 | 19.60 | 18.17 | 16.54 |
| Scaled MDD | 22.28 | 16.53 | 17.85 | 14.11 | 23.91 | 12.29 | 14.65 | 11.16 |
| #Obs | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 |

*Note*: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., $\beta^1_{HML}$, $\beta^2_{HML}$, $\beta^3_{HML}$, and $\beta^4_{HML}$) as well as common FX risk factors such as dollar $DOL$, carry $CAR$, volatility $VOL$, and tangency $TAN$. Systematic (market) and currency pair specific (idiosyncratic) liquidity is based on the relative bid–ask spread. $DOL$ is based on an equally weighted long portfolio of all USD currency pairs, $CAR$ on the forward discount/ premium $f_{t,t+1} - s_t$ (Lustig et al., 2011), $VOL$ is based on currency pairs' exposure to the global volatility factor $\beta^v$ (Menkhoff et al., 2012a), and $TAN$ is a strategy that sorts on exposures to the tangency portfolio $\beta^M$ (Markowitz, 1952). Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*), annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

**Table 10: Summary Statistics Portfolio Sorts - CS Spread**

| | $DOL$ | $CAR$ | $VOL$ | $TAN$ | $\beta^1_{HML}$ | $\beta^2_{HML}$ | $\beta^3_{HML}$ | $\beta^4_{HML}$ |
|---|---|---|---|---|---|---|---|---|
| *Mean* in % | 0.39 | ***4.49 | −1.44 | **3.25 | **2.77 | *−2.21 | −1.14 | **−2.20 |
| | [0.34] | [3.33] | [1.18] | [2.32] | [2.56] | [1.83] | [1.42] | [2.24] |
| $\sigma$ | 1.44 | 1.73 | 1.57 | 1.81 | 1.41 | 1.59 | 1.10 | 1.30 |
| SR | 0.27 | ***2.60 | −0.92 | **1.79 | ***1.96 | *−1.39 | −1.03 | **−1.69 |
| | [0.34] | [3.04] | [1.18] | [2.24] | [2.61] | [1.79] | [1.42] | [2.22] |
| Skewness | −0.15 | −0.87 | 0.07 | −0.49 | 0.36 | 0.32 | −0.02 | 0.15 |
| Kurtosis-3 | 2.10 | 4.71 | 1.52 | 2.68 | 1.32 | 3.15 | 0.22 | 1.29 |
| Min | −1.55 | −2.16 | −1.27 | −1.88 | −0.76 | −1.26 | −0.60 | −0.87 |
| Max | 0.91 | 1.68 | 1.53 | 1.55 | 1.33 | 1.92 | 0.77 | 1.08 |
| MDD in % | 31.97 | 28.60 | 28.03 | 25.57 | 19.17 | 30.58 | 16.98 | 15.61 |
| Scaled MDD | 22.28 | 16.53 | 17.85 | 14.11 | 13.56 | 19.23 | 15.45 | 12.00 |
| #Obs | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 |

*Note*: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., $\beta^1_{HML}$, $\beta^2_{HML}$, $\beta^3_{HML}$, and $\beta^4_{HML}$) as well as common FX risk factors such as dollar $DOL$, carry $CAR$, volatility $VOL$, and tangency $TAN$. Systematic (market) and currency pair specific (idiosyncratic) liquidity is based on the $CS$ spread (Corwin and Schultz, 2012). $DOL$ is based on an equally weighted long portfolio of all USD currency pairs, $CAR$ on the forward discount/ premium $f_{t,t+1} - s_t$ (Lustig et al., 2011), $VOL$ is based on currency pairs' exposure to the global volatility factor $\beta^v$ (Menkhoff et al., 2012a), and $TAN$ is a strategy that sorts on exposures to the tangency portfolio $\beta^M$ (Markowitz, 1952). Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*), annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

## Table 11: Summary Statistics Portfolio Sorts - AAA Bond Yield

| | $DOL$ | $CAR$ | $AAA$ | $TAN$ | $\beta^1_{HML}$ | $\beta^2_{HML}$ | $\beta^3_{HML}$ | $\beta^4_{HML}$ |
|---|---|---|---|---|---|---|---|---|
| *Mean* in % | 0.39 | ***4.49 | 0.07 | **3.25 | 1.33 | ***−3.94 | −1.22 | ***−3.65 |
| | [0.34] | [3.33] | [0.06] | [2.32] | [1.32] | [3.19] | [1.38] | [3.31] |
| $\sigma$ | 1.44 | 1.73 | 1.50 | 1.81 | 1.35 | 1.62 | 1.21 | 1.46 |
| SR | 0.27 | ***2.60 | 0.04 | **1.79 | 0.99 | ***−2.43 | −1.01 | ***−2.51 |
| | [0.34] | [3.04] | [0.06] | [2.24] | [1.33] | [2.97] | [1.39] | [3.32] |
| Skewness | −0.15 | −0.87 | −0.33 | −0.49 | 0.22 | 0.66 | −0.13 | −0.14 |
| Kurtosis-3 | 2.10 | 4.71 | 1.82 | 2.68 | 0.63 | 5.19 | 1.00 | 1.28 |
| Min | −1.55 | −2.16 | −1.35 | −1.88 | −0.76 | −1.27 | −1.13 | −1.27 |
| Max | 0.91 | 1.68 | 0.89 | 1.55 | 1.04 | 2.20 | 0.68 | 1.02 |
| MDD in % | 31.97 | 28.60 | 44.25 | 25.57 | 20.22 | 23.14 | 14.49 | 17.28 |
| Scaled MDD | 22.28 | 16.53 | 29.57 | 14.11 | 14.95 | 14.24 | 11.94 | 11.87 |
| #Obs | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 |

*Note*: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., $\beta^1_{HML}$, $\beta^2_{HML}$, $\beta^3_{HML}$, and $\beta^4_{HML}$) as well as common FX risk factors such as dollar $DOL$, carry $CAR$, volatility $AAA$, and tangency $TAN$. $DOL$ is based on an equally weighted long portfolio of all USD currency pairs, $CAR$ on the forward discount/ premium $f_{t,t+1} - s_t$ (Lustig et al., 2011), $AAA$ is based on currency pairs' exposure to the bond yield on AAA-rated US corporate debt, and $TAN$ is a strategy that sorts on exposures to the tangency portfolio $\beta^M$ (Markowitz, 1952). To compute the illiquidity betas $\beta^1$, $\beta^2$, and $\beta^3$ we orthogonalise systematic illiquidity $c^M$ against the yield on AAA-rated US corporate debt. Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*), annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

## Table 12: Summary Statistics Portfolio Sorts - TED Spread

| | $DOL$ | $CAR$ | $TED$ | $TAN$ | $\beta^1_{HML}$ | $\beta^2_{HML}$ | $\beta^3_{HML}$ | $\beta^4_{HML}$ |
|---|---|---|---|---|---|---|---|---|
| *Mean* in % | 0.39 | ***4.49 | −1.27 | **3.25 | **2.71 | ***−4.13 | −1.22 | ***−3.65 |
| | [0.34] | [3.33] | [0.96] | [2.32] | [2.54] | [3.04] | [1.38] | [3.31] |
| $\sigma$ | 1.44 | 1.73 | 1.50 | 1.81 | 1.24 | 1.55 | 1.21 | 1.46 |
| SR | 0.27 | ***2.60 | −0.84 | **1.79 | **2.18 | ***−2.66 | −1.01 | ***−2.51 |
| | [0.34] | [3.04] | [0.95] | [2.24] | [2.57] | [2.78] | [1.39] | [3.32] |
| Skewness | −0.15 | −0.87 | 0.50 | −0.49 | 0.17 | 0.77 | −0.13 | −0.14 |
| Kurtosis-3 | 2.10 | 4.71 | 3.59 | 2.68 | 0.39 | 5.53 | 1.00 | 1.28 |
| Min | −1.55 | −2.16 | −1.02 | −1.88 | −0.76 | −1.27 | −1.13 | −1.27 |
| Max | 0.91 | 1.68 | 1.82 | 1.55 | 0.95 | 1.96 | 0.68 | 1.02 |
| MDD in % | 31.97 | 28.60 | 21.26 | 25.57 | 14.49 | 23.76 | 14.49 | 17.28 |
| Scaled MDD | 22.28 | 16.53 | 14.13 | 14.11 | 11.67 | 15.33 | 11.94 | 11.87 |
| #Obs | 6179 | 6179 | 4667 | 6179 | 4667 | 4667 | 6179 | 6179 |

*Note*: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., $\beta^1_{HML}$, $\beta^2_{HML}$, $\beta^3_{HML}$, and $\beta^4_{HML}$) as well as common FX risk factors such as dollar $DOL$, carry $CAR$, volatility $TED$, and tangency $TAN$. $DOL$ is based on an equally weighted long portfolio of all USD currency pairs, $CAR$ on the forward discount/ premium $f_{t,t+1} - s_t$ (Lustig et al., 2011), $TED$ is based on currency pairs' exposure to the spread between the 3-month LIBOR rate and 3-month T-bill rate, and $TAN$ is a strategy that sorts on exposures to the tangency portfolio $\beta^M$ (Markowitz, 1952). To compute the illiquidity betas $\beta^1$, $\beta^2$, and $\beta^3$ we orthogonalise systematic illiquidity $c^M$ against the TED spread. Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*), annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

**Table 13: Summary Statistics Portfolio Sorts - VIX Index**

| | $DOL$ | $CAR$ | $VIX$ | $TAN$ | $\beta^1_{HML}$ | $\beta^2_{HML}$ | $\beta^3_{HML}$ | $\beta^4_{HML}$ |
|---|---|---|---|---|---|---|---|---|
| *Mean* in % | 0.39 | ***4.49 | *−2.20 | **3.25 | 1.49 | ***−3.09 | −1.22 | ***−3.65 |
| | [0.34] | [3.33] | [1.73] | [2.32] | [1.47] | [2.73] | [1.38] | [3.31] |
| $\sigma$ | 1.44 | 1.73 | 1.65 | 1.81 | 1.36 | 1.49 | 1.21 | 1.46 |
| SR | 0.27 | ***2.60 | *−1.34 | **1.79 | 1.10 | ***−2.07 | −1.01 | ***−2.51 |
| | [0.34] | [3.04] | [1.69] | [2.24] | [1.48] | [2.58] | [1.39] | [3.32] |
| Skewness | −0.15 | −0.87 | 0.41 | −0.49 | 0.25 | 0.63 | −0.13 | −0.14 |
| Kurtosis-3 | 2.10 | 4.71 | 2.95 | 2.68 | 0.84 | 5.44 | 1.00 | 1.28 |
| Min | −1.55 | −2.16 | −1.42 | −1.88 | −0.76 | −1.00 | −1.13 | −1.27 |
| Max | 0.91 | 1.68 | 1.92 | 1.55 | 1.04 | 2.08 | 0.68 | 1.02 |
| MDD in % | 31.97 | 28.60 | 23.73 | 25.57 | 19.43 | 20.14 | 14.49 | 17.28 |
| Scaled MDD | 22.28 | 16.53 | 14.41 | 14.11 | 14.31 | 13.50 | 11.94 | 11.87 |
| #Obs | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 |

*Note*: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., $\beta^1_{HML}$, $\beta^2_{HML}$, $\beta^3_{HML}$, and $\beta^4_{HML}$) as well as common FX risk factors such as dollar $DOL$, carry $CAR$, volatility $VIX$, and tangency $TAN$. $DOL$ is based on an equally weighted long portfolio of all USD currency pairs, $CAR$ on the forward discount/ premium $f_{t,t+1} - s_t$ (Lustig et al., 2011), $VIX$ is based on currency pairs' exposure to the Chicago Board Options Exchange's volatility index, and $TAN$ is a strategy that sorts on exposures to the tangency portfolio $\beta^M$ (Markowitz, 1952). To compute the illiquidity betas $\beta^1$, $\beta^2$, and $\beta^3$ we orthogonalise systematic illiquidity $c^M$ against the VIX volatility index. Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*), annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

**Table 14: Summary Statistics Portfolio Sorts Without Orthogonalisation**

| | $DOL$ | $CAR$ | $VOL$ | $TAN$ | $\beta^1_{HML}$ | $\beta^2_{HML}$ | $\beta^3_{HML}$ | $\beta^4_{HML}$ |
|---|---|---|---|---|---|---|---|---|
| *Mean* in % | 0.39 | ***4.49 | −1.44 | **3.25 | **2.39 | ***−3.58 | *−1.58 | ***−3.61 |
| | [0.34] | [3.33] | [1.19] | [2.32] | [2.21] | [2.81] | [1.71] | [3.08] |
| $\sigma$ | 1.44 | 1.73 | 1.57 | 1.81 | 1.41 | 1.67 | 1.22 | 1.54 |
| SR | 0.27 | ***2.60 | −0.92 | **1.79 | **1.69 | ***−2.15 | *−1.30 | ***−2.34 |
| | [0.34] | [3.04] | [1.18] | [2.24] | [2.25] | [2.63] | [1.68] | [3.00] |
| Skewness | −0.15 | −0.87 | 0.07 | −0.49 | 0.32 | 0.73 | 0.17 | 0.19 |
| Kurtosis-3 | 2.10 | 4.71 | 1.52 | 2.68 | 0.95 | 4.84 | 1.95 | 3.18 |
| Min | −1.55 | −2.16 | −1.27 | −1.88 | −0.77 | −1.27 | −1.13 | −1.50 |
| Max | 0.91 | 1.68 | 1.53 | 1.55 | 1.20 | 2.20 | 1.00 | 1.57 |
| MDD in % | 31.97 | 28.60 | 28.03 | 25.57 | 19.36 | 22.65 | 20.47 | 16.07 |
| Scaled MDD | 22.28 | 16.53 | 17.85 | 14.11 | 13.74 | 13.58 | 16.83 | 10.43 |
| #Obs | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 |

*Note*: This table presents the performance of portfolio sorts based on the four liquidity betas (i.e., $\beta^1_{HML}$, $\beta^2_{HML}$, $\beta^3_{HML}$, and $\beta^4_{HML}$) as well as common FX risk factors such as dollar $DOL$, carry $CAR$, volatility $VOL$, and tangency $TAN$. $DOL$ is based on an equally weighted long portfolio of all USD currency pairs, $CAR$ on the forward discount/ premium $f_{t,t+1} - s_t$ (Lustig et al., 2011), $VOL$ is based on currency pairs' exposure to the global volatility factor $\beta^v$ (Menkhoff et al., 2012a), and $TAN$ is a strategy that sorts on exposures to the tangency portfolio $\beta^M$ (Markowitz, 1952). Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*), annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

## Appendix A.2. Double Sorting

To mitigate the effect of volatility risk on liquidity risk we also perform a dependent double-sorting exercise. For instance, we first sort currency pairs into two groups[16] based on their volatility beta (i.e., $\beta^v$) and then conditionally into two subsets based on one of the liquidity betas (i.e., $\beta^1$, $\beta^2$, $\beta^3$, and $\beta^4$). This leaves us with four groups of currency pairs in total. Liquidity trading strategies are formed by taking long positions in high illiquidity beta currencies and short positions in low illiquidity beta currencies across the subsets of low and high volatility beta currencies. Each of the four portfolios consists of three currency pairs that all receive an equal weight of 1/3. To isolate the effect of orthogonalising liquidity against volatility from the impact of the dependent double-sorting we extract rolling window estimates from the following regressions:

$$\Delta c^i = \alpha + \beta^1 \Delta c^M + \varepsilon, \tag{20}$$

$$r^i = \alpha + \beta^2 \Delta c^M + \varepsilon, \tag{21}$$

$$\Delta c^i = \alpha + \beta^3 r^M + \varepsilon, \tag{22}$$

$$r^i = \alpha + \beta^4 \Delta c^i + \varepsilon, \tag{23}$$

where the chief difference compared to Eqs (13) to (16) is the fact that $c^i$ and $c^M$ have *not* been orthogonalised against currency specific and global volatility, respectively.

Figure 11 provides a schematic overview of the four double-sorted portfolios. Specifically, we are interested in the linear combination of two characteristic portfolios that are defined as: i) $LVO = Q_2 - Q_1$, that is the spread between high and low liquidity beta currencies across low *volatility* beta currency pairs as well as ii) $HVO = Q_4 - Q_3$, that is the spread between high and low liquidity beta currencies across high *volatility* beta currency pairs. The average return across $LVO$ and $HVO$ possess an intuitive interpretation (see Fama and French, 1993) as being the average (il)liquidity premium across low and high volatility beta currencies. Specifically, we define $\beta^{q,D}_{HML} = 1/2 \cdot LVO^q + 1/2 \cdot HVO^q \ \forall q \in \{1,2,3,4\}$ and we label these trading strategies $\beta^{q,D}_{HML} \ \forall q \in \{1,2,3,4\}$, where $D$ stands for *double-sort*.

Table 15 reports summary statistics for these four portfolios as well as the $DOL$, $CAR$, $VOL$, and $TAN$. Figure 12 depicts the cumulative out-of-sample (simple excess) returns of the four trading strategies. The key differences between Figure 1 (single-sort) and Figure 12 (double-sort) can be summarised in two points. First, $\beta^{2,D}_{HML}$, $\beta^{3,D}_{HML}$, and $\beta^{4,D}_{HML}$ are much less confounded by volatility risk than $\beta^{1,D}_{HML}$. Second, the cumulative returns to $\beta^{1,D}_{HML}$ are essentially zero implying that commonality in liquidity (i.e., $cov(\Delta c^i, \Delta c^M)$) does not matter after controlling for exposures to volatility risk (i.e., $\beta^v$).

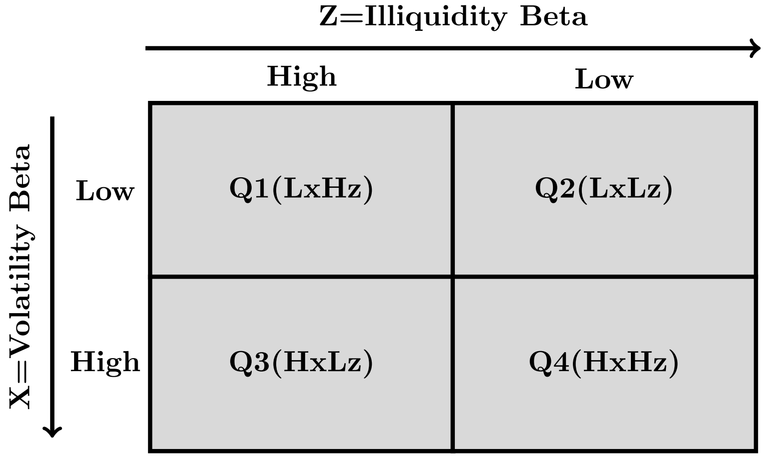
In Table 16 we test if the four liquidity beta based trading strategies (i.e., $\beta^{1,D}_{HML}$, $\beta^{2,D}_{HML}$, $\beta^{3,D}_{HML}$, $\beta^{4,D}_{HML}$) are subsumed by existing FX risk factors. Specifically, we control for common FX risk factors based on the USD–based currency pairs basket (i.e., $DOL$)[17], carry trade (i.e., $CAR$)[18], volatility risk

[16]We exclude any mid-ranked pairs such that the number of currency pairs in each of the two subgroups is divisible by two without remainder. For example, with 15 currency pairs we leave out the three mid-ranked ones.

[17]The $DOL$ portfolio is long only and equally weights across USD–based currency pairs.

[18]For $CAR$ (see Lustig et al., 2011), currency pairs are sorted based on the forward discount/ premium ($F_t - S_t$) and a 'high minus low' portfolio is formed that is long (*short*) the currency pairs in the top tertile with the highest forward premium (*discount*).

**Figure 11: $2 \times 2$ Double Sorted Portfolios**



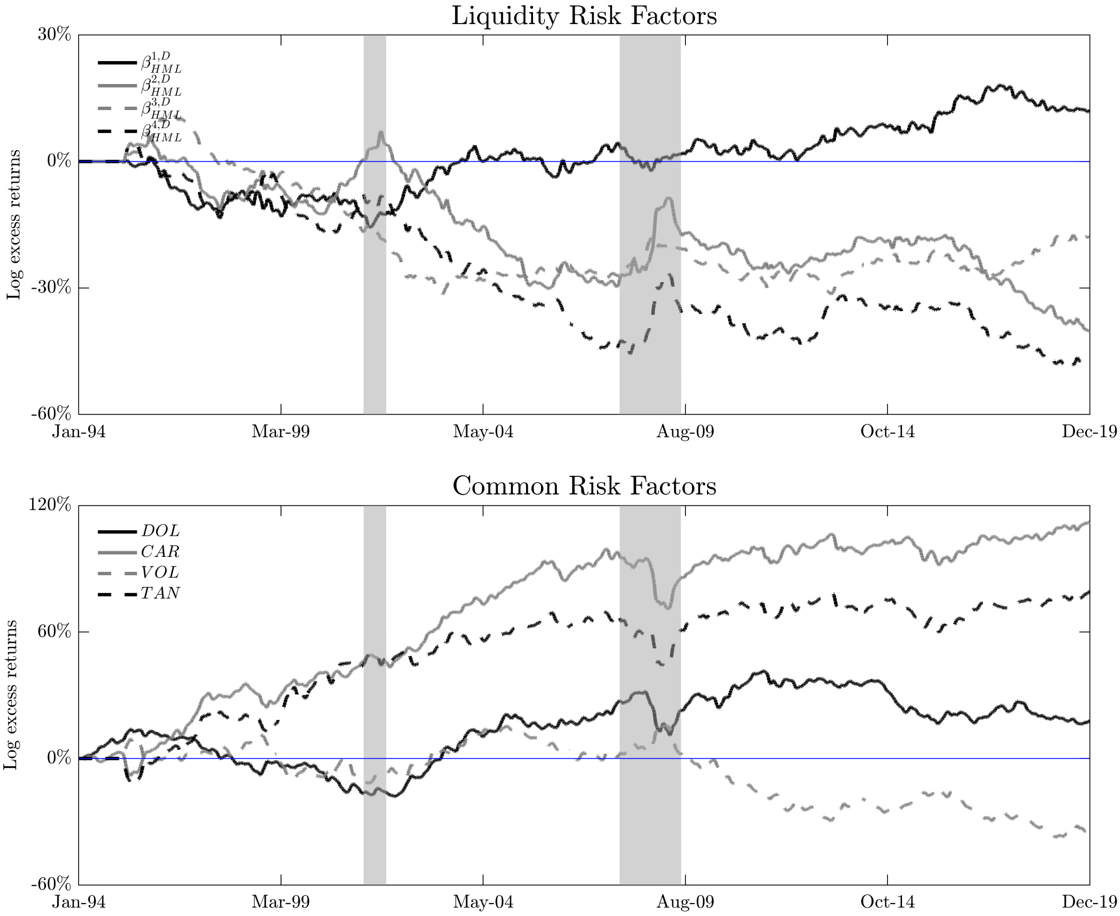

*Note*: Each quartile ($Q_1$ to $Q_4$) consists of *three* currency pairs. The characteristic portfolio combinations are $LVO^q = Q_2 - Q_1$, $HVO^q = Q_4 - Q_3$, and $\beta^{q,D}_{HML} = 1/2 \cdot LVO^q + 1/2 \cdot HVO^q$.

**Table 15: Summary Statistics Portfolio Sorts**

| | $DOL$ | $CAR$ | $VOL$ | $TAN$ | $\beta^{1,D}_{HML}$ | $\beta^{2,D}_{HML}$ | $\beta^{3,D}_{HML}$ | $\beta^{4,D}_{HML}$ |
|---|---|---|---|---|---|---|---|---|
| *Mean* in % | 0.39 | ***4.49 | −1.44 | **3.25 | 0.50 | *−1.63 | −0.73 | **−1.92 |
| | [0.34] | [3.33] | [1.19] | [2.32] | [0.70] | [1.92] | [1.17] | [2.40] |
| $\sigma$ | 1.44 | 1.73 | 1.57 | 1.81 | 1.00 | 1.14 | 0.91 | 1.08 |
| SR | 0.27 | ***2.60 | −0.92 | **1.79 | 0.50 | *−1.43 | −0.81 | **−1.78 |
| | [0.34] | [3.04] | [1.18] | [2.24] | [0.71] | [1.83] | [1.17] | [2.33] |
| Skewness | −0.15 | −0.87 | 0.07 | −0.49 | 0.11 | 0.82 | 0.03 | 0.35 |
| Kurtosis-3 | 2.10 | 4.71 | 1.52 | 2.68 | 0.58 | 5.59 | 0.59 | 2.35 |
| Min | −1.55 | −2.16 | −1.27 | −1.88 | −0.55 | −0.82 | −0.70 | −0.82 |
| Max | 0.91 | 1.68 | 1.53 | 1.55 | 0.69 | 1.69 | 0.59 | 1.24 |
| MDD in % | 31.97 | 28.60 | 28.03 | 25.57 | 16.81 | 21.65 | 14.06 | 19.51 |
| Scaled MDD | 22.28 | 16.53 | 17.85 | 14.11 | 16.78 | 18.92 | 15.50 | 18.02 |
| #Obs | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 |

*Note*: This table presents the performance of the conditional double-sort based on the three liquidity betas (i.e., $\beta^{1,D}_{HML}$, $\beta^{2,D}_{HML}$, $\beta^{3,D}_{HML}$, $\beta^{4,D}_{HML}$) as well as common FX risk factors such as dollar $DOL$, carry $CAR$, volatility $VOL$, and tangency $TAN$. $DOL$ is based on an equally weighted long portfolio of all USD currency pairs, $CAR$ on the forward discount/ premium $f_{t,t+1} - s_t$ (Lustig et al., 2011), $VOL$ is based on currency pairs' exposure to the global volatility factor $\beta^v$ (Menkhoff et al., 2012a), and $TAN$ is a strategy that sorts on exposures to the tangency portfolio $\beta^M$ (Markowitz, 1952). Returns do not take into account transaction cost. Portfolios are rebalanced on a daily basis. The panel reports the annualised average (simple) *gross* excess return (*Mean*), annualised Sharpe ratio (SR), skewness, excess kurtosis (Kurtosis-3), minimum (Min), maximum (Max), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and the number of observations (#Obs). The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for serial correlation up to 22 lags.

**Figure 12: Equity Curves for Liquidity and Common Risk Factors**




*Note*: These figures plot the cumulative gross (log) excess returns of the four liquidity betas sorted portfolios (i.e., $\beta^{1,D}_{HML}$, $\beta^{2,D}_{HML}$, $\beta^{3,D}_{HML}$, $\beta^{4,D}_{HML}$; top figure) as well as four common FX risk factors (i.e., $DOL$, $CAR$, $VOL$, and $TAN$; bottom figure). Grey shaded areas correspond to recession periods as they are defined by the National Bureau of Economic Research (NBER). The sample covers the period from 3 January 1994 to 31 December 2019.

(i.e., $VOL$)[19], and exposures to the tangency portfolio (i.e., $TAN$).[20] The regressions are based on simple excess returns and abstract away from transaction costs.

In contrast to the single-sorting, none of the four trading strategies generates significant risk-adjusted returns after controlling for the carry trade ($CAR$). Furthermore, $\beta^{4,D}_{HML}$ is the only factor that is not subsumed by volatility risk ($VOL$). On the other hand, the coefficient on $VOL$ drops significantly across all four strategies in both economic and statistical terms compared to the single sort in Table 3. These findings have two important implications: First, the economically small and statistically insignificant

[19]The $VOL$ factor is constructed based on Menkhoff et al. (2012a), where currency pairs are sorted based on their exposure to innovations in global volatility. The strategy is long (*short*) currency pairs with small (*large*) exposures to global volatility $\beta^v$. Thus, $VOL$ is a 'low minus high' portfolio where the bottom (*top*) tertile currencies receive a positive (*negative*) weight.

[20]The $TAN$ factor is a 'high minus low' portfolio that is long (*short*) currency pairs with a positive (*negative*) exposure to the tangency portfolio $\beta^M$ (see Markowitz, 1952)

**Table 16: Exposure Regressions**

| | $\beta^{1,D}_{HML}$ | | | | | $\beta^{2,D}_{HML}$ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| $\alpha$ in % | 0.499 | 0.419 | 0.372 | 0.459 | 0.507 | *−1.634 | *−1.572 | 0.108 | −1.319 | −0.521 |
| | [0.705] | [0.618] | [0.493] | [0.646] | [0.696] | [1.916] | [1.876] | [0.147] | [1.604] | [0.705] |
| $DOL$ | | ***0.203 | | | | | **−0.158 | | | |
| | | [5.436] | | | | | [2.440] | | | |
| $CAR$ | | | 0.028 | | | | | ***−0.388 | | |
| | | | [0.846] | | | | | [10.004] | | |
| $VOL$ | | | | −0.027 | | | | | ***0.218 | |
| | | | | [0.950] | | | | | [4.625] | |
| $TAN$ | | | | | −0.002 | | | | | ***−0.343 |
| | | | | | [0.082] | | | | | [8.415] |
| $\bar{R}^2$ in % | | 8.42 | 0.24 | 0.18 | 0.00 | | 3.92 | 34.37 | 8.97 | 29.44 |
| IR | 0.03 | 0.03 | 0.02 | 0.03 | 0.03 | −0.09 | −0.09 | 0.01 | −0.08 | −0.03 |
| #Obs | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 |
| | $\beta^{3,D}_{HML}$ | | | | | $\beta^{4,D}_{HML}$ | | | | |
| | (1) | (2) | (3) | (4) | (5) | (1) | (2) | (3) | (4) | (5) |
| $\alpha$ in % | −0.730 | −0.711 | −0.523 | −0.757 | −0.590 | **−1.925 | **−1.860 | −0.375 | **−1.704 | −0.875 |
| | [1.173] | [1.140] | [0.813] | [1.217] | [0.946] | [2.396] | [2.381] | [0.545] | [2.181] | [1.286] |
| $DOL$ | | −0.048 | | | | | ***−0.166 | | | |
| | | [1.499] | | | | | [3.474] | | | |
| $CAR$ | | | −0.046 | | | | | ***−0.345 | | |
| | | | [1.480] | | | | | [12.243] | | |
| $VOL$ | | | | −0.019 | | | | | ***0.153 | |
| | | | | [0.710] | | | | | [3.600] | |
| $TAN$ | | | | | −0.043 | | | | | ***−0.323 |
| | | | | | [1.501] | | | | | [11.780] |
| $\bar{R}^2$ in % | | 0.58 | 0.77 | 0.10 | 0.74 | | 4.86 | 30.41 | 4.92 | 29.26 |
| IR | −0.05 | −0.05 | −0.04 | −0.05 | −0.04 | −0.11 | −0.11 | −0.03 | −0.10 | −0.06 |
| #Obs | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 | 6179 |

*Note*: This table shows the results of regressing daily gross excess returns associated with the four liquidity beta based trading strategies (i.e., $\beta^{1,D}_{HML}$, $\beta^{2,D}_{HML}$, $\beta^{3,D}_{HML}$, and $\beta^{4,D}_{HML}$) on excess returns associated with common FX risk factors. $DOL$ is based on an equally weighted long portfolio of all USD currency pairs, $CAR$ is based on the forward discount/ premium $f_{t,t+1} - s_t$ (Lustig et al., 2011), $VOL$ is based on currency pairs' exposure to the global volatility factor $\beta^v$ (Menkhoff et al., 2012a), and $TAN$ is a strategy that sorts on exposures to the tangency portfolio $\beta^M$ (Markowitz, 1952). The intercept ($\alpha$) has been annualised ($\times 252$). The information ratio (IR) is defined as $\alpha$ divided by the residual standard deviation. The sample covers the period from 21 February 1995 to 31 December 2019. Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on heteroskedasticity- and autocorrelation-consistent standard errors (Newey and West, 1987) correcting for correlation up to 22 lags.

loadings on the volatility factor imply that the double-sorting methodology successfully disentangles liquidity from volatility risk. Second, the significant exposures to the carry trade factor give rise to the idea of replacing the carry factor by liquidity risk in an FX asset pricing model.

## Appendix A.3. Determinants of Currency Illiquidity

Following the work by Menkhoff et al. (2012a) and Mancini et al. (2013) we expect that currency illiquidity $c_t$, volatility $RV_t$, and interest rate differentials $F_t - S_t$ move in locksteps. To test this hypothesis, we consider the following fixed effects panel regression:

$$\Delta c_t = \lambda_t + a_i + b_1 \Delta(F_t - S_t) + b_2 \Delta RV_t + \epsilon, \tag{24}$$

where both dependent and independent variables enter our regression as 22-day changes (i.e., $\Delta = 22$). In addition, we standardise every time series by dividing by the standard deviation of the respective variable across all currency pairs. Hence, all variables are in units of standard deviation across currency pairs. Notice that standardising does neither alter the relative sizes between currencies nor change the sign or significance of the regression estimates. $\lambda_t$ and $a_i$ denote time series and currency pair fixed effects, respectively. The frequency of this regression is daily and robust standard errors are computed based on Driscoll and Kraay (1998) allowing for random clustering and serial correlation up to 22 lags.

Table 17 reports the estimation results of the panel regression in Eq. (24). Two results emerge from our analysis. First, in line with our hypothesis above, a positive change in the interest rate differential $F_t - S_t$ is accompanied by an increase in currency specific illiquidity $c_t$. Second, although well expected, realised volatility $RV_t$ and illiquidity $c_t$ move in lockstep: on average, a one standard deviation increase in realised volatility is associated with a 0.09 standard deviation increase in illiquidity. In sum, we have identified interest rate differentials as a potentially exogenous driver of currency specific illiquidity. The exclusionary restriction in our empirical identification is that interest rates are infrequently adjusted by central banks and hence exogenous to short-run currency specific illiquidity. Contrarily, the link between realised volatility and liquidity is less identified and prone to reverse causality issues that are beyond the scope of this paper.

**Table 17: Determinants of Currency Illiquidity**

| | (1) | (2) | (3) |
|---|---|---|---|
| $\Delta(F_t - S_t)$ | ***0.034 | | ***0.032 |
| | [5.745] | | [5.449] |
| $\Delta RV_t$ | | ***0.088 | ***0.083 |
| | | [12.500] | [11.478] |
| Adj. $R^2$ in % | 0.10 | 0.78 | 0.81 |
| Avg. #Time periods | 6439 | 6417 | 6417 |
| #Exchange rates | 15 | 15 | 15 |
| Currency FE | yes | yes | yes |
| Time series FE | yes | yes | yes |

*Note*: This table reports results from daily fixed effects panel regressions of the form $\Delta c_t^i = \lambda_t + a_i + b_1 \Delta(F_t - S_t) + b_2 \Delta RV_t + \epsilon$, where the dependent variable is currency specific illiquidity $c_t$ and the regressors are the interest rate differential $F_t - S_t$ and realised volatility $RV_t$ (Barndorff-Nielsen and Shephard, 2002), respectively. Both dependent and independent variables enter our regression as 22-day changes (i.e., $\Delta = 22$). We standardise every time series by dividing by the standard deviation of the respective variable across currency pairs. $\lambda_t$ and $a_i$ denote time series and cross-sectional fixed effects, respectively. The sample covers the period from 03 January 1994 to 31 December 2019. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation up to 22 lags are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% levels, respectively.

# Part III

# Appendix

# Curriculum Vitae

# Fabricius Somogyi - CV

## EDUCATION

**PhD in Finance**, University of St.Gallen, Switzerland — Feb 2018 – Present

- Visiting PhD Fellow at the Bank for International Settlements, Switzerland (Feb – Nov 2021)
- Visiting Student Researcher at Stanford University, US (Jan – Dec 2020)

**MSc in Finance** (Distinction), Imperial College London, UK — Sep 2016 – Sep 2017

**BSc in Economics**, University of Mannheim, Germany — Sep 2013 – Jul 2016

## RESEARCH INTERESTS

International Finance, Asset Pricing, and Market Microstructure

## JOB MARKET PAPER

**Dollar Dominance in FX Trading**
Winner of the

- *8th Econ Job Market Best Paper Award*
- *2021 SFA Best Paper Award in International Finance*

## PUBLICATIONS

**Asymmetric Information Risk in FX Markets** with A. Ranaldo
*Journal of Financial Economics*, Volume 140(2):391-411, May 2021

## WORKING PAPERS

**FX Liquidity Risk and Carry Trade Premia** with P. Söderlind
**Constrained Dealers and Market Efficiency** with W. Huang, A. Ranaldo, and A. Schrimpf

## CONFERENCE PRESENTATIONS & SEMINARS

**Dollar Dominance in FX Trading**: Tilburg University; Federal Reserve Board; Baruch College; Analysis Group; Northeastern University; UVA Darden; Wharton; INSEAD; CUHK; Cornerstone Research; Copenhagen Business School; ESCP Paris; BI Oslo; Babson College; 2022 American Finance Association Meetings; 2021 Southern Finance Association Meetings; University of Nottingham; 2021 FMA Annual Meeting; 27th Annual Meeting of the German Finance Association; 2nd PhD Student Symposium at the University of Texas at Austin; Bank for International Settlements; 2021 World Finance Conference; 2021 Oxford-ETH Macro-Finance Conference; 33rd Asian Finance Conference; 2021 IBEFA Summer Meeting; 37th International Conference of the French Finance Association; Imperial College London; 2021 Southwestern Finance Association Meetings; 33rd Australasian Finance & Banking Conference; Inter Finance PhD Seminar; University of St.Gallen; Stanford University

**Asymmetric Information Risk in FX Markets**: 2020 Southern Finance Association Meetings; 3rd World Symposium on Investment Research; 2020 Northern Finance Association Meetings; 2020 European Finance Association Meetings; 2020 Vienna Symposium on Foreign Exchange Markets*; 95th Annual WEAI Conference; 2020 SFI Research Days; Microstructure Exchange Webinar*; 9th ECB Workshop on Exchange Rates; 2019 Annual Conference in International Finance*; 18th Colloquium on Financial Markets; 2019 American Finance Association Meetings (poster session); 14th Central Bank Conference on the Microstructure of Financial Markets; CEU Cardenal Herrera University*; University of St.Gallen

**FX Liquidity Risk and Carry Trade Premia**: 24th Annual Meeting of the Swiss Society for Financial Market Research; 2020 American Finance Association Meetings (poster session); University of St.Gallen

*Note*: List includes scheduled and accepted conferences. (*) indicates co-author presentation.

## CONFERENCE DISCUSSIONS

**2022**: 24th Annual Meeting of the Swiss Society for Financial Market Research, *Earnings Growth Uncertainty and the Cross-section of Equity Valuation* by Ella D.S. Patelli

**2021**: Southern Finance Association Meetings, *Cash Is Not King* by S. Klingler, O. Syrstad, and G. Vuillemey; 27th Annual Meeting of the German Finance Association, *The Case of Fleeting Orders and Flickering Quotes* by M. Ulze, J. Stadler, and A. Rathgeber; World Finance Conference, *Feasibility of a potential currency union in Asia – Panel Data Analysis* by W. Song and Z. Xie; 33rd Asian Finance Conference, *Currency Puzzles and the Oil Connection* by G. Panayotov; Southwestern Finance Association Meetings, *Geopolitical Risk and its Impact on Currency Portfolios* by I. Dergunov and M. Mukhamadieva

**2020**: 33rd Australasian Finance & Banking Conference, *A Model of Maker-Taker Fees and Quasi-Natural Experimental Evidence* by Y. Lin, P. Swan, and F. Harris; Southern Finance Association Meetings, *Currency Anomalies* by S. Bartram, L. Djuranovik, and A. Garratt; 95th Annual WEAI Conference, *Procyclical Asset Management and Bond Risk Premia* by A. Barbu, C. Fricke, and E. Moench; SFI Research Days, *The Global Factor Structure of Exchange Rates* by S. Korsaye, F. Trojani, and A. Vedolin

**2019**: 22nd Annual Meeting of the Swiss Society for Financial Market Research, *Mind the (Convergence) Gap: Forward Rates Strike Back!* by A. Berardi, M. Markovich, A. Plazzi, and A. Tamoni

## REFEREE ACTIVITY

The Review of Financial Studies

## PRIZES, AWARDS, & FELLOWSHIPS

- University of St.Gallen FT50 Publication Success Fee, CHF 5,000 (Jan 2021)
- Swiss National Science Foundation Doc.Mobility Fellowship, CHF 33,500 (Jul – Dec 2020)
- AFA PhD Student Travel Grant, USD 1,050 (Jan 2019)
- Dean's List for Academic Excellence at Imperial College London (Nov 2017)
- Bundesverband Deutscher Volks- und Betriebswirte *Aktivit* Fellowship for exceptional service at the University of Mannheim as Chairman of the Board (May 2014 – Jul 2015)

## TEACHING ASSISTANT POSITIONS

| | |
|---|---|
| Julia - A Fresh Approach to Numerical Computing (MA, University of St.Gallen) | Fall 2017 – 2021 |
| Statistical Methods and Applications (BA, University of St.Gallen) | Fall 2019 |
| Financial Econometrics (MA, University of St.Gallen) | Spring 2018 |
| Mathematics for Economic Analysis (BA, University of Mannheim) | Fall 2014 |

## NON-ACADEMIC EMPLOYMENT

| | |
|---|---|
| Morgan Stanley, London (United Kingdom), Visiting PhD Student Researcher | Jun – Jul 2019 |
| Bank of America Merrill Lynch, London (United Kingdom), Summer Analyst | Jun – Aug 2017 |
| Morgan Stanley, Frankfurt a. M. (Germany), Investment Banking Intern | Mar – May 2016 |
| Simon-Kucher & Partners, Munich (Germany), Associate Consultant Intern | Jun – Sep 2015 |

## PERSONAL SKILLS

| | |
|---|---|
| **Languages** | English (fluent), German & Hungarian (bilingual), French (advanced) |
| **Coding** | Julia, MATLAB, R, STATA, VBA |
| **Databases** | Bloomberg, Capital IQ, Datastream, FactSet |
| **Sports** | Passionate alpine skier and keen tennis player |

## REFERENCES

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