Dollar Dominance in FX Trading*

Fabricius Somogyi†

This version: August 16, 2021

JOB MARKET PAPER

Working paper and subject to change.

Abstract

More than 85% of all foreign exchange (FX) transactions have the US dollar on one side. I show that the US dollar dominates FX trading volume because of strategic avoidance of price impact. To demonstrate this, I exploit that non-dollar currency pairs can be traded indirectly by using the US dollar as an intermediate 'vehicle' currency. I present a model of FX trading that embraces this idea and derive a set of sufficient conditions for dollar dominance. I then empirically test these conditions using a granular FX trade data set and provide evidence that is consistent with my model. To establish causality, I show that dollar dominance increases by 7% after quasi-exogenous spikes in the liquidity of dollar currency pairs occurring on days with scheduled US monetary policy announcements.

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

Keywords: Dollar dominance, Foreign exchange, Price impact, Strategic complementarity, Trading volume

---

*I am especially grateful to Darrell Duffie, Angelo Ranaldo, and Paul Söderlind as well as Georgia Bush (discussant), Jens Christensen, Lauren Cohen, Egemen Eren (discussant), Nils Friewald, Ben Hébert, Bob Hodrick, Arvind Krishnamurthy, Ji Yong Lee (discussant), Yeonjeong Lee (discussant), Hanno Lustig, Matteo Maggiori, Albert Menkveld (discussant), Vitaly Orlov, Christopher Polk, Vesa Pursiainen, Marzena Rostek, Jonas Schirm, Andreas Schrimpf, Jonathan Wallen, and Matthias Weber for providing constructive comments and suggestions while working on this project. I also thank seminar and conference participants at Stanford University, University of St.Gallen, Inter Finance PhD Seminar, 33rd Australasian Finance and Banking Conference, 2021 SWFA Meetings, Imperial College London, 37th International Conference of the French Finance Association, 2021 IBEFA Summer Meetings, 33rd Asian Finance Conference, 2021 Oxford-ETH Macro-finance Conference, 2021 World Finance Conference, and 2nd PhD Student Symposium at the University of Texas at Austin. Scheduled presentations include the Bank for International Settlements, 2021 DGF Meetings and Doctoral Workshop, 2021 FMA Meetings, 2021 SFA Meetings, and 2022 AFA Meetings in Boston. I acknowledge financial support from the Swiss National Science Foundation (SNSF grant 195095). Parts of this paper were written while I visited the Stanford Graduate School of Business whose hospitality is gratefully acknowledged. All errors are my own.

†University of St.Gallen, Switzerland. E-mail: fabricius.somogyi@unisg.ch.

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. More than 85% of all FX trades have the US dollar on one side. On the contrary, the United States (US) accounts for less than one quarter of global economic activity. From an economist and policy maker perspective the conspicuous dominance of the US dollar in FX trading raises the following question: what conditions need to be satisfied for a currency, say the US dollar, to dominate FX trading volume?

I show both theoretically and empirically that the US dollar dominates because participants in the FX market strategically avoid to *directly* transact in non-dollar currency pairs due to the larger expected price impact.[1] To demonstrate this, I exploit the fact that non-dollar currency pairs can be exchanged *indirectly* by using the US dollar as an intermediate 'vehicle' currency. That is, market participants first exchange into US dollars, and then trade US dollars for their target currency. I show theoretically that if the fundamental demand in dollar pairs is sufficiently large and the volatility of dollar exchange rates is sufficiently low, then US dollar pairs enjoy a lower expected price impact that leads them to dominate FX trading volume. To validate these conditions empirically, I use a granular FX trade data set and provide evidence that is consistent with the predictions of my theoretical framework.

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 generates both benefits and threats to the world economy.[2] Potential benefits stem from economies of scale and network effects that can reduce trading costs in dollar pairs which in turn facilitates international trade and investment. However, the 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 policy makers. Central banks and governments may strengthen the importance of their own currency by influencing these conditions through monetary policy. The motivation to do so comes directly from the fact that dollar dominance in FX trading volume implies that the hegemon, currently the US, enjoys lower transaction costs than the rest of the world.

The contribution of this paper is both theoretical and empirical. On the theory side, I introduce a market (micro)structure view of currency dominance in FX trading volume. Specifically, I identify strategic price impact avoidance as a novel economic channel through which a currency can become dominant. My model incorporates this intuition and provides a set of sufficient conditions for dollar dominance. These conditions can also predict which non-dollar currency pairs are more likely to trade indirectly via the US dollar. On the empirical side, I make two key contributions: First, I provide evidence of consistency between the model–based sufficient conditions and the observed dollar dominance in the data. Second,

[1] Note that the inverse of price impact is a common measure of market liquidity: the lower the expected price impact, the smaller the price concession a trader must accept and hence the more liquid the market.

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

I establish a causal link between the model–based drivers of trading volume in US dollar pairs and my empirical measure of dollar dominance. For identification, I exploit that dollar dominance increases by 7% after quasi-exogenous spikes in the liquidity of US dollar currency pairs occurring on days with scheduled US monetary policy announcements.

This paper proceeds in two parts. In the first part, I develop a model of FX trading that is mainly inspired by the work of Rostek and Yoon (2020). In general, my modelling approach reflects the key features of the FX market, which is a decentralised over-the-counter (OTC) market that is organised via a network of limit order books. The model assumes a finite number of currency pairs, trading venues, and strategic traders who submit a package of limit orders to each venue. The objective of each trader is to maximise her quadratic mean-variance utility subject to the conjectured order submission strategies of all other traders. The trading game is static and only has one period. At the beginning of the period, each trader learns her initial trading demand in every currency pair. One can think of these trading demands as a trader's fundamental demand in a particular currency pair, for example, the need to exchange euros for Japanese yen. Eventually, the trader decides how to satisfy her fundamental trading demand. That is, whether to directly exchange euros to Japanese yen or to first convert euros to US dollars and then exchange US dollars to Japanese yen.

In equilibrium, the optimal traded quantity for a representative trader is decreasing in the expected price impact. Specifically, the equilibrium quantity is a function of three primitives: fundamental trading demand, variance of fundamental trading demands, and the volatility of currency returns. Using comparative statics analysis, I show that the optimal quantity is increasing in the mean and variance of fundamental trading demands. An increase in the variance of currency returns has an ambiguous effect on the equilibrium quantity. Underlying this ambiguity is the assumption that the FX market is decentralised and hence lacks coordination in market clearing among traders and venues. However, if the increase in the volatility of currency returns is sufficiently large, then this boosts the expected price impact and thereby lowers the optimally traded quantity.

Equipped with the intuition from the comparative statics, I derive a set of sufficient conditions for dollar dominance that I define as follows: A triplet of currency pairs is dominated by the US dollar if trading volume in dollar currency pairs exceed trading volume in currency pairs involving any other non-dollar currency 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 hold with equality: 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 pairs.

The economic intuition for these three conditions is as follows: The first condition emerges because fundamental trading demand has no direct effect on expected price impact but linearly increases the equilibrium trading volume. The second condition arises since in a decentralised market model the expected price impact is decreasing in the variance of fundamental trading demands. The last condition stems from the fact that expected price impact is concave in the variance of currency returns due to the Gaussian mean-variance setting. Perhaps surprisingly, these conditions imply that even a symmetric market with identical initial trading demand across currency pairs is prone to dollar dominance if dollar currency pairs exhibit either more variability in trading demands or less volatile currency returns.

In the second part of the paper, I test 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 for academic research on intraday FX rates.

The key empirical challenge for testing the model's predictions is to identify a suitable proxy for fundamental trading demand that is not directly observable. By construction, the CLS order flow data only comprises transactions between customers and FX dealer banks but excludes any trades between two dealers. This allows me to use customer flows as a proxy for dealer banks' fundamental trading demands. The identifying assumption is that bank trading is mainly driven by customer flows rather than proprietary bank trading demands. This is reasonable given that the sample covers the post-financial crisis period, which is characterised by an exodus of proprietary trading across all major FX dealer banks.[3]

The empirical evidence is presented in four parts. First, I use panel regressions with fixed effects to test whether the model–based drivers of trading volume are also economically relevant. Consistent with the comparative statics of the model, I find that trading volume significantly increases with larger and more volatile fundamental trading demands and currency returns, respectively. For instance, a one percentage point change in fundamental trading demand translates into a 0.57 percentage point increase in trading volume. Furthermore, I perform a simple variance decomposition to show that trading volume is not only driven by the level of fundamental trading demand. Changes in the variance of fundamental trading demands and currency returns account for 12% and 4%, respectively, of the variation in FX trading volume, whereas fundamental trading demand explains around 22%.

Second, I find strong evidence that all three model–based sufficient conditions are jointly satisfied for 8 out of 15 triplets of currency pairs in my sample. The seven notable exceptions fall into two categories: i) only the first two conditions based on the mean and variance of fundamental trading demands are satisfied (e.g., USD-AUD-NZD or USD-EUR-GBP); and ii) none of the three conditions is satisfied (e.g., USD-EUR-NOK or USD-EUR-SEK). In line with my model, I find that the corresponding triplets of currency pairs in the former category are dominated by the US dollar (USD) in terms of trading volume, whereas the ones in the latter are dominated by the euro (EUR).

Third, I examine if the cross-sectional variation in dollar dominance can be explained by a simple gravity model of exchange rates (Lustig and Richmond, 2019). I show that the im-

[3]The reduction in proprietary trading activities in the FX spot market is driven by two factors: First, post-crisis regulation has shifted the scope of banks' business models from proprietary trading to market-making (Moore, Schrimpf, and Sushko, 2016). Second, even if spot FX is excluded from the Volcker Rule it is indirectly affected by the consequences that regulation has on FX derivatives (e.g., forwards and swaps).

portance of the US dollar as a vehicle currency is increasing in measures of distance between two non-dollar countries. The gravity variables that explain the cross-sectional dispersion in dollar dominance are not only physical distance but also shared border and shared legal origin. Doubling the distance between two non-dollar countries increases dollar dominance on average by 8.7%. However, a shared border or legal origin significantly lowers the effect of physical distance. The explanatory power of these gravity variables is fairly high and amounts to almost one fifth of the cross-sectional variation in dollar dominance.

Lastly, I test if the time-variation in dollar dominance can be explained by the three model-based determinants. Within every triplet of currency pairs, I define dollar dominance as the ratio of indirect trading volume in dollar pairs relative to the direct trading volume in non-dollar pairs. Note that my empirical measure of dollar dominance is consistent with the one in my model. To address endogeneity issues, I use an instrumental variable approach to estimate the causal impact of each model-based primitive on my empirical measure of dollar dominance. For identification, I exploit the exogenous variation in the liquidity of dollar currency pairs associated with *scheduled* US monetary policy announcements (FOMC). I argue that FOMC announcement days satisfy the exclusionary restriction since they resolve uncertainty, which fosters FX trading activity (e.g., Chaboud, Chernenko, and Wright, 2008; Fischer and Ranaldo, 2011), whereas high FX trading volume does not cause scheduled FOMC meetings. Given this assumption, I show that the impact of FOMC announcements is significant along both the extensive and intensive margin. On average, dollar dominance is about 7% higher on days with FOMC meetings than on all other days. The local average treatment effect of a one percentage point increase of fundamental trading demand in US dollar pairs on dollar dominance is 1.6 percentage points. Moreover, I use FOMC days to instrument the variance of fundamental trading demands in dollar currency pairs as well as the variance of US dollar exchange rate returns. In line with the vehicle currency channel, I find that an increase in either of the two measures induces a significant surge in dollar dominance.

To summarise, my paper makes two key contributions: First, I present a simple model of FX trading that demonstrates how strategic price impact avoidance can lead to dollar dominance in FX transaction volume. Second, I take my model to the data and provide empirical evidence that corroborates the economic intuition of my theoretical framework.

Related literature. This paper contributes to at least three strands of literature. First, I add to the monetary economics literature on vehicle currency trading. My main contribution is to derive explicit sufficient conditions for dollar dominance in FX trading volume. Methodologically, my model subsumes the market-size (e.g., Krugman, 1980; Rey, 2001; Devereux and Shi, 2013), risk-aversion (e.g., Black, 1991; Hartmann, 2004), and (asymmetric) information (i.e., Lyons and Moore, 2009) driven approaches to international currencies. As a result, FX trading volume in my model is a function of both fundamental and vehicle currency trading demand for a currency. Hence, the equilibrium in my model 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 the scarcity of data. I fill this gap by employing a variety of different empirical tools 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[4] 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 price impact avoidance in thinly traded non-dollar currency pairs that favours the use of the US dollar as a vehicle currency. Current explanations can be classified into three categories. First is the "trade view", arguing that the reason for dollar dominance is trade invoicing in dollars (e.g., Portes and Rey, 1998; Goldberg and Tille, 2008; Gopinath and Stein, 2020). Second is the "safe asset view", wherein in the dollar dominance arises due to its safe haven properties (e.g., Hassan, 2013; Maggiori, 2017; Farhi and Maggiori, 2017; He et al., 2019; Jiang, Krishnamurthy, and Lustig, 2021) and the growing demand for safe assets (e.g., Caballero et al., 2008; Caballero, Farhi, and Gourinchas, 2017, 2021). Third is the "debt view" of dollar dominance that emphasises the role of debt currency denomination of firms and global bond portfolios (e.g., Maggiori, Neiman, and Schreger, 2020; Eren and Malamud, 2021), respectively.

Third, I expand on the literature on FX volume by providing both theoretical and empirical underpinning for the determinants of trading volume. 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 much focused on the inter-dealer segment, which is dominated by two platforms, namely Reuters (e.g., Evans, 2002; Payne, 2003) and EBS (e.g., Chaboud et al., 2008; Mancini, Ranaldo, and Wrampelmeyer, 2013). Alternative sources of spot FX trading volume are proprietary data sets from specific bank holding companies (e.g., Bjønnes and Rime, 2005; Menkhoff, Sarno, Schmeling, and Schrimpf, 2016) or central banks. The 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.[5] Hasbrouck and Levich (2018) and Ranaldo and Santucci de Magistris (2018) use CLS data to study commonality in FX volatility and trading volume, whereas Cespa, Gargano, Riddiough, and Sarno (2021) introduce a novel trading strategy based on FX 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 real FX trade and quote data. Section 5 concludes with policy implications.

[4]For example see Rey (2001), Caballero and Krishnamurthy (2003), Caballero, Farhi, and Gourinchas (2008), Caballero and Krishnamurthy (2009), Bruno and Shin (2017), Chahrour and Valchev (2019), He, Krishnamurthy, and Milbradt (2019), Ilzetzki, Reinhart, and Rogoff (2019), and Jiang, Krishnamurthy, and Lustig (2019).

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

2. FX Market Structure and Dollar Dominance

The purpose of this section is threefold: First, provide a schematic overview of the decentralised FX market structure and introduce key trading platforms and players. Second, supply *prima facie* evidence of dollar dominance in spot FX trading volume. Third, illustrate the real economic consequences of dollar dominance for the global economy.

Market structure. The FX market is organised as a two-tier OTC market network that is intermediated by liquidity providers (e.g., Citigroup and UBS) called dealers (see King, Osler, and Rime, 2012). On the one hand, there is a professional inter-bank OTC market organised around electronic limit order books (e.g., EBS and Reuters). In recent years, this market has become less liquid and 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 consequently seen 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. The 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 summary, modern FX trading is organised via a network of central limit order books that transact independently from each other.[6]

Dollar dominance. Despite its decentralised and OTC nature, electronification of the FX market has skyrocketed over the past 10 years and the market is nowadays dominated by execution algorithms. Following Rahmouni-Rousseau and Churm (2018), more than 80% of total trading volume is executed electronically and roughly 70% of total FX spot volume on EBS is 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 predominantly done via the phone. What is more, at least 85% of all FX spot trades that pass though CLS have a US dollar leg. It is instructive to contrast this number with the 35 to 51 percent share of the United States (US) in global economic activity. I use the US share in global GDP, trade, equity, and debt capital markets as a benchmark for the relative importance of the US dollar in FX trading.[7]

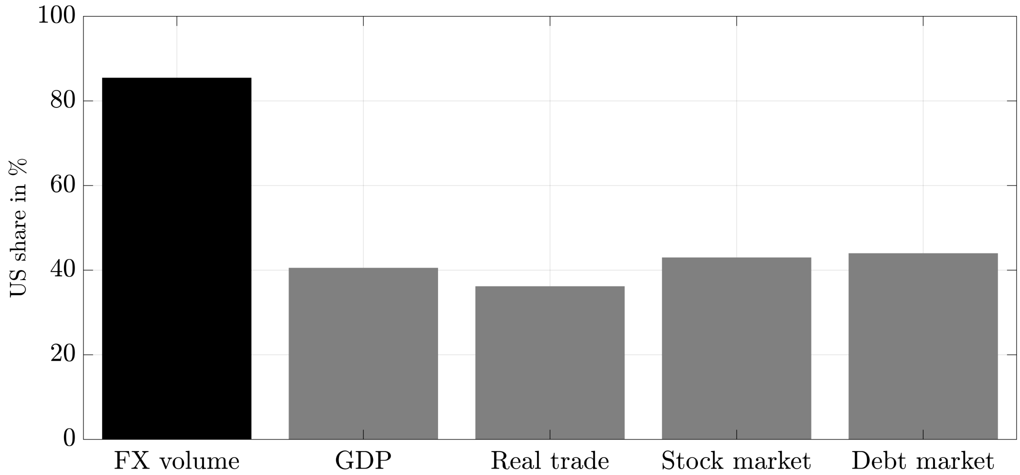
Figure 1 illustrates the pervasive dominance of the US dollar (USD) in FX trading volume. The underlying data come from five sources: First, spot FX trade data is from CLS Group. Second, yearly GDP data by country and currency comes from the World Bank and OECD national accounts data, respectively. Third,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

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

[7] 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 estimate of global GDP or world trade, respectively. There are 16 such 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).

exports between two countries. Note that the US share in world trade accounts for trades that are either invoiced in US dollars (Gopinath and Stein, 2020) or originated in countries where the US dollar is the official currency (e.g., Ecuador or Puerto Rico).[8] Fourth, the share of the US in global stock markets is from Bloomberg and is based on the market value of all available equity securities. Fifth, the estimates of US dollar-denominated international debt securities are based on the BIS locational banking statistics (LBS) 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, trade, equities, and debt markets, respectively. The underlying data come from five sources: First, hourly spot FX trade data is from CLS. Second, yearly GDP data by country and currency comes from the World Bank and OECD national accounts data, respectively. Third, monthly trade data by country and currency come from the World Trade Organisation. Trade is defined as the sum of imports and exports between two countries. Fourth, the share of the US in global stock markets is from Bloomberg. Fifth, the estimates of US dollar-denominated international debt securities are based on the BIS locational banking statistics (LBS). The sample covers the period from 1 November 2011 to 29 September 2020.

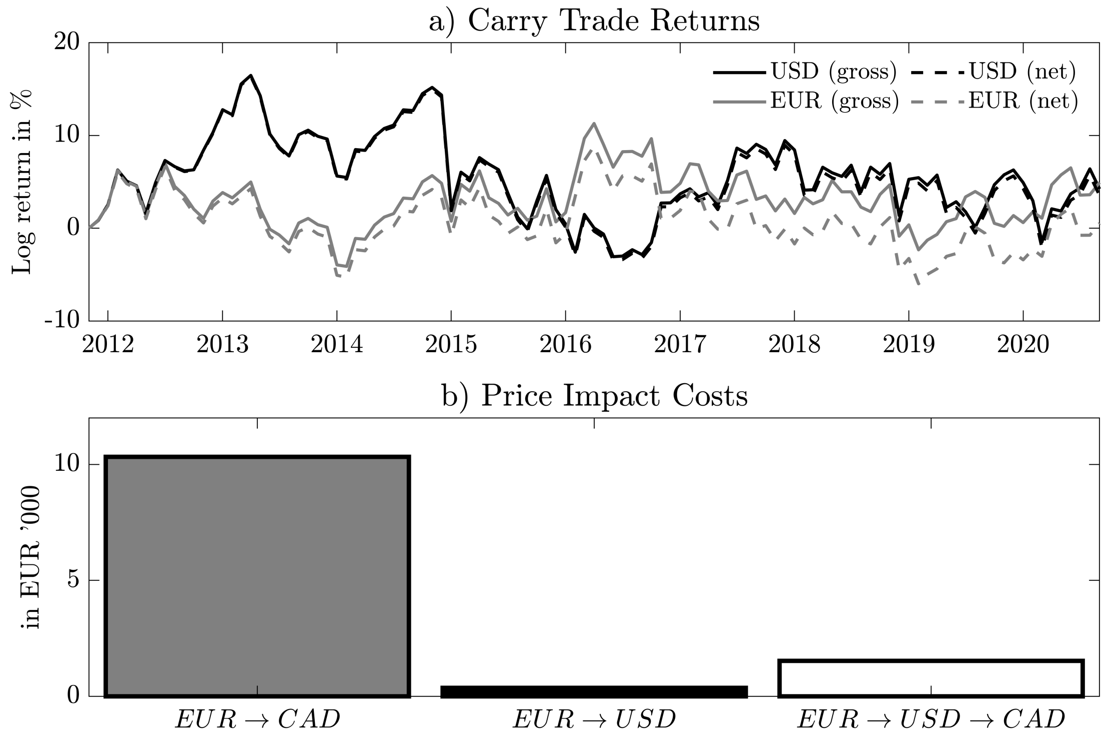
Real economic effect. What are the real economic consequences of dollar dominance? Who wins and who loses from FX liquidity being concentrated in dollar currency pair? A thorough welfare analysis goes beyond the scope of this paper but I will illustrate the ramifications of dollar dominance in FX trading using two simple examples.

First, consider the case of a carry trade speculator operating in Germany vs the US. Both traders sort five currencies (i.e., AUD, CAD, CHF, GBP, and JPY) into long-short portfolios based on the interest rate differential relative to their home currency, that is, the euro and US dollar, respectively. Before taking price impact into account, both traders realise a cumulative excess returns of about 5% over the period from 1 November 2011 to 29 September 2020.

[8]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). To be specific, the sum of US, Hong Kong, and Singapore GDP jointly accounts for just above 41% in world output.

However, once I account for the fact that rebalancing the portfolio allocation each month incurs price impact the performance of the EUR based carry strategy plummets to 0%. Subfigure a) in Figure 2 illustrates this point graphically. Net cumulative excess returns include price impact for exchanging 100 mn units of the base for the quote currency and are estimated from CLS order flow data following Kyle (1985).

Figure 2: Economic Consequences of Dollar Dominance



Note: Subfigure a) shows the cumulative log excess returns of sorting five currencies (i.e., AUD, CAD, CHF, GBP, and JPY) into long-short portfolios based on the interest rate differential relative to the USD or EUR being the home currency (Lustig and Verdelhan, 2007). The solid (*dashed*) lines show gross (*net*) cumulative excess returns for a USD and EUR based investor, respectively. Subfigure b) shows the price impact cost of exchanging EUR 300 mn directly or indirectly to CAD as well as directly to USD. Price impacts are estimated from CLS order flow data following Kyle (1985). The sample covers the period from 1 November 2011 to 29 September 2020.

Second, imagine that a UK domiciled mutual fund (e.g., Jupiter or Schroders) receives an inflow of EUR 350 mn and has a mandate to invest either in Canada or the US.[9] Subfigure b) in Figure 2 illustrates how foreign exchange transactions costs can influence such an investment decision. If the mutual fund directly invests the inflows into US assets it incurs less than 500 euros in terms of aggregate price impact. However, when using the flows to gain exposure to Canada instead the associated price impact cost is at least fivefold when exchanging the euros indirectly via the US dollar. As a result, UK mutual funds might be inclined to invest more flows into US assets than any other foreign country.

[9]According to Morningstar, the top 10 UK based mutual funds saw inflows of beyond GBP 3,500 mn per month in 2020/21. See "Fund Flows Commentary United Kingdom," Morningstar Direct, April 2021.

3. Theory of FX Trading

The goal of this section is twofold: First, I adapt the Rostek and Yoon (2020) model to the FX market to formalise the trade-off faced by a trader who wishes to exchange one non-dollar currency for another non-dollar currency. Second, I use comparative statics analysis to derive a set of sufficient conditions for dollar dominance in FX trading volume. In an effort to present the model in a clear yet concise manner, I relegate the step-by-step solution of the equilibrium to the online appendix Section B.

3.1. Model Overview

Traders buy and sell currencies from each other in an OTC market setting. Some of these transactions take place directly between two traders whereas others occur between traders and dealers. The model does not explicitly distinguish between trader types or dealers. The objective of each trader is to satisfy her fundamental trading demand in a particular currency pair. When doing so, each trader considers her price impact. As a result, a trader is only willing to deviate from her fundamental trading demand if she is sufficiently compensated by price.[10] Following this intuition, I show that in equilibrium such a behaviour may result in a lower expected price impact and hence more trading volume for dollar currency pairs. Lastly, I use comparative statics to understand the determinants of trading volume and then derive a sufficient statistic for dollar dominance.

The left subfigure in Figure 3 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 average price impact of selling the amount of quote currency required to buy 100 mn units of the base currency.[11] 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.

Note that my model has no traditional transaction costs in the form of relative bid-ask spreads. This is motivated by the observation that the average relative bid-ask spread in non-dollar currency pairs is only marginally higher than in dollar pairs. Contrarily, the average price impact in non-dollar pairs is on average 4 times larger than in dollar pairs.

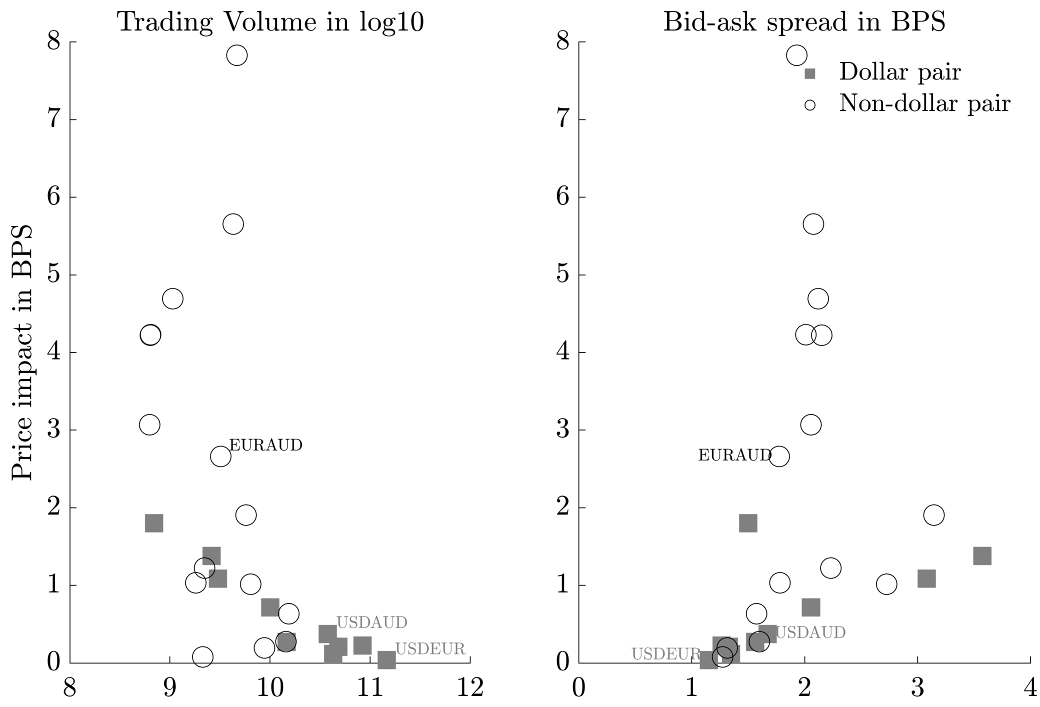
The right subfigure in Figure 3 illustrates this point graphically. The y-axis is the same as in the left subfigure and shows the average price impact for dollar and non-dollar currency pairs. The x-axis plots the average relative bid-ask spread in basis points (BPS) based on indicative quotes from Olsen 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 that has no central limit order book.

[10] Studies of price impact of a trade include among others Glosten and Harris (1988), Stoll (1989), Foster and Viswanathan (1990), and Hasbrouck (1991a,b).

[11] In the spirit of Kyle (1985), I estimate hourly price impact separately for every currency pair as the rolling regression coefficient of log currency returns on customer order flows from CLS Group. Order flow is defined as the aggregate net buying or selling pressure against the base currency (Evans, 2002). The rolling window length is equal to 480 hours and I account for intraday seasonalities using hourly dummies.

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, she would be better off exchanging AUD directly to EUR and on average incur the half spread of 1.77 BPS rather than first exchanging AUD to USD and then USD to EUR paying around 2.82 BPS in total. However, this intuition does not hold for price impact. On average, the same trade would incur a price impact of just about 0.41 BPS when executed via the US dollar and at least 2.66 BPS when completed directly.

Figure 3: Price Impact, Bid-ask Spread, and Trading Volume



Note: The left subfigure shows the time series average of price impact and relative half bid-ask spreads for 10 dollar and 15 non-dollar currency pairs, respectively. The y-axis depicts the average price impact of buying 100 mn units of the base currency for the quote currency. I estimate hourly price impact for each currency pair as the rolling regression coefficient of log currency returns on customer order flows (Kyle, 1985) from CLS Group. Order flow is defined as the aggregate net buying or selling pressure against the base currency (Evans, 2002). The window length is equal to 480 hours and I account for intraday seasonalities using hourly dummies. The x-axis plots the average relative half bid-ask spread in BPS based on indicative quotes from Olsen Data. The right subfigure covers the same 25 currency pairs and plots the time series average of price impact and trading volume, respectively. Again, the y-axis shows the same as in the left subfigure whereas the x-axis plots the average daily trading volume (log10 scale) settled by CLS. The sample period is from 1 September 2012 to 29 September 2020.

3.2. Setup

I fix the probability space Ω, F, P augmented with the filtration $\mathbb{F} = \{F_t : 0 \leq t\}$, satisfying the usual regularity conditions as in Protter (1990). In particular, I consider a market with $I \geq 3$ traders who trade $K \geq 3$ risky currency pairs in N trading venues. In particular, I assume that all traders behave strategically in the game theoretic sense. Traders and currency pairs are indexed by i and k, respectively. The payoffs of the K currency pairs are exogenous and Gaussian $\mathbf{r} = r_k \sim N(\delta, \mathbf{\Sigma})$ with a vector of payoffs $\delta = \delta_k$ and a positive semi-definite covariance matrix $\mathbf{\Sigma}$. Throughout this paper, vectors and matrices are **bold face**, whereas scalars are in normal font. The numéraire is a riskless asset with zero interest rate. Furthermore, I assume that each trader i has a quadratic mean-variance utility function:

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

where $\mathbf{q}^i = q_k^i$ is the (effectively) traded quantity, $\mathbf{q}_0^i = q_{0,k}^i$ represents every trader's *initial trading demand* in each currency pair, and γ^i is trader i's risk aversion.[12]

Initial trading demand. In the context of currency pairs, one can think of initial or fundamental trading demand 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.[13] The trading demands (i.e., $\mathbf{q_0^i}$) at the beginning of every period are traders' private information and independent of the currency pairs' payoff vector $\mathbf{r}$. Each trader derives her utility from the post-trade allocation defined by $\mathbf{q}^i + \mathbf{q}_0^i$ and chooses $\mathbf{q}^i$ to maximise her expected payoff.

What determines fundamental trading demand 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, the cross-border purchase and sale of financial assets such as stocks and bonds is the single most important source of FX trading growth according to a recent BIS study.[14] 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 can especially fuel FX trades in periods of market stress. Against this backdrop, providing a micro-foundation for fundamental trading demand that can encompass each of the aforementioned motives goes beyond the scope of this paper.

[12] It is well known 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 (CARA) and normally distributed returns. Unlike with constant relative risk aversion (CRRA) the amount invested in the risky assets is constant in absolute terms for CARA utility functions. For many applications in finance and economics this is unrealistic because it implies that with CARA preferences risk aversion increases with wealth. However, this equivalence does not hold in an *uncontingent* market where equilibria also depend on the *distribution* of fundamental trading demands.

[13] An FX dealer provides immediacy by standing ready to sell the currency that the customer wants to buy in exchange of the currency that the customer wants to sell. If the dealer cannot match these imbalances internally with offsetting flows from other customers or her existing trading demands then she has to submit buy and sell orders in the inter-dealer market to avoid carrying over inventory risk to the next trading period. Evans and Lyons (2002) describe this behaviour as risk-averse dealers 'going flat home at night'. Thus, the profit maximisation problem in Eq. (3) can be thought of as the decision problem of a risk-averse dealer who trades off the expected return against the variance of initial trading demands.

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

Following the related literature (e.g., Kyle, 1989; Vayanos, 1999; Vives, 2011; Gârleanu and Pedersen, 2013; Rostek and Weretka, 2015; Kyle, Obizhaeva, and Wang, 2017) on imperfectly competitive markets, 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 $q_{0,k}^i \sim N(E[q_{0,k}^{cv}], \sigma_{cv}^2)$ and I assume that for each trader i

$$q_{0,k}^i = q_{0,k}^{cv} + q_{0,k}^{i,pv}, \tag{2}$$

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 her 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 price is random in the limit large market as the number of traders approaches infinity. What is more, I allow for correlated trading demands $q_{0,k}^i$ across currency pairs and denote the covariance matrix $Cov(q_{0,k}^i, q_{0,l\neq k}^i)$ by $\mathbf{\Omega}$.

Demand schedules. The exchange of currencies in my model is organised in the form of 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.[15] For $q_{0,k}^i > 0$, trader i is *long* in currency pair k and for $q_{0,k}^i < 0$ she is *short*. 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* demand schedules is that orders to a given trading venue cannot be made contingent on the market clearing exchange rates at other venues.[16] As a result, the FX market in my model clears *exchange by exchange* rather than jointly as it would be the case with *contingent* schedules.[17] Even if the FX market is possibly less decentralised from a large primary FX dealer's point of view it is still not plausible 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 market makers and trading venues. Consistent with the notion of uncoordinated market clearing, Ranaldo and Santucci de Magistris (2018) document significant empirical deviations from triangular no-arbitrage over time and across currency pairs.

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

[16]To the best of my knowledge, Wittwer (2021), Chen and Duffie (2021), and Rostek and Yoon (2020) were the first to study markets with multiple heterogeneous assets and uncontingent demand schedules.

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

3.3. *Equilibrium Characterisation*

To derive the equilibrium exchange rates and optimal traded quantity for a representative trader I apply the solution concept of Bayesian Nash equilibria. Every trader i submits her demand schedules q^i_k simultaneously across $N = K$ exchanges, each for one currency pair. The demand schedules are optimal if they maximise a traders' expected payoff for each currency pair k subject to her residual supply function $S^i_l(\cdot) \equiv -\sum_{j \neq i} q^j_l(\cdot)$ for all currency pairs and her demand for other pairs $q^i_{l \neq k}(\cdot)$. The following definition formalises market equilibrium:

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

$$max_{q^i_k(\cdot)} E[\delta \cdot (\mathbf{q}^i + \mathbf{q}^i_0) - \frac{\gamma^i}{2}(\mathbf{q}^i + \mathbf{q}^i_0) \cdot \mathbf{\Sigma}(\mathbf{q}^i + \mathbf{q}^i_0) - \mathbf{p} \times \mathbf{q}^i | p_k, q^i_0], \tag{3}$$

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

The trader's objective function with *uncontingent* demand schedules in Eq. (3) is similar to the case where all markets clear jointly. The main difference is that the demand for currency pair k is contingent on both the exchange rate p_k as well as fundamental trading demand q^i_0. As a result, the equilibrium characterisation is more challenging compared to the *contingent* market since the requirements for *ex post* optimisation are not met.[18] That is, the best response quantities cannot be solved pointwise with respect to the exchange rate vector $\mathbf{p}$ since expected trade $E[q^i_l | p_k, q^i_0]$ depends on the functional form of $q^i_l(\cdot)$.

Given that the best-response demands are not ex post and depend on the distribution of the conditioning variable $\mathbf{p}$, the price impact $\mathbf{\Lambda}^i$ itself is *not* a sufficient statistic for a trader's residual supply. The solution to this issue is based on Rostek and Yoon (2020) and involves transforming the fixed point problem for best-response schedules $q^i_k(\cdot)$ to one for demand coefficients, given residual supplies.[19] To keep it interesting, I will only consider markets that are not frictionless and hence only look at the case where the number of traders I is finite.

Equilibrium. In equilibrium, the total residual supply $S^{-i}_k(p_k)$ must be zero, otherwise markets do not clear. This allows me to derive the equilibrium exchange rate $\mathbf{p}^*$ as a function of demand coefficients $\mathbf{B}$ and $\mathbf{C}$:

$$\mathbf{p}^* = \Big(\delta - (\gamma \mathbf{\Sigma} - \mathbf{C}^{-1}\mathbf{B}) E[\bar{\mathbf{q}}_0]\Big) - \mathbf{C}^{-1}\mathbf{B}\bar{\mathbf{q}}_0, \tag{4}$$

where demand coefficients $\mathbf{B}$ and $\mathbf{C}$ are positive semi-definite matrices that stem from conjecturing that trader i's best-response for all other pairs $l \neq k$ is a linear function of the exchange

[18] Rostek and Yoon (2020) provide an in-depth analysis of contingent vs uncontingent demand schedules and how equilibrium outcomes differ. Equilibria are *ex post* if equilibrium demands $q^i_k(\cdot)$ are optimal for all i, given the trading demands of *all* traders $j \neq i$. The online appendix Section A derives the equilibrium exchange rate and quantity for contingent demand schedules.

[19] I am grateful to Marzena Rostek and Ji H. Yoon for providing access to their unpublished online appendix.

rate p_l and initial trading demand $\mathbf{q}_0^i$. In particular, I assume the following functional form:

$$q_l^i(p_l) \equiv a_l^i - b_l \mathbf{q}_0^i - c_l p_l, \qquad \forall l \neq k \tag{5}$$

where $a_l^i \equiv \mathbf{a}^i$ is the vector of demand intercepts, $b_l \equiv \mathbf{B}$ the matrix of demand coefficients, and $diag(c_k) \equiv \mathbf{C}$ the demand slope matrix on p_l. Note that for simplicity I assume that all traders have identical risk preferences, that is, $\gamma^i = \gamma$, $\forall i$.

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,

$$\mathbf{q}^{i,*} = \left((\gamma \boldsymbol{\Sigma} + \boldsymbol{\Lambda})^{-1} \gamma \boldsymbol{\Sigma} \right) (E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i]), \tag{6}$$

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 $\boldsymbol{\Lambda}$ is *endogenous* and characterised by the slope coefficients of the inverse residual supply function $\mathbf{C}^{-1}$:

$$\boldsymbol{\Lambda} = \frac{1}{I-1} \mathbf{C}^{-1} = \frac{\gamma}{I-2} \Big[\boldsymbol{\Sigma} \underbrace{(\mathbf{B} \boldsymbol{\Omega} \mathbf{B}') \left[\mathbf{B} \boldsymbol{\Omega} \mathbf{B}' \right]_d^{-1}}_{\text{Inference coefficient}} \Big]_d, \tag{7}$$

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. Note that $\boldsymbol{\Lambda}$ 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. (6), it is only optimal to trade a non-zero amount 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 she is a net-buyer or net-seller of the quote currency. Intuitively, a net-buyer's fundamental trading demand is below the average (i.e., $\bar{q}_{0,k} > q_{0,k}^i$), whereas the opposite is true for a net-seller (i.e., $\bar{q}_{0,k} < q_{0,k}^i$). I hereinafter 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 $\boldsymbol{\Lambda}$ is a positive definite matrix trader i trades less relative to her *net* initial trading demand $E[\bar{\mathbf{q}}_0] - E[\mathbf{q}_0^i]$.[20]

Price impact. The one-to-one mapping between price impact $\boldsymbol{\Lambda}$ and trading volume $\mathbf{q}^{i,*}$ 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 pairs may find it optimal to trade a combination of dollar pairs and non-dollar pairs. In equilibrium, this can result in a lot of trading volume in dollar currency pairs even if there is little or even no fundamental trading demand for dollar currency pairs.

There are two key determinants of price impact in this model: First, the price impact

[20] There is a growing literature showing that the traditional (theoretical) view of only 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).

of every trader i emanates from the concavity of preferences of her residual market: it is increasing and concave in her risk aversion γ_i and the variance of currency returns $\mathbf{\Sigma}$. Hence, the residual market is less elastic when currency pairs are either more risky (i.e., the larger $\mathbf{\Sigma}$ in the positive-definite order) or other traders $j \neq i$ are more risk averse (i.e., larger γ_j). Consequently, if the residual market is very inelastic, an additional trade by i has a greater effect because of the larger price concession required to absorb the extra marginal unit such that markets clear (Rostek and Yoon, 2021).

Second, since demand schedules are uncontingent, price impact $\mathbf{\Lambda}$ also depends on the distribution of fundamental trading demands.[21] Intuitively, this stems from the fact that trader i's demand for currency pair k is contingent on expected rather than realised trades for all other currency pairs $l \neq k$. This is captured by the inference coefficient $(\mathbf{B\Omega B'})\left[\mathbf{B\Omega B'}\right]_d^{-1}$ that is determined by the variance of trader i's residual supply intercept s_k^{-i} conditional on fundamental trading demands $\mathbf{q}_0^i$. Since I assume that both variables are jointly normally distributed conditioning acts as a linear projection. Thus, the conditional variance of a trader's residual supply intercept s_k^{-i} is decreasing in the variance of the conditioning variable, that is, fundamental trading demand $\mathbf{\Omega}$. As a result, a larger variance of fundamental trading demand in currency pair k lowers the associated price impact λ_k.

Summary. To sum up, the goal of this model was to epitomise the trade-off that a trader faces when deciding on how to satisfy her fundamental trading demands. So far, the key economic insight from the model is twofold: First, traders will 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 the distribution of fundamental trading demands in the given currency pair on the other hand. Hence, if each trader plays equilibrium then strategic complementarity[22] creates a deeper and more liquid market for currency pairs that are either less risky or exhibit more volatile fundamental trading demands.

3.4. Comparative Statics

The equilibrium trading volume in Eq. (6) is characterised by three *exogenous* drivers: initial trading demand $\mathbf{q}_0^i$, covariance of initial trading demands $\mathbf{\Omega}$, and covariance of currency returns $\mathbf{\Sigma}$. I denote the $(k,l)^{th}$ element of a matrix (e.g., $\mathbf{\Sigma}$) by $\Sigma_{k,l}$. In particular, I am interested in the comparative statics of equilibrium trading volume with respect to $q_{0,k}^i$, $\Omega_{k,k}$, and $\Sigma_{k,k}$, respectively. For clarity, I assume that both the covariance matrix of initial trading demands $\mathbf{\Sigma}$ and the covariance matrix of currency returns $\mathbf{\Omega}$ are 'balanced' in the following sense: $\Sigma_{k,k} = \sigma^2$, $\forall k$ 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

[21]This is in stark contrast to centralised markets (i.e., contingent demand schedules) where price impact is directly proportional to the covariance matrix of currency returns and independent of the distribution of traders' fundamental trading demands.

[22]The notion of strategic complementarity was originally coined by Bulow, Geanakoplos, and Klemperer (1985) and refers to strategic decisions that mutually reinforce each other.

currency pairs, that is, $\lambda_k = \lambda$, $\forall k$.[23] 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 initial trading demand* $q^i_{0,k}$*, variance of initial trading demands* $\Omega_{k,k}$*, and variance of currency returns* $\Sigma_{k,k}$ *are given by the following expressions: for every* $k \neq l$

$$\frac{\partial \mathbf{q}^{i,*}}{\partial q^i_{0,k}} = ((\gamma\boldsymbol{\Sigma} + \boldsymbol{\Lambda})^{-1}\gamma\boldsymbol{\Sigma})\frac{\partial \mathbf{d}^i_0}{\partial d^i_{0,k}}, \text{ where } \mathbf{d}^i_0 = |\bar{\mathbf{q}}_0 - \mathbf{q}^i_0| \text{ and } \frac{\partial q^{i,*}_k}{\partial d^i_{0,k}} > \frac{\partial q^{i,*}_j}{\partial d^i_{0,k}}, \text{ as } \frac{\partial d^i_{0,l}}{\partial d^i_{0,k}} = 0; \tag{8}$$

$$\frac{\partial \mathbf{q}^{i,*}}{\partial \Omega_{k,k}} = -(\gamma\boldsymbol{\Sigma} + \boldsymbol{\Lambda})^{-2}\gamma\boldsymbol{\Sigma}\frac{\partial \boldsymbol{\Lambda}}{\partial \Omega_{k,k}}(E[\bar{\mathbf{q}}_0] - E[\mathbf{q}^i_0]), \text{ where } \frac{\partial q^{i,*}_k}{\partial \Omega_{k,k}} > \frac{\partial q^{i,*}_j}{\partial \Omega_{k,k}} \text{ as } \frac{\partial \Lambda_{k,k}}{\partial \Omega_{k,k}} < \frac{\partial \Lambda_{l,l}}{\partial \Omega_{k,k}}; \tag{9}$$

$$\frac{\partial \mathbf{q}^{i,*}}{\partial \Sigma_{k,k}} = \Big((\gamma\boldsymbol{\Sigma} + \boldsymbol{\Lambda})^{-1}\gamma\frac{\partial \boldsymbol{\Sigma}}{\partial \Sigma_{k,k}} - (\gamma\boldsymbol{\Sigma} + \boldsymbol{\Lambda})^{-2}\gamma\boldsymbol{\Sigma}(\gamma\frac{\partial \boldsymbol{\Sigma}}{\partial \Sigma_{k,k}} + \frac{\partial \boldsymbol{\Lambda}}{\partial \Sigma_{k,k}})\Big)(E[\bar{\mathbf{q}}_0] - E[\mathbf{q}^i_0]), \tag{10}$$

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

See the 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. A change in initial trading demand $\mathbf{q}^i_0$ directly affects the equilibrium quantity. The effect of a change in the covariance matrix of initial trading demands $\boldsymbol{\Omega}$ and currency returns $\boldsymbol{\Sigma}$ depends on the partial derivative with respect to price impact $\boldsymbol{\Lambda}$. Specifically, a marginal increase in the variance of initial trading demands $\Omega_{k,k}$ scales down the level of the associated price impact $\Lambda_{k,k}$. This induces a surge in the equilibrium allocation $q^i_{0,k}$. Furthermore, an increase in the variance of currency returns $\Sigma_{k,k}$ does not only directly affect the equilibrium allocation but also indirectly by inducing a change in price impact (i.e., $\frac{\partial \boldsymbol{\Lambda}}{\partial \Sigma_{k,k}}$). The latter offsets the former if the increase in the variance of currency returns $\Sigma_{k,k}$ is sufficiently large such that price impact $\Lambda_{k,k}$ increases at a faster rate than $\Sigma_{k,k}$.[24]

3.5. *Simulation Exercise*

To illustrate the equilibrium dynamics, I simulate the model for a simple market setting with $I = 20$ market participants trading $K = 3$ currency pairs. For concreteness, I assume that there are two US dollar ($) currency pairs (e.g., USDGBP and USDJPY) and one non-dollar cross (e.g., GBPJPY). Trader i has identical initial trading demands in each currency pair, that is, $\mathbf{q}^i_0 = [100, 100, 100]^\top$ \$mn. For simplicity, I set the average initial trading demand $\bar{\mathbf{q}}_0 \equiv \frac{1}{I}\sum_{j=1}^{I}\bar{\mathbf{q}}^j_0$ equal to zero and hence $|\bar{\mathbf{q}}_0 - \mathbf{q}^i_0| = \mathbf{q}^i_0$. Note that for the ease of comparison, I covert both initial trading demands $\mathbf{q}^i_0$ and trading volume $\mathbf{q}^{i,*}$ to US dollars irrespective of

[23] Note that the $\boldsymbol{\Sigma}$ and $\boldsymbol{\Omega}$ only scale the level of price impact and hence the sign of ρ and η has no impact on any rankings of price impact across currency pairs.

[24] Mathematically, the partial derivative of price impact $\boldsymbol{\Lambda}$ with respect to the variance of currency returns $\Sigma_{k,k}$ in Eq. (10) must be such that $\Lambda_{k,k} < \boldsymbol{\Sigma}\frac{\partial \boldsymbol{\Lambda}}{\partial \Sigma_{k,k}}$.

the base and quote currency.[25] To avoid ambiguity, I have to 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, both covariance matrices are positive definite but I shut down the effect that heterogeneous covariance terms have on equilibrium trading volume.

Figure 4 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 $q^i_{0,\$}$, 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 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 $\mathbf{\Lambda}^i$ is a positive semi-definite matrix if the market is not perfectly competitive (i.e., I is finite).[26]

There are four key takeaways from Figure 4: 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 the risk aversion coefficient.

Second, following subfigure b.), an increase in fundamental trading demands in dollar pairs $q^i_{0,\$}$ corresponds to a linear increase in the equilibrium allocation. However, given the positive correlation in trading demands across currency pairs, also the trading volume in non-dollar pairs increases, albeit at a slower rate. Notice that a change in the level of fundamental trading demands in dollar pairs $q^i_{0,\$}$ has no effect on price impact in dollar pairs $\Lambda_{\$,\$}$ because the covariance matrix of fundamental trading demands is mean invariant.

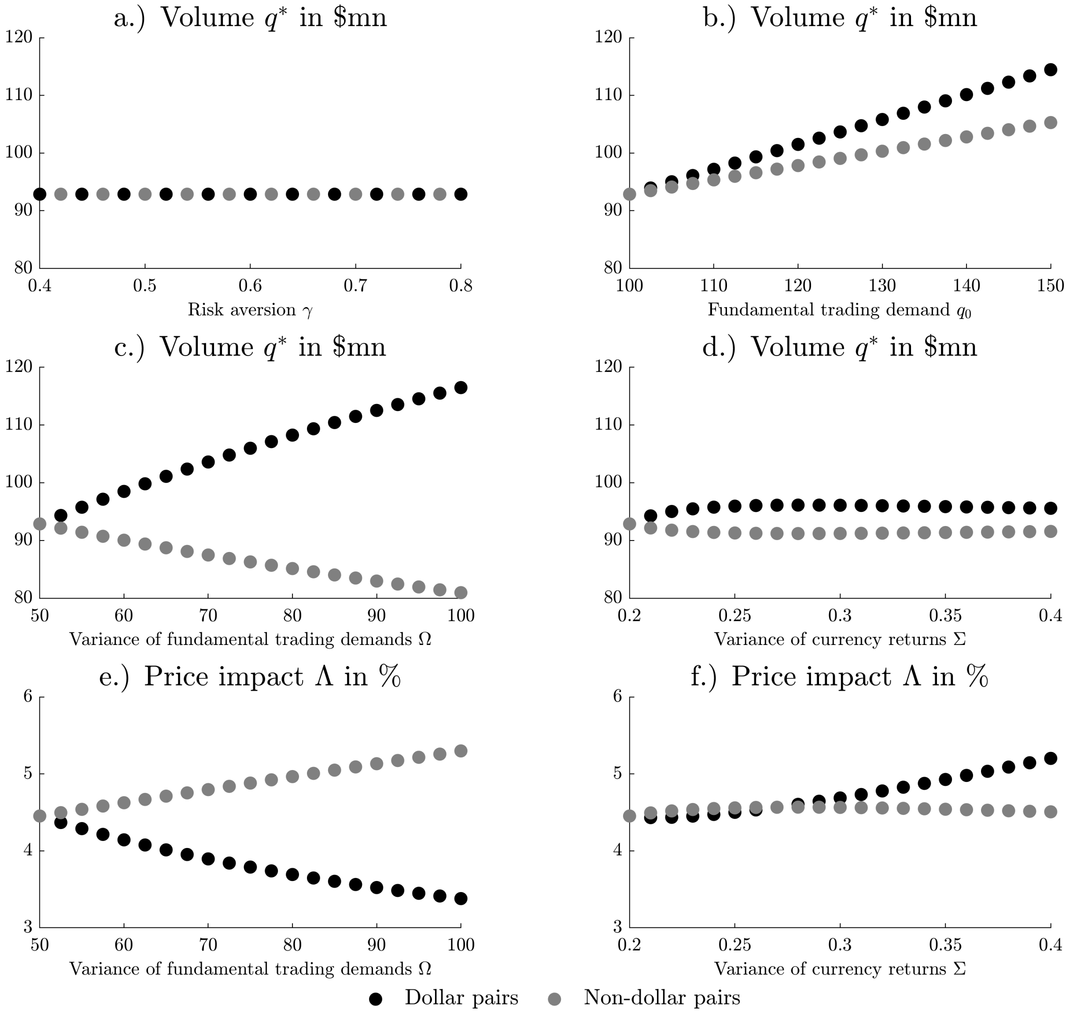
Third, subfigure c.) shows that a trader, with identical fundamental trading demand $q^i_{0,k}$ in each currency pair, on average, ends up trading relatively more dollar currency pairs relative to non-dollar pairs as the variance of fundamental trading demands in dollar pairs $\Omega_{\$,\$}$ increases. This wedge is driven by the assumption that traders are strategic about their price impact and thus find it optimal to trade more via dollar pairs where the expected price impact is lower due the increase in the variance of trading demands in dollar pairs. The economic reason for this drop in price impact shown in subfigure e.) is the fact that in decentralised markets the inference coefficient $(\mathbf{B\Omega B'})\left[\mathbf{B\Omega B'}\right]^{-1}_d$ is decreasing in $\Omega_{\$,\$}$.

Lastly, subfigure d.) illustrates that an increase in the variance of currency returns in dollar pairs $\Sigma_{\$,\$}$ increases the price impact in dollar currency pairs relative to non-dollar currency pairs if the variance of dollar pairs increases by more than 7 percentage points. Contrarily, an increase in the variance of currency returns in dollar pairs $\Sigma_{\$,\$}$ by less than 7 percentage points increases trading volume in dollar currency pairs. The increase is due to a drop in the

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

[26]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, respectively.

Figure 4: Comparative Statics: Trading Volume and Price Impact



Note: This figure plots the comparative statics of equilibrium trading volume $\mathbf{q}^*$ 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. The subfigures a.), b.), c.), and 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 $q_{0,\$}^i$, variance of initial trading demands in dollar pairs $\Omega_{\$,\$}$, and variance of currency returns in dollar pairs $\Sigma_{\$,\$}$. The subfigures e.) and f.) illustrate how the endogenous price impact $\mathbf{\Lambda}$ differs across dollar pairs (black dots) and non-dollar pairs (grey dots) given a change in $\Omega_{\$,\$}$ and $\Sigma_{\$,\$}$, respectively.

price impact of dollar pairs $\Lambda_{\$,\$}$. The non-linear effect in subfigure f.) stems from the fact that $\mathbf{\Sigma}$ directly impacts trading volume through $(\gamma\mathbf{\Sigma} + \mathbf{\Lambda})^{-1}\gamma\mathbf{\Sigma}$ and also endogenously via $\mathbf{\Lambda}$.

Summary. To summarise, 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 symmetric market with identical net trading demands across currency pairs can become skewed towards a single base-currency (e.g., the US dollar) if there is a minor disparity in the variance of fundamental trading demands or 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.

3.6. *Dollar Dominance*

Equipped with the model above, I define dollar dominance on the basis 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) that are required to synthetically replicate the non-dollar pair. Hence, my definition of dollar dominance is as follows:

Definition 3 (**Dollar Dominance**): *A triplet of currency pairs (i.e., USDXXX, USDYYY, and XXXYYY) is dominated by the USD if the trading volume in currency pairs involving the USD exceeds the trading volume in currency pairs that have any other currency (i.e., XXX or YYY) on one side:* $\sum_{k \in USD} q_k^{i,*} > max(\sum_{k \in XXX} q_k^{i,*}, \sum_{k \in YYY} q_k^{i,*})$ *has to hold on average for every trader i.*

To be specific, consider, for example, the three currency pairs GBPJPY, USDGBP, and USDJPY with an associated trading volume of 90, 120, and 110 $mn, respectively. Following Definition 3, the US dollar dominates because the total trading volume in US dollar $(110 + 120)$ currency pairs is larger than the total trading volume in pound sterling $(90 + 110)$ or Japanese yen $(90 + 120)$ currency pairs. 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 both fundamental *and* vehicle currency demand. Moreover, given a measure for fundamental trading demands, it allows me to quantify the amplification effect in volume that stems from vehicle currency trading.

Sufficient conditions. Next, I derive a necessary and sufficient statistic for dollar dominance based on the primitives of my model. 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 clarity, I assume that both $\mathbf{\Sigma}$ and $\mathbf{\Omega}$ are 'balanced', that is, the covariance terms are down-scaled versions of the variances (e.g., $\Sigma_{k,l} = \sigma^2 \rho$, $\forall l \neq k$, where $|\rho| < 1$) that 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 the equilibrium quantity.

Theorem 2 (**Asymmetric Equilibrium: Sufficient Conditions**): *Trading volume in a triplet of currency pairs (i.e., USDXXX, USDYYY, and XXXYYY) will be dominated by the USD ($) if the following three conditions are satisfied* simultaneously *for currency pairs involving the USD:*

1. larger fundamental trading demands, $\sum_{k \in \$} q_{k,0}^i > max(\sum_{k \in XXX} q_{k,0}^i, \sum_{k \in YYY} q_{k,0}^i)\ \forall i$;
2. more volatile trading demands, $\sum_{k \in \$} \Omega_{k,k} > max(\sum_{k \in XXX} \Omega_{k,k}, \sum_{k \in YYY} \Omega_{k,k})$;

3. less volatile currency returns, $\sum_{k\in\$}\Sigma_{k,k} < min(\sum_{k\in XXX}\Sigma_{k,k}, \sum_{k\in YYY}\Sigma_{k,k})$.

The last condition only holds if $\Lambda_{k\in\$} - \mathbf{\Sigma}\frac{\partial\mathbf{\Lambda}}{\partial\Sigma_{k\in\$}} < min(\Lambda_{k\in XXX} - \mathbf{\Sigma}\frac{\partial\mathbf{\Lambda}}{\partial\Sigma_{k\in XXX}}, \Lambda_{k\in YYY} - \mathbf{\Sigma}\frac{\partial\mathbf{\Lambda}}{\partial\Sigma_{k\in YYY}})$. *The proof of Theorem 2 follows from Corollaries 1 to 3 in the online appendix Section B.*

Individually, each of the three conditions in Theorem 2 is sufficient if and only if the other two hold with equality. Conversely, the necessary condition for dollar dominance is that at least one of the three conditions has to hold. Thus, these three conditions are also useful to predict which currency is unlikely to be dominant: a currency will *not* dominate trading volume if none of the conditions is satisfied. The proof of Theorem 2 (see online appendix Section B) directly builds on the economic intuition gained from the comparative static results that are summarised in Theorem 1.

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

3.7. *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 that 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 thereby obscure the main message.

Second, I only focus on linear Bayesian Nash equilibria in the uniform-price double auction. In principle, one could imagine that a trader's conjectured best response in all other currency pairs $l \neq k$ is non-linear in the exchange rate p_l as well as 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 are beyond the scope of this paper.

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

3.8. *Testable Implications*

The purpose of my model was two-fold: First, 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, deliver a set of empirically testable hypotheses that can be evaluated using actual FX trade and quote data.

The testable implications of the model can be split into three parts: First, I can use panel regressions to test the model's empirical validity. Specifically, I am interested in whether the model–based 'exogenous' determinants of equilibrium trading volume are also significant drivers of actual FX volume. Based on the comparative statics in Theorem 1, I expect trading volume to increase in the mean and variance of fundamental trading demands but to decrease with the variance of currency returns. In a similar vein, I can also test if price impact negatively correlates with the variance of fundamental trading demands and if it increases with more volatile exchange rate returns. A key challenge of the empirical analysis is to identify meaningful empirical measures for each of the three model–based drivers.

Second, the set of sufficient conditions for dollar dominance in Theorem 2 can be evaluated for the cross-section of non-dollar currency pairs. The aim is to understand if there is consistency between the empirical counterparts of the three sufficient conditions and the observed dollar dominance in actual FX trade data. This is not only useful to determine which triplets of currency pairs will be dominated by the US dollar, but also to identify which ones are on the edge of switching to another dominant currency (e.g., the euro). What is more, I can directly test if there is evidence of vehicle currency trading by comparing dollar dominance in trading volume to dollar dominance in fundamental trading demands.

Lastly, I can test whether the time series variation in dollar dominance is also affected by the model–based drivers of volume. For this, I first derive a time-varying empirical measure of dollar dominance. In a second step, I regress this proxy on the empirical counterparts of the model–based drivers. Following the intuition of my model, I presume that dollar dominance increases in the mean and variance of fundamental trading demands of US dollar pairs but decreases with the variance of dollar exchange rate returns. This is because an increase in the mean or variance of fundamental trading demands in dollar pairs lowers the expected price impact of dollar pairs relative to non-dollar pairs. The same intuition holds for a surge in the variance of US dollar exchange rate returns that corresponds to a larger expected price impact in dollar pairs. As a result, trading non-dollar pairs directly rather than indirectly via the US dollar becomes more attractive which should result in less dollar dominance.

4. Empirical Analysis

This section presents empirical evidence that is consistent with my model in four parts. First, I begin by describing the data. Second, I use panel regression analysis to test the model empirically 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 sufficient conditions in Theorem 2 have empirical support. Lastly, I explore the empirical determinants of the cross-sectional and time series variation in dollar dominance. In particular, I test whether the cross-sectional dispersion can be explained by a simple gravity model (Lustig and Richmond, 2019) and how the time series variation is driven by the three model-based determinants of FX trading volume.

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 from CLS Group (CLS), which is directly available from CLS or via Quandl, a financial and economic data provider. CLS operates the largest multi-currency cash settlement system in the world handling over 40% of global spot FX transaction volume. At settlement, CLS alleviates principal and operational risk by simultaneously settling both sides of the trade. The data have been used in prior research by Hasbrouck and Levich (2018, 2021), Ranaldo and Santucci de Magistris (2018), Cespa et al. (2021), and Ranaldo and Somogyi (2021). The aforementioned papers provide a comprehensive description of both CLS volume and order flow data.

The CLS system itself is owned by its 72 settlement members that are mostly large multinational banks. Hence, to protect the anonymity of their members, 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. Specifically, the volume data include the sum of all dealer-to-customer and inter-dealer trades, whereas the order flow data contain separate entries for buying and selling activity but only for trades between customers and dealers. Therefore, the CLS volume data is particularly well-suited for my analysis because it allows me to study the properties of dollar dominance at a global scale rather than just for a specific market segment or trading platform. To be precise, the buy and sell volume in a given hour and currency pair refers to how much of the base currency was purchased and sold by the price takers (i.e., customers) from the market makers (i.e., dealer banks).

Price takers can be categorised into four customer groups, namely, 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 member of CLS, then this trade would show up as a bank/bank transaction. However, inter-bank trades are excluded from the flow (but not the volume) data set unless one of the counterparties is classified as a price taker (i.e., non-dealer bank). The online appendix Section C provides further details on how CLS categorises market participants into customers, as well as dealer and non-dealer banks, respectively. Furthermore, note that CLS does not provide any information about the initiator of a particular trade since it solely observes the executed trade price used for settlement rather than the market behaviour of bids and offers that precede the 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 such as IDC, Morningstar, and Reuters these quote data are also representative of the entire FX spot market rather than just a specific segment (e.g., inter-dealer or customer-dealer). The full sample period spans from 1 September 2012 to 29 September 2020 and includes data for 11 major currencies and 25 currency pairs.[27] 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

The theoretical framework in Section 3 derives an inverse relation between equilibrium price impact and trading volume. In my model, this reciprocity is governed by three primitives: i) fundamental trading demand, ii) variance of fundamental trading demands, and iii) the variance of exchange rate returns. The goal of this section is twofold: First, derive a meaningful empirical counterpart for each of the three theoretical determinants of FX trading volume. Second, use a panel regression approach to test if the contemporaneous relation between trading volume, price impact, and the three aforementioned drivers is consistent with the comparative statics in Theorem 1.

Identifying assumptions. The main challenge for testing the model's predictions is to identify a meaningful empirical proxy for fundamental trading demands. The reason is 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", that is, offering immediacy to their clients by completing their customers' trades using their own inventory. Some of these customer flows are netted internally, whereas others create an inventory imbalance. Since dealers have limited risk bearing capacity (Evans and Lyons, 2002) they try to flatten these open position until the end of the FX trading day.[28] Thus, one can think of customer flows as a proxy for dealer banks' initial trading demand.

There are two potential limitations of this measure: First, it implicitly assumes that bank trading is mainly driven by customer flows rather than proprietary bank trading demands. This assumption is not unreasonable 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).[29] The amount of proprietary trading is unobservable in my data set and hence I cannot directly control for it. However, by including currency pair and time series fixed effects in my panel

[27] In particular, the data set contains 15 non-dollar currency 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) that are used to synthetically replicate each of the non-dollar pairs.

[28] This usually takes place either bilaterally or on two major inter-bank trading platforms, namely EBS and Reuters. Whether these trades show up in the CLS volume data does only depend on the two counterparties being CLS members but not on the platform per se.

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

regression setup I can mitigate any bias that stems from proprietary trading activity that 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 shall be interpreted as a lower bound that potentially underestimates the 'true' effect.

The CLS volume and order flow data are ideal for my identification strategy for two reasons: First, by construction the CLS order flow data only comprises transactions between customers and FX dealer banks but excludes any trades between two dealers.[30] Second, CLS volume is the sum of all customer-dealer and inter-dealer trades. Inter-bank trading accounts on average for 58% of CLS trading volume and is driven by two key factors: customer flows and inter-dealer "hot-potato" trading (Lyons, 1997). The latter refers to the idea that the order imbalance initiated by the customers of one bank is passed on to multiple other banks. This is particularly true for either exotic or illiquid currency pairs. Hence, the findings in this paper are unlikely to be driven by excessive hot-potato trading in dollar pairs that 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. Notice that the difference between buy and sell volume is commonly referred to as order flow in the literature (Evans, 2002). However, order flow is not the right proxy for fundamental trading demand for two reasons: First, looking at order flow would likely underestimate the aggregate trading demand at a given point in time due to the netting effect. Second, aggregate trading volume has no sign and is hence driven by both buy and sell order volume. CLS order flow data is available to me at the hourly frequency. This allows me to proxy the variance of fundamental trading demands $var(flow)_{k,t}$ as the intraday realised variance of $flow_{k,t}$ that is straightforward to compute from hourly data .

Next, to measure the relative riskiness $volatility_{k,t}$ of every currency pair, I compute the daily realised variance (Barndorff-Nielsen and Shephard, 2002) of currency pair k at time t as

$$rv_{k,t} = \sum_{j=1}^{1440} (r_{k,t,j})^2, \tag{11}$$

where $r_{k,t,j}$ is the log difference in the midquote FX rate $s_{k,t,j}$ over a one minute interval j:

$$r_{k,t,j} = \Delta s_{k,t,j} = s_{k,t,j} - s_{k,t,j-1}, \tag{12}$$

[30] 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 to avoid double counting. Importantly, trades between a price taker and market maker bank are not excluded.

where natural logarithms are denoted by lowercase letters. All spot rates $s_{k,t,j}$ are quoted as the price of the base currency in units of the quote currency. Returns are always calculated from the perspective of the base currency.

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 over the full sample. This simple 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 (531 $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 around the concentration of trading volume in dollar pairs, but on the other hand it is evidence in favour of the notion that price impact rather than bid-ask spreads are the primary cost of trading.

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

$$volume_{k,t} = \mu_t + \alpha_k + \beta' \mathbf{f}_{k,t} + \gamma' \mathbf{w}_{k,t} + \epsilon_{k,t}, \tag{13}$$

where μ_t are time series fixed effects, α_k denotes currency pair fixed effects, and $\mathbf{f}_{k,t}$ may include trading demands $flow_{k,t}$, variance of 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 variables are taken in absolute values because trading volume by definition is unsigned.

I construct these three control variables as follows: First, I compute the relative bid-ask spread as the ratio of the absolute bid-ask spread and midquote (average of bid and ask rates). Second, I approximate the daily interest rate differential between the base and quote currency country by the forward discount or premium that I compute as the difference between the overnight forward rate f_t and the spot midquote s_t.[31] Third, I estimate the cross-currency basis following Du, Tepper, and Verdelhan (2018) 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.[32]

The rationale for including each of these three variables as controls can be summarised

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

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

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 over the full sample. The sample is balanced (54,292 hourly observations per currency pair) and covers the period from 1 September 2012 to 29 September 2020.

in three points. First, the role of the relative bid-ask spread as a control is to address the concern that traditional transaction costs are an important determinant of trading volume. Second, the link between interest rate differentials and FX trading volume stems from the fact that carry trade speculators are long (*short*) in high (*low*) interest rate currencies (Lustig and Verdelhan, 2007). Hence, currency pairs that exhibit 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 that dealer funding costs are a significant determinant of dealer-intermediated trading volume. Following Andersen, Duffie, and Song (2018) the cross-currency basis can be interpreted as a proxy for dealer funding costs.

The equilibrium expression for optimal trading volume (see Eq. (6) in Section 3) is *linear* because traders' demand schedules are assumed to be linear in the primitives (e.g., fundamental trading demands). However, as highlighted in the simulations, any cross-sectional heterogeneity in fundamental trading demands gets amplified by the fact that low price impact currency pairs are often 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.

Across all specifications, both dependent and independent variables are taken in logs and first differences. There are two key advantages of running these regressions with log-differences. First, regression coefficients are straightforward to be interpreted as percentage point changes. Second, FX volume in levels is non-stationary and persistent, hence taking first-differences is an effective remedy to make the time series stationary. In addition, I divide each time series by the standard deviation of the respective variable across all currency pairs. Notice that standardising does neither alter the relative sizes between currency pairs nor change the sign or significance of the regression estimates.

The frequency of these regressions is daily, which guards me against the possibility that well-know intraday seasonalities (e.g., Ranaldo, 2009; Breedon and Ranaldo, 2013) affect my estimations. Robust standard errors are computed based on Driscoll and Kraay (1998) allowing for random clustering and serial correlation up to 7 lags. The optimal lag length is based on the plug-in procedure for automatic lag selection by Newey and West (1994).

Table 2 collects the results of running various specifications of Eq. (13) and shows strong empirical evidence that is consistent with the comparative statics in Theorem 1: changes in log trading volume $volume_{k,t}$ positively covary with changes in log trading demands $flow_{k,t}$, log variance of trading demands $var(flow)_{k,t}$, as well as log realised variance of currency returns $volatility_{k,t}$. Through the lenses of the theory developed in Section 3, the latter result is intuitive because volatility carries information about dispersion in fundamental trading demands (i.e., investor disagreement), which induces trading volume.[33] This empirical finding is particularly useful in light of the fact that the sign of the elasticity of volume with respect to volatility is ambiguous (see Theorem 1).

All regression results are qualitatively unchanged when including interaction terms in addition to the main effects (columns 4 and 5). Both interaction effects are statistically significant at the 1% level and similar in terms of economic magnitude. To be specific, trading volume is on average 5 percentage points higher across currency pairs during periods of high volatility combined with large or very volatile trading demands. This result corroborates the idea that the multiplicative effect that is 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 do not include interest rate differentials $interest\,rate_{k,t}$ and cross-currency bases $cip\text{-}basis_{k,t}$ in the same specification because the two are by construc-

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

tion 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 indeed have a significant impact on dealer-intermediated FX trading volume.

Relative importance measure. Given that the three drivers of trading volume are correlated one might wonder about their relative importance. In particular, I am interested in the importance of fundamental trading demand relative to vehicle currency trading due to strategic price impact avoidance. In my model, the expected price impact in a currency pair hinges on the variance of trading demands and currency returns, respectively.

Following Johnson and Lebreton (2004), I define relative importance as the contribution that each regressor makes to the coefficient of determination (i.e., R^2). I estimate the relative importance of each driver using an averaging over orderings approach proposed by Lindeman, Merenda, and Gold (1980). The key advantage of this method is that it takes both the direct (i.e., the correlation with the outcome variable) and indirect effect (i.e., when combined with other explanatory variables) of a regressor into account. The relative importance measure lmg of the m-th regressor X_m is given as:

$$lmg(X_m) = \frac{1}{p!} \sum_{r \in \mathcal{P}} R^2(X_p | S_p(r)), \tag{14}$$

where $R^2(X_p|S_p(r))$ is the difference in R^2 of a model with and without the regressor $S_p(r)$ based on the order $r = \{r_1, ..., r_p\}$, where $\mathcal{P}$ denotes the set of all permutations of r.

Figure 5 visualises the relative importance of the three model–determinants of trading volume. There are two takeaways from this figure: First, as expected, changes in fundamental trading demand $flow$ are the most important determinant of volume and account on average for 22% of the time series variation. Second, changes in the variance of fundamental trading demands $var(flow)$ and currency returns $volatility$ account for 12% and 4% of the dispersion volume. Notice that the sum of these relative importance measures is equal to the R^2 of a regression that simultaneously includes all three variables as regressors in Eq. (13).

The last two findings provide compelling evidence in favour of the vehicle currency trading channel. This is because they stress the importance of strategic price impact impact avoidance in addition to the size of fundamental trading demand as a key driver of FX volume. Both results are fully in line with the predictions of the market (micro)structure view.

Elasticity of price impact. 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. Em-

Table 2: Economic Drivers of Trading Volume

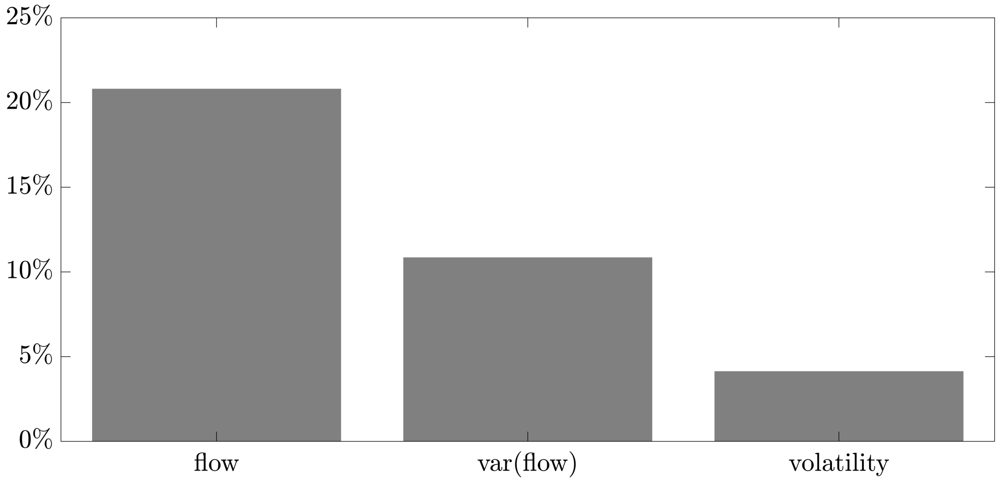
	$\text{volume}_{k,t}$				
	(1)	(2)	(3)	(5)	(6)
$\text{flow}_{k,t}$	***0.57			***0.55	
	[43.13]			[40.45]	
$\text{var(flow)}_{k,t}$		***0.41			***0.39
		[40.03]			[37.85]
$\text{volatility}_{k,t}$			***0.29	***0.15	***0.20
			[27.18]	[20.17]	[20.10]
$\text{bid-ask spread}_{k,t}$	***−0.07	***−0.09	***−0.05	***−0.05	***−0.06
	[11.36]	[9.95]	[6.32]	[7.09]	[6.08]
$\text{abs(interest rate}_{k,t})$	**−0.01		***−0.02	−0.01	
	[2.13]		[3.73]	[1.54]	
$\text{abs(cip-basis}_{k,t})$		***−0.02			***−0.02
		[3.19]			[2.62]
$\text{flow} \times \text{volatility}_{k,t}$				***0.04	
				[4.79]	
$\text{var(flow)} \times \text{volatility}_{k,t}$					***0.05
					[5.46]
Adj. R^2 in %	33.14	21.15	8.10	34.85	24.32
Avg. #Time periods	2068	2065	2068	2068	2065
#Exchange rates	25	25	25	25	25
Currency FE	yes	yes	yes	yes	yes
Time series FE	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. 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 (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 the plug-in procedure by Newey and West (1994). Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels.

pirically, I am interested in whether price impact is purely driven 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:

$$\lambda_{k,t} = \mu_t + \alpha_k + \beta' \mathbf{f}_{k,t} + \epsilon_{k,t}, \tag{15}$$

Figure 5: Relative Importance Measure of Economic Drivers



Note: This figure shows the relative importance measure lmg of the three model–determinants of trading volume, that is, fundamental trading demand $flow$, variance of fundamental trading demands $var(flow)$, and variance of currency returns $volatility$. The estimation follows an averaging over orderings approach proposed by Lindeman et al. (1980). Notice that the sum of the three relative importance measures is equal to the R^2 of including all three variables as regressors in Eq. (13). The sample covers the period from 1 September 2012 to 29 September 2020.

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 fundamental 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. The dependent variable is the price impact $\lambda_{k,t}$ in currency pair k at time t. In the spirit of Kyle (1985), I estimate $\lambda_{k,t}$ separately for every currency pair as the rolling regression coefficient of currency returns on customer order flows:

$$r_{t+1,t+w} = \alpha + \lambda order\ flow_{t+1,t+\omega} + \nu_{t+1,t+w} \qquad t = 0, ..., T - w, \tag{16}$$

where w is the rolling window length that is equal to 365 days, r_t is the log currency return (see Eq. (12)), and $order\ flow_t$ is defined as the aggregate net buying or selling pressure against the base currency (Evans, 2002).[34] Hence, the dependent variable in the regression model is estimated. This does not bias the estimates, but may introduce heteroskedasticity into the residuals (Lewis and Linzer, 2005). Both dependent and independent variables are measured in units of standard deviation. The frequency of these regressions is daily.

Table 3 shows the results of estimating different variants of the panel regression setup in Eq. (16). There are three main results to highlight: First, an increase in the variance of

[34]Note that my empirical results are robust to using alternative price impact measures including Hasbrouck (1991b), Amihud (2002), and Gabaix, Gopikrishnan, Plerou, and Stanley (2006). The advantage of the classic Amihud price impact measure is that it does not require order flow data but can only capture past average price changes per unit of volume. On the other hand, the impulse response functions in Hasbrouck (1991b) are forward looking but are sensitive to the forecast horizon. Gabaix et al. (2006) is identical to Eq. (16) but assumes that prices react to large signed orders with a change proportional to the square root of the order size.

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) is decreasing in the variance of trading demands. Second, price impact positively covaries with the variance of currency returns $volatility_{k,t}$. Conceptually, this is in line with my model, where Gaussian conditioning is the reason why price impact is concave in the variance of currency returns. Third, the relation between price impact and variance of currency returns is partially confounded by the relative bid-ask spread $\textit{bid-ask spread}_{k,t}$. Contrarily, the variance of trading demands is a novel and resilient determinant of price impact.

Table 3: Economic Drivers of Price Impact

	$\lambda_{k,t}$			
	(1)	(2)	(3)	(4)
$vol(flow)_{k,t}$	***−0.02		***−0.02	***−0.02
	[5.78]		[6.01]	[5.46]
$volatility_{k,t}$		*0.02	*0.02	0.01
		[1.68]	[1.71]	[0.53]
$\text{bid-ask spread}_{k,t}$				***0.03
				[2.99]
R^2 in %	0.01	0.05	0.06	0.11
Avg. #Time periods	1706	1706	1706	1706
#Exchange rates	25	25	25	25
Currency FE	yes	yes	yes	yes
Time series FE	yes	yes	yes	yes

Note: This table reports results from daily fixed effects panel regressions of the form $\lambda_{k,t} = \mu_t + \alpha_k + \beta' f_{k,t} + \epsilon_{k,t}$, where $f_{k,t}$ may include several regressors. The dependent variable is the price impact $\lambda_{k,t}$ in currency pair k at time t that I estimate following Kyle (1985). μ_t and α_k denote time series and currency pair fixed effects, respectively. $var(flow)_{k,t}$ is the daily variance of hourly customer flows. $volatility_{k,t}$ is the daily realised variance of currency returns computed from one minute spot rates. $\textit{bid-ask spread}_{k,t}$ is the daily average relative bid-ask spread. All variables are measured in units of standard deviation. The sample covers the period from 1 September 2012 to 29 September 2020. The test statistics based on Driscoll and Kraay (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, the primitive drivers of the model are also empirically relevant determinants of inter-dealer FX trading volume. Second, price impact is contingent on both the relative riskiness of currency pairs as well as the distribution of fundamental trading demands. Taken together, the evidence in this section lends support to the market (micro)structure view of dollar dominance.

4.3. Evidence of Dollar Dominance

Here, I provide empirical evidence of dollar dominance that is consistent with the economic intuition of my model. Theoretically, a triplet of currency pairs (e.g., GBPJPY, USDGBP and USDJPY) will be dominated by the dollar if at least one of the following three conditions is satisfied, while the other two hold with equality: 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, the goal of this section is twofold: First, pin down which of the three conditions are supported by the data. Second, test if there is a consistent mapping between the conditions and my estimates of dollar dominance in FX volume.

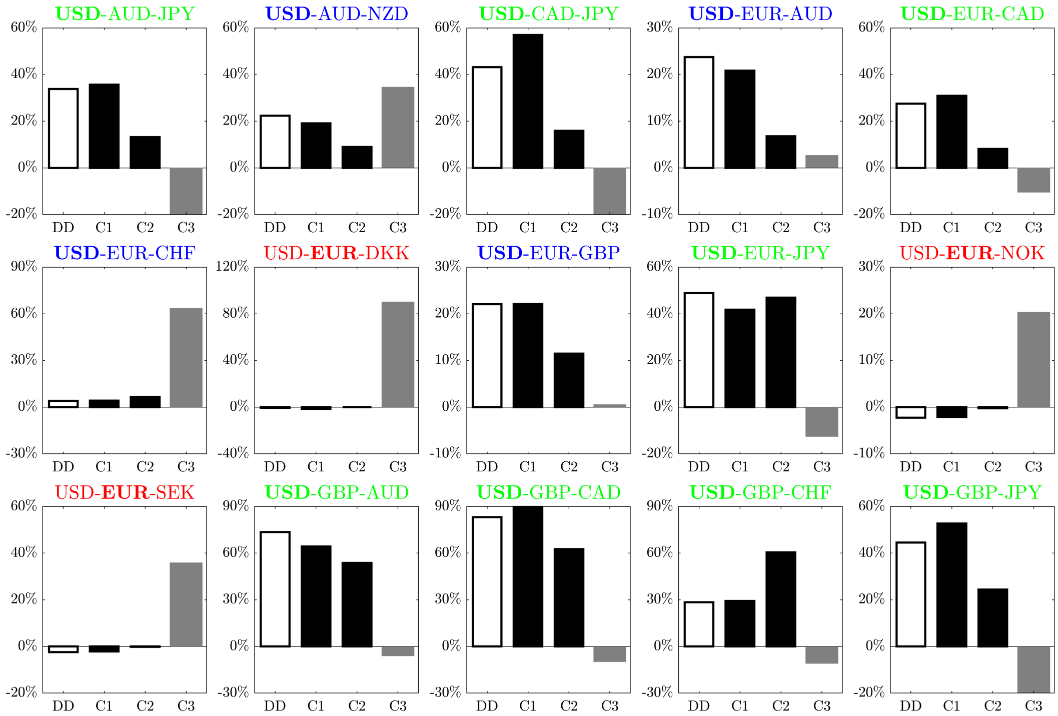
Sufficient conditions. Figure 6 summarises the empirical counterparts of the three sufficient conditions. For every triplet of currency pairs I plot four bars. The first bar from the left named DD corresponds to my empirical measure of dollar dominance: A positive number implies dollar dominance, whereas a negative number is evidence against it. The three other bars labelled $C1$, $C2$, and $C3$, respectively, each represent one of the sufficient conditions in Theorem 2. To derive an empirical measure of dollar dominance DD I proceed in three steps: First, for each currency pair k, I compute the time series average of (inter-dealer) trading volume $volume_{k,t}$ and hence drop the time-subscript t. Second, I focus on triplets of currency pairs (e.g., GBPJPY, USDGBP, and USDJPY) and compute the cross-sectional average in trading volume $volume_k$ across two currency pairs that involve the same currency (i.e., GBP, JPY, or USD). I denote these cross-sectional averages by $volume^j$ where j contains the USD as well as the base and quote currency of the non-dollar currency pair (i.e., GBP and JPY for GBPJPY). Third, I compute the relative difference in percent between $volume^{USD}$ and the maximum of $volume^{j \notin USD}$. I proceed analogously for the three sufficient conditions (i.e., $C1$, $C2$, and $C3$) based on fundamental trading demand $flow_{k,t}$, the volatility of fundamental trading demands $std(flow_{k,t})$, and the realised volatility $\sqrt{rv}_{k,t}$ of currency returns, respectively. However, note that for the realised volatility of currency returns I compute the difference between $\sqrt{rv}^{USD}$ and the minimum of $\sqrt{rv}^{j \notin USD}$. This is because the third conditions implies that less volatile currency pairs should exhibit lower price impacts and thus more trading volume.

Next, I compare my estimates of dollar dominance and the three sufficient conditions focusing on two null hypotheses: First, dollar dominance DD is equal to the first sufficient condition $C1$ implying that the inter-dealer market is Walrasian in the sense that dealers just pass through what customers want to trade. Clearly, this would mean that there is no scope for vehicle currency trading. Second, sufficient conditions $C2$ and $C3$ are equal to zero, which would lend support against price impact being a relevant determinant of vehicle currency trading. To carry out these tests, I compute DD, $C1$, $C2$, and $C3$ analogously to above except that I do not compute any time series averages in the first step. The inference is based on a Newey and West (1994) covariance matrix with a bandwidth of 7 lags.

Two results stand out from this analysis: First, in line with the graphical evidence shown in Figure 6, for 6 out of 15 triplets DD is significantly larger than $C1$.[35] Second, the sufficient conditions $C2$ and $C3$ are both significantly different from zero at the 1% significance level for

[35] To save space, I relegate the test statistics for both hypothesis tests to Table D.1 in the online appendix.

Figure 6: Sufficient Conditions: Empirical Evidence



Note: This figure summarises the empirical counterparts of the sufficient 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 named *DD* corresponds to my empirical measure of dollar dominance: A positive percentage implies dollar dominance, whereas a negative percentage is evidence against it. The other three bars labelled *C*1, *C*2, and *C*3, respectively, each represent one of the sufficient conditions in Theorem 2. The sample covers the period from 1 September 2012 to 29 September 2020.

all 15 triplets of currency pairs except the EURSEK. Therefore, I find circumstantial evidence that FX dealers in the inter-bank market strategically avoid to directly transact in illiquid non-dollar currency pairs. Moreover, the economic and statistical significance of the second and third sufficient condition lends further support to the idea that cross-sectional heterogeneity in price impact can explain the concentration of trading volume in dollar pairs.

Classification. Based on the empirical estimates of dollar dominance *DD* as well as the three sufficient conditions *C*1, *C*2, and *C*3, respectively, I classify triplets of currency pairs into three regions: i) dollar dominance, ii) multiplicity, and iii) non-dollar dominance. First, a triplet of currency pairs is in the region of dollar dominance if all three conditions are satisfied. Second, the region of multiplicity characterises triplets for which only two out of three conditions are satisfied while the remainder creates a counterbalance. This lends support to the idea that the status-quo of the US dollar as a dominant (vehicle) currency has the potential to be scrutinised in triplets that are currently within the region of multiplicity. Lastly, triplets of currency pairs are in the region of non-dollar dominance if at least two out of three conditions (see Theorem 2) are violated in the data.

Following this classification, 12 out of 15 triplets of currency pairs are either in the region of multiplicity or dollar dominance. The USD-AUD-NZD, USD-EUR-AUD, USD-EUR-CHF, and USD-EUR-GBP triplets are in the region of multiplicity because the third sufficient condition on realised volatility is not satisfied. Nevertheless, these four triplets of currency pairs are still dominated by the dollar (i.e., positive DD). This is consistent with the evidence in Figure 5 with the implication that the volatility of currency returns is the least important determinant of trading volume. On the contrary, the first two conditions with respect to the mean and variance of fundamental trading demands are empirically 'necessary' for dollar dominance. This stems from the observation that there is no evidence of dollar dominance unless these two conditions are jointly satisfied.

In my sample, only the USD-EUR-DKK, USD-EUR-NOK, and USD-EUR-SEK triplets are *not* dominated by the dollar as a vehicle currency. This finding is also consistent with the idea that certain geographic regions adopt regionally dominant vehicle currencies for intra-regional trade (Devereux and Shi, 2013). Based on the evidence in Figure 6, the euro seems to enjoy a 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. Through my model, the necessary open market operations for maintaining the peg directly influence the distribution of fundamental trading demands in the EURDKK.

Summary. To conclude, there are two novel insights from this empirical exercise. For one, the two conditions on fundamental trading demands are empirically not only sufficient but also necessary, whereas the third conditions on the variance of currency returns does not seem to play a pivotal role for dollar dominance. Second, there is consistency between the predictions of my model and the data in the sense that I observe dollar or euro dominance in currency pair triplets where the model would predict so but not otherwise.

4.4. *Drivers of Dollar Dominance*

The goal of this section is fourfold: First, derive a time-varying empirical measure of dollar dominance that is tightly linked to the formal definition in my model (see Definition 3). Second, examine if the cross-sectional variation in dollar dominance can be explained by a simple gravity model of exchange rates (Lustig and Richmond, 2019). Third, test whether the three model–based determinants of trading volume can explain the time series variation in dollar dominance. Lastly, provide causal identification by exploiting the idea that uncertainty resolution on days with scheduled FOMC meetings creates plausible exogenous variation in the liquidity of dollar currency pairs.

In line with my model, I define dollar dominance as the ratio of indirect trading volume in dollar pairs (e.g., the average of USDGBP and USDJPY) relative to the direct trading volume in non-dollar pairs (e.g., GBPJPY). In principle, it would be interesting to distinguish between trading volume in dollar pairs due to fundamental and vehicle currency trading demands.

However, trading motives are unobservable in the CLS data and I am not aware of any comprehensive FX data set where they are. In an effort to disentangle the two effects, I use a novel identification method based on non-overlapping holidays in the online appendix Section D. In particular, I find as a conservative lower bound that on average at least 6.3% of the daily trading volume in dollar pairs are due to vehicle currency trading motives.

The solid black lines in Figure 7 plot my empirical measure of dollar dominance $doldom_{j,t}$ for $j = 1, 2, ..., 15$ triplets of currency pairs. In addition to that, the dashed black and solid grey lines are dominance scores for the two other non-dollar currencies within each triplet (e.g., GBP and JPY). My proxy for dollar dominance has sensible properties along two dimensions: First, dollar dominance increases during periods of recessions (e.g., Covid19 period in 2020) and well known episodes of financial turmoil (e.g., European sovereign debt crisis in 2015 and Brexit referendum in 2016). These periods of market stress are associated with a flight to safety in dollar assets (Jiang et al., 2021). From the perspective of my model, the surge in dollar dominance may stem both from an increase in trading flows in dollar currency pairs as well as reduced uncertainty about movements in dollar exchange rates.

Second, the cross-sectional differences in dollar dominance corroborate the classification in the previous section. Specifically, triplets of currency pairs that are either in the region of multiplicity (e.g., USD-EUR-CHF and USD-EUR-GBP) or non-dollar dominance (e.g., USD-EUR-NOK, and USD-EUR-SEK) exhibit higher levels of euro dominance than the other triplets. Furthermore, the USD-EUR-DKK triplet provides a counterfactual to the vehicle currency trading hypothesis because the dominance scores are much larger for the euro than the US dollar. Clearly, this must stem from the fact that the Danish krone is effectively pegged against the euro, which makes vehicle currency trading via the dollar irrelevant. Note that the case of the USD-EUR-CHF triplet is fully consistent with this evidence in the sense that removing the Swiss Franc cap on 15 January 2015 has induced a sharp decline in the liquidity of the EURCHF and led to a persistent increase in the dollar dominance score.

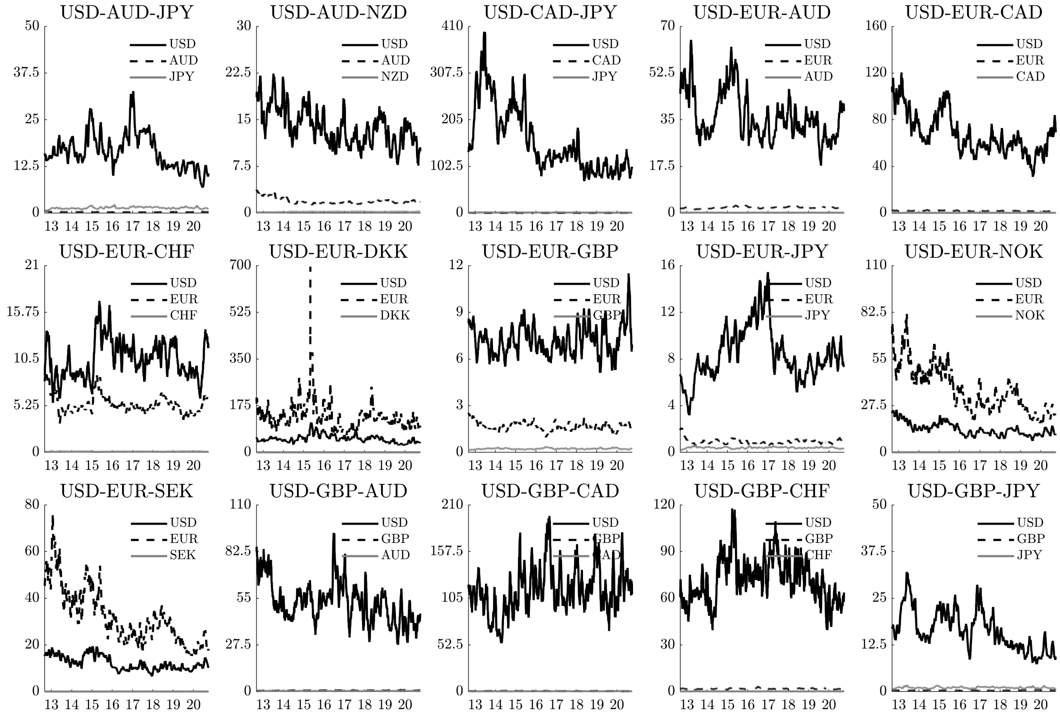
4.4.1. Cross-sectional Variation in Dollar Dominance

Here, I link the dollar dominance characteristics of currency pair triplets to measures of physical, cultural, and institutional distance (Lustig and Richmond, 2019). Following the gravity literature, I hypothesise that the importance of the US dollar as an intermediate 'vehicle' currency is increasing in the distance between two non-dollar countries. To answer this question, I run the following panel regression with *time series* fixed effects:

$$doldom_{j,t} = \mu_t + \beta' \mathbf{g}_j + \epsilon_{j,t}, \tag{17}$$

where μ_t denotes time series fixed effects, and $\mathbf{g}_j$ may include several measures of economic distance between two non-dollar currency countries (e.g., the UK and Japan). In particular, I include physical distance, shared border, linguistic similarity, shared legal origin, and time-zone difference. Note that these gravity variables are time-invariant and by construction exogenous to the share of trading activity in dollar and non-dollar pairs, respectively.

Figure 7: Time-variation of Dollar Dominance



Note: This figure shows the time variation in dollar dominance $doldom_{j,t}$ for 15 triplets of currency pairs. Dollar dominance is defined as the ratio of indirect trading volume in dollar pairs (e.g., USDGBP and USDJPY) relative to the direct trading 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.

These gravity data are available from Head, Mayer, and Ries (2010) and Mayer and Zignago (2011) unless otherwise indicated. Physical distance is the population-weighted average distance between large cities in each non-dollar country pair. Shared border is a binary variable that is equal to 1 if two countries have a common border on land or sea and 0 otherwise. Common language is equal to 1 if a language is spoken by more than 9% of the population in both countries. Common legal origin is a dummy variable from a classification of countries' legal origins (see La Porta, Lopez-de-Silanes, and Shleifer, 2008). Time-zone differences are equal to the average number of hours between each non-dollar country dyad.

Table 4 reports the results for various specifications of Eq. (17). Each of these cross-sectional regressions indicates that an increase in economic distance between two non-dollar countries increases my empirical measure of dollar dominance $doldom_{j,t}$. The interdependent nature of exchange rates may lead to correlation in the residuals. Therefore, the inference is based on Driscoll and Kraay (1998) standard errors that are robust to conditional heteroskedasticity and serial and cross-sectional correlation within as well as between "clusters". Physical distance, shared border, shared legal origin, and time difference carry the expected sign and are significant at any conventional confidence level. The average dollar dominance $doldom_{j,t}$ is 43.4, while the cross-sectional standard deviation is 53.5.

A 1,000 km increase in the physical distance increases my measure of dollar dominance by 1.88. This estimate is robust across different specifications. Shared border lowers dollar dominance by about 5.1. Surprisingly, shared language is associated with a strong increases in dollar dominance. This is presumably due to the fact that in my sample some of the countries with shared language, for instance, Australia and Canada are geographically distant. Shared legal origin lowers dollar dominance by up to 62.0. Note that time difference and physical distance are correlated and hence not included in the same specification.[36] The second specification accounts for almost one fifth of all the variation in dollar dominance. In sum, the evidence in this section strongly supports a gravity based approach to explaining the cross-sectional dispersion in dollar dominance.

Table 4: Cross-sectional Determinants of Dollar Dominance

	(1)	(2)	(3)
Distance in 1,000 km	***1.88		***0.91
	[31.23]		[13.57]
Shared border		***−5.09	***−27.45
		[8.11]	[59.79]
Shared language		***59.71	***48.63
		[69.23]	[73.94]
Shared legal		***−62.04	***−48.32
		[44.04]	[49.69]
Time difference		***5.37	
		[27.52]	
Adj. R^2 in %	3.58	19.75	11.57
Avg. #Time periods	2070	2070	2070
#Currency triplets	15	15	15
Time series FE	yes	yes	yes

Note: This table reports results from daily fixed effects panel regressions of the form $doldom_{j,t} = \mu_t + \beta' \mathbf{g}_{j,t} + \epsilon_{j,t}$, where the dependent variable $doldom_{j,t}$ is my measure of dollar dominance, μ_t denotes time series fixed effects, and $\mathbf{g}_j$ may include several measures of economic distance between two non-dollar countries. The sample covers the period from 1 September 2012 to 29 September 2020. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for heteroskedasticity, random clustering, and serial correlation (up to 7 lags) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels.

4.4.2. *Time Series Variation in Dollar Dominance*

To test the empirical linkages between my empirical measure of dollar dominance $doldom_{j,t}$ and the three model–based drivers of trading volume I consider the following panel regression with *cross-sectional* fixed effect:

$$doldom_{j,t} = \alpha_j + \beta' \mathbf{f}_{j,t}^{USD} + \epsilon_{j,t}, \tag{18}$$

[36]Consistent with the evidence in this section, the online appendix Section D shows that dollar dominance significantly decreases intraday when two non-dollar countries' stock markets are simultaneously open.

where α_j denotes currency pair triplet fixed effects to control for any potential omitted variable that is constant across triplets of currency pairs. Thus, if fundamental trading demands are relatively stable over time then $doldom_{j,t}$ minus the fixed effects effectively captures variation in vehicle currency trading. Moreover, $\mathbf{f}_{j,t}^{USD}$ may include fundamental trading demand $flow_{j,t}$, variance of fundamental trading demands $var(flow)_{j,t}$, and realised variance $volatility_{j,t}$ of currency returns. In some specifications, I also add the relative bid-ask spread $bid\text{-}ask\,spread_{j,t}$ as a regressor to control for general market liquidity.

The objective of this regression is to tease out how changes in the mean and variance of fundamental trading demands in dollar currency pairs as well as the variance of dollar exchange rate returns affect dollar dominance. Hence, I compute each of the regressors in $\mathbf{f}_{j,t}^{USD}$ separately within every triplet of currency pairs as an average across the two dollar pairs. Both the dependent and independent variables are taken in logs and first differences to facilitate the interpretation of the regression coefficients as percentage point changes.

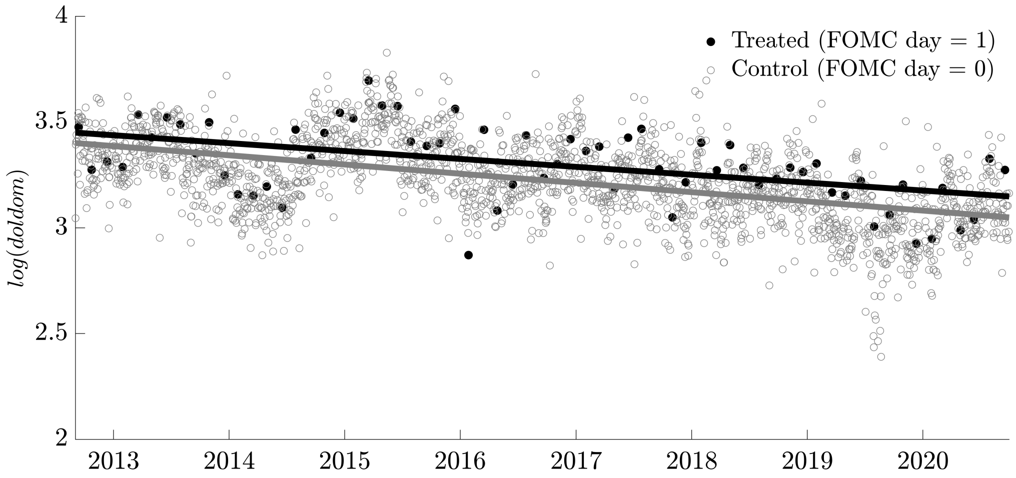
Endogeneity. The regression setup in Eq. (18) may suffer from reverse causality due to the fact that dollar dominance, fundamental trading demands, and volatility of currency returns are all determined simultaneously in equilibrium. To overcome this endogeneity issue I need an instrument that directly affects my endogenous regressors but not the other way around. Days with scheduled FOMC meetings[37] arguably satisfy this exclusionary restriction. Specifically, FOMC events are empirically associated with increased FX trading activity. This effect is presumably due to the resolution of uncertainty about US monetary policy (e.g., Berger, Chaboud, Chernenko, Howorka, and Wright, 2008; Chaboud et al., 2008). However, high FX volume does not cause scheduled FOMC meetings (Fischer and Ranaldo, 2011).

Scheduled FOMC announcement days are not a random experiment. This may impede the internal validity of my instrumental variable (IV) regression if it leads to a violation of the common trend assumption. Figure 8 provides evidence in favour of the parallel trend assumption. The treated period comprises days with scheduled FOMC meeting, whereas the control period consists of all other days. Every observation (black dots and grey circles) corresponds to the cross-sectional average of dollar dominance $doldom_{j,t}$ (in natural log units). The bold black and grey lines are least squares regression lines of the treated and control period, respectively. In sum, scheduled FOMC meetings are as good as randomly assigned with respect to the counterfactual level of dollar dominance across all other days.

Elasticity of dollar dominance. The panel regression analysis proceeds in two steps: In the first step, motivated by the evidence in Figure 8, I estimate Eq. (18) in reduced form. Specifically, I regress the log of dollar dominance $doldom_{j,t}$ on my FOMC dummy that is equal to 1 on days with scheduled FOMC meetings and 0 otherwise. This is equivalent to computing the difference in means of $doldom_{j,t}$ on days with FOMC meetings and all other days, given that we have subtracted group means from $doldom_{j,t}$. The point estimate of the reduced form is 0.07 and statistically significant at the 1% significance level (standard

[37] The FOMC meets every five to eight weeks to make decisions about interest rates and the growth of the United States money supply.

Figure 8: Common Trend Assumption: FOMC Announcement Days



Note: This figure provides evidence for the internal validity of the parallel trend assumption. The treated period comprises days with scheduled FOMC meeting, whereas the control period consists of all other days. Every observation (black dots and grey circles) corresponds to the cross-sectional average of dollar dominance $doldom_{j,t}$ (in natural log units), that is, the ratio of indirect trading volume in US dollar pairs relative to direct trading in non-dollar pairs. 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.

errors are based on Driscoll and Kraay (1998) with 7 lags following the plug-in procedure by Newey and West (1994)). Put differently, dollar dominance is on average 7% higher after a quasi-exogenous spike in the liquidity of dollar pairs that is induced by the resolution of uncertainty on days with scheduled FOMC meetings.

In the second step, I compare the results from estimating Eq. (18) by ordinary least squares (OLS) and two-stage least squares (2SLS), respectively. In Table 5, Panel A presents the OLS estimates, whereas panel B shows the first and second stage results of the IV regression. There are three key takeaways: First, the relevance of FOMC announcement days as an instrument is strongly supported by the significant (F-statistic well above 10) first stage estimates in the row headed $FOMC\,dummy_t$. For instance, fundamental trade interest in dollar currency pairs is on average 11% higher on days with scheduled FOMC meetings than on all other days.

Second, both OLS and 2SLS estimates are highly significant and the signs of the coefficients are consistent with the predictions of my model. For instance, a one percentage point increase of fundamental trading demand in dollar currency pairs induces a 1.57 percentage point increase in dollar dominance on days with scheduled FOMC meetings. Note that the average of the dollar dominance measure across time and currency triplets is 43.4, hence a 1.57 percentage point increase amounts to a change of around 0.68 per day.

Third, controlling for changes in the average relative bid-ask spread does neither change the economic nor statistical significance of my estimates.[38] Diagnostic tests suggest weak first

[38]All results remain qualitatively unchanged when including either the interest rate differential or cross-currency basis as a control variable. These robustness tests are available upon request.

but no second order autocorrelation and some degree of heteroskedasticity. Therefore, the inference is based on a Driscoll and Kraay (1998) covariance matrix with a bandwidth of 1 lag. It is worth emphasising that the IV approach may not fully compensate for endogeneity due to omitted variables. This is because all three model-based drivers of volume are correlated. Hence, ideally, I would like to use a different instrument for each of three drivers before jointly including them in the same regression specification.

4.4.3. Robustness

Here, I briefly summarise three additional robustness checks that support my empirical findings. The online appendix Section D documents these additional analyses. First, to guard myself against the possibility that my results are driven by seasonalities I follow Fischer and Ranaldo (2011) and filter the deterministic effect by running the following regression for every currency pair: $vol_{k,t} = \alpha_k + \sum_{i=1}^{4} \beta_{k,i} Day_i + \sum_{m=1}^{6} \gamma_{k,m} vol_{k,m,t-1} + \nu_{k,t}$, where Day_i is a dummy that captures day-of-the-week effects and $vol_{k,t}$ is trading volume in currency pair k. The fitted values from this regression $vol^S_{k,t}$ are robust to daily and weekly effects.

Second, I follow the approach in Cespa et al. (2021) to de-trend trading volume and divide today's volume in each currency pair by a moving average over the previous 22 days' trading volume: $vol^T_{k,t} = vol_{k,t} / (\frac{1}{M} \sum_{m=1}^{M} vol_{k,t-m})$, setting $M = 22$. All results remain qualitatively unchanged when computing $doldom_{j,t}$ based on de-seasonalised $vol^S_{k,t}$ and de-trended $vol^T_{k,t}$ volume, respectively. Third, I condition on the direction of the change in the federal funds rate target and distinguish between interest rate cuts, hikes, and neutral announcements. I find that dollar dominance increases more on days with cuts and hikes than neutral policy announcements. In sum, all these robustness checks corroborate my main results.

Summary. To summarise, this section has supplied evidence that dollar dominance in FX trading is tightly linked to the model–based drivers of trading volume in dollar currency pairs. Specifically, I have established a causal link between changes in the mean and variance of fundamental trading demands in dollar pairs, the variance of dollar exchange rate returns, and my empirical measure of dollar dominance.

5. Conclusion and Policy Implications

This paper studies the origins of dollar dominance in FX trading, contributing 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. The key economic insight from my model is a set of sufficient conditions for dollar dominance that can predict which non-dollar currency pairs are more likely to trade indirectly via the US dollar. Perhaps surprisingly, I show that even a symmetric market with identical initial trading demands across currency pairs can be dominated by the US dollar if dollar pairs are either less risky or exhibit more variability in trading demands.

On the empirical side, I take my model to the data and document three novel empirical facts that illustrate the relevance of my theory. First, I estimate the model in reduced form

Table 5: Time Series Determinants of Dollar Dominance

	$\text{doldom}_{\text{j,t}}$					
Panel A: OLS	(1)	(2)	(3)	(4)	(5)	(6)
$\text{flow}_{\text{j,t}}$	***0.20			***0.20		
	[11.30]			[8.63]		
$\text{var(flow)}_{\text{j,t}}$		***0.07			***0.07	
		[13.70]			[11.77]	
$\text{volatility}_{\text{j,t}}$			***0.06			**0.03
			[6.53]			[2.39]
$\text{bid-ask spread}_{\text{j,t}}$				−0.02	0.03	***0.15
				[0.48]	[0.93]	[3.55]
Adj. R^2 in %	3.09	3.09	0.47	3.10	3.10	0.55
Panel B: 2SLS	(1)	(2)	(3)	(4)	(5)	(6)
$\text{flow}_{\text{j,t}}$	**1.57			**1.20		
	[2.28]			[1.98]		
$\text{var(flow)}_{\text{j,t}}$		**0.59			*0.45	
		[2.03]			[1.88]	
$\text{volatility}_{\text{j,t}}$			***0.16			***0.12
			[5.82]			[4.20]
$\text{bid-ask spread}_{\text{j,t}}$				*0.23	**0.23	***0.23
				[1.77]	[2.33]	[4.93]
$\text{FOMC dummy}_{\text{t}}$	***0.11	***0.29	***0.40	***0.11	***0.29	***0.40
	[4.80]	[4.65]	[5.43]	[4.80]	[4.65]	[5.43]
Avg. #Time periods	2069	2069	2069	2069	2069	2069
#Currency triplets	15	15	15	15	15	15
Currency FE	yes	yes	yes	yes	yes	yes

Note: This table reports results from daily fixed effects panel regressions of the form $doldom_{j,t} = \alpha_j + \beta' \mathbf{f}^{USD}_{j,t} + \epsilon_{j,t}$, where the dependent variable $doldom_{j,t}$ is my measure of dollar dominance, α_j denotes currency triplet fixed effects, and $\mathbf{f}^{USD}_{j,t}$ may include several regressors. $flow_{j,t}$ is the aggregate daily customer order flow (buy plus sell volume) measured in US dollars. $var(need)_{j,t}$ is the daily realised variance of hourly order flow. $volatility_{j,t}$ is the daily realised variance of currency returns computed from one minute spot rates. Both dependent and independent variables are taken in logs and changes. Each of these three regressors is computed separately within every triplet of currency pairs j as the average across the two dollar currency pairs. $bid\text{-}ask\,spread_{j,t}$ is the daily average relative bid-ask spread. Panel A reports ordinary least squares (OLS) estimates. Panel B shows two-stage least square estimates using FOMC announcement days as an instrument for $flow_{j,t}$, $var(flow)_{j,t}$, and $volatility_{j,t}$, respectively. The row headed $FOMC\,dummy_t$ refers to the first stage estimates of regressing the endogenous regressor on a dummy that is equal to 1 if day t is a scheduled FOMC meeting and 0 otherwise. The sample covers the period from 1 September 2012 to 29 September 2020. The test statistics based on Driscoll and Kraay (1998) robust standard errors allowing for random clustering and serial correlation (up to 1 lag) are reported in brackets. Asterisks *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels.

and find compelling empirical evidence that the three primitives of my model, namely, the mean and variance of initial 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 sufficient conditions for dollar dominance with the data and find that all three conditions are jointly satisfied for at least 50% of non-dollar currency pairs. Lastly, I use

FOMC announcement days to establish a causal relation between the three model–based drivers of trading volume and my empirical measure of dollar dominance.

My paper should be relevant for academics and policy makers alike. For academics, it provides a tractable theoretical framework to study 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 for welfare analysis since they do not rely on the presence of noise traders or not-fully-optimising traders (Rostek and Yoon, 2021). 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, namely the size and variability of initial trading demands as well as the variance of exchange rate returns. Thus, ousting the dollar from its current dominant role would require a central bank to influence at least one of these three levers. For instance, sterilized and non-sterilized currency interventions may directly affect both the size and variability of initial trading demands in currency pairs involving the domestic currency. Depending on the nature of theses intervention they may or may not dampen exchange rate fluctuations. To this end, pegging the domestic currency 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 just a mirror image of 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., 2018. Funding value adjustments. *The Journal of Finance*, 74(1): 145–192.

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.

Berger, D. W., Chaboud, A. P., Chernenko, S. V., Howorka, E., and Wright, J. H., 2008. Order flow and exchange rate dynamics in electronic brokerage system data. *Journal of International Economics*, 75 (1):93–109.

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. *The Review of Financial Studies*, 30(3):703–749.

Bulow, J. I., Geanakoplos, J. D., and Klemperer, P. D., 1985. Multimarket oligopoly: Strategic substitutes and complements. *Journal of Political Economy*, 93(3):488–511.

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. A. and Valchev, R., 2019. The international medium of exchange. *SSRN Electronic Journal*.

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

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.

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.

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.

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.

Head, K., Mayer, T., and Ries, J., 2010. The erosion of colonial trade linkages after independence. *Journal of International Economics*, 81(1):1–14.

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*.

Johnson, J. W. and Lebreton, J. M., 2004. History and use of relative importance indices in organizational research. *Organizational Research Methods*, 7(3):238–257.

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.

La Porta, R., Lopez-de-Silanes, F., and Shleifer, A., 2008. The economic consequences of legal origins. *Journal of Economic Literature*, 46(2):285–332.

Lewis, J. B. and Linzer, D. A., 2005. Estimating regression models in which the dependent variable is based on estimates. *Political Analysis*, 13(4):345–364.

Lindeman, R. H., Merenda, P. F., and Gold, R. Z., 1980. *Introduction to bivariate and multivariate analysis*. Scott, Foresman, Glenview, Ill.

Lustig, H. and Richmond, R. J., 2019. Gravity in the exchange rate factor structure. *The Review of Financial Studies*, 33(8):3492–3540.

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.

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.

Mayer, T. and Zignago, S., 2011. Notes on CEPII's distances measures: The GeoDist database. *SSRN Electronic Journal*.

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*.

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*.

Protter, P., 1990. *Stochastic Integration and Differential Equations : A New Approach*. Springer Berlin Heidelberg, Berlin, Heidelberg.

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.

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

Rostek, M. J. and Yoon, J. H., 2020. Exchange design and efficiency. *SSRN Electronic Journal*.

Rostek, M. J. and Yoon, J. H., 2021. 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.

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.[39] Every trader i submits her 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.[40]

Since maximising the expected payoff in Eq. (3) is identical to maximising the *ex-post* payoff pointwise for each asset k:

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

given trader i's demand for other assets $q_l^{i,c}$, $\forall l \neq k$ 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 because 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 cross-asset price impact $\frac{\partial p_l}{\partial q_k^{i,c}} \equiv \lambda_{k,l}^{i,c}$ 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

[39] The derivations in this section are closely following Rostek and Yoon (2020).

[40] The idea of considering the optimisation problem of an individual trader against the 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:

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

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

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:

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

where the price impact of trader i is the transpose of the Jacobian of $(\mathbf{S}^{-i,c}(\cdot))^{-1}$, $\boldsymbol{\Lambda}^{i,c} \equiv \left(\frac{\partial p_l}{\partial q_k^{i,c}}\right)_{k,l} = \left(\left(\frac{\partial \mathbf{S}^{-i,c}(\cdot)}{\partial \mathbf{p}}\right)^{-1}\right)'$. The equilibrium 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 her price impact* $\boldsymbol{\Lambda}^{i,c}$*;*

2. *(Correct price impact) The price impact of trader i equals the transpose of the Jacobian matrix of her inverse residual supply function:*

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

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 i:

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

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: $\boldsymbol{\Lambda}^{i,c} = \frac{\gamma}{I-2} \boldsymbol{\Sigma}$. As $I \to \infty$, then $\boldsymbol{\Lambda}^{i,c} \to 0$ for all i. Hence, the competitive limit case coincides with the inverse marginal utility, given the quasilinearity of the payoff function. With a positive price impact (i.e., $\mathbf{\Lambda}^{i,c} > 0$), trader i demands (or sells) less than her 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:

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

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

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

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 $\mathbf{p}^c = \delta - \gamma\mathbf{\Sigma}\bar{\mathbf{q}}_0$, the second moment of the distribution of equilibrium price $Var(\mathbf{p})$ is independent from the distribution of initial transaction demands and only depends on the *exogenous* covariance matrix $\mathbf{\Sigma}$.

There are three properties of the contingent market that do *not* hold when traders submit uncontingent demand schedules. First, the equilibrium price impact of every trader is proportional to the fundamental covariance matrix of currency returns $\mathbf{\Sigma}$ (see Eq. (A.6)). Rostek and Yoon (2020) show that this proportionality has important 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 twofold: first, provide a detailed step-by-step derivation of the equilibrium exchange rate in Eq. (4) and quantity in Eq. (6) along the lines of Rostek and Yoon (2020). Second, collect the proofs of Theorems 1 and 2.

Appendix B.1. Equilibrium

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

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

subject to her residual supply function $S_l^i(\cdot) \equiv -\sum_{j\neq i} q_l^j(\cdot)$ for all currency pairs and her 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 her expected payoff pointwise for each currency pair with respect to p_k and given her 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.[41] 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. her demands are a best response, given i's residual supply;
2. her 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);

[41] Rostek and Yoon (2020) 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 $\mathbf{q}_0^i$:

$$q_l^i(p_l) \equiv a_l^i - \mathbf{b}_l^i q_0^i - c_l^i p_l, \tag{B.4}$$

where a_l^i is the demand intercept, $\mathbf{b}_l^i q_0^i$ 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 (2020) 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, that is, $\gamma^i = \gamma$, $\forall i$. This ensures that the best response fixed point has a unique solution. 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 structure 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:*

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

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

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

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 (2020) and imply that the price impact $\mathbf{\Lambda}$ is characterised by the slope of the inverse residual supply function:*

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

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

Building on Theorem B2 and plugging the demand intercept $\mathbf{a}^i$ into Eq. (B.6) yields the equilibrium exchange rate:

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

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

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

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

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

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

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. 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 **bold face** 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 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 of initial transaction 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.[42] What is more, note that the partial derivatives $\frac{\partial \mathbf{q}^{i,*}}{\partial d_{0,k}^i}$, $\frac{\partial \mathbf{q}^{i,*}}{\partial \Omega_{\{k,k\}}}$, and $\frac{\partial \mathbf{q}^{i,*}}{\partial \Sigma_{\{k,k\}}}$ in Theorem 1 are $K \times 1$ vectors.

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

Lemma 1: $(\gamma\mathbf{\Sigma} + \mathbf{\Lambda})^{-1}\gamma\mathbf{\Sigma}$ *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. (8)): *Note that 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.*

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

Corollary 2 (Proof of Eq. (9)): *From Lemma 1 it follows directly that* $(\gamma\boldsymbol{\Sigma}+\boldsymbol{\Lambda})^{-2}\gamma\boldsymbol{\Sigma}$ *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* $\boldsymbol{\Omega}$ *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* $\boldsymbol{\Lambda}$ *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. (10)): *Note that the partial derivative* $\frac{\partial\boldsymbol{\Sigma}}{\partial\Sigma_{k,k}}$ *is a* $K \times 1$ *vector where element k is equal to 1 and all other elements are equal to 0.* $\frac{\partial\Lambda_{k,k}}{\partial\Sigma_{k,k}} > \frac{\partial\Lambda_{l,l}}{\partial\Sigma_{k,k}}$, $\forall l \neq k$ *because* $(\mathbf{B\Omega B'})\left[\mathbf{B\Omega B'}\right]_d^{-1}$ *is positive semi-definite and symmetric. In Eq. (10), 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 effects exactly offset each other if* $\Lambda_{k,k} = \boldsymbol{\Sigma}\frac{\partial\boldsymbol{\Lambda}}{\partial\Sigma_{k,k}}$ *(see Section B.2). Hence,* $\Lambda_{k,k} - \boldsymbol{\Sigma}\frac{\partial\boldsymbol{\Lambda}}{\partial\Sigma_{k,k}} < \Lambda_{l,l} - \boldsymbol{\Sigma}\frac{\partial\boldsymbol{\Lambda}}{\partial\Sigma_{l,l}}\Sigma_{l,l}$, $\forall l \neq k$ *is a sufficient statistic for* $\frac{\partial q_k^{i,*}}{\partial\Sigma_{k,k}} < \frac{\partial q_{l,l}^{i,*}}{\partial\Sigma_{k,k}}$.

Proof of Corollary 3. Setting Eq. (10) equal to zero and rearranging yields:

$$
\begin{aligned}
(\gamma\boldsymbol{\Sigma}+\boldsymbol{\Lambda})\frac{\partial\Sigma}{\partial\Sigma_{k,k}} &= \gamma\boldsymbol{\Sigma}\frac{\partial\Sigma}{\partial\Sigma_{k,k}} + \boldsymbol{\Sigma}\frac{\partial\boldsymbol{\Lambda}}{\partial\Sigma_{k,k}} \\
\Lambda_{k,k} &= \boldsymbol{\Sigma}\frac{\partial\boldsymbol{\Lambda}}{\partial\Sigma_{k,k}},
\end{aligned}
$$

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

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 $d_{k,0}^i$. Hence, $\sum_{k\in USD} d_{k,0}^i > max(\sum_{k\in XXX} d_{k,0}^i, \sum_{k\in yyy} d_{k,0}^i)$, $\forall i$ is, all else equal, a sufficient condition for Definition 3. The second conditions 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, $\sum_{k\in\$} \Omega_{k,k} > max(\sum_{k\in XXX} \Omega_{k,k}, \sum_{k\in YYY} \Omega_{k,k})$ implies more trading volume in dollar currency pairs than non-dollar 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 $\Lambda_{k\in\$} - \boldsymbol{\Sigma}\frac{\partial\boldsymbol{\Lambda}}{\partial\Sigma_{k\in\$}} < min(\Lambda_{k\in XXX} - \boldsymbol{\Sigma}\frac{\partial\boldsymbol{\Lambda}}{\partial\Sigma_{k\in XXX}}, \Lambda_{k\in YYY} - \boldsymbol{\Sigma}\frac{\partial\boldsymbol{\Lambda}}{\partial\Sigma_{k\in YYY}})$ (see Section B.2). □

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/bank, fund/bank, and non-bank/bank.[43]

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

Empirically, transactions between market makers make up most of the activity in the FX market. Typically, a price taker does an initial trade with one market maker, and that market maker hedges the resulting risk by trading with other market makers. A single initial trade can lead to a chain of downstream transactions where various market makers pass the 'hot potato' around or slice up the risk in various ways. Consequently, the activity among market makers will be higher than that between price takers and market makers. There are three further reasons why transactions between non-bank price takers and market maker banks represent a relatively low share of total FX turnover settled by CLS. First, many hedge funds and proprietary trading firms settle through prime brokers. CLS does not have look-through on these trades, and hence, they appear as bank/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.

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

Appendix D. Additional Empirical Results

Appendix D.1. Details: Sufficient Conditions

Table D.1: Sufficient Conditions: Hypothesis Tests

	DD	C1	C2	C3	DD−C1
AUDJPY	***35.53	***37.78	***25.47	***−29.74	***−2.25
	[66.09]	[62.07]	[37.57]	[41.38]	[8.32]
AUDNZD	***23.35	***19.73	***11.84	***17.91	***3.62
	[71.09]	[65.54]	[31.19]	[26.10]	[16.62]
CADJPY	***47.69	***59.49	***54.02	***−32.42	***−11.79
	[64.77]	[76.85]	[77.24]	[57.98]	[24.92]
EURAUD	***24.31	***21.45	***4.62	***−15.66	***2.86
	[91.47]	[85.03]	[35.95]	[19.87]	[19.31]
EURCAD	***29.46	***32.47	***18.49	***−18.02	***−3.01
	[74.74]	[75.72]	[34.51]	[29.96]	[14.30]
EURCHF	***4.35	***4.14	***1.30	***26.09	*0.21
	[42.86]	[29.80]	[12.89]	[18.98]	[1.94]
EURDKK	***−0.61	***−1.62	***−0.16	***85.59	***1.00
	[24.73]	[42.74]	[11.90]	[145.49]	[22.49]
EURGBP	***23.00	***22.82	***14.44	***−10.00	0.18
	[75.83]	[71.71]	[36.64]	[13.63]	[1.28]
EURJPY	***49.17	***42.67	***21.15	***−21.64	***6.50
	[67.51]	[54.84]	[34.53]	[30.40]	[21.24]
EURNOK	***−2.40	***−2.21	***−0.38	***−10.41	***−0.19
	[45.20]	[39.73]	[17.42]	[9.73]	[3.28]
EURSEK	***−2.59	***−2.24	***−0.45	*−1.79	***−0.35
	[46.42]	[39.19]	[15.14]	[1.80]	[6.84]
GBPAUD	***70.41	***63.45	***32.48	***−19.96	***6.96
	[126.30]	[106.68]	[42.09]	[33.70]	[20.96]
GBPCAD	***75.50	***76.12	***56.80	***−22.11	−0.62
	[145.62]	[167.93]	[86.23]	[38.67]	[1.54]
GBPCHF	***29.71	***29.75	***17.09	***−16.98	−0.05
	[71.36]	[71.14]	[34.57]	[27.98]	[0.17]
GBPJPY	***46.82	***53.74	***53.10	***−29.63	***−6.92
	[77.13]	[88.76]	[81.34]	[50.47]	[17.92]

Note: This table summarises the empirical counterparts of the sufficient 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 sufficient conditions. 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.

Appendix D.2. Evidence of Vehicle Currency Trading

Here, 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 use *non-overlapping holidays* as an identification tool for *fundamental* trading demands. 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 April 25). On such a day, trading volume in USDJPY is presumably mainly driven by fundamental demand in USDJPY rather than vehicle currency trading demand. This is because the number of counterparties with Australian dollars is heavily reduced due to the bank holiday. Eventually, my proxy for vehicle currency trading is the difference between aggregate trading volume and my implied measure of fundamental demand.

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

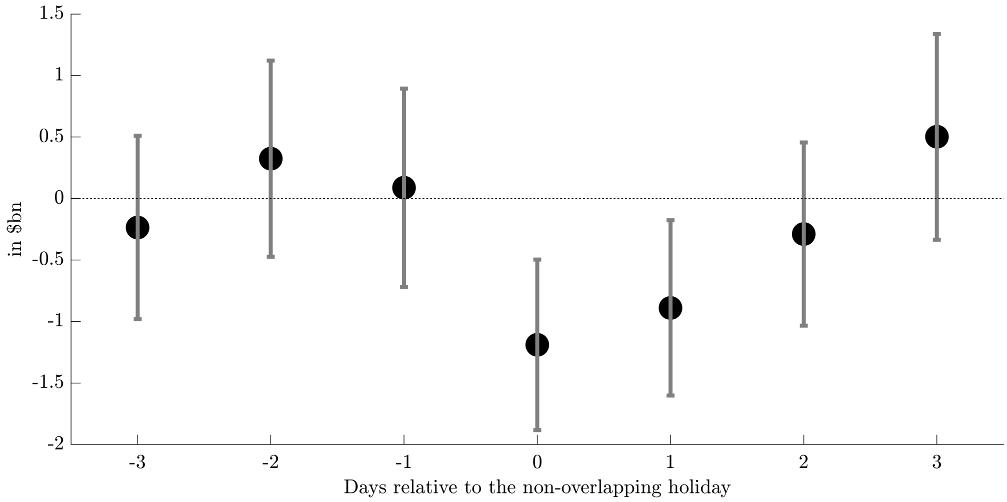
$$volume_{k,t} = \mu_t + \alpha_k + \sum_{m=M^-}^{M^+} \beta_m D_m + \epsilon_{k,t}, \tag{D.1}$$

where the dependent variable is 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. The main regressor is D_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 pairs changes before and after a non-overlapping holiday when controlling for time and currency pair specific unobservables.

Figure D.1 shows that trading volume in dollar pairs is on average 1.5 \$bn lower on non-overlapping holidays than on all other days. Note that the average daily trading volume in dollar currency pairs is 24.2 \$bn. Put differently, on average 6.3% of the volume in dollar pairs on days that are *not* non-overlapping holidays is due to vehicle currency trading motives. This is a conservative estimate because a particular non-overlapping holiday can only capture vehicle currency trading motives in a specific currency pair triplet. For instance, on ANZAC Day it is plausible to assume that vehicle trading demand in USDJPY stemming from the need to exchange AUD against JPY is close to zero. However, this cannot control for the use of USDJPY as a vehicle currency to intermediate in other non-dollar pairs (e.g., CADJPY).

Figure D.2 further illustrates the aforementioned caveat by showing estimates for the case $\beta = \beta_0$ separately for 15 triplets of currency pairs. The grey (*black*) bars correspond to significant (*insignificant*) coefficients at the 95% confidence level. For example, average vehicle trading volume in USDJPY amounts to almost 20 \$bn per day when estimated based on the USD-GBP-JPY currency pair triplet. On the contrary, vehicle trading volume in USDJPY is less than 5 \$bn when estimated from the USD-AUD-JPY currency pair triplet. 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 sufficient conditions

Figure D.1: Event Study: Evidence of Vehicle Currency Trading

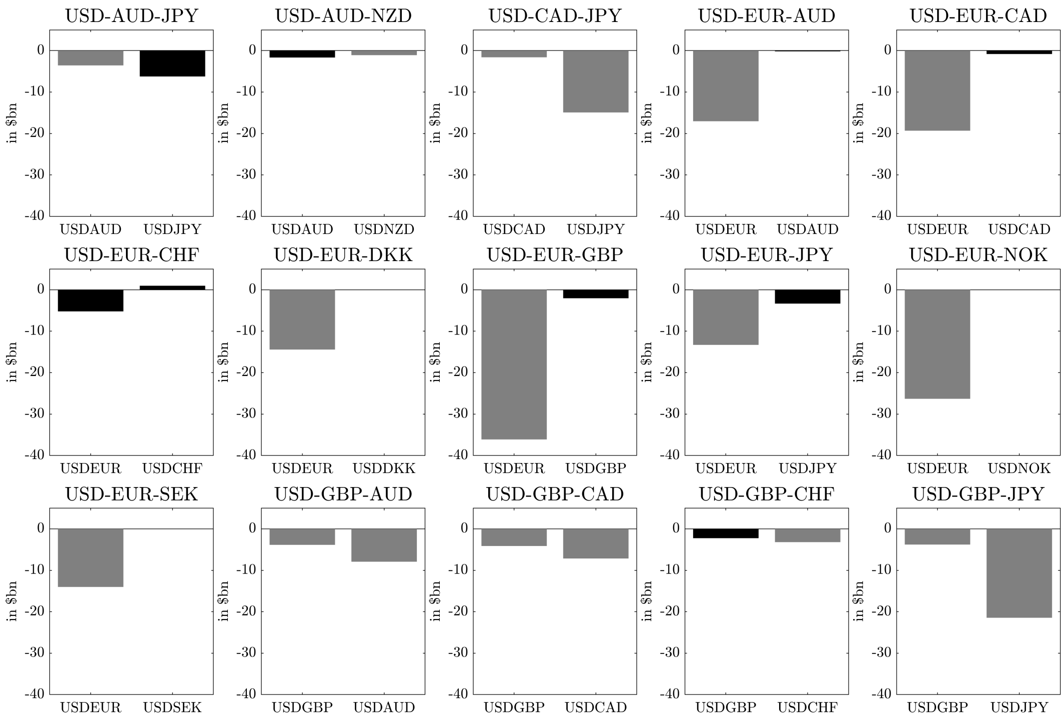


Note: This figure shows the β_m estimates and the 95% confidence intervals of the event study regression of the form $volume_{k,t} = \lambda_t + \alpha_k + \sum_{m=M^-}^{M^+} \beta_m D_m + \epsilon_{k,t}$ for 3 days before and after a non-overlapping holiday. D_m is an indicator variable equal to 1 m 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 the plug-in procedure by Newey and West (1994). The sample covers the period from 1 September 2012 to 29 September 2020.

suggesting that directly exchanging one of these three Nordic currencies against euros is optimal in terms of price impact.

Table D.2 provides a detailed breakdown of my estimates of trading volume due to fundamental vs vehicle currency trading motives across 10 dollar currency pairs. There are two key takeaways from this table: First, the amount of vehicle currency trading is largest in the USDEUR, USDJPY, and USDCHF currency pairs. Second, trading volume in USDDKK, USDNOK, and USDSEK is only driven by fundamental trading motives resulting in zero estimates of vehicle currency trading demands.

Figure D.2: Evidence of Vehicle Currency Trading in Dollar Currency Pairs



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

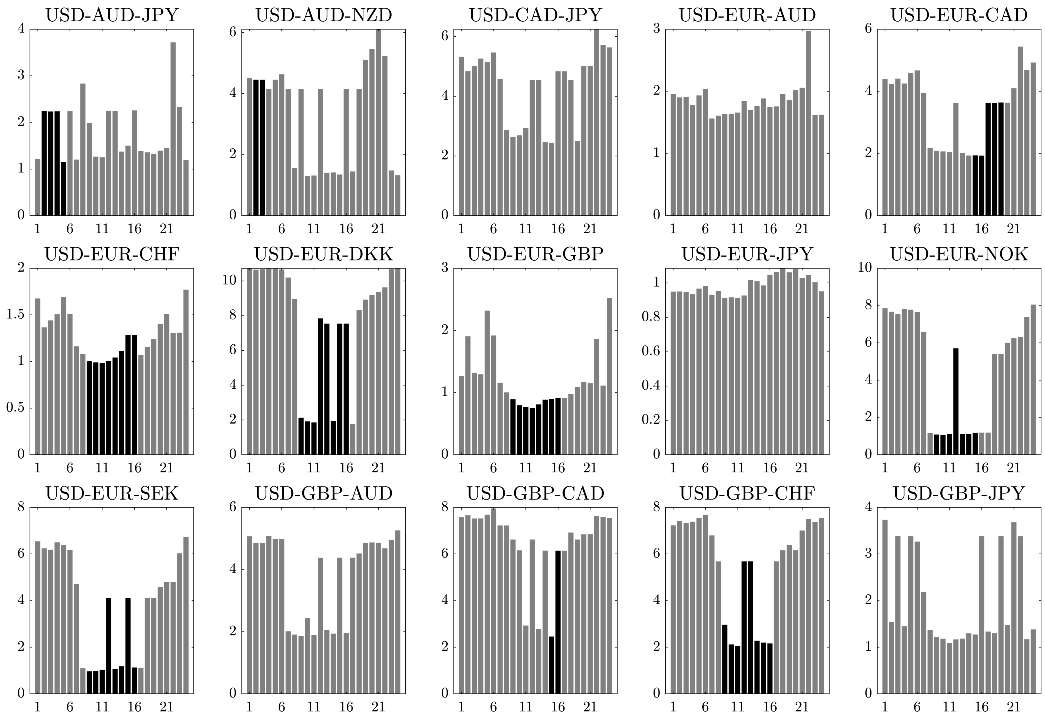
Table D.2: Evidence of Vehicle Currency Trading in Dollar Currency Pairs

	non-VCT in$bn	VCT in $bn	non-VCT in %	VCT in %
USDAUD	20.17	2.95	87.23	12.77
USDCAD	23.48	1.96	92.28	7.72
USDCHF	7.69	1.19	86.58	13.42
USDDKK	0.45	0.06	88.37	11.63
USDEUR	76.17	13.08	85.34	14.66
USDGBP	26.91	3.17	89.47	10.53
USDJPY	50.02	7.80	86.51	13.49
USDNOK	1.45	0.00	100.00	0.00
USDNZD	5.46	1.10	83.20	16.80
USDSEK	1.62	0.00	100.00	0.00

Note: This table reports the breakdown of trading volume due to fundamental (non-VCT) vs vehicle currency trading (VCT) motives across 10 dollar currency pairs. These numbers are based on estimates of $\beta = \beta_0$ from the regression $volume_t = \alpha + \beta D_t + \epsilon_t$, where D_t is an indicator variable equal to 1 if day t is a non-overlapping holiday and is 0 otherwise. Note that if β_0 is positive, that is, there is no evidence of VCT, I report zero in the second and last column, respectively. The sample covers the period from 1 September 2012 to 29 September 2020.

Appendix D.3. Intraday Variation of Dollar Dominance

Figure 1: Intraday Variation of Dollar Dominance



Note: This figure shows the intraday variation of dollar dominance $doldom_{j,t}$ for 15 triplets of currency pairs on a log-10 scale. Dollar dominance is defined as the ratio of indirect 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.

Appendix D.4. Seasonalities in Dollar Dominance

In this section, I briefly describe three additional analyses and robustness checks that I have done. First, to guard myself against the possibility that my findings in Table 5 on page 41 are driven by weekly seasonalities I follow Fischer and Ranaldo (2011) and filter out the deterministic effect by running the following regression for every currency pair:

$$vol_{k,t} = \alpha_k + \sum_{i=1}^{4} \beta_{k,i} Day_i + \sum_{m=1}^{6} \gamma_{k,m} vol_{k,m,t-1} + \nu_{k,t}, \tag{D.2}$$

where Day_i is a dummy that captures day-of-the-week effects and $vol_{k,t}$ is trading volume in currency pair k. In particular, the fitted values from this regression $vol^S_{k,t}$ are robust to daily and weekly effects. Second, I follow the approach in Cespa et al. (2021) to de-trend trading volume and divide today's volume in each currency pair by a moving average over the previous 22 days' trading volume:

$$vol^T_{k,t} = \frac{vol_{k,t}}{\frac{1}{M}\sum_{m=1}^{M} vol_{k,t-m}}, \tag{D.3}$$

where I set $M = 22$. All results are qualitatively unaffected when the window is extended to 66 or 132 days. Tables D.3 and D.4 provide compelling evidence that the baseline results in Table 5 on page 41 remain qualitatively unchanged when computing $doldom_{j,t}$ based on de-seasonalised $vol^S_{k,t}$ and de-trended $vol^T_{k,t}$ volume, respectively. Third, I condition on the direction of the change in the federal funds rate target and distinguish between interest rate cuts, hikes, and neutral announcements. Tables D.5 and D.6 show that dollar dominance increases more on days with cuts and hikes than neutral policy announcements. In sum, all these robustness checks corroborate the results in the main text.

Table D.3: Determinants of Dollar Dominance (De-seasonalised)

	$\text{doldom}_{\text{j,t}}$					
Panel A: OLS	(1)	(2)	(3)	(4)	(5)	(6)
$\text{flow}_{\text{j,t}}$	***0.11			*0.05		
	[4.44]			[1.90]		
$\text{var(flow)}_{\text{j,t}}$		**0.02			0.00	
		[2.11]			[0.24]	
$\text{volatility}_{\text{j,t}}$			**0.04			***−0.10
			[2.30]			[4.16]
$\text{bid-ask spread}_{\text{j,t}}$				***0.39	***0.47	***0.78
				[4.45]	[5.33]	[6.91]
Adj. R^2 in %	0.22	0.01	0.02	0.51	0.47	0.65
Panel B: 2SLS	(1)	(2)	(3)	(4)	(5)	(6)
$\text{flow}_{\text{j,t}}$	*3.05			2.32		
	[1.73]			[1.46]		
$\text{var(flow)}_{\text{j,t}}$		1.14			0.86	
		[1.57]			[1.38]	
$\text{volatility}_{\text{j,t}}$			***0.31			***0.23
			[4.20]			[3.00]
$\text{bid-ask spread}_{\text{j,t}}$				0.44	**0.44	***0.44
				[1.61]	[2.04]	[3.78]
$\text{FOMC dummy}_{\text{t}}$	***0.11	***0.29	***0.40	***0.11	***0.29	***0.40
	[4.80]	[4.65]	[5.43]	[4.80]	[4.65]	[5.43]
Avg. #Time periods	2069	2069	2069	2069	2069	2069
#Currency triplets	15	15	15	15	15	15
Currency FE	yes	yes	yes	yes	yes	yes

Note: This table reports results from daily fixed effects panel regressions of the form $doldom_{j,t} = \alpha_j + \beta' f^{USD}_{j,t} + \epsilon_{j,t}$, where the dependent variable $doldom_{j,t}$ is my empirical measure of dollar dominance, α_j denotes currency triplet fixed effects, and $f^{USD}_{j,t}$ may include several regressors. $doldom_{j,t}$ is computed based on de-seasonalised trading volume $vol^S_{k,t}$ that I define as the fitted value of the following regression: $vol_{k,t} = \alpha_k + \sum_{i=1}^{4} \beta_{k,i} Day_i + \sum_{m=1}^{6} \gamma_{k,m} vol_{k,m,t-1} + \nu_{k,t}$, where Day_i is a dummy that captures day-of-the-week effects and $vol_{k,t}$ is trading volume in currency pair k. $flow_{j,t}$ is the aggregate daily customer order flow (buy plus sell volume) measured in US dollars. $var(need)_{j,t}$ is the daily realised variance of hourly order flow. $volatility_{k,t}$ is the daily realised variance of currency returns computed from one minute spot rates. Both dependent and independent variables are taken in logs and changes. Each of these three regressors is computed separately within every triplet of currency pairs j as the average across the two dollar currency pairs. $bid\text{-}ask\,spread_{j,t}$ is the daily average relative bid-ask spread. Panel A reports ordinary least squares (OLS) estimates. Panel B shows two-stage least square estimates using FOMC announcement days as an instrument for $flow_{j,t}$, $var(flow)_{j,t}$, and $volatility_{j,t}$, respectively. The row headed $FOMC\,dummy_t$ refers to the first stage estimates of regressing the endogenous regressor on a dummy that is equal to 1 if day t is a scheduled FOMC meeting and 0 otherwise. The sample covers the period from 1 September 2012 to 29 September 2020. The test statistics based on Driscoll and Kraay (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.4: Determinants of Dollar Dominance (De-trended)

	$\text{doldom}_{\text{j,t}}$					
Panel A: OLS	(1)	(2)	(3)	(4)	(5)	(6)
$\text{flow}_{\text{j,t}}$	***0.42			***0.20		
	[6.74]			[3.45]		
$\text{var(flow)}_{\text{j,t}}$		***0.17			***0.10	
		[8.71]			[5.53]	
$\text{volatility}_{\text{j,t}}$			***0.35			***0.11
			[13.19]			[3.36]
$\text{bid-ask spread}_{\text{j,t}}$				***1.44	***1.41	***1.36
				[13.60]	[14.24]	[10.67]
Adj. R^2 in %	1.53	1.73	2.25	3.28	3.56	3.10
Panel B: 2SLS	(1)	(2)	(3)	(4)	(5)	(6)
$\text{flow}_{\text{j,t}}$	***4.15			*1.35		
	[3.34]			[1.72]		
$\text{var(flow)}_{\text{j,t}}$		**1.55			*0.50	
		[2.57]			[1.75]	
$\text{volatility}_{\text{j,t}}$			***0.42			0.13
			[4.12]			[1.37]
$\text{bid-ask spread}_{\text{j,t}}$				***1.69	***1.69	***1.69
				[8.62]	[10.35]	[13.35]
$\text{FOMC dummy}_{\text{t}}$	***0.11	***0.29	***0.40	***0.11	***0.29	***0.40
	[4.80]	[4.65]	[5.43]	[4.80]	[4.65]	[5.43]
Avg. #Time periods	2069	2069	2069	2069	2069	2069
#Currency triplets	15	15	15	15	15	15
Currency FE	yes	yes	yes	yes	yes	yes

Note: This table reports results from daily fixed effects panel regressions of the form $doldom_{j,t} = \alpha_j + \beta' f_{j,t}^{USD} + \epsilon_{j,t}$, where the dependent variable $doldom_{j,t}$ is my empirical measure of dollar dominance, α_j denotes currency triplet fixed effects, and $f_{j,t}^{USD}$ may include several regressors. $doldom_{j,t}$ is computed based on de-trended trading volume $vol_{k,t}^{T}$ that I define as today's volume divided by a moving average over the previous 22 days' trading volume: $vol_{k,t}^{T} = vol_{k,t} / (\frac{1}{M} \sum_{m=1}^{M} vol_{k,t-m})$, setting $M = 22$. $flow_{j,t}$ is the aggregate daily customer order flow (buy plus sell volume) measured in US dollars. $var(need)_{j,t}$ is the daily realised variance of hourly order flow. $volatility_{j,t}$ is the daily realised variance of currency returns computed from one minute spot rates. Both dependent and independent variables are taken in logs and changes. Each of these three regressors is computed separately within every triplet of currency pairs j as the average across the two dollar currency pairs. $bid\text{-}ask\,spread_{j,t}$ is the daily average relative bid-ask spread. Panel A reports ordinary least squares (OLS) estimates. Panel B shows two-stage least square estimates using FOMC announcement days as an instrument for $flow_{j,t}$, $var(flow)_{j,t}$, and $volatility_{j,t}$, respectively. The row headed $FOMC\,dummy_t$ refers to the first stage estimates of regressing the endogenous regressor on a dummy that is equal to 1 if day t is a scheduled FOMC meeting and 0 otherwise. The sample covers the period from 1 September 2012 to 29 September 2020. The test statistics based on Driscoll and Kraay (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.5: Determinants of Dollar Dominance (Cuts and Hikes)

	$\text{doldom}_{j,t}$					
Panel A: OLS	(1)	(2)	(3)	(4)	(5)	(6)
$\text{flow}_{j,t}$	***0.20			***0.20		
	[11.28]			[8.62]		
$\text{var(flow)}_{j,t}$		***0.07			***0.07	
		[13.66]			[11.73]	
$\text{volatility}_{j,t}$			***0.06			**0.03
			[6.52]			[2.38]
$\text{bid-ask spread}_{j,t}$				−0.02	0.03	***0.15
				[0.48]	[0.93]	[3.57]
Adj. R^2 in %	3.09	3.09	0.46	3.09	3.09	0.55
Panel B: 2SLS	(1)	(2)	(3)	(4)	(5)	(6)
$\text{flow}_{j,t}$	***1.24			***1.06		
	[4.35]			[3.79]		
$\text{var(flow)}_{j,t}$		***0.35			***0.30	
		[4.18]			[3.88]	
$\text{volatility}_{j,t}$			***0.26			***0.23
			[6.13]			[5.08]
$\text{bid-ask spread}_{j,t}$				**0.23	***0.23	***0.23
				[2.03]	[3.48]	[3.50]
FOMC dummy_t	*0.10	**0.31	***0.45	*0.10	**0.31	***0.45
	[1.71]	[2.21]	[3.23]	[1.71]	[2.21]	[3.23]
Avg. #Time periods	2069	2069	2069	2069	2069	2069
#Currency triplets	15	15	15	15	15	15
Currency FE	yes	yes	yes	yes	yes	yes

Note: This table reports results from daily fixed effects panel regressions of the form $doldom_{j,t} = \alpha_j + \beta' f^{USD}_{j,t} + \epsilon_{j,t}$, where the dependent variable $doldom_{j,t}$ is my empirical measure of dollar dominance, α_j denotes currency pair fixed effects, and $f^{USD}_{j,t}$ may include several regressors. $flow_{j,t}$ is the aggregate daily customer order flow (buy plus sell volume) measured in US dollars. $var(need)_{j,t}$ is the daily realised variance of hourly order flow. $volatility_{j,t}$ is the daily realised variance of currency returns computed from one minute spot rates. Both dependent and independent variables are taken in logs and changes. Each of these three regressors is computed separately within every triplet of currency pairs j as the average across the two dollar currency pairs. *bid-ask spread*$_{j,t}$ is the daily average relative bid-ask spread. Panel A reports ordinary least squares (OLS) estimates. Panel B shows two-stage least square estimates using FOMC announcement days as an instrument for $flow_{j,t}$, $var(flow)_{j,t}$, and $volatility_{j,t}$, respectively. The row headed *FOMC dummy*$_t$ refers to the first stage estimates of regressing the endogenous regressor on a dummy that is equal to 1 if day t is a scheduled FOMC meeting announcing a cut or hike in the federal funds target rate and 0 otherwise. The sample covers the period from 1 September 2012 to 29 September 2020. The test statistics based on Driscoll and Kraay (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.6: Determinants of Dollar Dominance (Neutral)

	$\text{doldom}_{j,t}$					
Panel A: OLS	(1)	(2)	(3)	(4)	(5)	(6)
$\text{flow}_{j,t}$	***0.20			***0.20		
	[11.28]			[8.62]		
$\text{var(flow)}_{j,t}$		***0.07			***0.07	
		[13.66]			[11.73]	
$\text{volatility}_{j,t}$			***0.06			**0.03
			[6.52]			[2.38]
$\text{bid-ask spread}_{j,t}$				−0.02	0.03	***0.15
				[0.48]	[0.93]	[3.57]
Adj. R^2 in %	3.09	3.09	0.46	3.09	3.09	0.55
Panel B: 2SLS	(1)	(2)	(3)	(4)	(5)	(6)
$\text{flow}_{j,t}$	1.99			1.33		
	[1.04]			[0.93]		
$\text{var(flow)}_{j,t}$		1.33			0.89	
		[0.53]			[0.51]	
$\text{volatility}_{j,t}$			***0.12			***0.08
			[4.14]			[2.63]
$\text{bid-ask spread}_{j,t}$				0.23	0.23	***0.23
				[1.64]	[1.22]	[5.87]
FOMC dummy_{t}	***0.12	***0.28	***0.39	***0.12	***0.28	***0.39
	[4.55]	[4.10]	[4.55]	[4.55]	[4.10]	[4.55]
Avg. #Time periods	2069	2069	2069	2069	2069	2069
#Currency triplets	15	15	15	15	15	15
Currency FE	yes	yes	yes	yes	yes	yes

Note: This table reports results from daily fixed effects panel regressions of the form $doldom_{j,t} = \alpha_j + \beta' f^{USD}_{j,t} + \epsilon_{j,t}$, where the dependent variable $doldom_{j,t}$ is my empirical measure of dollar dominance, α_j denotes currency triplet fixed effects, and $f^{USD}_{j,t}$ may include several regressors. $flow_{j,t}$ is the aggregate daily customer order flow (buy plus sell volume) measured in US dollars. $var(need)_{j,t}$ is the daily realised variance of hourly order flow. $volatility_{j,t}$ is the daily realised variance of currency returns computed from one minute spot rates. Both dependent and independent variables are taken in logs and changes. Each of these three regressors is computed separately within every triplet of currency pairs j as the average across the two dollar currency pairs. $bid\text{-}ask\,spread_{j,t}$ is the daily average relative bid-ask spread. Panel A reports ordinary least squares (OLS) estimates. Panel B shows two-stage least square estimates using FOMC announcement days as an instrument for $flow_{j,t}$, $var(flow)_{j,t}$, and $volatility_{j,t}$, respectively. The row headed $FOMC\,dummy_t$ refers to the first stage estimates of regressing the endogenous regressor on a dummy that is equal to 1 if day t is a scheduled FOMC meeting announcing no change in the federal funds target rate and 0 otherwise. The sample covers the period from 1 September 2012 to 29 September 2020. The test statistics based on Driscoll and Kraay (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.

References: Online Appendix

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

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.

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

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.

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

Rostek, M. J. and Yoon, J. H., 2020. Exchange design and efficiency. *SSRN Electronic Journal*.