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"Dollar Dominance in FX Trading"

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Dollar Dominance in FX Trading*

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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.

J.E.L. classification: F31, G12, G15

Keywords: Dollar dominance, foreign exchange, price impact, strategic complementarity, trading volume

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1. Introduction

The US dollar dominates the international monetary and financial system (Gourinchas, Rey, and Sauzet, 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

[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, Israel, and Moskowitz, 2018).

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

a set 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 interbank 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, Schrimpf, and Sushko, 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 and Stein, 2020; Tille, Mehl, Georgiadis, and Mezo, 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, Krishnamurthy, and Milbradt, 2019; Jiang, Krishnamurthy, and Lustig, 2021) and from the growing demand for safe assets (e.g., Caballero, Farhi, and Gourinchas, 2008, 2017, 2021). The third category is the "debt view" of dollar dominance (Eren and Malamud, 2021), which emphasises the role of firms' debt currency denomination. Maggiori, Neiman, and Schreger (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, Chernenko, and Wright, 2008; Mancini, Ranaldo, and Wrampelmeyer, 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, Sarno, Schmeling, and Schrimpf, 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, Gargano, Riddiough, and Sarno (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, Kiyotaki, and Matsui (1993), Rey (2001), Caballero and Krishnamurthy (2003, 2009), Bruno and Shin (2017), Doepke and Schneider (2017), Bruno, Kim, and Shin (2018), Ilzetzki, Reinhart, and Rogoff (2019), Jiang, Krishnamurthy, and Lustig (2019), Chahrour and Valchev (2021), and Mukhin (2021).

[4] The authors use a confidential data set based on *settlement* rather than *trade* data, which hence differs from the CLS order flow and volume data made publicly available in July 2016.

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, Osler, and Rime, 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]

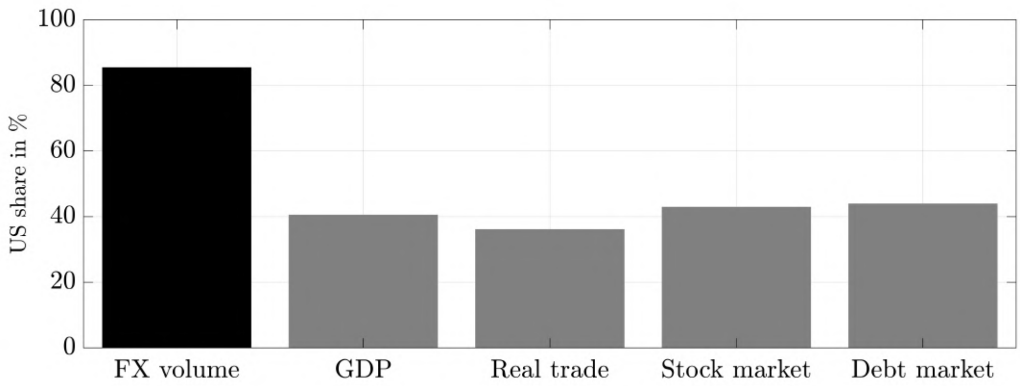
Figure 1 illustrates the pervasive dominance of the US dollar (USD) in FX trading volume. The underlying data come from five sources: First, spot FX trade data stem from CLS Group. Second, yearly GDP data by country and currency come from the World Bank and OECD national accounts data, respectively.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

[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).

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 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.

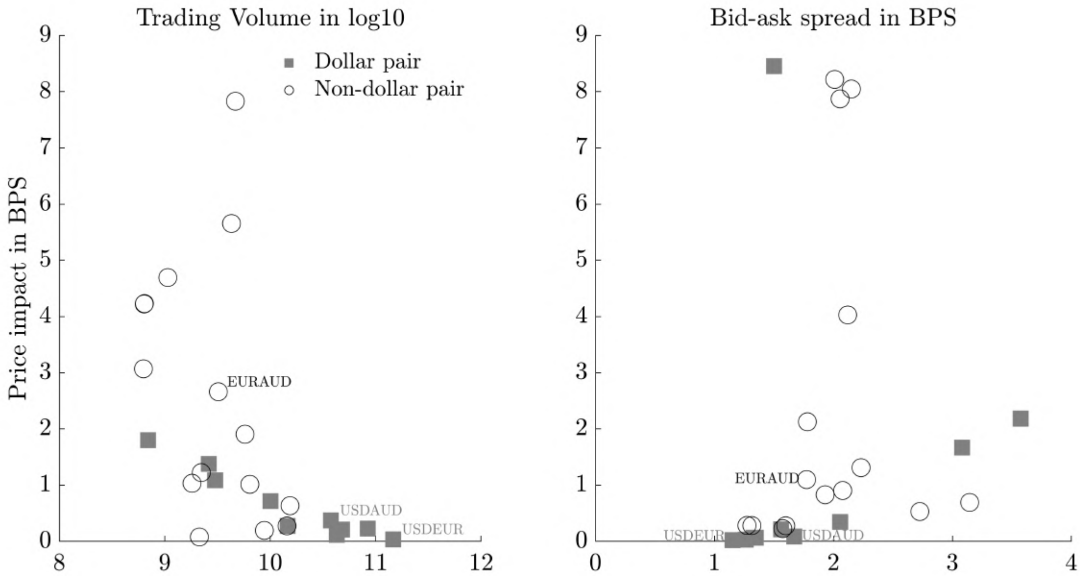
[7]The stark discrepancy between trading volume and real economic activity persists even after accounting for any currencies that are pegged to the US dollar (i.e., Hong Kong and Singapore dollar).

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.

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.

My model includes no traditional transaction costs in the form of relative bid-ask spreads.

[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).

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.

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:

$$u^i(q^i) = \delta_k \cdot (\mathbf{q}^i + \mathbf{q}^i_0) - \frac{\gamma^i}{2}(\mathbf{q}^i + \mathbf{q}^i_0) \cdot \boldsymbol{\Sigma}(\mathbf{q}^i + \mathbf{q}^i_0), \tag{1}$$

where $\mathbf{q}^i = q^i_k$ is the (effectively) traded quantity, $\mathbf{q}^i_0 = q^i_{0,k}$ represents every trader's *fundamental trading demand* in each currency pair, and γ^i is trader i's risk aversion.[9]

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

[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.

[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.

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, Scharfstein, and Stein, 2015; Eren and Malamud, 2021) 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, Obizhaeva, and Wang, 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 *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

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

[12] See Foucault, Pagano, and Röell (2013) for an overview of models based on limit-orders.

[13] To my best knowledge, Wittwer (2021), Chen and Duffie (2021), and Rostek and Yoon (2021a) were the first

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:*

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

given the 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 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.

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.

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

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

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:

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

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 γ.

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 $\mathbf{C}^{-1}$:

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

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.

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]

[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, Mizrach, and Nguyen (2018), Brogaard, Hendershott, and Riordan (2019), and Chaboud, Hjalmarsson, and Zikes (2021).

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 $(\mathbf{B}\boldsymbol{\Omega}\mathbf{B}')\left[\mathbf{B}\boldsymbol{\Omega}\mathbf{B}'\right]_d^{-1}$ in Eq. (6), which increases in the variance fundamental trading demands $\boldsymbol{\Omega}$ 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 λ_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.

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 $\boldsymbol{\Omega}$, and covariance of currency returns $\boldsymbol{\Sigma}$. I denote the $(k,l)^{th}$ element of a matrix (e.g., $\boldsymbol{\Sigma}$) 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 $\boldsymbol{\Sigma}$ and the covariance matrix of currency returns $\boldsymbol{\Omega}$ 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 trading volume* $\mathbf{q}^{i,*}$ *with respect to fundamental trading demand* $q^i_{0,k}$*, variance of fundamental trading demands* $\Omega_{k,k}$*, and variance of currency returns* $\Sigma_{k,k}$ *are given by the following expressions: for every* $k \neq l$

$$\frac{\partial \mathbf{q}^{i,*}}{\partial q^i_{0,k}} = (\mathbf{\Sigma}+\mathbf{\Lambda})^{-1}\mathbf{\Sigma}\frac{\partial \mathbf{d}^i_0}{\partial d^i_{0,k}},\ \text{where } \mathbf{d}^i_0 = |\bar{\mathbf{q}}_0 - \mathbf{q}^i_0| \text{ and } \frac{\partial q^{i,*}_k}{\partial d^i_{0,k}} > \frac{\partial q^{i,*}_l}{\partial d^i_{0,k}},\ \text{as } \frac{\partial d^i_{0,l}}{\partial d^i_{0,k}} = 0; \tag{7}$$

$$\frac{\partial \mathbf{q}^{i,*}}{\partial \Omega_{k,k}} = -(\mathbf{\Sigma}+\mathbf{\Lambda})^{-2}\mathbf{\Sigma}\frac{\partial \mathbf{\Lambda}}{\partial \Omega_{k,k}}(E[\bar{\mathbf{q}}_0] - E[\mathbf{q}^i_0]),\ \text{where } \frac{\partial q^{i,*}_k}{\partial \Omega_{k,k}} > \frac{\partial q^{i,*}_l}{\partial \Omega_{k,k}} \text{ as } \frac{\partial \Lambda_{k,k}}{\partial \Omega_{k,k}} < \frac{\partial \Lambda_{l,l}}{\partial \Omega_{k,k}}; \tag{8}$$

$$\frac{\partial \mathbf{q}^{i,*}}{\partial \Sigma_{k,k}} = \left((\mathbf{\Sigma}+\mathbf{\Lambda})^{-1}\frac{\partial \mathbf{\Sigma}}{\partial \Sigma_{k,k}} - (\mathbf{\Sigma}+\mathbf{\Lambda})^{-2}\mathbf{\Sigma}\left(\frac{\partial \mathbf{\Sigma}}{\partial \Sigma_{k,k}} + \frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k,k}}\right)\right)(E[\bar{\mathbf{q}}_0] - E[\mathbf{q}^i_0]), \tag{9}$$

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

See Online Appendix, Section 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 $q^i_{0,k}$, $\Omega_{k,k}$, 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 $q^i_{0,k}$ 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 $(\mathbf{B\Omega B'})\left[\mathbf{B\Omega B'}\right]^{-1}_d$ 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 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 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

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

[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 $\mathbf{\Sigma}^{-1}\Lambda_{k,k} < \frac{\partial \mathbf{\Lambda}}{\partial \Sigma_{k,k}}$.

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 A of the Online Appendix for a formal derivation of the contingent market 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.

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 $\mathbf{q}_0^i$, 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 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 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.

[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.

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 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

[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.

[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.

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., 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.

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 μ_t are time series fixed effects, α_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 $bid\text{-}ask\ spread_{k,t}$, interest rate differential $interest\ rate_{k,t}$, and cross-currency basis $cip\text{-}basis_{k,t}$ as control variables in $\mathbf{w}_{k,t}$. Note that all three controls are given in absolute

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.

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, Tepper, and Verdelhan (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

[24] I obtain overnight forward points from Bloomberg using London closing rates.
[25] Daily LIBOR and interbank fixing rates are also obtained from Bloomberg.

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, Duffie, and Song (2019) and Rime, Schrimpf, and Syrstad (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.

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

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

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 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:

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

Table 2: Economic Drivers of Trading Volume

	volume$_{k,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
flow$_{k,t}$	***0.58			***0.57		***0.12	***0.53	
	[44.85]			[43.13]		[26.25]	[33.41]	
var(flow)$_{k,t}$		***0.43			***0.38	***0.27		***0.41
		[50.83]			[36.49]	[18.21]		[47.16]
volatility$_{k,t}$			***0.30		***0.20	***0.51	***0.16	***0.20
			[28.13]		[20.00]	[47.07]	[16.44]	[24.47]
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 rate$_{k,t}$)				**−0.01		0.00		***−0.01
				[2.13]		[1.42]		[2.85]
abs(cip-basis$_{k,t}$)					***−0.02		**−0.01	
					[2.65]		[2.07]	
flow×volatility$_{k,t}$							***0.04	
							[4.06]	
var(flow)×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. μ_t and α_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. $bid\text{-}ask\,spread_{k,t}$ is the daily average relative bid-ask spread. $interest\,rate_{k,t}$ is the interest rate differential computed as the difference between the overnight forward rate f_t and the spot midquote s_t. $cip\text{-}basis_{k,t}$ 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.

where μ_t are time series fixed effects, α_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

[27]Note that my empirical results are robust to using alternative price impact measures including Kyle (1985), Hasbrouck (1991b), and Gabaix, Gopikrishnan, Plerou, and Stanley (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

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 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.

Table 3: Economic Drivers of Price Impact

	$\lambda_{k,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{var(flow)}_{k,t}$	***−0.03		***−0.04		***−0.06	***−0.06
	[5.01]		[6.71]		[10.55]	[10.30]
$\text{volatility}_{k,t}$		***0.14		***0.17	***0.16	***0.19
		[19.74]		[20.25]	[21.41]	[21.71]
$\text{bid-ask spread}_{k,t}$			***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. μ_t and α_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. $\textit{bid-ask spread}_{k,t}$ 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.

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.

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,

that prices react to large signed orders with a change proportional to the square root of the order size.

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.

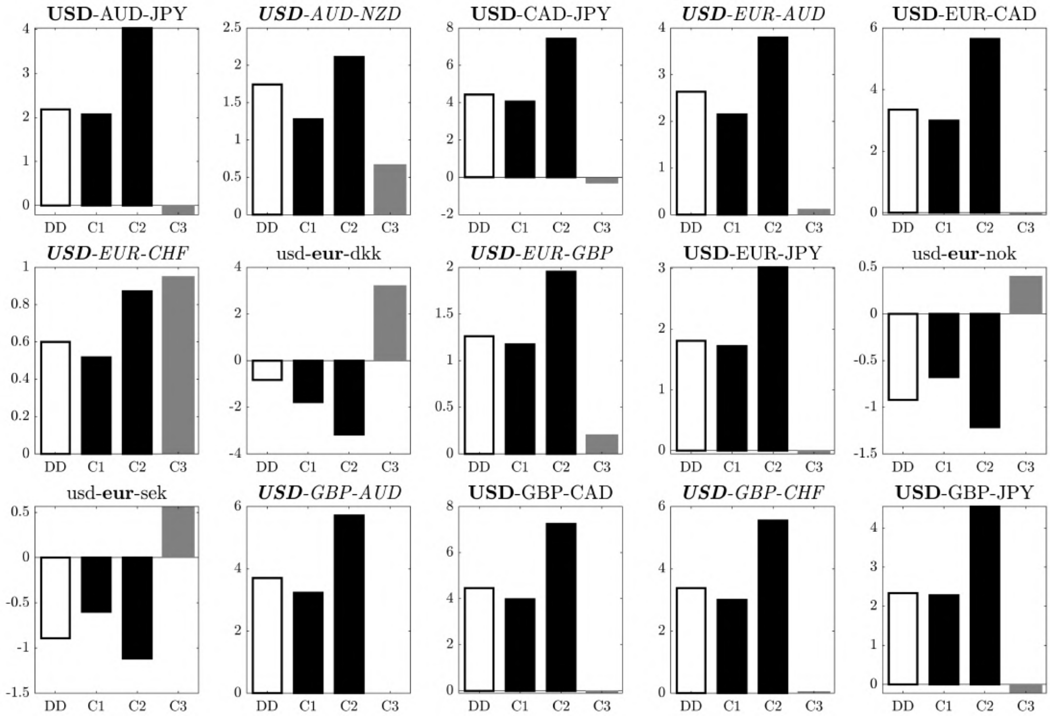
Equilibrium conditions. Figure 3 summarises the empirical counterparts of the three equilibrium conditions. I plot four bars for every triplet of currency pairs. The first bar from the left (i.e, DD) corresponds to the time series average of my empirical measure of dollar dominance: A positive figure 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.

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.

[28] To save space, I relegate the test statistics for both hypothesis tests to Table D.1 in the Online Appendix.

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., *C*1, *C*2, and *C*3) 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.

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 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 μ_t and currency pair triplet α_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 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.,

[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 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.

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 $bid\text{-}ask\,spread_{j,t}$ and cross-currency basis $cip\text{-}basis_{j,t}$ 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 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%.

Robustness. What follows summarises two additional robustness checks that support my empirical findings. Section 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

Table 4: Dollar Dominance and Equilibrium Conditions

	$doldom_{j,t}$						$amihud_{j,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$C1_{j,t}$	***0.46			***0.46		***0.61			
	[36.28]			[36.04]		[21.55]			
$C2_{j,t}$		***0.35			***0.35	***0.36	***−0.04		***−0.05
		[35.58]			[35.46]	[33.00]	[4.76]		[4.66]
$C3_{j,t}$			***0.06		***0.04	***0.04		***0.09	***0.09
			[5.30]		[3.80]	[3.40]		[6.83]	[6.51]
bid-ask $spread_{j,t}$				***−0.06	***−0.09	***−0.04			0.02
				[4.03]	[5.89]	[2.77]			[0.73]
cip-$basis_{j,t}$						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 μ_t and α_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. *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.

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:

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

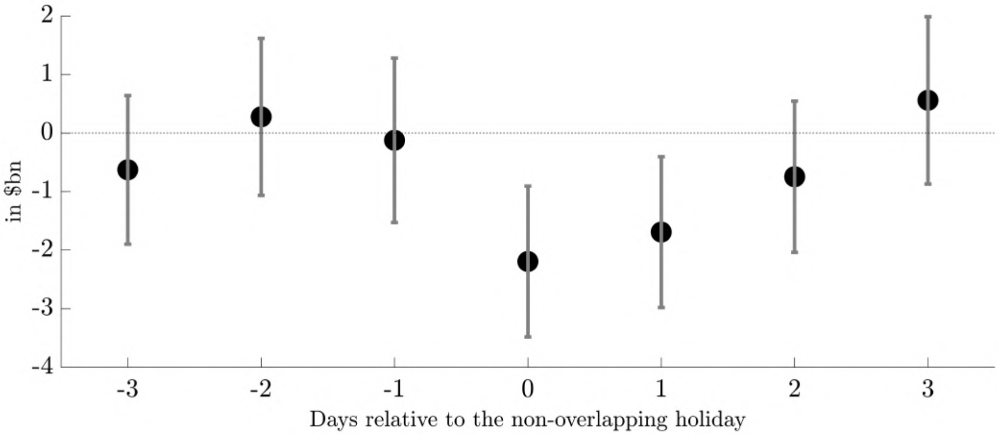
where the dependent variable is inter-dealer trading volume in dollar currency pair k on day t. μ_t are time series fixed effects and α_k denotes currency pair fixed effects that control for any unobserved variation that is either constant across currency pairs or over time. The main regressor is $D_{k,m}$, 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 β's) are identified from how trading volume in dollar currency pairs changes before and after 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 5 further illustrates the aforementioned caveat by showing estimates for the case β=β_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.

[30] Non-overlapping holidays do not constitute a random experiment. Figure D.7 in the Online Appendix provides evidence that the parallel trend assumption seems to hold for eight out of ten dollar currency pairs.

Figure 4: Event Study: Evidence of Vehicle Currency Trading



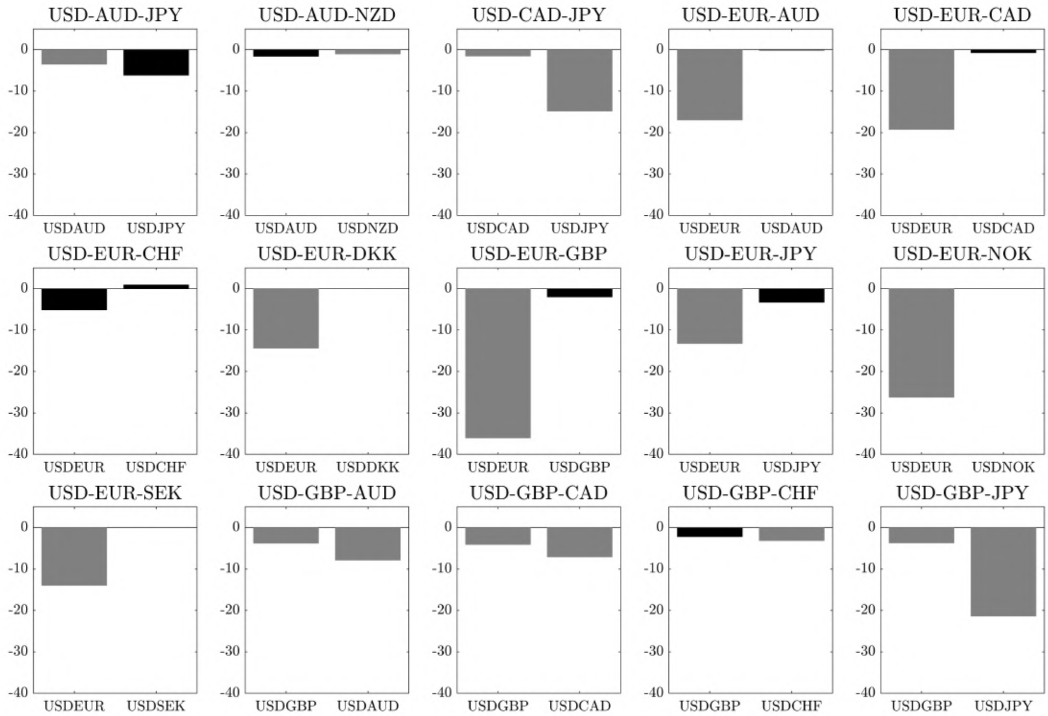
Note: This figure shows the β_m estimates and the 95% confidence intervals of the event study regression of the form $volume_{k,t} = \mu_t + \alpha_k + \sum_{m=M^-}^{M^+} \beta_m D_{k,m} + \epsilon_{k,t}$ for 3 days before and after a non-overlapping holiday. $D_{k,m}$ is an indicator variable equal to 1 m days before/after there is a non-overlapping holiday on day t. Each β_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.

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).

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.

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



Note: This figure shows individual estimates for β=β_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.

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

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 β=β_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.

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.

References

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

Andersen, L., Duffie, D., and Song, Y., 2019. Funding value adjustments. *The Journal of Finance*, 74(1): 145–192.

Bahaj, S. and Reis, R. A., 2020. Jumpstarting an international currency. *Bank of England Working Paper No.874*.

Barndorff-Nielsen, O. E. and Shephard, N., 2002. Econometric analysis of realized volatility and its use in estimating stochastic volatility models. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 64(2):253–280.

Bjønnes, G. H. and Rime, D., 2005. Dealer behavior and trading systems in foreign exchange markets. *Journal of Financial Economics*, 75(3):571–605.

Black, S. W., 1991. Transactions costs and vehicle currencies. *Journal of International Money and Finance*, 10(4):512–526.

Breedon, F. and Ranaldo, A., 2013. Intraday patterns in FX returns and order flow. *Journal of Money, Credit and Banking*, 45(5):953–965.

Brogaard, J., Hendershott, T., and Riordan, R., 2019. Price discovery without trading: Evidence from limit orders. *The Journal of Finance*, 74(4):1621–1658.

Bruno, V. and Shin, H. S., 2017. Global dollar credit and carry trades: A firm-level analysis. *Review of Financial Studies*, 30(3):703–749.

Bruno, V., Kim, S.-J., and Shin, H. S., 2018. Exchange rates and the working capital channel of trade fluctuations. *AEA Papers and Proceedings*, 108:531–536.

Caballero, R. J. and Krishnamurthy, A., 2003. Excessive dollar debt: Financial development and underinsurance. *The Journal of Finance*, 58(2):867–893.

Caballero, R. J. and Krishnamurthy, A., 2009. Global imbalances and financial fragility. *American Economic Review*, 99(2):584–588.

Caballero, R. J., Farhi, E., and Gourinchas, P.-O., 2008. An equilibrium model of “global imbalances” and low interest rates. *American Economic Review*, 98(1):358–393.

Caballero, R. J., Farhi, E., and Gourinchas, P.-O., 2017. The safe assets shortage conundrum. *Journal of Economic Perspectives*, 31(3):29–46.

Caballero, R. J., Farhi, E., and Gourinchas, P.-O., 2021. Global imbalances and policy wars at the zero lower bound. *The Review of Economic Studies*.

Cespa, G., Gargano, A., Riddiough, S. J., and Sarno, L., 2021. Foreign exchange volume. *Review of Financial Studies*.

Chaboud, A., Hjalmarsson, E., and Zikes, F., 2021. The evolution of price discovery in an electronic market. *Journal of Banking & Finance*, 130:106171.

Chaboud, A. P., Chernenko, S. V., and Wright, J. H., 2008. Trading activity and macroeconomic announcements in high-frequency exchange rate data. *Journal of the European Economic Association*, 6 (2-3):589–596.

Chahrour, R. and Valchev, R., 2021. Trade finance and the durability of the dollar. *The Review of Economic Studies*.

Chen, D. and Duffie, D., 2021. Market fragmentation. *American Economic Review*, 111(7):2247–2274.

Chrystal, K. A., 1977. Demand for international media of exchange. *The American Economic Review*, 67 (5):840–850.

Clark, P. K., 1973. A subordinated stochastic process model with finite variance for speculative prices. *Econometrica*, 41(1):135–155.

Devereux, M. B. and Shi, S., 2013. Vehicle currency. *International Economic Review*, 54(1):97–133.

Doepke, M. and Schneider, M., 2017. Money as a unit of account. *Econometrica*, 85(5):1537–1574.

Driscoll, J. C. and Kraay, A. C., 1998. Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, 80(4):549–560.

Du, W., Tepper, A., and Verdelhan, A., 2018. Deviations from covered interest rate parity. *The Journal of Finance*, 73(3):915–957.

Eren, E. and Malamud, S., 2021. Dominant currency debt. *Journal of Financial Economics*.

Evans, M. D., 2002. FX trading and exchange rate dynamics. *The Journal of Finance*, 57(6):2405–2447.

Evans, M. D. and Lyons, R. K., 2002. Order flow and exchange rate dynamics. *Journal of Political Economy*, 110(1):247–290.

Evans, M. D. and Lyons, R. K., 2005. Do currency markets absorb news quickly? *Journal of International Money and Finance*, 24(2):197–217.

Farhi, E. and Maggiori, M., 2017. A model of the international monetary system. *The Quarterly Journal of Economics*, 133(1):295–355.

Fischer, A. M. and Ranaldo, A., 2011. Does FOMC news increase global FX trading? *Journal of Banking and Finance*, 35(11):2965–2973.

Fleming, M. J., Mizrach, B., and Nguyen, G., 2018. The microstructure of a U.S. treasury ECN: The BrokerTec platform. *Journal of Financial Markets*, 40:2–22.

Foster, F. D. and Viswanathan, S., 1990. A theory of the interday variations in volume, variance, and trading costs in securities markets. *Review of Financial Studies*, 3(4):593–624.

Foucault, T., Pagano, M., and Röell, A., 2013. *Market Liquidity: Theory Evidence, and Policy*. Oxford University Press.

Frazzini, A., Israel, R., and Moskowitz, T. J., 2018. Trading costs. *SSRN Electronic Journal*.

Gabaix, X., Gopikrishnan, P., Plerou, V., and Stanley, H. E., 2006. Institutional investors and stock market volatility. *The Quarterly Journal of Economics*, 121(2):461–504.

Gabaix, X. and Koijen, R. S. J., 2020. Granular instrumental variables. *SSRN Electronic Journal*.

Gârleanu, N. and Pedersen, L. H., 2013. Dynamic trading with predictable returns and transaction costs. *The Journal of Finance*, 68(6):2309–2340.

Glosten, L. R. and Harris, L. E., 1988. Estimating the components of the bid/ask spread. *Journal of Financial Economics*, 21(1):123–142.

Goldberg, L. S. and Tille, C., 2008. Vehicle currency use in international trade. *Journal of International Economics*, 76(2):177–192.

Gopinath, G. and Stein, J. C., 2020. Banking, trade, and the making of a dominant currency. *The Quarterly Journal of Economics*, 136(2):783–830.

Gourinchas, P.-O., Rey, H., and Sauzet, M., 2019. The international monetary and financial system. *Annual Review of Economics*, 11(1):859–893.

Hartmann, P., 2004. *Currency Competition and Foreign Exchange Markets*. Cambridge University Press.

Hasbrouck, J., 1991a. Measuring the information content of stock trades. *The Journal of Finance*, 46(1): 179–207.

Hasbrouck, J., 1991b. The summary informativeness of stock trades: An econometric analysis. *Review of Financial Studies*, 4(3):571–595.

Hasbrouck, J. and Levich, R. M., 2018. FX market metrics: New findings based on CLS bank settlement data. *SSRN Electronic Journal*.

Hasbrouck, J. and Levich, R. M., 2021. Network structure and pricing in the FX market. *Journal of Financial Economics*, 141(2):705–729.

Hassan, T. A., 2013. Country size, currency unions, and international asset returns. *The Journal of Finance*, 68(6):2269–2308.

Hautsch, N. and Huang, R., 2012. The market impact of a limit order. *Journal of Economic Dynamics and Control*, 36(4):501–522.

He, Z., Krishnamurthy, A., and Milbradt, K., 2019. A model of safe asset determination. *American Economic Review*, 109(4):1230–1262.

Hoffmann, P., 2014. A dynamic limit order market with fast and slow traders. *Journal of Financial Economics*, 113(1):156–169.

Huang, R. D. and Stoll, H. R., 1997. The components of the bid-ask spread: A general approach. *Review of Financial Studies*, 10(4):995–1034.

Ilzetzki, E., Reinhart, C. M., and Rogoff, K. S., 2019. Exchange arrangements entering the twenty-first century: Which anchor will hold? *The Quarterly Journal of Economics*, 134(2):599–646.

Ivashina, V., Scharfstein, D. S., and Stein, J. C., 2015. Dollar funding and the lending behavior of global banks. *The Quarterly Journal of Economics*, 130(3):1241–1281.

Jiang, Z., Krishnamurthy, A., and Lustig, H. N., 2019. Dollar safety and the global financial cycle. *SSRN Electronic Journal*.

Jiang, Z., Krishnamurthy, A., and Lustig, H., 2021. Foreign safe asset demand and the dollar exchange rate. *The Journal of Finance*, 76(3):1049–1089.

King, M. R., Osler, C., and Rime, D., 2012. *Foreign Exchange Market Structure, Players, and Evolution*. John Wiley & Sons, Inc.

Krugman, P. R., 1980. Vehicle currencies and the structure of international exchange. *Journal of Money, Credit and Banking*, 12(3):513–526.

Kyle, A. S., 1985. Continuous auctions and insider trading. *Econometrica*, 53(6):1315–1335.

Kyle, A. S., 1989. Informed speculation with imperfect competition. *The Review of Economic Studies*, 56 (3):317–355.

Kyle, A. S., Obizhaeva, A. A., and Wang, Y., 2017. Smooth trading with overconfidence and market power. *The Review of Economic Studies*, 85(1):611–662.

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

Lyons, R. K., 1997. A simultaneous trade model of the foreign exchange hot potato. *Journal of International Economics*, 42(3-4):275–298.

Lyons, R. K. and Moore, M. J., 2009. An information approach to international currencies. *Journal of International Economics*, 79(2):211–221.

Maggiori, M., 2017. Financial intermediation, international risk sharing, and reserve currencies. *American Economic Review*, 107(10):3038–3071.

Maggiori, M., Neiman, B., and Schreger, J., 2020. International currencies and capital allocation. *Journal of Political Economy*, 128(6):2019–2066.

Malamud, S. and Rostek, M., 2017. Decentralized exchange. *American Economic Review*, 107(11):3320–3362.

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

Matsuyama, K., Kiyotaki, N., and Matsui, A., 1993. Toward a theory of international currency. *The Review of Economic Studies*, 60(2):283–307.

Menkhoff, L., Sarno, L., Schmeling, M., and Schrimpf, A., 2016. Information flows in foreign exchange markets: Dissecting customer currency trades. *The Journal of Finance*, 71(2):601–634.

Moore, M., Schrimpf, A., and Sushko, V., 2016. Downsized FX markets: Causes and implications. *BIS Quarterly Review*.

Mukhin, D., 2021. An equilibrium model of the international price system. *American Economic Review*.

Newey, W. K. and West, K. D., 1994. Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies*, 61(4):631–653.

Payne, R., 2003. Informed trade in spot foreign exchange markets: an empirical investigation. *Journal of International Economics*, 61(2):307–329.

Portes, R. and Rey, H., 1998. The emergence of the euro as an international currency. *Unpublished working paper. NBER*.

Rahmouni-Rousseau, I. and Churm, R., 2018. Monitoring of fast-paced electronic markets. *BIS Markets Committee Report*.

Ranaldo, A., 2009. Segmentation and time-of-day patterns in foreign exchange markets. *Journal of Banking and Finance*, 33(12):2199–2206.

Ranaldo, A. and Santucci de Magistris, P., 2018. Trading volume, illiquidity, and commonalities in FX markets. *SSRN Electronic Journal*.

Ranaldo, A. and Somogyi, F., 2021. Asymmetric information risk in FX markets. *Journal of Financial Economics*, 140(2):391–411.

Rey, H., 2001. International trade and currency exchange. *The Review of Economic Studies*, 68(2):443–464.

Rime, D., Schrimpf, A., and Syrstad, O., 2021. Covered interest parity arbitrage. *Review of Financial Studies*.

Rostek, M. and Weretka, M., 2015. Dynamic thin markets. *Review of Financial Studies*, 28(10):2946–2992.

Rostek, M. J. and Yoon, J. H., 2021a. Exchange design and efficiency. *Econometrica*.

Rostek, M. J. and Yoon, J. H., 2021b. Equilibrium theory of financial markets: Recent developments. *Journal of Economic Literature*.

Roşu, I., 2009. A dynamic model of the limit order book. *Review of Financial Studies*, 22(11):4601–4641.

Schrimpf, A. and Sushko, V., 2019. FX trade execution: Complex and highly fragmented. *BIS Quarterly Review*.

Stoll, H. R., 1989. Inferring the components of the bid-ask spread: Theory and empirical tests. *The Journal of Finance*, 44(1):115–134.

Tauchen, G. E. and Pitts, M., 1983. The price variability-volume relationship on speculative markets. *Econometrica*, 51(2):485–505.

Tille, C., Mehl, A., Georgiadis, G., and Mezo, H. L., 2021. Fundamentals vs. policies: Can the US dollar's dominance in global trade be dented? *ECB Working Paper No. 2021/2574*.

Vayanos, D., 1999. Strategic trading and welfare in a dynamic market. *Review of Economic Studies*, 66 (2):219–254.

Vives, X., 2011. Strategic supply function competition with private information. *Econometrica*, 79(6): 1919–1966.

Wittwer, M., 2021. Connecting disconnected financial markets? *American Economic Journal: Microeconomics*, 13(1):252–282.

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:

$$max_{q_k^i(\cdot)} \delta \cdot (\mathbf{q}^{i,c} + \mathbf{q}_0^i) - \frac{\gamma^i}{2}(\mathbf{q}^{i,c} + \mathbf{q}_0^i) \cdot \mathbf{\Sigma}(\mathbf{q}^{i,c} + \mathbf{q}_0^i) - \mathbf{p} \cdot \mathbf{q}^{i,c}, \tag{A.1}$$

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. (A.1) 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

$$\underbrace{\delta_k - \gamma^i(\sigma_{k,k}(q_k^{i,c} + q_{0,k}^i) + \sum_{l \neq k} \sigma_{k,l}(q_l^{i,c} + q_{0,l}^i))}_{\text{Marginal utility}} = \underbrace{p_k + \frac{\partial p_k}{\partial q_k^{i,c}} q_k^{i,c} + \sum_{l \neq k} \frac{\partial p_l}{\partial q_k^{i,c}} q_l^{i,c}}_{\text{Marginal cost}}. \tag{A.2}$$

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:

$$\delta - \gamma^i \mathbf{\Sigma}(\mathbf{q}^{i,c} + \mathbf{q}_0^i) = \mathbf{p} + \mathbf{\Lambda}^{i,c} \mathbf{q}^{i,c}, \tag{A.3}$$

where $\mathbf{\Lambda}^{i,c} = \frac{\partial \mathbf{p}}{\partial \mathbf{q}_k^{i,c}}$ is a $K \times K$ Jacobian matrix characterising the price impact of trader i. The off-diagonal elements in $\mathbf{\Lambda}^{i,c}$ 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. (A.3) yields the

[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.

best-response demand of trader i:

$$\mathbf{q}^{i,c}(\mathbf{p}) = (\gamma^i \mathbf{\Sigma} + \mathbf{\Lambda}^{i,c})^{-1}(\delta - \mathbf{p} - \gamma^i \mathbf{\Sigma} \mathbf{q}_0^i), \tag{A.4}$$

given their price impact $\mathbf{\Lambda}^{i,c}$, 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 pointwise optimisation problem of trader i must be correct in equilibrium. Put differently, the price impact must 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. (A.4) for traders $j \neq i$ yields the residual supply function $\mathbf{S}^{-i,c}(\cdot)$ of trader i:

$$\mathbf{S}^{-i,c} = -\sum_{j \neq i} (\gamma^j \mathbf{\Sigma} + \mathbf{\Lambda}^{j,c})^{-1}(\delta - \gamma^j \mathbf{\Sigma} \mathbf{q}_0^j) + \sum_{j \neq i} (\gamma^i \mathbf{\Sigma} + \mathbf{\Lambda}^{j,c})^{-1} \mathbf{p}, \tag{A.5}$$

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

Theorem A1 (**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. (A.3), given their price impact $\mathbf{\Lambda}^{i,c}$;*
2. *(Correct price impact) The price impact of trader i equals the transpose of the Jacobian matrix of their inverse residual supply function:*

$$\mathbf{\Lambda}^{i,c} = ((\sum_{j \neq i} (\gamma^j \mathbf{\Sigma} + \mathbf{\Lambda}^{j,c})^{-1})^{-1})' \tag{A.6}$$

With contingent demands the fixed point for price impact matrices is defined by a system of I equations in Eq. (A.6) and can be solved in closed form: for each trader i

$$\mathbf{\Lambda}^{i,c} = \beta^{i,c} \gamma^i \mathbf{\Sigma}, \tag{A.7}$$

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:

$$\sum_j (\gamma_i b + 2 + \sqrt{(\gamma^j b)^2 + 4})^{-1} = 1/2. \tag{A.8}$$

For the case where risk aversions are symmetric, that is, $\gamma^i = \gamma$, $\forall i$ the price impact is simply proportional to fundamental risk: $\mathbf{\Lambda}^{i,c} = \frac{1}{I-2} \mathbf{\Sigma}$. As $I \to \infty$, then $\mathbf{\Lambda}^{i,c} \to 0$ 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., $\mathbf{\Lambda}^{i,c} > 0$), trader i demands (or sells) less than their competitive schedule.

Combining Eqs (A.4) and (A.7) yields the following expressions for demand coefficients $\mathbf{B}^c$, $\mathbf{C}^c$, and price impact $\mathbf{\Lambda}^c$, respectively:

$$\mathbf{B}^c = (\mathbf{\Sigma} + \mathbf{\Lambda}^c)^{-1}\mathbf{\Sigma} = \frac{I-2}{I-1} Id; \tag{A.9}$$

$$\mathbf{C}^c = (\mathbf{\Sigma} + \mathbf{\Lambda}^c)^{-1}; \tag{A.10}$$

$$\mathbf{\Lambda}^c = \frac{1}{I-2}\mathbf{\Sigma}, \tag{A.11}$$

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 $\mathbf{\Lambda}^c$ are independent of the *distribution* of traders' initial transaction demands, that is, σ_0^2 and $\mathbf{\Omega}$, respectively. What is more, in the contingent market, where $\mathbf{p} = \delta - \gamma \mathbf{\Sigma} \bar{\mathbf{q}}_0$, 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

$$\mathbf{q}^{i,c,*} = (\mathbf{\Sigma} + \mathbf{\Lambda}^c)^{-1}\mathbf{\Sigma}(E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i]). \tag{A.12}$$

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. (A.6)). 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 $s^{-i} \equiv -\sum_{j \neq i}(\gamma^j \mathbf{\Sigma} + \mathbf{\Lambda}^{j,c})^{-1}(\delta - \gamma^j \mathbf{\Sigma} \mathbf{q}_0^j)$) 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:

$$max_{q_k^i(\cdot)} E[\delta \cdot (\mathbf{q}^i + \mathbf{q}_0^i) - \frac{\gamma^i}{2}(\mathbf{q}^i + \mathbf{q}_0^i) \cdot \mathbf{\Sigma}(\mathbf{q}^i + \mathbf{q}_0^i) - \mathbf{p} \cdot \mathbf{q}^i | p_k, q_0^i], \tag{B.1}$$

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:

$$\delta_k - \gamma^i \mathbf{\Sigma}_n \mathbf{q}_{0,l}^i - \gamma^i \mathbf{\Sigma}_n \underbrace{E[\mathbf{q}^i | \mathbf{p}_n, \mathbf{q}_0^i]}_{\substack{\text{Expected trade of} \\ \text{currency pairs } l}} = \mathbf{p}_n + \underbrace{\mathbf{\Lambda}_n^i}_{\substack{\text{Zero cross-exchange} \\ \text{price impact}}} \mathbf{q}_n^i, \tag{B.2}$$

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: $\lambda_{k,l}^i \equiv \frac{\partial p_k}{\partial q_k^i} = 0$ 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:

$$\Lambda^i \equiv \frac{\partial p_l}{\partial q_k^i} = diag(\lambda_k^i). \tag{B.3}$$

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 $E[q_l^i | p_k, q_0^i]$ depends on the functional form of $q_l^i(\cdot)$. 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 $E[q_l^i | p_k, q_0^i]$ (step 1);

[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.

2. replace p_k as a contingent variable by trader i's residual supply intercept s_k^{-i} (step 2).

The chief advantage of *step 2* is that unlike the distribution of p_k, that of s_k^{-i} 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 $\mathbf{q}_0^i$:

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

where a_l^i is the demand intercept, $\mathbf{b}_l^i \mathbf{q}_0^i$ the demand coefficients, and c_l^i 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_k^{-i} 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 $q_k^i(\cdot)$ 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 γ. In order to derive the optimal exchange rates and quantities, I apply market clearing conditions to the best response schedules $q_k^{j\neq i}$ for each k:

$$S_k^{-i}(p_k) = -\sum_{j\neq i}(a_k^j - \mathbf{b}_k^j \mathbf{q}_0^j) + \sum_{j\neq i} c_k^j p_k = s_k^{-i} + \frac{p_k}{(\lambda_k^i)}, \tag{B.5}$$

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 $\mathbf{C}^i = diag(c_k^i)$:

$$\mathbf{p}^* = (\sum_i a^i - \sum_i B^i q_0^i) \cdot (\sum_i C^i)^{-1}. \tag{B.6}$$

Theorem B2 (**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:*

$$\mathbf{a}^i = \underbrace{\mathbf{C}(\delta - (\gamma\mathbf{\Sigma} - \mathbf{C}^{-1}\boldsymbol{B})E[\bar{\mathbf{q}}_0]))}_{=\mathbf{p}-\mathbf{C}^{-1}\mathbf{B}\bar{\mathbf{q}}_0} + \underbrace{((\gamma\mathbf{\Sigma} + \mathbf{\Lambda})^{-1}\gamma\mathbf{\Sigma} - \mathbf{B})(E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i])}_{\textit{Adjustment due to cross-asset inference}}; \tag{B.7}$$

$$\mathbf{B} = \Big((1-\sigma_0^2)(\gamma\boldsymbol{\Sigma}+\boldsymbol{\Lambda}) + \underbrace{\mathbf{C}^{-1}\sigma_0^2}_{\substack{\textit{Adjustment due to}\\ \textit{cross-asset inference}}}\Big)^{-1}\gamma\boldsymbol{\Sigma}; \tag{B.8}$$

$$\mathbf{C} = \Big[(\boldsymbol{\Sigma}+\boldsymbol{\Lambda})\underbrace{(\mathbf{B}\boldsymbol{\Omega}\mathbf{B}')[\mathbf{B}\boldsymbol{\Omega}\mathbf{B}']_d^{-1}}_{\textit{Inference coefficient}}\Big]_d^{-1}, \tag{B.9}$$

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* $\boldsymbol{\Lambda}$ *is characterised by the slope of the inverse residual supply function:*

$$\boldsymbol{\Lambda} = \frac{1}{I-1}\mathbf{C}^{-1} = \frac{1}{I-2}\Big[\boldsymbol{\Sigma}\underbrace{(\mathbf{B}\boldsymbol{\Omega}\mathbf{B}')\,[\mathbf{B}\boldsymbol{\Omega}\mathbf{B}']_d^{-1}}_{\textit{Inference coefficient}}\Big]_d, \tag{B.10}$$

where $\boldsymbol{\Lambda}$ *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 B2 and plugging the demand intercept $\mathbf{a}^i$ into Eq. (B.6) yields the equilibrium exchange rate:

$$\mathbf{p}^* = \Big(\sum_i \mathbf{C}(\delta - (\gamma\boldsymbol{\Sigma} - (\mathbf{C}^i)^{-1}\mathbf{B}^i)E[\bar{\mathbf{q}}_0])) - \sum_i \mathbf{B}^i q_0^i\Big)\cdot(\sum_i C^i)^{-1} \tag{B.11}$$

$$\mathbf{p}^* = \Big(\delta - (\gamma\boldsymbol{\Sigma} - (\mathbf{C})^{-1}\mathbf{B})E[\bar{\mathbf{q}}_0]\Big) - \mathbf{C}^{-1}\mathbf{B}\bar{\mathbf{q}}_0 \tag{B.12}$$

Notice that $\sum_i \mathbf{a}^i = \sum_i \mathbf{C}(\delta - (\gamma\boldsymbol{\Sigma} - \mathbf{C}^{-1}\mathbf{B})E[\bar{\mathbf{q}}_0]))$, since $((\gamma\boldsymbol{\Sigma}+\boldsymbol{\Lambda})^{-1}\gamma\boldsymbol{\Sigma} - \mathbf{B})\sum_i(E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i])$ 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 $\boldsymbol{\Sigma}$. 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. (B.4) yields the equilibrium quantity: for every i,

$$\mathbf{q}^{i,*} = ((\boldsymbol{\Sigma}+\boldsymbol{\Lambda})^{-1}\boldsymbol{\Sigma} - \mathbf{B})(E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i]) + \mathbf{B}(\bar{\mathbf{q}}_0 - \mathbf{q}_0^i), \tag{B.13}$$

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

$$\mathbf{q}^{i,*} + \mathbf{q}_0^i = ((\boldsymbol{\Sigma}+\boldsymbol{\Lambda})^{-1}\boldsymbol{\Sigma} - \mathbf{B})(E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i]) + \mathbf{B}\bar{\mathbf{q}}_0 + (Id - \mathbf{B})\mathbf{q}_0^i, \tag{B.14}$$

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 B.1 depicts the simulated comparative statics of equilibrium trading volume $\mathbf{q}^{i,*}$ with respect to the risk aversion coefficient γ, 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]

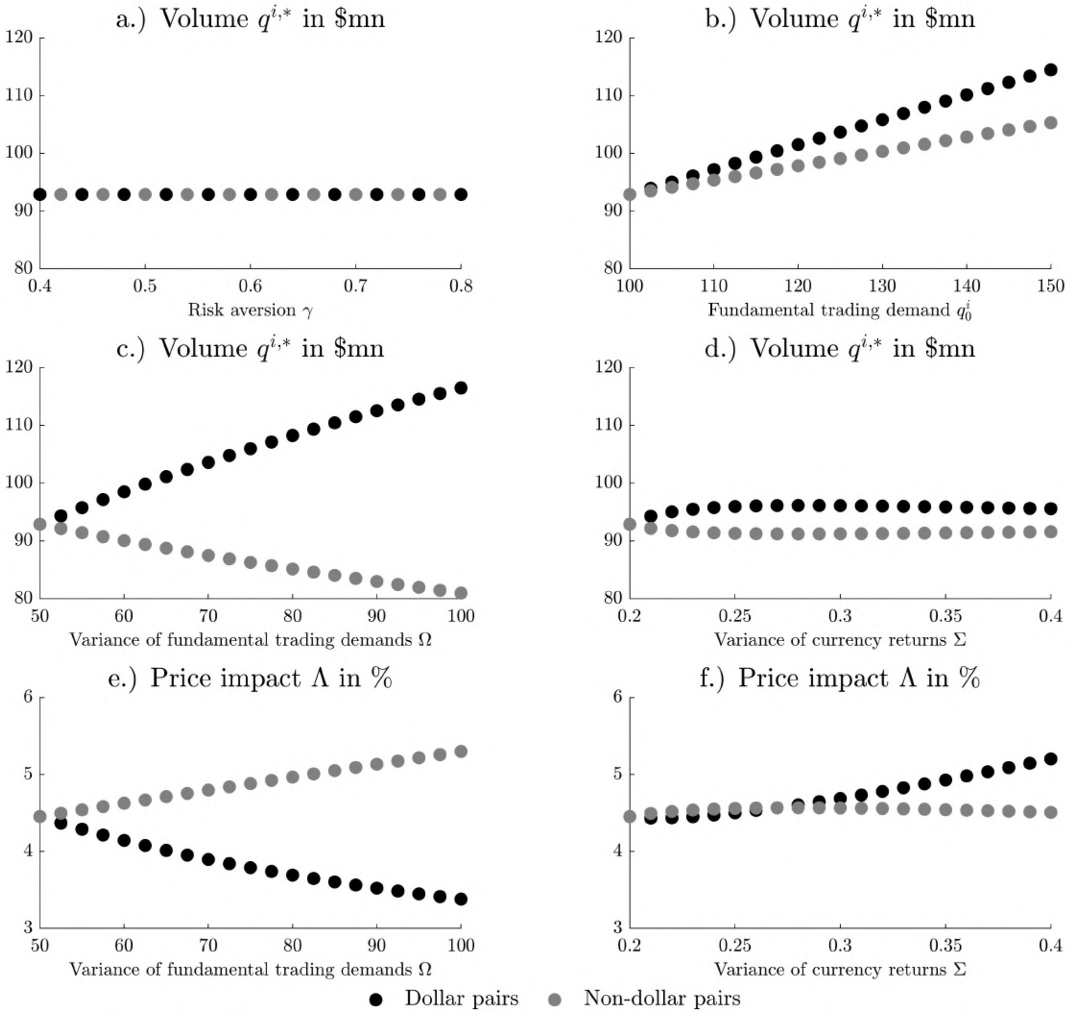
There are four key takeaways from Figure B.1: First, following subfigure a.), the optimal traded quantity in each currency pair is independent of risk aversion γ. This is because the equilibrium volume is a combination of fundamental trading demands and the covariance matrix of currency returns with weights that do not depend on risk aversion.

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

[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 B.1: 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 γ, initial trading demand in dollar pairs $q^i_{0,\$}$, 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.

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 $(\mathbf{B}\mathbf{\Omega}\mathbf{B}')\left[\mathbf{B}\mathbf{\Omega}\mathbf{B}'\right]_d^{-1}$ 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.

[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.

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.*

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* $(\mathbf{B\Omega B}')\left[\mathbf{B\Omega B}'\right]_d^{-1}$ *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* $(\mathbf{B\Omega B}')\left[\mathbf{B\Omega B}'\right]_d^{-1}$ *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-

[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."

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.

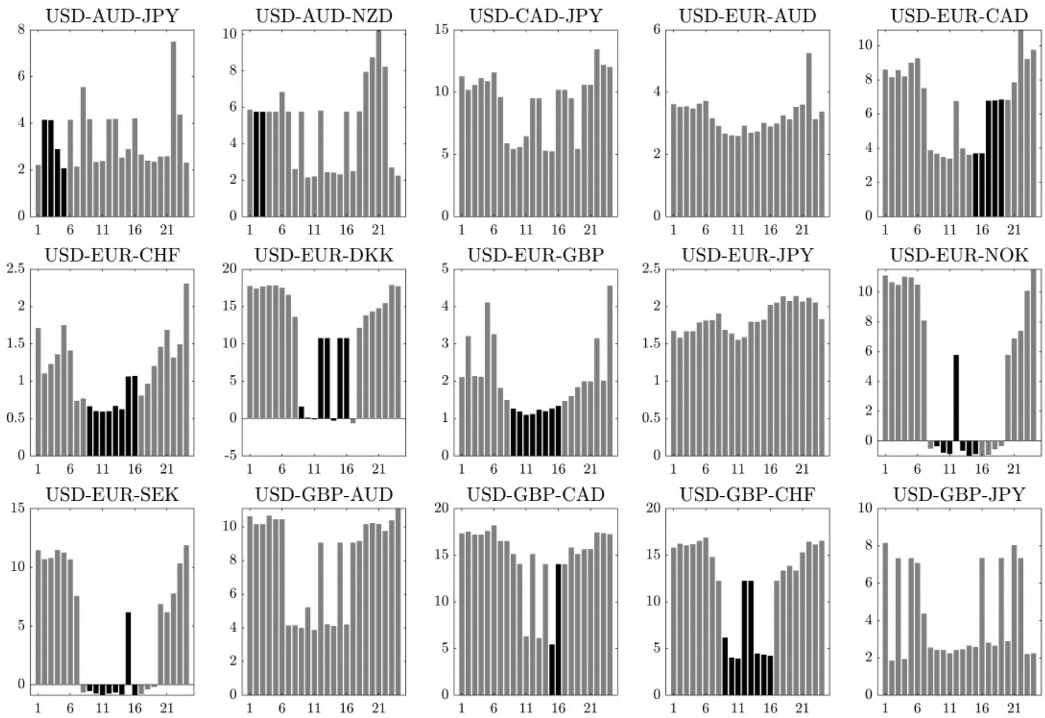
Appendix D. Additional Empirical Results

Table D.1: 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]

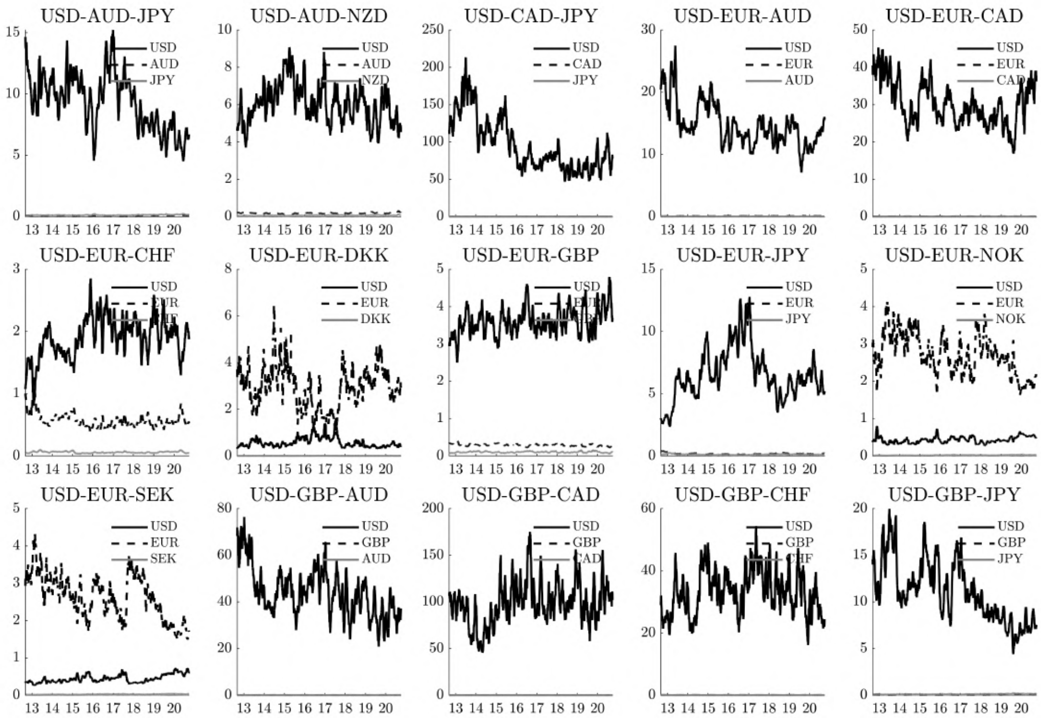
Note: This table summarises the empirical counterparts of the equilibrium conditions in Theorem 2 for 15 triplets of currency pairs. A triplet is defined as one non-dollar currency pair (e.g., GBPJPY as shown at the beginning of each row) plus the two USD legs (e.g., USDGBP and USDJPY). The first bar named *DD* refers to my empirical measure of dollar dominance, whereas the next three columns labelled *C*1, *C*2, and *C*3 each correspond to one of the three conditions (in logs). The last column reports the difference between the columns labelled *DD* and *C*1. 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 D.1: Intraday Variation of Dollar Dominance



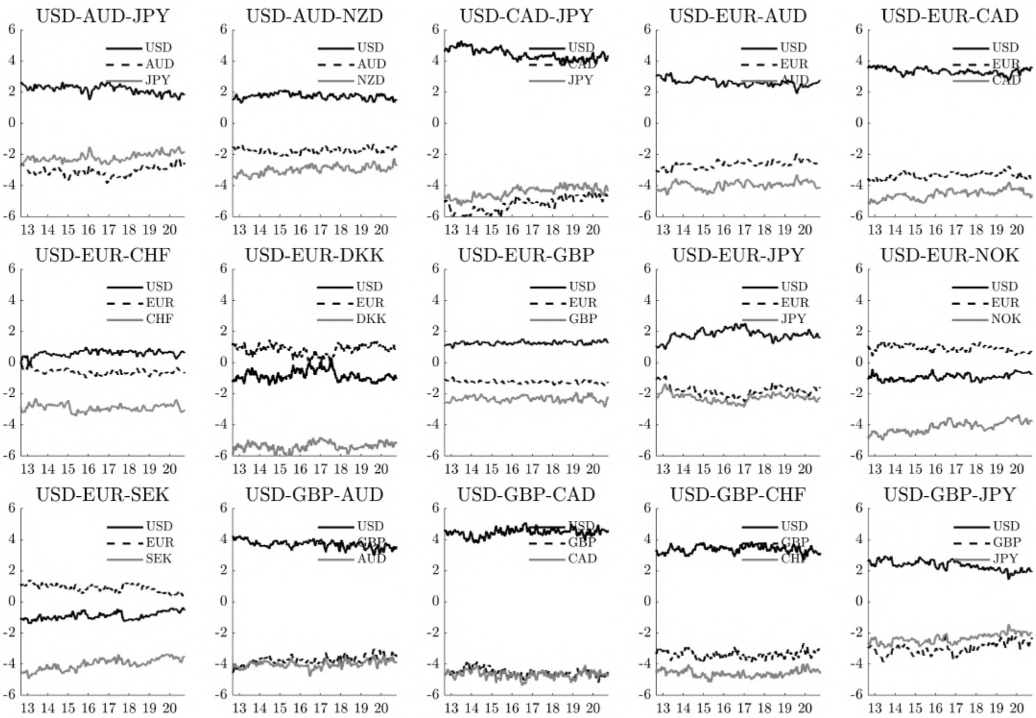
Note: This figure shows the intraday variation of log dollar dominance (i.e., $log(doldom)_{j,t}$) for 15 triplets of currency pairs. Dollar dominance is defined as the ratio of the minimum inter-dealer trading volume in dollar pairs (e.g., USDGBP and USDJPY) relative to the direct trading volume in 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 D.2: Time-variation of Dollar Dominance in Volume (levels)



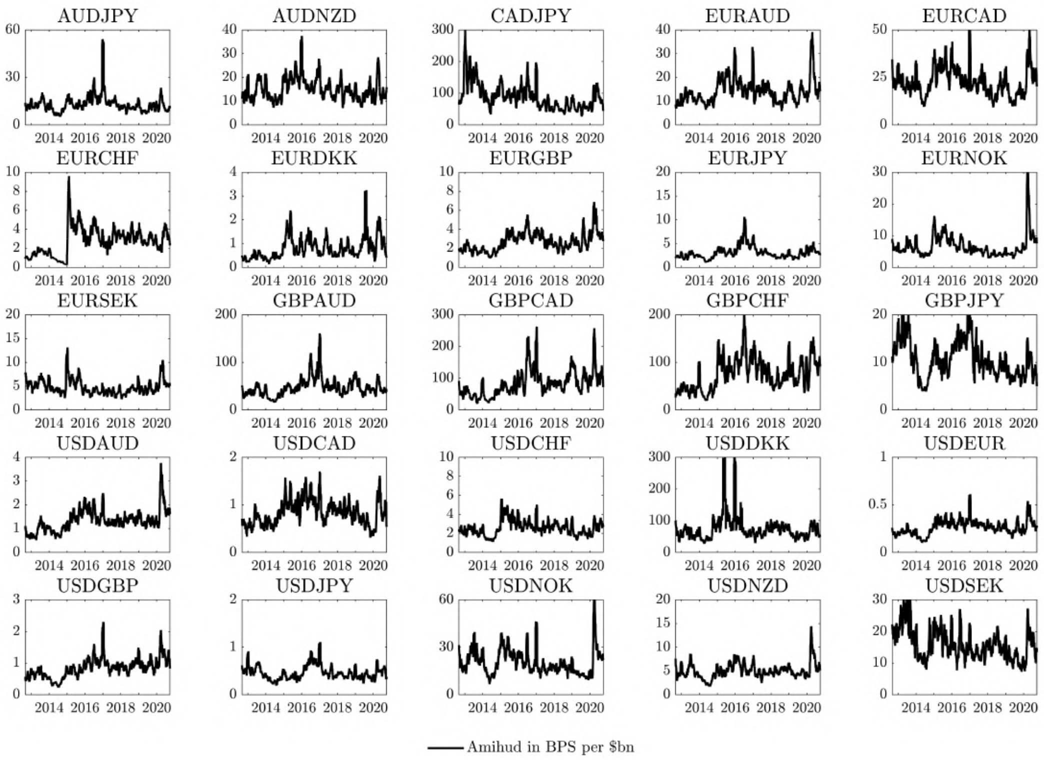
Note: This figure shows the time-variation of dominance scores based on trading volume for the US dollar (i.e., $doldom_{j,t}$, solid black lines) as well as two other non-dollar currencies (dashed black and solid grey lines) within each of the 15 triplets of currency pairs. Dollar dominance in trading 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 D.3: Time-variation of Dollar Dominance in Volume (logs)



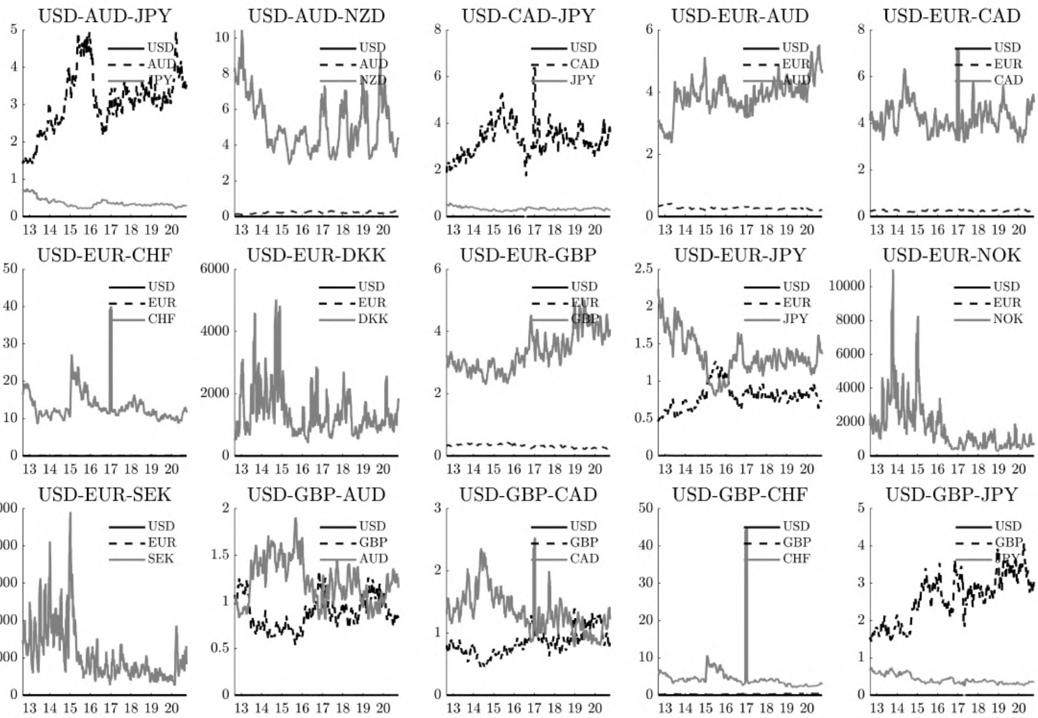
Note: This figure shows the time-variation of log dominance scores based on trading volume for the US dollar (i.e., $log(doldom)_{j,t}$, solid black lines) as well as two other non-dollar currencies (dashed black and solid grey lines) within each of the 15 triplets of currency pairs. Dollar dominance 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 D.4: Time-variation of Amihud Price Impact



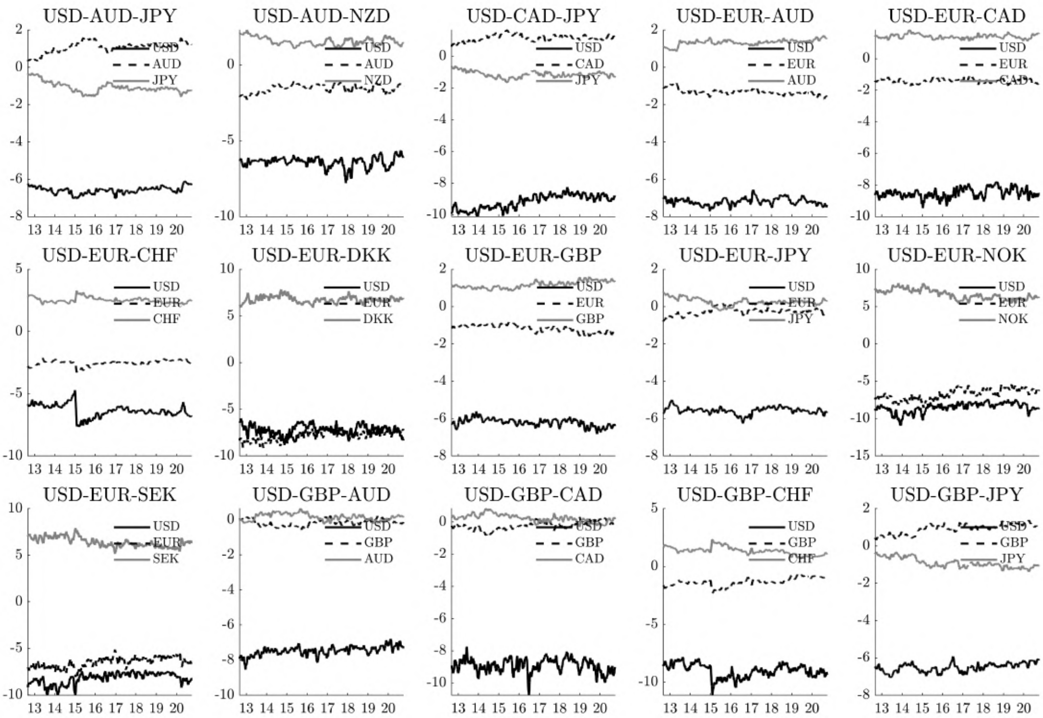
Note: This figure shows the time-variation of Amihud's (2002) price impact measure for 15 triplets of currency pairs. Following Ranaldo and Santucci de Magistris (2018), I estimate Amihud in BPS per $bn as the ratio between intraday realised volatility and aggregate daily trading volume. The plotted 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 D.5: 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 D.6: 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 D.2: Dollar Dominance and Equilibrium Conditions (De-seasonalised)

	$\text{doldom}_{j,t}$						$\text{amihud}_{j,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{C1}_{j,t}$	***0.39			***0.39		***0.53			
	[34.27]			[33.99]		[21.16]			
$\text{C2}_{j,t}$		***0.30			***0.29	***0.30	***−0.04		***−0.04
		[33.89]			[33.54]	[30.73]	[5.15]		[4.98]
$\text{C3}_{j,t}$			***0.04		***0.03	***0.03		***0.07	***0.07
			[5.07]		[3.49]	[3.20]		[6.07]	[5.75]
$\text{bid-ask spread}_{j,t}$				***−0.06	***−0.09	***−0.05			0.02
				[4.59]	[6.59]	[3.50]			[0.96]
$\text{cip-basis}_{j,t}$						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 μ_t and α_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. $bid\text{-}ask\ spread_{j,t}$ 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.

Table D.3: Dollar Dominance and Equilibrium Conditions (De-trended)

	$\text{doldom}_{\text{j,t}}$						$\text{amihud}_{\text{j,t}}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{C1}_{\text{j,t}}$	***0.46			***0.45		***0.60			
	[36.21]			[35.96]		[21.47]			
$\text{C2}_{\text{j,t}}$		***0.35			***0.35	***0.36	***−0.04		***−0.05
		[35.57]			[35.44]	[32.97]	[4.76]		[4.66]
$\text{C3}_{\text{j,t}}$			***0.06		***0.04	***0.04		***0.09	***0.09
			[5.29]		[3.80]	[3.40]		[6.83]	[6.51]
$\text{bid-ask spread}_{\text{j,t}}$				***−0.06	***−0.09	***−0.04			0.02
				[3.97]	[5.81]	[2.72]			[0.73]
$\text{cip-basis}_{\text{j,t}}$						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 μ_t and α_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:

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

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 setup 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.

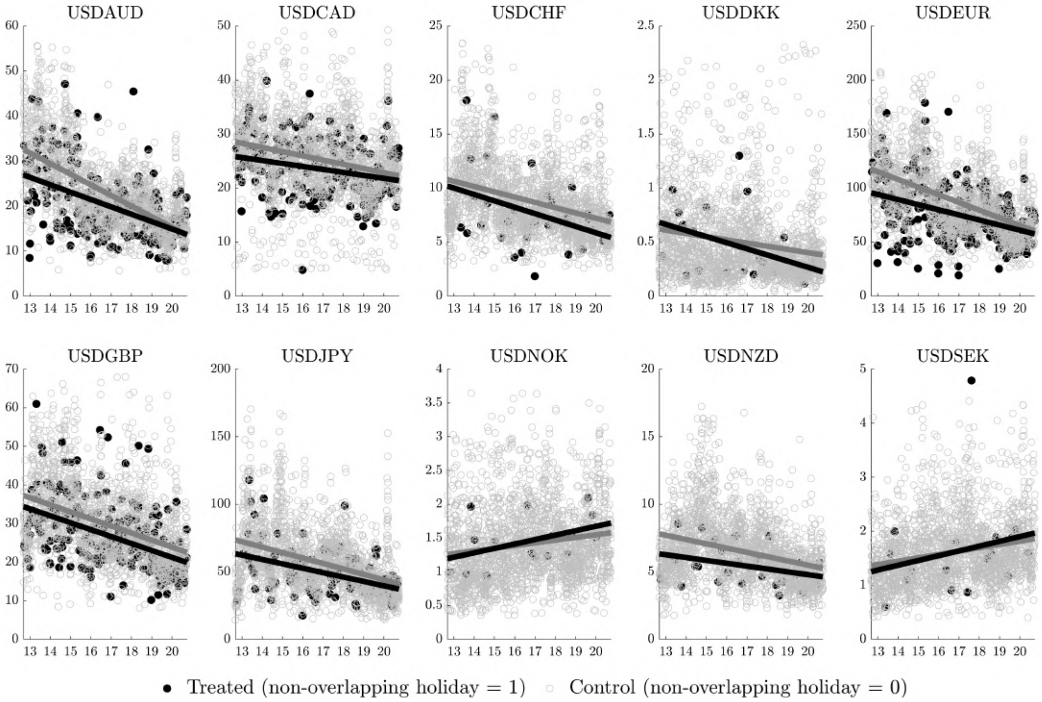
In Table D.4, I compare the results from estimating Eq. (12) with ordinary least squares (OLS) and two-stage least squares (2SLS), respectively. Panel A presents the OLS estimates, while Panel B shows the first and second stage results of the IV regression. There are three key takeaways: First, the relevance 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 D.4: Dollar Dominance and Equilibrium Conditions

	$\text{doldom}_{j,t}$						$\text{amihud}_{j,t}$		
Panel A: OLS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{C1}_{j,t}$	***0.45			***0.45		***0.56			
	[33.80]			[33.81]		[18.29]			
$\text{C2}_{j,t}$		***0.12			***0.12	***0.12	***−0.04		***−0.05
		[35.85]			[35.66]	[33.44]	[6.15]		[6.47]
$\text{C3}_{j,t}$			***0.12		***0.09	***0.08		***0.25	***0.24
			[9.29]		[7.60]	[6.24]		[7.88]	[6.86]
$\text{bid-ask spread}_{j,t}$				0.03	***−0.09	−0.02			**0.20
				[0.98]	[3.42]	[0.69]			[2.56]
$\text{cip-basis}_{j,t}$						***0.01			***0.02
						[6.02]			[3.98]
$\text{S\&P 500}_t$						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)
$\text{C1}_{j,t}$	***0.51			***0.51		*0.36			
	[8.29]			[8.26]		[1.88]			
$\text{C2}_{j,t}$		***0.22			***0.22	***0.18	*−0.06		**−0.10
		[11.92]			[11.43]	[7.90]	[1.75]		[2.25]
$\text{C3}_{j,t}$			***0.18		***0.13	***0.09		***0.34	***0.21
			[4.73]		[3.98]	[2.70]		[5.09]	[2.61]
$\text{bid-ask spread}_{j,t}$				−0.04	***−0.14	***−0.11			***0.30
				[1.38]	[4.23]	[3.38]			[3.62]
$\text{cip-basis}_{j,t}$						***0.02			***0.02
						[8.26]			[3.99]
$\text{S\&P 500}_t$						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 α_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. $bid\text{-}ask\,spread_{j,t}$ 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. 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 D.7: 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.

References: Online Appendix

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

Cragg, J. G. and Donald, S. G., 1993. Testing identifiability and specification in instrumental variable models. *Econometric Theory*, 9(2):222–240.

Driscoll, J. C. and Kraay, A. C., 1998. Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, 80(4):549–560.

Du, W., Tepper, A., and Verdelhan, A., 2018. Deviations from covered interest rate parity. *The Journal of Finance*, 73(3):915–957.

Gabaix, X. and Koijen, R. S. J., 2020. Granular instrumental variables. *SSRN Electronic Journal*.

Klemperer, P. D. and Meyer, M. A., 1989. Supply function equilibria in oligopoly under uncertainty. *Econometrica*, 57(6):1243–1277.

Kyle, A. S., 1989. Informed speculation with imperfect competition. *The Review of Economic Studies*, 56 (3):317–355.

Malamud, S. and Rostek, M., 2017. Decentralized exchange. *American Economic Review*, 107(11):3320–3362.

Newey, W. K. and West, K. D., 1994. Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies*, 61(4):631–653.

Ranaldo, A. and Santucci de Magistris, P., 2018. Trading volume, illiquidity, and commonalities in FX markets. *SSRN Electronic Journal*.

Rostek, M. and Weretka, M., 2015. Dynamic thin markets. *Review of Financial Studies*, 28(10):2946–2992.

Rostek, M. J. and Yoon, J. H., 2021. Exchange design and efficiency. *Econometrica*.

Staiger, D. and Stock, J. H., 1997. Instrumental variables regression with weak instruments. *Econometrica*, 65(3):557.

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