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Abstract

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

Keywords: Asymmetric information, Currency portfolios, Order flow, OTC, Risk premium

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

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1 Introduction

One of the most important questions in financial economics is how security prices are determined. This is especially true for the foreign exchange (FX) market, which is the largest financial market in the world, with an average daily trading volume of $6.6 trillion (see BIS, 2019). Since it is almost entirely an over-the-counter (OTC) market, FX trading activity is relatively opaque and fragmented. Without a centralised trading mechanism, information is dispersed across various types of market participants such as commercial banks or asset managers, which maintain heterogeneous relationships with another. All these participants possess distinct information sets and may contribute differently to FX determination.

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

The asymmetric information paradigm first formalised by Glosten and Milgrom (1985) and Kyle (1985) prescribes, that when some agents[1] have superior information about the fundamental value of an asset, their trades covey information to the market. This body of the literature outlines two main empirical predictions: First, asymmetric information is positively related to the price impact of the trade. Second, the price impact tends to be persistent given the information content. Under asymmetric information, a representative agent faces the risk of being adversely selected (Easley et al., 2002). As a result, she demands an additional risk premium for trading against better informed investors (Wang, 1993, 1994). In addition to this, adverse selection also increases the required return through its allocation cost rather than through bid-

[1]We use the terms 'agents' and 'market participants' interchangeably.

ask spreads (Gârleanu and Pedersen, 2003). This paper provides empirical evidence supporting these theories and novel insights into price formation and asymmetric information issues. Specifically, we dissect order flow into end-user segments of the global FX market and find that asymmetric information risk is priced.

What are the potential sources of asymmetric information risk in FX markets? To begin with, asymmetric information is inherent in FX trading due to its OTC nature that is characterised by distinct infrastructural features such as a decentralised network (Babus and Kondor, 2018) and dealership (Liu and Wang, 2016) structure giving rise to information dispersion. In recent years, structural changes of the FX market, such as the rise of electronic and (high-frequency) automated trading and settlement, have exacerbated market fragmentation and asymmetric information issues across market participants (BIS, 2018). Thus, individual investors have private information on currency values (Lyons, 1997, Evans and Lyons, 2006) or order flows that can also be exploited by dealers (Perraudin and Vitale, 1996). Furthermore, adverse selection in global FX markets can arise from information asymmetries in other asset classes (e.g. fixed income and equities) that are factored in FX trading via fundamental valuation, speculation and portfolio rebalancing (Hau and Rey, 2004). Alternatively, asymmetric information premia can stem from political uncertainty (Pástor and Veronesi, 2013), central bank decisions (Mueller et al., 2017) or monetary policy interventions (Peiers, 1997) such that constrained global financial intermediaries require a compensation for adverse selection risk and uncertainty (Gabaix and Maggiori, 2015, He and Krishnamurthy, 2013).

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

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

Across agents, we find that some agents are always more informed than others providing empirical evidence that asymmetric information and adverse selection are systematically present in the global FX market. For instance, corporates have on average a 1–2 basis points (BPS) lower permanent price impact across currency pairs than funds, non-bank financials or banks do, whose order flows are positively autocorrelated. This is consistent with the idea that sophisticated market participants have superior access to global FX markets allowing them to engage in order splitting and price impact smoothing (Kervel and Menkveld, 2019). Moreover, the order flows of funds, non-bank financials and banks are strongly linked to common FX trading strategies (i.e. carry (cf. Lustig et al., 2011) and value (cf. Menkhoff et al., 2017)). This behaviour is in line with speculative trading motives and higher adverse selection risk when trading against such sophisticated speculators (Payne, 2003).

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

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

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

Related literature. We contribute to the microstructure and FX asset pricing literature in several ways. First, our analysis of heterogeneous FX order flows provides empirical evidence of information asymmetries across market participants.[2] Starting from the key contributions of Evans (2002) and Evans and Lyons (2002, 2005), several papers provide indirect evidence of information asymmetries by investigating how aggregate order flow determines FX rates[3]. The only few papers that study the order flow disaggregated by market participants focus on a specific market segment, such as a single inter-dealer trading platform or on customers' order flow for a specific bank.[4] However, these findings are not generalisable to the entire FX market.[5] This study represents the first analysis of order flow data representative for the entire global FX spot market with a large cross-section of FX rates and relatively long sample period. Building on the seminal work by Hasbrouck (1988, 1991a,b) and the notion of the permanent price impact, we propose a general model for detecting information

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

[3]This vast literature on FX order flow includes, for example, Payne (2003), Bjønnes and Rime (2005), Evans and Lyons (2008), Breedon and Vitale (2010), Evans (2010), Menkhoff and Schmeling (2010), Rime et al. (2010), and Mancini et al. (2013).

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

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

asymmetries across agents. Thus, our findings provide direct empirical evidence of systematic information asymmetries in the world's largest OTC market. A battery of robustness checks suggests that this is a general result and does not hinge on specific assumptions such as risk neutrality that is assumed in many microstructure models with information asymmetry (e.g. Kyle, 1985, Glosten and Milgrom, 1985, Easley and O'Hara, 1987, 1991, Holden and Subrahmanyam, 1992).

Second, our paper contributes to the asset pricing literature by building a novel long–short trading strategy capturing asymmetric information risk. This is an effective method of extracting superior information inherent in order flow that can be applied to other asset classes beyond FX. In the FX asset pricing literature, Lustig and Verdelhan (2007), Lustig et al. (2011), Menkhoff et al. (2012a,b) and Asness et al. (2013) identify common risk factors in currency markets based on the interest rate differential, real exchange rate, global FX volatility and momentum. Other FX risk factors include macro-variables like global imbalances (e.g. Della Corte et al., 2016b) or volatility risk premia (e.g. Della Corte et al., 2016a). Using data from a specific dealer bank, Menkhoff et al. (2016) analyse whether that bank can extract valuable information from its disaggregated customer FX order flow data to predict next-day's FX rates. More specifically, they sort currency pairs into portfolios based on past order flows to assess the economic value as dealers' "smart money". To summarise, our paper makes two key contributions: First, we extend the methodology to isolate and analyse the information driven component of order flow with disaggregated customer flows. Second, we provide compelling empirical evidence that asymmetric information risk is priced in the global FX market.

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

2 Data

Our dataset on spot FX order flow by market participant comes from CLS Group (CLS), which is publicly available directly from CLS or via Quandl.com, a financial and economic data provider.[6] CLS operates the world's largest multi-currency cash settlement system, handling over 50% of global spot, swap and forward FX transac-

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

tion volume. CLS *volume* data (rather than *order flow*) have been used in prior research by Fischer and Ranaldo (2011), Hasbrouck and Levich (2018), Gargano et al. (2018) and Ranaldo and Santucci de Magistris (2019). To the best of our knowledge, this is the first paper to study CLS order flow data.

2.1 Heterogeneous FX Order Flow

Volume is recorded separately for buy and sell side market participants after instructions are received from both counterparties to the trade. Within the dataset, CLS records the time of the transaction as if it had occurred at the first instruction being received. CLS receives confirmation for more than 90% of trade instructions from settlement members within 2 minutes of trade execution. Most of the 72 current settlement members are large multinational banks. Furthermore, there are over 25 000 'third party' clients of the settlement members, including other banks, funds, non-bank financial institutions and corporations. At settlement, CLS mitigates principal and operational risk by simultaneously settling both sides of the FX transaction (Hasbrouck and Levich, 2018).

This dataset has several features that make it suitable to investigating asymmetric information risk in FX trading. First, CLS records the buy and sell trading volume in the base currency, as well as the number of transactions on an hourly basis from Sunday 9 *pm* to Friday 9 *pm* (London time, GMT), and thus, it matches the whole FX trading week. Second, CLS sorts FX market participants into the following four distinct categories: corporates (CO), funds (FD), non-bank financial firms (NB) and banks (BA). These labels refer to the identities of the entities trading and not to the behaviour they exhibit.[7] 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. Hence, there is substantial heterogeneity in the motives for market participation and the access to price-relevant information across the end-user groups.

Corporates, funds and non-bank financial firms are always considered to be price takers and are a subgroup of the total aggregate buy side. Banks acting as market makers are always reported on the sell side. In any given hour, CLS records the buy volume referring to how much of the base currency was purchased by the price takers from the market makers. The sell volume indicates the amount of base currency sold by the same price takers to the same market makers. The online appendix

[7] 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.

Section A provides further institutional details and describes how CLS categorises market participants into price takers and market makers.

Our full sample period spans from 2 September 2012 to 31 December 2019 and includes data for 16 major currencies and 30 currency pairs.[8] The order flow dataset is limited to spot transactions. Three characteristics of the dataset merit being discussed in more detail: First, it contains around 7 years of hourly data, which is relatively long compared with previous studies on FX microstructure. Furthermore, using a high-frequency dataset raises the statistical value of order flow in a time series setting by mitigating potential reverse causality issues.

Second, despite being the most comprehensive time-series dataset on FX order flow, it does not cover the full FX (spot) market. The 2019 BIS triennial survey (see BIS, 2019) reports an average daily trading volume of $6.6 trillion. Conversely, CLS settles approximately $5.1 trillion per day, which translates to an average daily trading volume of $1.9 trillion if one accounts for double-counting prime brokered trades. This is equivalent to covering 29% of the total FX volume based on BIS (2019). The reasons for this lack of coverage are manifold: First, FX options and non-deliverable forwards are not settled by CLS. Second, small banks with little FX turnover are seldom a settlement member. Third, CLS does not settle every currency, for instance, the Chinese renminbi and Russian rubel are not yet eligible for settlement. Both Gargano et al. (2018) and Hasbrouck and Levich (2018) demonstrate that the CLS coverage is underestimated compared to the BIS survey, since a large fraction of the volume reported by the BIS is related to inter-bank trading across desks and double-counts prime brokered 'give-up' trades.[9] Adjusting for these facts shrinks total FX volume to $3.8 trillion per day, and thus CLS covers at least 50% of it.[10]

Third, this dataset does not cover all transactions originated by one of the three static price taker categories. More precisely, if a hedge fund settles a trade via a prime broker who is member of CLS, then this trade would show up as a bank/bank

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

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

[10]In their online appendix Gargano et al. (2018) further mitigate concerns about the representativeness of the sample by providing evidence that an almost perfect relationship exists between the share of currency-pair volume in the BIS Triennial Surveys and the CLS data.

transaction.[11] This is because CLS does not observe the originator of such a trade but only the settlement itself. Consequently, such a transaction would either be excluded from the dataset, if the prime broker is a market maker, or it would show up as a transaction originated by banks acting as price takers, if it behaves as a price taker.

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

$$T_t = \begin{cases} +1 & \text{if } z_t > 0 \\ 0 & \text{if } z_t = 0 \, , \\ -1 & \text{if } z_t < 0 \end{cases} \tag{2.1}$$

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

2.2 *Exchange Rate Returns*

We pair the hourly FX volume data with intra-day spot rates obtained from Olsen, a market-leading provider of high-frequency data and time-series management systems.[12] Thus, the FX order flow and exchange rate return are both measured hourly. The exchange rate return (r_t) is calculated as the log difference in the mid-quote FX rate over a trading hour:

$$r_t = \Delta s_t = s_t - s_{t-1}, \tag{2.2}$$

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

3 Summary Statistics

In this section, we present summary statistics for our data on FX quotes and signed net volume, which is the buy minus sell volume (e.g. −USD100 mn or +EUR150 mn). In Table 1, we report the summary statistics for the quote in each currency pair. The first five rows report the sample mean, standard deviation of the mean, minimum

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

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

and maximum hourly return, as well as the average relative spread ($[ask - bid]/mid$) over the full sample. The last row reports the first-order autocorrelation.

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

Table 2 reports detailed summary statistics for the hourly (absolute) net volume for the entire cross-section of currency pairs. Unsurprisingly, the currency pairs with the highest hourly volumes are the EURUSD (USD433 mn), USDJPY (USD237 mn) and USDCAD (USD229 mn). Our ranking is largely in line with the BIS Triennial Survey (BIS, 2019) and Gargano et al. (2018). Funds and non-bank financials are the largest categories after price taker banks, whilst corporates form the smallest group.

Figure 1 fleshes out the idea that market participants behave heterogeneously during the day and provides *prima facie* evidence of market fragmentation. Notably, it shows that corporates trade at different times than funds or non-bank financials. For every market participant, we report the average aggregate hourly volume for each hour of the trading day based on London time. Investigating at which hours market participants are most active helps to identify time-fixed effects in the trading behaviour of FX market participants. Volume levels are closely related to stock market opening hours around the world. Specifically, volume is lowest during the night when only the Australian market is open and is highest when both European and North American markets are operating in the afternoon. This pattern persists across market participants. Banks, non-bank financials and funds all trade more around the clock. Banks are the largest subsection of the aggregate, with an average contribution of 30–50%. They reduce their activity by about two thirds outside of the London stock market trading hours[13] to limit inventory risk (Evans and Lyons, 2002).

To complete the descriptive analysis, the online appendix Section B addresses two possible problematic issues on order flow data segregated by market participants groups: intra-temporal and inter-temporal dependence, respectively.

4 Methodology

In this section, we describe the methodology used for investigating whether market participants exhibit a heterogeneous price impact in the FX market. The approach

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

builds on the framework developed by Hasbrouck (1988, 1991a), who introduces a VAR that makes almost no structural assumptions about the nature of information or order flow, but instead, infers the nature of information and trading from the observed sequence of quotes and trades.

Hasbrouck (1988) provides a useful model for separating the permanent (information) effects and temporary (inventory) effects of a trade, but suffers from the limitation that order flow is assumed to evolve exogenously. However, prices can feed back to the order flow. To overcome this issue, Hasbrouck (1991a,b) proposes a bivariate VAR model that allows the price moves to be decomposed into trade-related and trade-unrelated components. Such a VAR model has two important features that are key for our empirical analysis: First, it captures the *persistent* price impact of the trade innovation, which is a more precise and consistent estimate of processing superior fundamental information than the *immediate* price impact — the latter being contaminated by transient (liquidity) effects. Second, it is a model-free setting encompassing serial dependence of trades and returns, delays in the effect of a trade on the price and non-linear trade–price relationships that can arise, for example, from inventory control, price pressure effects and order fragmentation.

Consistent with this framework, we build an encompassing model that allows for heterogeneous order flows and controls for short-term mean reversion, as well as hourly seasonalities. Especially, Eq. (4.2) describes the trade-by-trade evolution of the quote midpoint, whilst Eq. (4.3) refers to the persistent effect of order flow. We define T_t to be the buy-sell indicator (+1 for buys, −1 for sells) for trade t in a specific currency pair k.[14] Furthermore, we define r_t as the log FX rate return based on the mid-quote. Easley and O'Hara (1987) present a theoretical asymmetric information model in which private information revealed by an order and the consequent change in quotes are positively related to order flow size. We account for these effects by introducing an order-size variable (cf. Hasbrouck, 1988) into the VAR specifications. Logarithms of the signed net volume (z_t) are taken to control for the effect of presumed non-linearities between order size and quote revisions:

$$v_t = \begin{cases} +log(z_t) & \text{if } z_t > 0 \\ 0 & \text{if } z_t = 0 \\ -log(-z_t) & \text{if } z_t < 0 \end{cases}. \tag{4.1}$$

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

To support the interpretation of the regression coefficients, v_t is transformed by regressing it against the current and lagged values of the trade indicator variable T_t. As proposed in Hasbrouck (1988), we extract the residuals from this regression, denoted by $\tilde{S}_t$, which are by construction uncorrelated with the indicator variable T_t.[15] Hourly dummies are included to control for daily seasonalities affecting FX rates and order flows. More importantly, the VAR accommodates both lagged returns and order flow in both the return (i.e. Eq. (4.2)) and order flow equations (i.e. Eq. (4.3)), since many microstructure imperfections, such as price discreteness, inventory effects, lagged adjustment to information, non-competitive behaviours and order splitting, are thought to cause lagged effects. The number of lags is selected to be 10 based on the Akaike/ Bayesian information criteria and the theoretical arguments in Hasbrouck (1991a,b):

$$r_t = \zeta_{1,l} D_{l,t} + \sum_{i=1}^{10} \rho_i r_{t-i} + \sum_{j \in C} \left(\sum_{i=0}^{10} \beta_i^j T_{t-i}^j + \sum_{i=0}^{10} \phi_i^j \tilde{S}_{t-i}^j \right) + \eta_1 \Delta s_{t;t-\tau} + \eta_2 \Delta s_{t;t-5\tau} + \epsilon_{r,t}, \tag{4.2}$$

$$T_t = \zeta_{2,l} D_{l,t} + \sum_{i=1}^{10} \gamma_i r_{t-i} + \sum_{j \in C} \left(\sum_{i=1}^{10} \delta_i^j T_{t-i}^j + \sum_{i=1}^{10} \omega_i^j \tilde{S}_{t-i}^j \right) + \epsilon_{T,t}, \tag{4.3}$$

where $D_{l,t}$ denotes a dummy variable matrix to account for time-fixed effects with $l = 24$ columns and $t = n$ rows, in which element l, t is 1 if there was a trade in that hour, and $C = \{CO, FD, NB, BA\}$ denotes disaggregated order flow categories. Moreover, the regression considers the lagged exchange rate changes over the previous day $\Delta s_{t;t-\tau}$ and over the prior week $\Delta s_{t;t-5\tau}$. Here, $\tau = 24$, and t is measured hourly. For convenience of exposition, currency specific subscripts (i.e. k) have been suppressed in Eqs (4.2) and (4.3). The error terms $\epsilon_{r,t}$ and $\epsilon_{T,t}$ can be interpreted as the (unexpected) public and private information components (Hasbrouck, 1991a). This dichotomy ensures that the permanent price impact $\alpha_m^{j,k}$ in Eq. (4.5) can be interpreted as a measure of asymmetric/private information.[16] Since we include contemporaneous T_t in Eq. (4.2) but not in Eq. (4.3), the system is exactly identified, and hence, the error terms shall have a zero mean and be jointly and serially uncorrelated:

$$\begin{aligned} &E(\epsilon_{T,t}) = E(\epsilon_{r,t}) = 0 \\ &E(\epsilon_{T,t}\epsilon_{T,s}) = E(\epsilon_{r,t}\epsilon_{r,s}) = E(\epsilon_{T,t}\epsilon_{r,s}) = 0, \text{ for } s \neq t. \end{aligned} \tag{4.4}$$

A possible concern about our VAR setting is that some endogeneity may origi-

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

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

nate from the contemporaneous returns having a simultaneous effect on order-flows. One way of mitigating this issue empirically would be to use instrumental variables, as proposed in Daníelsson and Love (2006). However, two issues arose when implementing this approach: First, the instruments are too weak when applying the Daníelsson and Love (2006) methodology to frequencies greater than 5 minutes. Second, none of the instruments, such as the contemporaneous order flow of another currency pair, passed the Wald–test for over-identification and exogeneity. Given the weakness of the instruments and limited data availability, the modified Hasbrouck (1991a,b) model remains the soundest method that can be applied in this setting.

Permanent Price Impact. We can derive the permanent price impact at the individual agent level as the sum of the asymmetric information coefficients from the VAR in Eq. (4.2). Following Hasbrouck (1988) and Payne (2003), the permanent price impact of agent $j \in C$, where $C = \{CO, FD, NB, BA\}$, within a particular currency pair k can be calculated as follows:

$$\alpha_m^{j,k} = \sum_{t=0}^{m} \beta_t^{j,k}, \tag{4.5}$$

where m indicates the number of lags, which is 10 in our case. Since $\alpha_m^{j,k}$ is cumulative over several hours (even weak effects can add up), VAR estimates of a lower order ($m \leqslant 10$) are likely to overstate the long-run price impact.[17] In other words, such a model would catch the initial positive impact of a trade on the quote but will miss the subsequent long-run reversion. Using the VAR representation, the average permanent price impact across agents capturing the systematic level of superior information within currency pair k is given by

$$\bar{\alpha}_m^{k} = \frac{1}{|C|} \sum_{j \in C} \sum_{t=0}^{m} \beta_t^{j,k} = \frac{1}{|C|} \sum_{j \in C} \alpha_m^{j,k}. \tag{4.6}$$

In this framework, the permanent price impact is a measure of asymmetric information and adverse selection that accounts for the persistence in order flow, as well as possible positive or negative feedback trading. The $\bar{\alpha}_m^{k}$ lies at the heart of the subsequent asset pricing analysis and possesses a natural interpretation as the information content of a trade net of transient effects inherent in global FX trading.

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

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

5 Heterogeneous Asymmetric Information

In this section, we analyse whether the price impact in the global FX spot market systematically varies across market participants, currency pairs and time. All the coefficients are reported using the notation introduced in Eqs (4.2) and (4.3).

5.1 *Estimation Method and the Contemporaneous Price Impact*

First, we estimate Eqs (4.2) and (4.3) using standard ordinary least squares (OLS) on the full sample, controlling for seasonal time-of-the day effects, lagged returns and order size.[18] Second, we apply a 12-month rolling window for measuring the time variation of both the contemporary β_0^j and permanent price impact α_m^j, respectively. The main advantage of the VAR approach lies in its potential for generalisation to gain a more nuanced view of the trade–quote interactions.[19] For the sake of clarity, we only present the results for lagged return equation coefficients ρ_1 and γ_1, the contemporary price impact β_0^j and lagged order flow δ_1^j, where $j \in C$ denotes one group of market participants. Table 3 shows the regression coefficients of the bivariate VAR estimated through 10 lags. The most important ones are those of T_0^j in Eq. (4.2) that measure the contemporary price impact of a trade.

For the great majority of currency pairs, regression coefficients bear the expected signs summarised in Table 3: Here, ρ_1 coefficients are negative and entail short-term mean reversion, while β_0^j coefficients are positive and in line with market microstructure theory (e.g. Kyle, 1985, Glosten and Milgrom, 1985). This is especially true for the most liquid and frequently traded currency pairs.[20] The true beauty of the log-level

[18]To avoid misspecification in our regression analysis and check the validity of our assumptions in Eq. (4.4), we conduct a battery of diagnostic tests that are summarised in the online appendix.

[19]As in Hasbrouck (1991a,b), T_t is defined as a limited dependent variable. If T_t and r_t are jointly covariance stationary and invertible, a VAR model as in Eqs (4.2) and (4.3) exists. However, while the error terms are serially uncorrelated, they are not serially independent in general. The disturbance properties in Eqs (4.2) and (4.3) further ensure that the coefficients are estimated consistently by OLS.

[20]One notable exception are the fixed pairs i.e. the EURDKK and USDHKD where contemporary price impacts are zero in economic terms.

model in Table 3 is its interpretability: Coefficients can be interpreted as percentage changes in the dependent variable for a one-unit change of the independent variable.[21] The coefficients at longer lags (i.e. beyond lags seven and eight) frequently alternate in sign, are seldom significant and quickly decay to zero. From these results, it is apparent that on average all agents except corporates have a significantly positive contemporary price impact.

For some currency pairs (e.g. EURGBP, EURNOK, EURUSD), corporates experience significantly negative contemporary price impact parameters. The negative β_0^{CO} is consistent with earlier work by Bjønnes et al. (2005), Lyons (2006), Carpenter and Wang (2007), Cerrato et al. (2011), Evans and Lyons (2012) and Menkhoff et al. (2016) and indicates that corporates often buy (*sell*) in a falling (*rising*) market.[22] Rather than from informational motives, a negative relation between order flow and return arises from liquidity needs (Grossman and Miller, 1988) and dealers' inventory features (Stoll, 1978). Thus, corporate trading seems to be driven by risk sharing, hedging and liquidity issues, as well as additional costs unrelated to adverse selection. This idea squares well with the different timing in their trading behaviour (see Figure 1). Whereas banks and other financial institutions access a richer information set by trading around the clock, the trading activity of corporates is more segmented and limited within a few hours.[23]

The negative β_0^{CO} is also consistent with risk averse FX dealers offsetting order flows coming from potentially more informed agents (e.g. other banks and financial firms) with the non-informative one from corporates to reduce their exposure to asymmetric information risk (Liu and Wang, 2016). The negative correlations between corporates' order flow and that of other financial agents reported above are fully in line with this picture. The coefficients of the return over the previous day (η_1) is negative and highly significant for all currency pairs, whilst the return over the prior week (η_2) is negative but insignificant for the majority of currency pairs.

Table 4 summarises the order flow equation coefficients, which also bear the ex-

[21]The results are extremely similar when we use (signed) net volume (without order size variable $\tilde{S}_t^j$), calculated as the net of buy volume by price takers minus the sell volume by market maker transactions, broken down into types of market participants instead of (binary) order flow and using transaction prices instead of mid-quotes for calculating r_t in Eq. (4.2). See the online appendix Section C for further results.

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

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

pected signs: Here, γ_1 is negative and highly significant, while δ_1^j coefficients are positively significant for most currency pairs and reflect the positive autocorrelation in trades. This is consistent with the findings in the stock market literature, for example, Hasbrouck and Ho (1987), Hasbrouck (1988) and Madhavan et al. (1997), and it shows that purchases tend to follow purchases and similarly for sales. Rather than with inventory control mechanisms, the short-run predominance of positive autocorrelation can be reconciled with delayed price adjustments to new information. Again, γ_1 implies negative autocorrelation in the quote revisions. In the order flow equation estimation, this implies Granger–Sims causality running from quote revisions to trades. This causality is in line with microstructure theory, where a negative relation between trades and lagged quote revisions is consistent with inventory control effects and/or the price experimentation hypothesis formulated by Leach and Madhavan (1992), in which the market maker sets quotes to extract information optimally from traders.

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

5.2 *Analysis of the Permanent Price Impact*

So far, we have centred our analysis on the contemporary price impact. We now turn to the permanent component. In the model of Hasbrouck (1991a), α_m^j can be interpreted as the measure of asymmetric/private information because trades are driven by a mixture of private (superior) information and liquidity needs rather than public information. Therefore, any persistent impact of a trade on prices arises from asymmetric information signalled by that trade. This intuition is reflected in Eqs (4.2) and (4.3), which identifies all public information with the quote revision innovation ($\epsilon_{r,t}$) and all private information with the trade innovation ($\epsilon_{T,t}$). The dichotomy above ensures that $\epsilon_{T,t}$ reflects no public information, and hence, the permanent price impact α_m^j can be interpreted as a measure of asymmetric/private information.

5.2.1 Heterogeneous Price Impact Across Agents

In Table 5 we summarise the estimates of the permanent price impact (α_m^j) for every agent category and currency pair and draw three key considerations: First, across all currency pairs, there is always at least one category of agents with a significant

α_m^j suggesting that some market participants always possess superior information. Second, the comparison of the permanent price impacts across traders' categories indicates that banks access superior information across almost all currencies, which is consistent with their privileged access to information that emanates from their central (network) role in the global FX market (Babus and Kondor, 2018, Perraudin and Vitale, 1996). Funds and non-bank financials also have superior information in many currency pairs generalising previous findings (Lyons, 1997, Evans and Lyons, 2006) at a global scale suggesting that banks themselves are also exposed to asymmetric information risk. On the flip-side, corporate trading is systematically not informationally driven. Third, for several currency pairs banks appear to be the only category with superior information. This result goes beyond the "smart money" hypothesis in Menkhoff et al. (2016), in the sense that it provides evidence that dealers access superior information regardless of their customers' order flows being informative.

To assess whether the permanent price impact parameter α_m^j significantly differs across groups of agents, we test if all coefficients in Eq. (4.5) for a specific agent category i are jointly significantly different from that of agent j. In line with asymmetric information theory (see Glosten and Milgrom, 1985, Grossman and Miller, 1988, Lyons, 2006), we find that order flows have a different effect on prices depending on the market participant behind them. For nearly every pairwise combination of agents, the F-test clearly rejects the null hypothesis of equal price impacts.[24] All in all, we provide evidence that superior information is pervasive and systematically varies across market participants. For asset pricing, this also implies that each market participant is exposed to asymmetric information and adverse selection risk, which should be priced in FX rates.

5.2.2 Fragmentation in the FX Market Across Currencies

In traditional market microstructure models (e.g. Kyle, 1985), the price impact depends on the precision of the private signal, variation in liquidity trades, as well as risk aversion coefficients of informed traders and liquidity providers (Subrahmanyam, 1991). All these factors vary across currencies and time creating systematically different price impacts across FX rates. Overall, currency pairs that are more affected by asymmetric information should reveal a larger permanent price impact. Table 5 shows that every currency pair is affected by multiple categories of agents' permanent price impact suggesting that asymmetric information risk is pervasive across FX rates. This result holds for both the most (e.g. EURUSD and USDJPY) and

[24] The results here and in the next two subsections are qualitatively similar for both the contemporary and permanent price impacts. Thus, the online appendix Section C collects the output tables and technical details. See Tables C.7 to C.15 on pages 16–26 in the online appendix.

least (e.g. EURCAD and USDSEK) liquid currency pairs. Generally, more (*less*) risk averse investor should be more (*less*) reluctant to invest in illiquid assets. However, our estimates seem to have general validity and are not biased towards less liquid FX rates potentially being more affected by risk aversion. As an additional test, we reiterate our analysis by estimating the permanent price impact during the main stock markets trading hours (i.e. from 7 *am* London open to 9 *pm* New York close, GMT), that is, when risk aversion should be less pronounced. We find a similar picture reinforcing the idea that asymmetric information risk is ubiquitous across FX rates.

Empirically, we find the global FX market to be fragmented in the sense that a specific agent i has a significantly different price impact parameter (both β_0^j/α_m^j) across currency pairs. As before, we estimate Eq. (4.2) on the full sample and construct a pairwise F-test, where we test whether all the coefficients in Eq. (4.5) for a particular agent category $i \in C = \{CO, FD, NB, BA\}$ are jointly significantly different in currency pair k compared with currency pair q.[25] The main result that emerges from this analysis is that corporates, funds, non-bank financials and banks acting as price takers have a permanent price impact α_m^j, which varies heavily across currencies. Overall, our empirical analysis extends earlier research on customer order flows (e.g. Evans and Lyons, 2006, Osler et al., 2011, Menkhoff et al., 2016) at a global scale. An avenue for future research would be to understand the effect of regulation on the local nature of FX price discovery.

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

5.2.3 Time-Varying Information Flows

In this section, we introduce *time* as a third dimension of heterogeneity and study the systematic time variation of both the contemporary and permanent price impacts. Again we estimate Eq. (4.2) by OLS, but now, we do so in a rolling window fashion instead of using the full sample. We choose a 1-year rolling window but our results are robust to shorter horizons.

In Figure 2, we plot the average permanent price impact (α_m^j) across currency pairs over time. Importantly, the α_m^j is present at all times and does not cluster in distressed periods. Furthermore, the α_m^j appears to be larger and more dispersed across agents during the European sovereign debt crisis (2010-2014), that is, when risk aversion was presumably high. Across agents, corporates seem to have the strongest time varia-

[25]For technical details and outputs, see Tables C.11 to C.19 on pages 21–31 in the online appendix.

tion, consistent with the idea that their trades are driven by uninformative reasons (e.g. market risk, hedging or liquidity shocks) rather than a systematic processing of superior information.[26]

The main difference across groups of market participants is that the permanent price impact of sophisticated agents, such as funds and banks, is rather stable on average across time, while financially less literate agents (i.e. corporates) experience stronger time variation in their permanent price impact. This is likely to reflect funds' and banks' superior financial sophistication for engaging in strategic and timely order submission behaviours, such as order splitting and price impact smoothing.[27] These results buttress our hypothesis that asymmetric information is time-varying and heterogeneously disseminated across agents over time.

5.3 *Drivers of Customer Order Flows*

To conclude our microstructure analysis, we analyse the key drivers of customer order flows. We focus on the following two aspects: First, we examine whether there are systematic spill-over effects across some customer groups. Second, we study whether customers' flows relate heterogeneously to the performance of common FX trading strategies such as carry, value, volatility and momentum (see Lustig et al., 2011, Menkhoff et al., 2017, 2012a,b, Asness et al., 2013). To answer these questions, we include further explanatory variables such as interest rate differentials ($f_{t-1,t} - s_t \approx i_t^* - i_t$), equity returns ($r_t^{equity}$) and changes in the 10-year government bond yield (y_t^{bond}). In particular, we estimate a fixed effects panel regression of the form:

$$NV_{k,t}^j = \lambda_t + \alpha_k + \beta' f_{k,t} + \varepsilon_{k,t}, \tag{5.1}$$

where $NV_{k,t}^j$ is the daily standardised[28] net volume, $f_{k,t}$ collects contemporaneous and lagged standardised net volume, other economic factors as well as the portfolio returns of common FX trading strategies and $j \in C = \{CO, FD, NB, BA\}$ denotes one group of market participants. Our baseline model includes both cross-sectional (α_k) and time fixed (λ_t) effects, hence the error term can be decomposed as $\epsilon_{k,t} = \lambda_t + \alpha_k +$

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

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

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

$\varepsilon_{k,t}$. Standard errors are clustered by currency pair. We use country equity indices and 10-year government bond yields from Bloomberg at the daily frequency. To obtain economically meaningful results, we focus on all USD–based currency pairs.[29]

For every customer segment the panel regression in Table 6 includes contemporary and lagged order flows plus economic variables as well as the portfolio returns of common FX trading strategies (e.g. value, carry and momentum). There are three key findings: First, corporates, funds and banks are significantly positively driven by their lagged flows, while non-bank financials trade rather independently of their past orders. The strong autocorrelation in order flows of funds and banks is consistent with the idea that sophisticated agents have superior access to FX markets allowing them to engage in strategic order splitting and price impact smoothing (Kervel and Menkveld, 2019). Moreover, the banking sector trades against all other market participants absorbing asymmetric information risk and being consistent with the two-tier market structure of FX markets. Second, all banks trade against the interest rate differential, which is in line with speculative activities. Albeit statistically not always significant, funds and non-bank financials buy more foreign currency when foreign equity markets are doing well and do the opposite for bond markets. This finding is in line with a general risk-taking attitude in upward markets inducing investments abroad (i.e. buy foreign currency and sell domestic currency) and an opposite pattern during flight-to-quality episodes (Ranaldo and Söderlind, 2010). Such a behaviour is also in line with the role of financial intermediaries absorbing global imbalances in the FX markets (Gabaix and Maggiori, 2015). Third, a general appreciation of the US dollar against all other currencies (higher DOL) is accompanied by a continuing buying pressure from corporates, funds and banks, perhaps due to the US dollar being the predominant reserve and invoice currency. What is more, the time variation in order flows of funds, non-bank financials and banks is closely tied to the performance of common FX trading strategies such as carry (CAR_{HML}) and value (RER_{HML}). This finding is in line with strategic behaviour and higher adverse selection risk when trading against more sophisticated agents (Payne, 2003).

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

[29] To save space, we only report results for USD–base currency pairs, whereas results for EUR-base currency pairs are reported in Table C.26 on page 42 of the online appendix.

6 Asymmetric Information Risk Premium

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

6.1 *Trading Strategy*

From an asset pricing perspective, a coherent method to capture asymmetric information risk is to construct a long–short portfolio based on the systematic level of asymmetric information across currency pairs. In the context of global FX trading, we consistently apply this idea by introducing a *novel* and readily *implementable* trading strategy based on a simple idea: Order flows of agents and currencies impounding a persistent price impact convey superior information. Put differently, holding currency pairs with higher informational asymmetries (i.e. high average permanent price impact) requires a positive risk premium for taking the risk of trading against informed investors. Thus, if a currency's return responds permanently (*weakly*) to order flows in the same direction it belongs to the long (*short*) basket.[30]

To be precise, the long–short strategy (AIP_{HML}) rests on the five following pillars: timing, weighting, signal extraction, rebalancing and excess returns. Investment takes place *immediately* the day after the signal is extracted.[31] Throughout the investment period, the strategy exhibits *equally weighted* long and short legs, resulting in zero net exposure.[32] To make our results comparable to other common FX risk factors (e.g. Lustig et al., 2011, Menkhoff et al., 2017), we form tertile portfolios (Q_1, Q_2, Q_3) based on the uniform distribution, and we build cross-sections of currency portfolios.

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

[31] Results are robust to investing with a lag of 1 day up to a week.

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

Trading signals are generated from estimating Eq. (4.2) in a 12-month *rolling window* fashion at a daily frequency based on binary order flow and mid-quotes with the number of lags equal to 10 days.[33] To avoid any look-ahead bias, we use yesterday's trading signals ($t-1$) to create portfolio weights today (t). The advantage of running this regression at daily rather than hourly frequency is twofold: First, it is computationally less expensive, and hence, easily replicable in a real world setting.[34] Second, forward rates are usually not available at an hourly frequency, and therefore, using daily data ensures that signals are extracted at the same frequency as excess returns.

Hence, investment starts in September 2013 after 1 year of formation period. This leaves us 6.3 years for testing out-of-sample performance. For every rolling window index and currency pair k, we obtain the average permanent price impact $\bar{\alpha}_m^k$ (see Eq. (4.6)). Next, we sort currency pairs by $\bar{\alpha}_m^k$ in ascending order.[35] The AIP_{HML} portfolio is long (*short*) currency pairs in the top (*bottom*) tertile that exhibit the highest (*lowest*) $\bar{\alpha}_m^k$. Portfolio rebalancing takes place at the *beginning* of every month.

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

$$rx_{t+1} = f_{t,t+1} - s_{t+1}, \tag{6.1}$$

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

To account for the possibility of investing in a non-USD currency pair such as the *EURGBP*, we modify Eq. (6.6) such that, instead of one forward contract[36], the US investor enters two forward contracts based on triangular no-arbitrage conditions:

$$rx_{t+1}^{X/Y} = f_{t,t+1}^{USD/Y} - s_{t+1}^{USD/Y} - (f_{t,t+1}^{USD/X} - s_{t+1}^{USD/X}), \tag{6.2}$$

[33]The trading strategy is robust to our choice of model specification, that is, (signed) net volume instead of binary order flow and transaction prices instead of mid-quotes. Especially, it renders positive and significant returns for several different combinations of baseline VAR model, rolling window length and number of lags. Note that by including the order size variable $\tilde{S}_t$ in Eq. (4.2), we do not have to weight the (permanent) price impact coefficients by their trading volume.

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

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

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

where X and Y are the base and quote currency of a non-USD currency pair.[37] The main advantage of this approach is that we do not have to distinguish between different investors (e.g. European, Japanese, etc.), which would heavily reduce the cross-section of currency pairs, since all returns are *dollar-neutral*.

Since we have bid (b) and ask (a) quotes for spot and forward contracts[38], we can compute the investor's true realised excess return net of transaction cost. The *net* log currency excess return for an investor who goes long in foreign currency y is

$$rx_{t+1}^{X/Y} = f_{t,t+1}^{USD/Y,b} - s_{t+1}^{USD/Y,a} - \left(f_{t,t+1}^{USD/X,a} - s_{t+1}^{USD/X,b}\right), \tag{6.3}$$

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

$$rx_{t+1}^{X/Y} = -f_{t,t+1}^{USD/Y,a} + s_{t+1}^{USD/Y,b} + \left(f_{t,t+1}^{USD/X,b} - s_{t+1}^{USD/X,a}\right), \tag{6.4}$$

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

$$RX_{t+1}^{p} = \sum_{k=1}^{K_t} w_{k,t} RX_{k,t+1}, \tag{6.5}$$

where $RX_{k,t+1}$ is a vector of simple excess returns based on Eq. (6.3) and Eq. (6.4), since log returns are not asset additive. Each tertile portfolio consists of 10 currency pairs, where each of them receives an equal weight of $w_{k,t} = 10\%$.

6.2 *Trading Performance*

In Table 7, we present the annualised Sharpe ratio (SR), the annualised mean excess return (Mean), the maximum drawdown (MDD), the Θ performance measure of Goetzmann et al. (2007), skewness and excess kurtosis (Kurtosis-3) based on monthly rebalancing, respectively.[39] The Θ performance measure of Goetzmann et al. (2007) is only slightly lower than the mean return, indicating that neither outliers nor non-

[37] For a detailed derivation and discussion of alternative methods, see the online appendix Section D.

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

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

normality are driving the superior performance.[40] Panel a) and b) of Table 7 tabulate the *before* and *after* transaction cost performances of the first (Q_1) and third (Q_3) tertile portfolios, where AIP_{HML} is a linear combination of going short in Q_1 and long in Q_3. The same table also considers the performance of common FX trading strategies.[41]

From Table 7 three main results emerge, which are as follows: First, an economically and statistically high performance of the AIP_{HML} strategy is observed both prior and after transaction cost. Second, our strategy clearly outperforms common FX risk factor strategies based on the USD–base currency pairs basket (i.e. DOL)[42], the real exchange rate (i.e. RER/RER_{HML})[43], momentum (i.e. MOM_{HML}/CAR_{HML})[44], or volatility risk (i.e. VOL_{LMH})[45]. Third, AIP_{HML} clearly outperforms BMS that is a pure order flow–based strategy buttressing our proposition that order flow itself is not an accurate proxy of asymmetric information risk as it can arise from both informational and non-informational motives (e.g. liquidity). Furthermore, it is also consistent with the idea that a dealer following a pure "smart money" strategy cannot extract all superior information disseminated in the global FX market.

Figure 3 depicts the cumulative (simple excess) returns of different rebalancing frequencies before and after transaction cost. Gross returns are based on mid-quotes for both the spot and forward rates. The investment period is the entire sample period (September 2012 to December 2019) minus 12 months of the formation period to retrieve the first trading signal; thus, it spans from September 2013 to January 2019. Two merits arise from Figure 3: First, daily rebalancing is substantially less profitable than monthly rebalancing due to higher transaction cost, but it bears similar cumulative returns prior to transaction cost. Second, the equity curves steadily increase over time and do not experience any regime switches. Note that the cumulative returns are also increasing after October 2018 (i.e. the first dissemination of this working paper) reinforcing the risk premium hypothesis rather than some unexploited trading opportunity or other forms of market inefficiency.

[40]The SR doest not take into account the effect of non-normalities, which may be important in a small-sample setting. The Θ performance measure of Goetzmann et al. (2007) overcomes this issue by re-estimating the sample mean but putting less weight on outlier returns.

[41]The summary statistics for these benchmark strategies differ from those in Gargano et al. (2018). Our correspondence with the authors revealed three potential reasons for the differences: First, different time-period with only 4 overlapping years. Second, the authors use 3 month averages to implement CAR_{HML}, MOM_{HML} and RER_{HML}. Third, they only use a subsample of 15 USD–base currencies.

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

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

[44]The MOM_{HML} strategy involves a currency sorting based on past excess returns (Asness et al., 2013). For CAR_{HML} (Lustig et al., 2011), currency pairs are sorted based on the forward discount.

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

In addition to the cumulative returns, the maximum drawdown curves are constructed. This drawdown measure corresponds to the cumulative return of the AIP_{HML} portfolio relative to the last peak. With monthly rebalancing, the AIP_{HML} strategy beats itself over extended periods of time and exhibits a maximum drawdown of 7.19% (*7.75%*) prior (*after*) transaction cost.[46]

Analysing the decomposition of the long and short legs of AIP_{HML} delivers two main findings: First, our trading strategy exhibits a balanced exposure across currency pairs, where all the pairs receive an average absolute weight of 3–5%. Second, we calculate the relative contribution of every agent category's $\alpha_m^{j,k}$ to the average permanent price impact $\bar{\alpha}_m^k$ per currency pair and then take the average across all currency pairs for AIP_{HML} with monthly rebalancing. This calculation clearly shows that both the long and short legs appear to be equally balanced across agents providing further evidence of asymmetric information across market participants.[47]

6.3 *Exposure Regression*

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

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

Consistent with the asymmetric information hypothesis, AIP_{HML} returns are more correlated (see Table 8) with factors related to (currency) fundamental values, that is, the real exchange rate (RER_{HML}) and carry (CAR_{HML}). As expected, AIP_{HML} is unrelated to the standardised *total* order flow (BMS), global volatility (VOL_{LMH}) and momentum (MOM_{HML}). All these results hold after controlling for relative changes in the VIX index, JP Morgan Global FX Volatility index (VXY), the North American

[46]To overcome the statistical limitations of a relatively short out-of-sample period, we use standard bootstrap techniques. Figure D.1 on page 55 in the online appendix presents bootstrapped p-values for AIP_{HML} before and after transaction cost, respectively. The bootstrapped p-values are fully in line with their asymptotic counterparts.

[47]See Figures D.2 to D.4 on pages 57–59 in the online appendix.

credit default swap index (CDX) and the TED spread, respectively. In addition, we decompose the VXY into an 'uncertainty' and 'risk aversion' component (Bekaert et al., 2013). The regression coefficient of 'risk aversion' bears the expected (negative) sign but is generally statistically insignificant and does *not* affect the abnormal returns (α) generated by AIP_{HML}. This corroborates the overall validity of our results and highlights that they seem to hold in both a *risk neutral* and *risk averse* framework, respectively. Overall, none of the control variables has a material impact on our trading strategy's superior performance.[48]

6.4 *Explaining the Asymmetric Information Risk Premium*

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

$$AIP_{HML,t} = \alpha + \beta' f_t + \epsilon_t, \tag{6.6}$$

where, based on a loose classification à la Karnaukh et al. (2015), f_t refers to the following three broad categories: First, demand-side factors such as the VIX and the AAA–rated corporate bond yield. An increase of global uncertainty (measured by the former) and demand for safe assets (captured by the latter) prompt market participants to reassess the intrinsic value of financial instruments that have become information sensitive (Dang et al., 2019) leading to possible currency devaluations via a reduction of the safety premium or liquidity services (Jiang et al., 2018). Second, supply-side drivers such as an equally weighted stock return of the 10 largest FX dealers and the North American credit default swap index (CDX) made up by 125 investment grade issuers of credit securities capture the equity capital and funding constraints of global FX dealers. A funding and capital erosion (i.e. increasing dealers' leverage and possibly funding needs) constrains global financial intermediaries requiring a compensation for adverse selection risk and uncertainty (Gabaix and Maggiori, 2015, He and Krishnamurthy, 2013). Third, we include a set of market conditions such as the world equity and bond returns. The economic rationale is that higher risk factors (Christiansen et al., 2011) and information asymmetries in other asset classes such as stocks and bonds are conveyed in FX markets via fundamental valuations and portfolio rebalancing (Hau and Rey, 2004).

[48]See the online appendix Section D for tables documenting these additional results.

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

6.5 Robustness Tests and Limitations

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

7 Conclusion

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

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

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

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

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8 Tables

Table 1: Summary Statistics for Hourly Spot Returns

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

Note: This table presents summary statistics for average hourly returns of all currency pairs in our sample. The first five rows report the sample mean (Mean(Δ_r)), standard deviation (Std(Δ_r)), minimum (Min(Δ_r)) and maximum (Max(Δ_r)) of the returns, as well as the average relative spread (Avg. Spread = $[ask - bid]/mid$) over the full sample in basis points (BPS). The last row reports the first-order autocorrelation (AC(1)) for hourly returns in per cent (%).

Table 2: Summary Statistics for Hourly (Net) Volume

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

Note: This table reports net (absolute value of buy side minus sell side) volume broken down by four categories of agents, namely, corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA). All numbers are in USD million.

Table 3: Return Equation Coefficients

The model is:

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

where agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA), $D_{l,t}$ denotes a dummy variable matrix to account for time-fixed effects. In addition, $\Delta s_{k,t;t-\tau}$ and $\Delta s_{k,t;t-5\tau}$ account for the return over the prior day and week. Here, $\tau = 24$ and t is measured at hourly frequency and $C = \{CO, FD, NB, BA\}$. Transactions are indexed by t, and r_t refers to the log return in the mid-quote. $\tilde{S}_t^j$ controls for order size and refers to the residuals of regressing signed log volume against current and lagged values of the trade indicator variable T_t (+1 for a buy order and −1 for a sell order).

Eq. (4.2)	ρ_1	β_0^{CO}	β_0^{FD}	β_0^{NB}	β_0^{BA}	$\bar{R}^2$ in %	Eq. (4.2)	ρ_1	β_0^{CO}	β_0^{FD}	β_0^{NB}	β_0^{BA}	$\bar{R}^2$ in %
AUDJPY	***−8.597	−0.018	***0.009	***0.007	***0.014	9.517	GBPCHF	***−11.915	**−0.033	−0.002	***0.008	***−0.004	9.915
	[7.005]	[1.621]	[3.213]	[5.251]	[17.868]			[4.078]	[2.533]	[1.031]	[3.396]	[5.937]	
AUDNZD	***−11.602	−0.006	−0.002	***−0.003	***−0.002	8.588	GBPJPY	***−7.688	−0.008	**0.003	***0.004	***0.010	9.793
	[17.792]	[0.276]	[0.933]	[4.666]	[5.176]			[4.117]	[0.915]	[2.050]	[4.034]	[10.430]	
AUDUSD	***−8.202	***−0.013	***0.004	***0.010	***0.003	9.358	GBPUSD	***−6.598	***−0.014	***0.004	***0.007	***0.005	9.485
	[11.634]	[2.602]	[5.377]	[16.976]	[5.513]			[5.484]	[5.155]	[5.168]	[11.177]	[9.580]	
CADJPY	***−7.497	0.002	−0.001	0.002	***0.004	8.353	NZDUSD	***−9.579	**−0.039	***0.007	***0.006	***0.006	8.601
	[6.129]	[0.129]	[0.435]	[1.506]	[5.515]			[14.234]	[2.544]	[6.788]	[8.402]	[8.771]	
EURAUD	***−6.910	**−0.015	**0.002	**0.002	***0.003	8.280	USDCAD	***−8.680	***−0.024	***0.003	***0.004	***0.002	9.213
	[6.617]	[2.358]	[2.180]	[2.386]	[6.023]			[10.932]	[5.493]	[4.152]	[8.924]	[5.230]	
EURCAD	***−7.980	***−0.028	0.001	***0.005	***−0.002	8.883	USDCHF	***−12.859	***−0.012	**0.002	***0.010	**0.001	10.595
	[7.430]	[6.152]	[0.961]	[5.581]	[3.641]			[3.532]	[4.120]	[1.999]	[14.811]	[2.374]	
EURCHF	***−11.741	***−0.012	0.002	0.000	***−0.005	10.359	USDDKK	***−6.728	***−0.042	−0.001	***0.007	***−0.002	8.248
	[2.939]	[5.023]	[1.542]	[0.477]	[6.002]			[7.463]	[5.676]	[1.205]	[2.643]	[2.896]	
EURDKK	***−28.951	0.000	***0.000	0.000	***0.000	15.163	USDHKD	***−20.058	0.000	***0.000	0.000	***0.000	12.558
	[18.486]	[1.306]	[3.646]	[0.865]	[4.289]			[11.718]	[0.279]	[5.398]	[0.948]	[3.540]	
EURGBP	***−9.385	***−0.012	**0.002	***0.002	***−0.003	8.682	USDILS	***−21.784	−0.001	***0.003	***−0.010	***0.002	12.746
	[12.004]	[5.639]	[2.565]	[3.345]	[5.942]			[26.444]	[0.128]	[2.882]	[7.185]	[3.878]	
EURJPY	***−7.433	***−0.019	**−0.002	***0.004	**−0.001	8.816	USDJPY	***−7.362	***−0.006	***0.005	***0.008	***0.005	9.457
	[5.935]	[6.317]	[1.960]	[6.144]	[2.390]			[7.059]	[3.346]	[6.709]	[14.995]	[8.725]	
EURNOK	***−9.768	***−0.019	***0.008	0.002	***0.002	9.494	USDMXP	**−6.609	*−0.015	0.002	***−0.008	0.000	8.404
	[10.742]	[5.174]	[6.775]	[1.570]	[4.211]			[2.278]	[1.826]	[1.528]	[6.410]	[0.141]	
EURSEK	***−9.996	***−0.010	***0.004	**0.002	***0.002	8.549	USDNOK	***−9.614	***−0.034	***0.004	***0.005	***0.004	9.271
	[12.360]	[4.961]	[5.101]	[2.379]	[4.143]			[10.544]	[3.104]	[3.459]	[4.140]	[5.170]	
EURUSD	***−6.685	***−0.015	0.000	***0.006	−0.001	9.475	USDSEK	***−8.518	***−0.023	***0.004	***0.004	***0.003	8.471
	[7.261]	[12.389]	[0.337]	[11.522]	[1.342]			[10.176]	[4.560]	[4.353]	[3.637]	[5.206]	
GBPAUD	***−7.873	0.026	***0.004	0.001	***0.003	8.624	USDSGD	***−10.698	***−0.013	***0.002	***0.002	***−0.001	9.577
	[9.974]	[1.620]	[2.703]	[1.266]	[5.525]			[15.594]	[4.712]	[4.259]	[4.071]	[4.468]	
GBPCAD	***−9.137	**−0.035	0.001	**0.003	0.000	8.392	USDZAR	***−9.591	*−0.030	***0.006	0.003	***0.007	9.695
	[11.353]	[2.436]	[0.594]	[2.500]	[0.780]			[10.749]	[1.934]	[3.417]	[1.433]	[6.707]	
Expected sign	-	+	+	+	+		Expected sign	-	+	+	+	+	

Note: The linear regression coefficients are estimated by ordinary least squares on the full sample. All coefficients are in %. The *t*-stats in square brackets are based on heteroscedasticity- and autocorrelation-consistent errors (Newey and West, 1987), and asterisks *, ** and *** denote significance at the 90%, 95% and 99% levels, respectively.

Table 4: Order Flow Equation Coefficients

The model is:

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

where agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA), $D_{l,t}$ denotes a dummy variable matrix to account for time-fixed effects, and $C = \{CO, FD, NB, BA\}$. Transactions are indexed by t and r_t refers to the log-return in the mid-quote. $\tilde{S}_t^j$ controls for order size and refers to the residuals of regressing signed log volume against current and lagged values of the trade indicator variable T_t (+1 for a buy order and −1 for a sell order).

Eq. (4.3)	γ_1	δ_1^{CO}	δ_1^{FD}	δ_1^{NB}	δ_1^{BA}	$\bar{R}^2$ in %	Eq. (4.3)	γ_1	δ_1^{CO}	δ_1^{FD}	δ_1^{NB}	δ_1^{BA}	$\bar{R}^2$ in %
AUDJPY	***34.453	−0.014	***0.041	0.001	***0.061	1.672	GBPCHF	***−28.160	**0.145	0.001	0.006	***0.023	0.377
	[8.661]	[0.208]	[2.694]	[0.107]	[12.407]			[4.300]	[2.029]	[0.121]	[0.612]	[4.671]	
AUDNZD	***−35.226	0.124	0.009	0.001	***0.051	0.585	GBPJPY	***42.777	−0.001	***0.029	0.006	***0.054	1.389
	[6.714]	[0.690]	[0.490]	[0.216]	[10.712]			[6.283]	[0.024]	[2.679]	[0.891]	[10.653]	
AUDUSD	**−8.763	0.010	0.008	***0.020	***0.039	0.507	GBPUSD	**−10.448	0.018	0.008	0.005	***0.048	0.836
	[2.276]	[0.328]	[1.426]	[4.102]	[8.036]			[2.525]	[1.142]	[1.350]	[0.894]	[9.976]	
CADJPY	−2.469	0.036	0.007	0.008	***0.030	0.209	NZDUSD	***−15.227	−0.059	**0.015	0.004	***0.056	0.694
	[0.718]	[0.395]	[0.328]	[0.828]	[6.156]			[4.343]	[0.896]	[2.039]	[0.819]	[11.678]	
EURAUD	***−14.415	0.023	0.003	0.003	***0.022	0.226	USDCAD	1.868	0.005	0.009	0.003	***0.054	1.117
	[3.626]	[0.493]	[0.306]	[0.458]	[4.523]			[0.383]	[0.177]	[1.377]	[0.557]	[11.158]	
EURCAD	***−27.702	***0.146	−0.005	**0.018	***0.037	0.620	USDCHF	***−15.953	***0.076	***0.025	0.001	***0.041	0.551
	[6.512]	[4.850]	[0.578]	[2.464]	[7.529]			[3.741]	[3.205]	[3.730]	[0.161]	[8.454]	
EURCHF	*−41.130	***0.079	***0.028	0.004	***0.064	1.791	USDDKK	**−8.360	0.008	*0.014	0.004	***0.020	0.543
	[1.739]	[3.636]	[3.609]	[0.537]	[12.341]			[1.967]	[0.199]	[1.669]	[0.196]	[3.528]	
EURDKK	133.740	−0.036	***0.026	***0.082	***0.074	1.070	USDHKD	***−301.884	**0.232	**0.015	0.021	***0.058	0.749
	[1.578]	[0.946]	[2.641]	[2.812]	[13.460]			[4.764]	[2.228]	[2.461]	[1.215]	[11.823]	
EURGBP	***−37.084	**0.029	***0.022	−0.004	***0.045	1.035	USDILS	4.110	0.165	***0.028	0.007	***0.075	1.369
	[8.007]	[1.972]	[3.366]	[0.630]	[9.419]			[0.917]	[1.419]	[2.592]	[0.495]	[13.396]	
EURJPY	0.970	0.004	**0.018	***0.025	***0.039	0.993	USDJPY	−2.790	*0.023	***0.027	***0.016	***0.028	0.503
	[0.261]	[0.190]	[2.178]	[4.777]	[8.076]			[0.681]	[1.698]	[4.699]	[3.235]	[5.819]	
EURNOK	***−38.956	***0.053	***0.038	***0.034	***0.075	1.376	USDMXP	***−24.825	*0.067	0.007	**0.014	***0.048	0.530
	[7.544]	[2.836]	[4.524]	[4.492]	[15.042]			[6.273]	[1.884]	[0.917]	[2.115]	[9.791]	
EURSEK	***−44.468	***0.054	***0.035	***0.024	***0.081	1.392	USDNOK	***8.968	0.079	***0.021	0.005	***0.071	0.924
	[8.165]	[3.875]	[4.707]	[3.149]	[16.525]			[2.670]	[1.541]	[2.663]	[0.616]	[14.005]	
EURUSD	***−35.157	0.010	***0.030	0.001	***0.051	1.815	USDSEK	**−7.691	***0.090	***0.026	0.006	***0.048	0.557
	[7.576]	[1.179]	[5.421]	[0.270]	[10.439]			[2.080]	[3.351]	[3.648]	[0.822]	[9.833]	
GBPAUD	−5.831	−0.191	0.016	0.012	***0.022	0.128	USDSGD	***−73.324	−0.014	0.011	−0.005	***0.049	0.705
	[1.576]	[1.022]	[1.605]	[1.533]	[4.616]			[9.593]	[0.310]	[1.547]	[0.557]	[10.229]	
GBPCAD	***13.404	**0.224	0.008	***0.028	***0.034	0.258	USDZAR	***−16.545	0.032	***0.022	**−0.016	***0.050	0.679
	[3.102]	[2.123]	[0.739]	[3.211]	[6.852]			[6.707]	[0.785]	[2.828]	[2.171]	[10.238]	
Expected sign	-	+	+	+	+		Expected sign	-	+	+	+	+	

Note: The linear regression coefficients are estimated by ordinary least squares on the full sample. The *t*-stats in square brackets are based on heteroscedasticity- and autocorrelation-consistent errors (Newey and West, 1987), and asterisks *, ** and *** denote significance at the 90%, 95% and 99% levels, respectively.

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

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

Note: The numbers in brackets correspond to the test statistic for a heteroscedasticity-consistent joint *F*-test, where the parameters in Eq. (4.5) are jointly different from zero. Asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests in the joint hypothesis. All regression coefficients are in basis points (BPS). Agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA).

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

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

Note: This table collects results from fixed effects panel regressions of the form $NV^j_{k,t} = \lambda_t + \alpha_k + \beta' f_{k,t} + \varepsilon_{k,t}$, where $NV^j_{k,t}$ is daily standardised net volume, $f_{k,t}$ collects contemporaneous and lagged standardised net volume (the standard deviation of flows is computed via a 60-day rolling window), market conditions such as the interest rate differential ($f_{t-1,t} - s_t \approx i^*_t - i_t$), equity returns ($r_t^{equity}$) and changes in the 10-year government bond yield (y_t^{bond}) as well as the portfolio returns of common FX trading strategies. The superscript $j \in C = \{CO, FD, NB, BA\}$ denotes one of the market participants, namely, corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA). All specifications are based on standardised regressors and include both cross-sectional (α_k) and time fixed (λ_t) effects, hence the error term can be decomposed as $\epsilon_{k,t} = \lambda_t + \alpha_k + \varepsilon_{k,t}$. Δ stands for *relative* changes. The test statistics based on cross-sectionally clustered White standard errors (White, 1980) are reported in brackets. Asterisks *, ** and *** denote significance at the 90%, 95% and 99% levels.

Table 7: Performance Benchmarking: AIP_{HML}

Panel a) Gross Returns	DOL	RER_{HML}	RER	MOM_{HML}	CAR_{HML}	BMS	VOL_{LMH}	Q_1	Q_3	AIP_{HML}
SR	−0.11	−0.22	−0.22	−0.13	0.05	0.68	−0.54	*0.65	0.23	**0.83
	[0.33]	[0.53]	[0.58]	[0.32]	[0.16]	[1.49]	[1.25]	[1.84]	[0.59]	[2.35]
Mean in %	−0.33	−1.08	−0.71	−0.91	0.39	2.79	−3.20	**3.01	1.04	***4.05
	[0.33]	[0.52]	[0.58]	[0.31]	[0.16]	[1.48]	[1.24]	[1.97]	[0.58]	[3.01]
MDD in %	6.48	14.26	10.14	28.56	19.31	8.30	29.30	8.05	11.24	7.19
Scaled MDD	7.40	9.40	10.22	12.19	8.34	6.71	15.00	5.78	8.23	4.95
Θ in %	−0.41	−1.32	−0.81	−1.41	−0.14	2.62	−3.55	2.79	0.84	3.81
Skewness	0.56	0.12	−0.02	−0.30	−0.70	0.16	0.11	−0.10	0.69	0.15
Kurtosis-3	1.55	−0.40	0.16	0.88	0.81	−0.31	−0.10	1.66	1.17	9.45

Panel b) Net Returns	DOL	RER_{HML}	RER	MOM_{HML}	CAR_{HML}	BMS	VOL_{LMH}	Q_1	Q_3	AIP_{HML}
SR	−0.24	−0.38	−0.38	−0.24	−0.07	0.47	−0.69	0.55	0.13	**0.65
	[0.69]	[0.91]	[1.02]	[0.61]	[0.19]	[1.04]	[1.59]	[1.59]	[0.33]	[1.96]
Mean in %	−0.70	−1.88	−1.24	−1.74	−0.48	1.95	−4.10	*2.57	0.59	**3.16
	[0.70]	[0.92]	[1.02]	[0.60]	[0.19]	[1.03]	[1.58]	[1.69]	[0.33]	[2.35]
MDD in %	7.67	17.51	12.01	31.57	21.24	10.19	35.65	8.58	12.35	7.57
Scaled MDD	8.71	11.38	12.03	13.29	9.07	8.20	17.83	6.13	9.01	5.18
Θ in %	−0.78	−2.12	−1.34	−2.24	−1.01	1.78	−4.45	2.36	0.39	2.92
Skewness	0.56	0.10	−0.03	−0.31	−0.70	0.14	0.09	−0.13	0.68	0.10
Kurtosis-3	1.53	−0.38	0.16	0.91	0.81	−0.34	−0.10	1.71	1.15	9.46

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

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

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

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

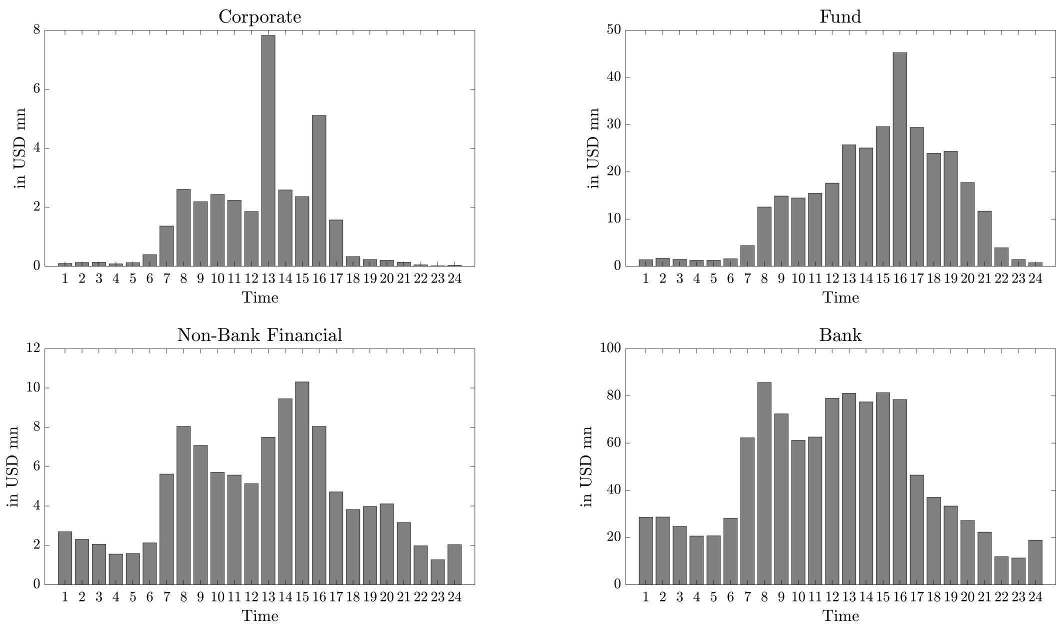
Table 9: Economic Drivers of AIP_{HML}

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

Note: This table shows results from multivariate regressions of daily gross AIP_{HML} returns on its potential drivers, $AIP_{HML,t} = \alpha + \beta' f_t + \epsilon_t$, where f_t denotes demand- and supply-side sources as well as a set of market conditions. *VIX* is the Chicago Board Options Exchange's volatility index measuring the stock market's expectation of volatility based on S&P 500 index options. *AAA Bond yields* is the bond yield on AAA–rated US corporate debt. *Top FX dealers* is an equally weighted equity portfolio consisting of the 10 largest FX dealers' stocks, *CDX* is the North American credit default swap index made up by 125 issuers of credit securities, *MSCI return* is the return on the MSCI world equity index and *BGBI return* is the return on the Barclays global-aggregate bond index. All variables enter the regressions contemporaneously as first differences, except for the *BGBI return*, which is lagged by one day. The intercept (α) has been annualised ($\times$252). All explanatory variables are in relative changes. The numbers in the brackets are the corresponding test statistics based on heteroscedasticity- and autocorrelation-consistent standard errors correcting for serial correlation and the small sample size (using the plug-in procedure for automatic lag selection by Andrews and Monahan, 1992, Newey and West, 1994). *VIF* is the *maximum* variance inflation factor. Asterisks *, ** and *** denote significance at the 90%, 95% and 99% levels, respectively.

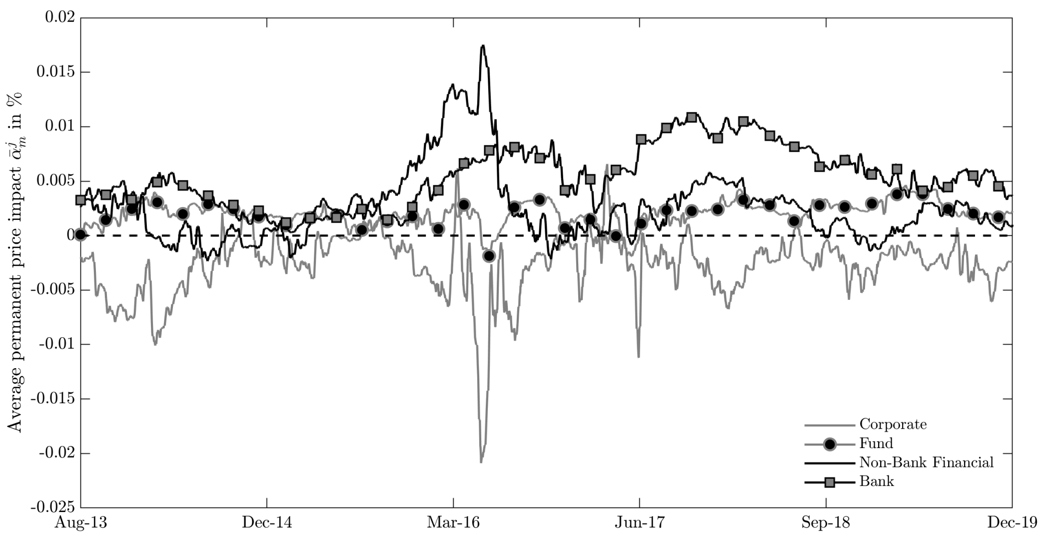
9 Figures

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



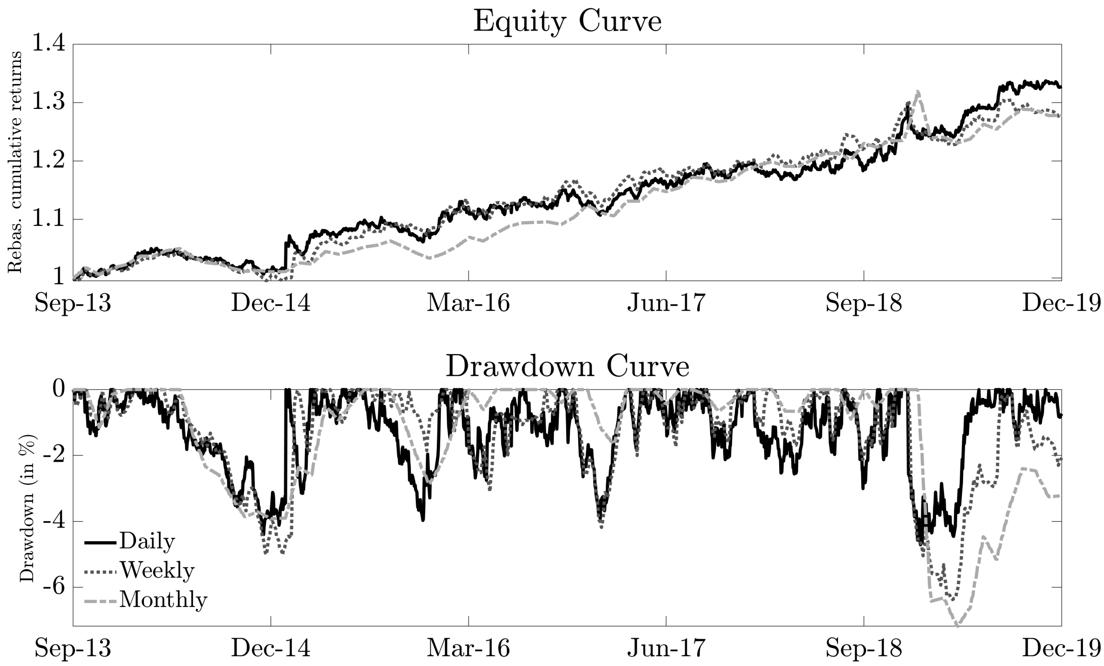
Note: This figure plots the average intraday hourly net volume (in USD mn). The average is computed across all trading days (2012-2019) and currency pairs. The horizontal axis denotes the closing time, for example, 17 refers to the volume between 4-5 *pm* (London time, GMT).

Figure 2: Twelve Months Rolling Window Regression for $\bar{\alpha}_m^j$

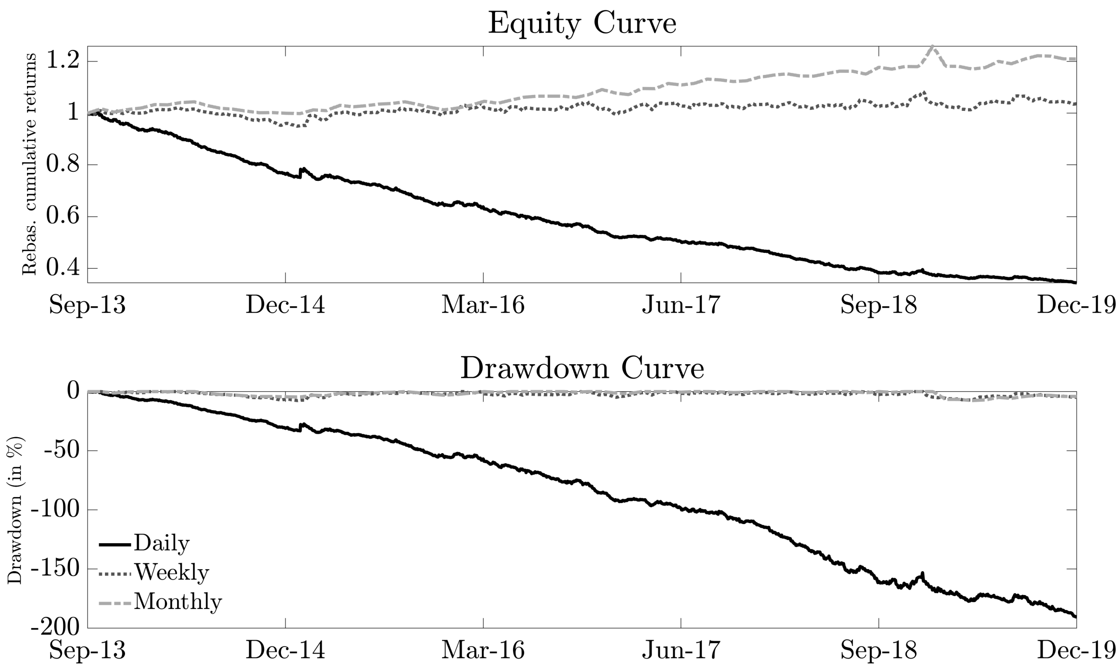


Note: The cross-sectional five-day-moving-average permanent price impact ($\bar{\alpha}_m^j$) is calculated after removing any coefficients that are heavy outliers in terms of the median.

Figure 3: Equity and Drawdown Curves



(a) Before Transaction Cost



(b) After Transaction Cost

Note: For non-daily rebalancing frequencies, missing data points are interpolated linearly.

Online Appendix to "Asymmetric Information Risk in FX Markets" by Angelo Ranaldo and Fabricius Somogyi

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Appendix A 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. 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.[1]

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.

[1] 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'.

Second, CLS has relatively low client penetration among corporates and real money funds that trade FX infrequently and do not need a dedicated third-party settlement service. Third, market maker banks may engage in price taking activity but price taker banks are unlikely to ever engage in market making activity.

Appendix B Summary Statistics

Here, we address two possible problematic issues on order flow data segregated by groups of market participants, which were first stressed in Evans and Lyons (2006), as follows, intra-temporal dependence and inter-temporal dependence. Rather than price impact parameters, the presence of these issues would force us to interpret the coefficients as a simple mapping of the variation in order flow segments into the flow of fundamental information that has yet to be fully assimilated by dealers across the market.

First, both order flow and (signed) net volume exhibit low levels of intra-temporal correlation among different order flow/(signed) net volume segments. Second, Figure B.1 plots the average correlation coefficients between customer order flows for horizons of 1,2, ..., and 60 trading days. Average correlations between flows are based on the average correlation across all 30 currency pairs. A horizon of 1 day corresponds to non-overlapping hourly observations, whilst for longer horizons we sum over daily (overlapping) observations using the full sample. We find global evidence that all correlations between financial (FD, NB and BA) and non-financial customers (CO) are negative at all horizons, while the flows of funds and non-bank financials are positively correlated over time. These results corroborate the risk-sharing hypothesis whereby financial players trade in the opposite direction of non-financial market participants. Therefore, our empirical analysis supports the idea that risk sharing takes place at a global scale and across customer segments rather than only in the inter-dealer segment or between customers of a given bank (Menkhoff et al., 2016). Furthermore, these patterns indicate that in the entire cross-section of currencies, serial autocorrelation is not an issue.[2]

[2]For more than 90% of the currency pairs we do *not* reject the null hypothesis of the Ljung–Box test of no residual autocorrelation in order flow up to lag 24.

Table B.1: Location Parameters of Hourly (Net) Volume

in USD mn	Corporate	Fund	Non-Bank Financial	Bank
Mean	1.45	13.88	4.64	46.64
Std(Mean Vol)	0.06	0.24	0.08	0.41
Median	0.00	1.60	1.13	19.78
90^{th}	1.53	30.93	9.91	113.63
10^{th}	0.00	0.00	0.06	2.24
AC(1) in %	8.85	13.31	14.84	17.31

Note: This table reports the sample mean (*Mean*), standard deviation of the mean (*Std(Mean Vol)*), median (*Median*), 90^{th} percentile and 10^{th} percentile of hourly (absolute) net volume for the cross-section of all currency pairs in USD million. The last row displays the first order autocorrelation for aggregate volume (*AC(1)*) in per cent (%).

Table B.2: Average Cross Correlation in %

Absolute/Order Flow

	CO	FD	NB
FD	0.54		
NB	0.52	0.44	
BA	2.55	8.73	4.69

Absolute/Net Volume

	CO	FD	NB
FD	0.68		
NB	0.91	0.53	
BA	8.22	25.46	8.11

Relative/Order Flow

	CO	FD	NB
FD	-0.13		
NB	-0.15	-0.29	
BA	-2.54	-8.73	-4.69

Relative/Net Volume

	CO	FD	NB
FD	-0.28		
NB	-0.18	0.16	
BA	-8.20	-25.46	-8.11

Note: This table documents the time series cross-correlation matrices at lag 0 of agent *i*'s order flow/(signed) net volume across all currency pairs. We filter for the main trading hours from 7 *am* to 5 *pm* GMT (no British Summer Time adjustment). Without filtering, the correlations are even lower due to market participants being active at different times of the day. For "absolute" we take the absolute value of order flow/net volume and in case of "relative" we take order flow/net volume as is, i.e. take into account the sign of order flow/volume. All numbers are in per cent (%).

Table B.3: Average Time Series Correlation Across Agents in %

(a) Correlations Based on Order Flow

#lags	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10
CO/FD	−0.02	−0.03	0.02	−0.12	−0.11	−0.07	−0.08	−0.05	0.01	0.01	−0.13	0.15	0.16	−0.03	0.06	0.07	0.07	−0.07	0.00	−0.16	−0.09
CO/NB	−0.11	−0.10	−0.15	−0.03	0.03	−0.04	0.02	−0.06	−0.08	−0.15	−0.15	0.06	0.09	0.08	−0.20	−0.20	−0.09	−0.05	−0.21	−0.09	−0.03
CO/BA	0.09	0.01	0.05	−0.01	−0.05	−0.10	−0.07	−0.18	−0.24	−0.30	*−2.54	−0.22	−0.28	−0.07	−0.11	0.12	−0.06	−0.01	0.04	0.01	0.00
FD/NB	0.05	0.03	0.06	−0.08	0.05	−0.02	0.08	0.19	0.13	−0.19	−0.29	0.01	−0.22	−0.09	0.10	0.11	0.08	0.00	−0.17	−0.17	0.05
FD/BA	−0.18	0.02	0.04	0.06	−0.08	−0.12	−0.21	−0.30	−0.35	−0.32	*−8.73	−0.67	−0.34	−0.24	−0.18	−0.33	−0.28	−0.10	−0.13	−0.07	−0.16
NB/BA	−0.05	−0.03	−0.27	−0.12	−0.12	−0.06	−0.11	−0.36	−0.63	*−1.00	*−4.69	−0.65	−0.33	−0.36	−0.23	−0.20	0.07	−0.08	0.11	−0.09	0.07

(b) Correlations Based on Net Volume

#lags	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10
CO/FD	0.01	0.03	0.06	−0.04	−0.05	0.05	0.04	−0.17	0.02	−0.01	−0.28	0.44	−0.10	0.11	0.10	−0.27	0.07	−0.02	0.13	0.01	0.00
CO/NB	−0.04	0.04	−0.03	0.08	0.02	−0.04	−0.03	0.01	0.02	0.30	−0.18	0.04	−0.11	−0.01	−0.15	−0.15	0.07	−0.10	0.03	0.10	0.03
CO/BA	0.06	0.01	0.08	0.00	0.11	−0.07	−0.10	−0.04	−0.18	−0.07	*−8.20	−0.45	−0.22	−0.29	−0.06	0.06	−0.13	0.08	0.00	−0.07	0.02
FD/NB	0.01	−0.05	−0.03	0.12	0.02	−0.04	−0.28	−0.23	0.04	−0.25	0.16	0.03	0.00	0.09	−0.02	0.06	0.08	−0.03	−0.07	0.12	0.03
FD/BA	0.03	−0.16	−0.12	−0.30	−0.11	−0.03	−0.32	−0.32	−0.26	−0.74	*−25.46	−0.90	−0.52	−0.23	−0.23	−0.14	−0.11	−0.21	−0.11	−0.18	−0.11
NB/BA	−0.04	0.01	−0.08	0.19	0.14	0.06	−0.06	−0.09	−0.20	−0.62	*−8.11	−0.53	−0.29	−0.07	−0.07	0.14	0.03	0.02	0.03	0.05	−0.02

Note: Panels a) and b) summarise the average time series correlation across currency pairs for all pairwise combinations of market participants. Panel a) is based on order flow, while Panel b) is based on (signed) net volume. Agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA). For every currency pair k the time series correlation $\rho_{i,j}$ is calculated for all pairwise combinations of agents, based on:

$$\rho_{i,j}(\tau) = \frac{1}{\sigma_i \sigma_j} E[(I_t - \mu_i)(J_{t+\tau} - \mu_j)], \tag{B1}$$

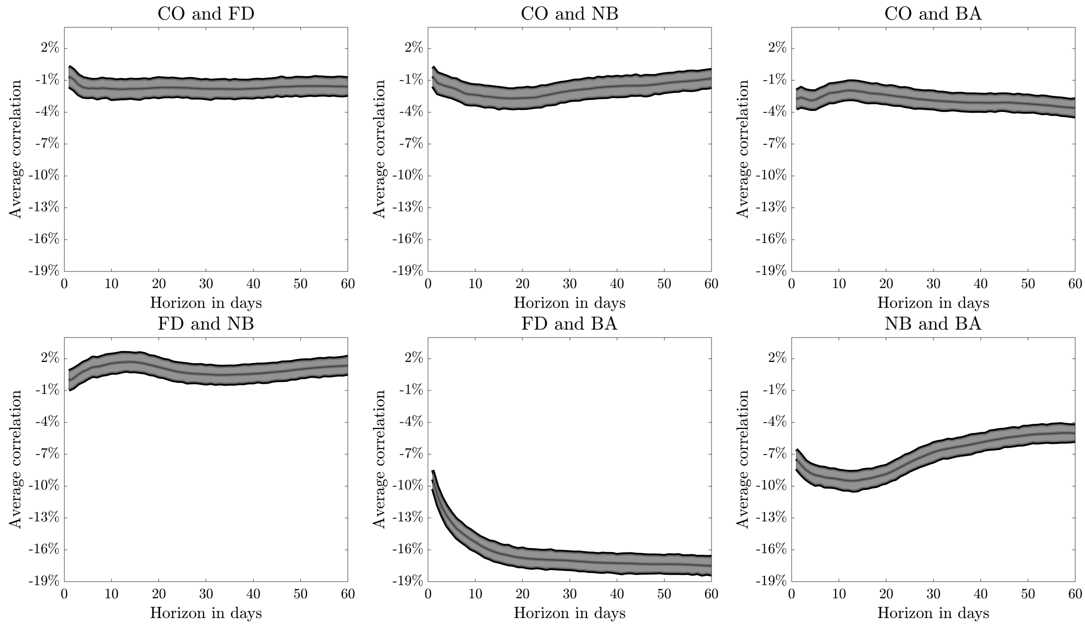
where $i \neq j \in C := \{CO, FD, NB, BA\}$, μ_i and σ_i are the mean and standard deviation of the process (I_t), that are constant over time due to stationarity; and similarly for J_t, respectively. $E[\ ]$ indicates the expected value. $\tau \in \Omega := \{x \in \mathbb{N} | x \geqslant -10 \wedge x \leqslant 10\}$ denotes the leads and lags, respectively. A star indicates that the time series correlation coefficient $\rho_{i,j}$ lies outside of the approximate 95% confidence bounds.

Table B.4: Per cent (%) of Average Daily Activity (USD Equivalent Notional)

Currency Pair	Funds	Corporates	Non-Bank Financials	Banks Acting as Price Takers	Banks Acting as Market Makers
AUDJPY	0.86	0.08	1.70	46.00	51.36
AUDNZD	1.38	0.01	3.44	54.24	40.94
AUDUSD	4.18	0.10	1.88	38.43	55.40
CADJPY	1.41	0.34	3.96	54.94	39.35
EURAUD	2.33	0.10	2.60	35.47	59.51
EURCAD	3.03	1.03	3.05	34.44	58.44
EURCHF	2.85	0.34	1.46	29.57	65.79
EURDKK	5.48	0.26	0.47	36.79	56.99
EURGBP	3.87	0.60	1.31	27.87	66.34
EURJPY	1.38	0.33	2.01	26.55	69.74
EURNOK	2.54	0.38	1.26	29.13	66.69
EURSEK	3.74	0.84	1.20	27.92	66.29
EURUSD	3.76	0.44	1.37	25.49	68.95
GBPAUD	3.06	0.02	3.60	26.54	66.78
GBPCAD	3.41	0.34	4.04	28.66	63.54
GBPCHF	4.20	0.07	3.20	27.16	65.37
GBPJPY	0.80	0.05	2.14	24.34	72.68
GBPUSD	3.48	0.19	1.40	21.40	73.53
NZDUSD	4.23	0.02	2.16	42.30	51.29
USDCAD	2.77	0.09	1.48	35.00	60.66
USDCHF	3.59	0.28	2.42	32.69	61.02
USDDKK	18.41	2.23	0.52	7.97	70.87
USDHKD	8.50	0.03	0.84	39.44	51.19
USDILS	2.53	0.07	0.59	47.38	49.44
USDJPY	2.37	0.19	1.35	29.41	66.69
USDMXP	3.39	0.09	1.19	32.46	62.87
USDNOK	5.90	0.20	2.04	37.83	54.02
USDSEK	8.54	0.50	1.95	36.55	52.46
USDSGD	1.94	0.06	0.56	40.14	57.30
USDZAR	2.83	0.03	0.90	37.43	58.82

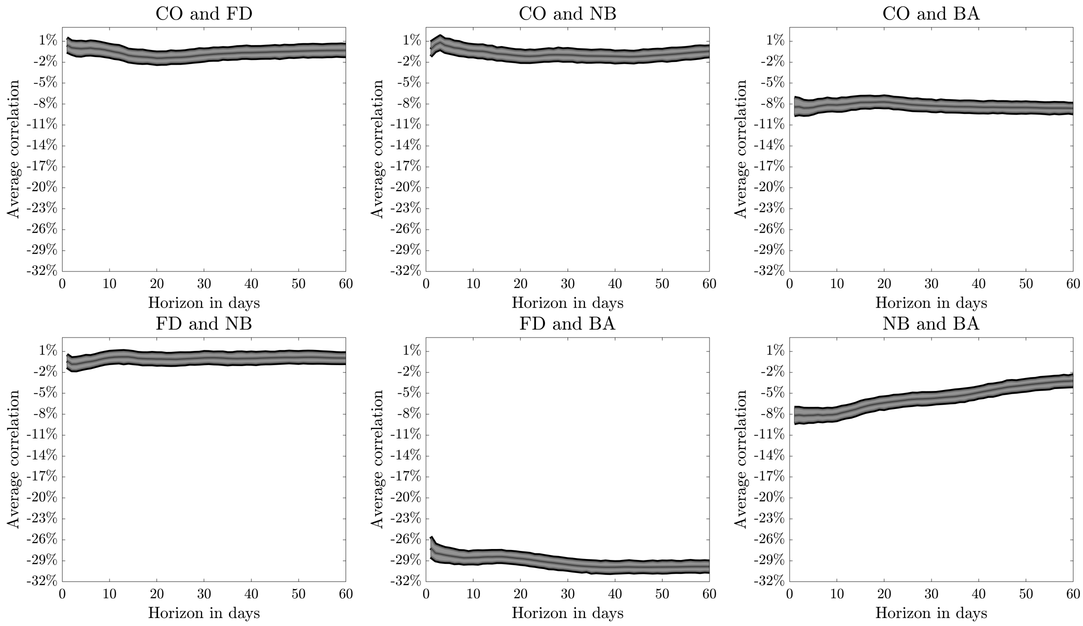
Note: In this table, the first three columns represent average daily trading activity by market participant. The fourth column represents activity by price taker banks that have been identified by CLS using network analysis. The sum of the first four columns represents the total share of activity settled by CLS Group that is covered by the order flow dataset. The fifth column is the difference between activity covered by the order flow dataset, and the activity covered by the volume dataset. The order flow dataset excludes transactions between two market makers, and transactions between two price takers. Trades between price takers are very rare, so essentially this column represents trades among market maker banks. The order flow dataset thus covers only a smaller fraction of FX market activity. See the online appendix Section B for potential reasons.

Figure B.1: Correlation of Customer Order Flows Over Longer Horizons



Note: Correlations are based on the average correlation across all currency pairs. A 1 day horizon corresponds to non-overlapping hourly observations. For horizons greater than 1 day we sum up the order flow over n days in an overlapping fashion and calculate correlations based on the sum of the n-day order flow. The shaded areas correspond to 95% confidence bands based on a moving-block bootstrap with 1000 repetitions.

Figure B.2: Correlation of Customer Net Volume Over Longer Horizons



Note: Correlations are based on the average correlation across all currency pairs. A 1 day horizon corresponds to non-overlapping hourly observations. For horizons greater than 1 day we sum up net volume over *n* days in an overlapping fashion and calculate correlations based on the sum of *n* day net volume. The shaded areas correspond to 95% confidence bands based on a moving-block bootstrap with 1000 repetitions.

Appendix C Estimating a Bivariate VAR Model

Table C.1: Return Equation Coefficients Based on Transaction Prices and Order Flow

The model is:

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

where agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA), $D_{l,t}$ denotes a dummy variable matrix to account for time-fixed effects. $\Delta s_{k,t;t-\tau}$ and $\Delta s_{k,t;t-5\tau}$ account for the return over the prior day and week. Here, $\tau = 24$ and t is measured at hourly frequency and $C = \{CO, FD, NB, BA\}$. Transactions are indexed by t. r_t refers to the log-return in the price, which depends on the aggregate trade indicator variable T_t (+1 for a buy order and −1 for a sell order). $\tilde{S}_t^j$ controls for order size and refers to the residuals of regressing signed log-volume against current and lagged values of the trade indicator variable T_t.

Eq. (4.2)	ρ_1	β_0^{CO}	β_0^{FD}	β_0^{NB}	β_0^{BA}	$\bar{R}^2$ in %	Eq. (4.2)	ρ_1	β_0^{CO}	β_0^{FD}	β_0^{NB}	β_0^{BA}	$\bar{R}^2$ in %
AUDJPY	***−8.793	*−0.019	***0.009	***0.007	***0.014	9.402	GBPCHF	***−10.970	**−0.031	−0.002	***0.008	***−0.004	9.762
	[7.640]	[1.669]	[3.228]	[5.239]	[17.939]			[4.472]	[2.392]	[1.066]	[3.510]	[5.678]	
AUDNZD	***−11.480	−0.006	−0.002	***−0.003	***−0.002	8.499	GBPJPY	***−7.606	−0.008	**0.004	***0.004	***0.010	9.678
	[17.597]	[0.291]	[0.929]	[4.339]	[5.406]			[3.836]	[0.918]	[2.108]	[4.089]	[10.177]	
AUDUSD	***−8.300	***−0.014	***0.004	***0.010	***0.003	9.344	GBPUSD	***−6.175	***−0.014	***0.004	***0.007	***0.005	9.416
	[11.626]	[2.654]	[5.550]	[17.019]	[5.487]			[4.044]	[5.119]	[5.047]	[10.981]	[9.433]	
CADJPY	***−7.430	0.002	−0.001	0.003	***0.004	8.297	NZDUSD	***−9.229	**−0.039	***0.007	***0.006	***0.006	8.434
	[5.854]	[0.144]	[0.458]	[1.629]	[5.530]			[13.705]	[2.473]	[6.909]	[8.461]	[8.652]	
EURAUD	***−6.968	**−0.015	**0.002	**0.002	***0.003	8.298	USDCAD	***−8.739	***−0.023	***0.003	***0.004	***0.002	9.132
	[6.704]	[2.382]	[2.199]	[2.452]	[5.989]			[11.193]	[5.335]	[4.109]	[8.911]	[5.218]	
EURCAD	***−7.902	***−0.028	0.001	***0.005	***−0.002	8.777	USDCHF	***−12.433	***−0.011	**0.002	***0.010	**0.001	10.492
	[7.203]	[6.110]	[1.080]	[5.675]	[3.549]			[3.684]	[3.812]	[2.126]	[14.921]	[2.411]	
EURCHF	***−12.085	***−0.012	0.002	0.000	***−0.005	10.417	USDDKK	***−6.554	***−0.042	−0.001	***0.007	**−0.002	8.128
	[3.062]	[5.024]	[1.553]	[0.507]	[6.016]			[7.284]	[5.684]	[1.083]	[2.640]	[2.333]	
EURDKK	***−16.382	0.000	***0.000	0.000	***0.000	6.490	USDHKD	***−16.750	0.000	***0.000	0.000	***0.000	8.961
	[13.412]	[1.158]	[3.899]	[0.106]	[11.170]			[9.909]	[0.178]	[4.564]	[0.928]	[2.995]	
EURGBP	***−8.943	***−0.012	**0.002	***0.002	***−0.003	8.556	USDILS	***−17.997	−0.007	*0.002	***−0.011	***0.003	9.265
	[10.574]	[5.610]	[2.574]	[3.052]	[5.781]			[23.477]	[0.662]	[1.757]	[6.861]	[4.306]	
EURJPY	***−7.408	***−0.019	**−0.003	***0.004	**−0.001	8.603	USDJPY	***−7.395	***−0.006	***0.005	***0.008	***0.005	9.418
	[6.605]	[6.346]	[1.972]	[6.189]	[2.337]			[7.282]	[3.494]	[6.688]	[14.944]	[8.772]	
EURNOK	***−9.742	***−0.018	***0.008	0.002	***0.003	9.209	USDMXP	**−6.286	*−0.015	*0.002	***−0.008	0.000	8.187
	[10.419]	[5.081]	[6.594]	[1.495]	[4.773]			[2.189]	[1.797]	[1.768]	[6.313]	[0.138]	
EURSEK	***−9.416	***−0.010	***0.004	**0.002	***0.002	8.093	USDNOK	***−9.440	***−0.032	***0.004	***0.006	***0.004	9.093
	[11.676]	[5.117]	[5.333]	[2.287]	[4.816]			[9.955]	[2.945]	[3.693]	[4.403]	[5.523]	
EURUSD	***−6.388	***−0.015	0.000	***0.006	−0.001	9.350	USDSEK	***−8.096	***−0.023	***0.005	***0.004	***0.004	8.285
	[6.916]	[12.420]	[0.412]	[11.600]	[1.187]			[9.749]	[4.495]	[4.629]	[3.791]	[5.583]	
GBPAUD	***−7.941	0.025	***0.004	0.001	***0.004	8.538	USDSGD	***−10.121	***−0.013	***0.002	***0.002	***−0.001	9.090
	[10.145]	[1.452]	[2.631]	[1.250]	[5.611]			[14.830]	[4.579]	[4.456]	[4.050]	[4.477]	
GBPCAD	***−8.862	**−0.034	0.001	***0.003	0.001	8.299	USDZAR	***−9.404	*−0.029	***0.006	0.003	***0.007	9.521
	[10.077]	[2.407]	[0.642]	[2.646]	[0.921]			[10.057]	[1.853]	[3.565]	[1.612]	[6.859]	
Expected sign	-	+	+	+	+		Expected sign	-	+	+	+	+	

Note: The linear regression coefficients are estimated by ordinary least squares on the full sample. All coefficients are in %. The t-stats in square brackets are based on heteroscedasticity- and autocorrelation-consistent errors (Newey and West, 1987), and asterisks *, ** and *** denote significance at the 90%, 95% and 99% levels, respectively.

Table C.2: Order Flow Equation Coefficients Based on Transaction Prices and Order Flow

The model is:

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

where agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA), $D_{l,t}$ denotes a dummy variable matrix to account for time-fixed effects, and $C = \{CO, FD, NB, BA\}$. Transactions are indexed by t. r_t refers to the log-return in the price, which depends on the aggregate trade indicator variable T_t (+1 for a buy order and −1 for a sell order). $\tilde{S}_t^j$ controls for order size and refers to the residuals of regressing signed log-volume against current and lagged values of the trade indicator variable T_t.

Eq. (4.3)	γ_1	δ_1^{CO}	δ_1^{FD}	δ_1^{NB}	δ_1^{BA}	$\bar{R}^2$ in %	Eq. (4.3)	γ_1	δ_1^{CO}	δ_1^{FD}	δ_1^{NB}	δ_1^{BA}	$\bar{R}^2$ in %
AUDJPY	***34.300	−0.014	***0.041	0.001	***0.061	1.674	GBPCHF	***−28.704	**0.146	0.001	0.006	***0.023	0.380
	[8.821]	[0.209]	[2.693]	[0.112]	[12.411]			[4.523]	[2.034]	[0.116]	[0.623]	[4.683]	
AUDNZD	***−35.240	0.124	0.009	0.002	***0.051	0.590	GBPJPY	***42.779	−0.001	***0.029	0.006	***0.054	1.388
	[6.777]	[0.691]	[0.492]	[0.225]	[10.690]			[6.431]	[0.026]	[2.675]	[0.891]	[10.662]	
AUDUSD	**−8.699	0.010	0.008	***0.020	***0.039	0.512	GBPUSD	**−10.457	0.018	0.008	0.005	***0.048	0.833
	[2.264]	[0.329]	[1.425]	[4.104]	[8.034]			[2.550]	[1.142]	[1.350]	[0.899]	[9.986]	
CADJPY	−2.593	0.036	0.007	0.008	***0.030	0.207	NZDUSD	***−14.901	−0.059	**0.015	0.004	***0.056	0.695
	[0.757]	[0.396]	[0.327]	[0.827]	[6.162]			[4.268]	[0.891]	[2.036]	[0.817]	[11.672]	
EURAUD	***−14.118	0.023	0.003	0.003	***0.022	0.224	USDCAD	1.788	0.005	0.009	0.003	***0.054	1.119
	[3.571]	[0.492]	[0.304]	[0.460]	[4.519]			[0.368]	[0.179]	[1.378]	[0.564]	[11.156]	
EURCAD	***−27.917	***0.146	−0.005	**0.018	***0.037	0.627	USDCHF	***−16.004	***0.076	***0.025	0.001	***0.041	0.550
	[6.596]	[4.850]	[0.577]	[2.473]	[7.521]			[3.802]	[3.208]	[3.731]	[0.164]	[8.456]	
EURCHF	*−41.880	***0.079	***0.028	0.004	***0.064	1.799	USDDKK	*−7.874	0.008	*0.014	0.004	***0.020	0.542
	[1.773]	[3.633]	[3.608]	[0.533]	[12.340]			[1.859]	[0.204]	[1.672]	[0.191]	[3.534]	
EURDKK	*113.899	−0.036	***0.026	***0.080	***0.073	1.063	USDHKD	***−209.441	**0.232	**0.014	0.021	***0.058	0.732
	[1.868]	[0.953]	[2.640]	[2.769]	[13.370]			[3.769]	[2.232]	[2.410]	[1.244]	[11.859]	
EURGBP	***−36.125	**0.029	***0.022	−0.004	***0.046	1.028	USDILS	3.604	0.165	***0.028	0.007	***0.075	1.374
	[7.846]	[1.986]	[3.367]	[0.641]	[9.440]			[0.872]	[1.417]	[2.594]	[0.483]	[13.398]	
EURJPY	0.761	0.004	**0.018	***0.025	***0.039	0.991	USDJPY	−2.409	*0.023	***0.027	***0.016	***0.028	0.502
	[0.205]	[0.189]	[2.177]	[4.778]	[8.080]			[0.590]	[1.695]	[4.696]	[3.228]	[5.813]	
EURNOK	***−38.441	***0.053	***0.038	***0.034	***0.075	1.376	USDMXP	***−24.786	*0.067	0.007	**0.014	***0.048	0.539
	[7.477]	[2.848]	[4.516]	[4.490]	[15.056]			[6.286]	[1.882]	[0.928]	[2.115]	[9.776]	
EURSEK	***−44.729	***0.053	***0.035	***0.024	***0.081	1.407	USDNOK	**8.428	0.078	***0.021	0.005	***0.071	0.920
	[8.345]	[3.861]	[4.695]	[3.145]	[16.543]			[2.531]	[1.531]	[2.665]	[0.615]	[14.010]	
EURUSD	***−35.217	0.010	***0.030	0.001	***0.051	1.814	USDSEK	**−7.865	***0.090	***0.027	0.006	***0.048	0.557
	[7.606]	[1.182]	[5.423]	[0.279]	[10.451]			[2.134]	[3.346]	[3.650]	[0.822]	[9.837]	
GBPAUD	−5.804	−0.190	0.016	0.012	***0.022	0.129	USDSGD	***−71.538	−0.013	0.011	−0.005	***0.049	0.696
	[1.573]	[1.020]	[1.609]	[1.535]	[4.613]			[9.434]	[0.299]	[1.546]	[0.552]	[10.246]	
GBPCAD	***13.477	**0.223	0.008	***0.028	***0.034	0.263	USDZAR	***−16.200	0.032	***0.022	**−0.016	***0.050	0.679
	[3.128]	[2.122]	[0.731]	[3.204]	[6.843]			[6.608]	[0.793]	[2.841]	[2.168]	[10.236]	
Expected sign	-	+	+	+	+		Expected sign	-	+	+	+	+	

Note: The linear regression coefficients are estimated by ordinary least squares on the full sample. The *t*-stats in square brackets are based on heteroscedasticity- and autocorrelation-consistent errors (Newey and West, 1987), and asterisks *, ** and *** denote significance at the 90%, 95% and 99% levels, respectively.

Table C.3: Return Equation Coefficients Based on Mid-Quotes and Net Volume

The model is:

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

where agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA), $D_{l,t}$ denotes a dummy variable matrix to account for time-fixed effects. $\Delta s_{k,t;t-\tau}$ and $\Delta s_{k,t;t-5\tau}$ account for the return over the prior day and week. Here, $\tau = 24$ and t is measured at hourly frequency and $C = \{CO, FD, NB, BA\}$. Transactions are indexed by t. r_t refers to the log-return in the mid-quote.

Eq. (4.2)	ρ_1	β_0^{CO}	β_0^{FD}	β_0^{NB}	β_0^{BA}	$\bar{R}^2$ in %	Eq. (4.2)	ρ_1	β_0^{CO}	β_0^{FD}	β_0^{NB}	β_0^{BA}	$\bar{R}^2$ in %
AUDJPY	***−8.169	**0.083	***0.034	***0.107	***0.047	9.270	GBPCHF	***−11.728	*−0.434	***−0.025	*0.048	***−0.040	9.693
	[7.143]	[2.058]	[3.896]	[4.279]	[9.519]			[4.020]	[1.785]	[2.688]	[1.757]	[3.410]	
AUDNZD	***−11.541	−0.132	−0.001	0.006	***−0.007	8.518	GBPJPY	***−7.295	0.069	**0.022	***0.113	***0.030	9.379
	[17.705]	[0.667]	[0.161]	[0.473]	[2.603]			[4.003]	[0.838]	[2.097]	[6.075]	[2.924]	
AUDUSD	0.000	0.000	**0.001	***0.025	**0.001	5.006	GBPUSD	0.000	0.001	0.001	***0.005	**0.001	4.786
	[0.000]	[0.016]	[2.373]	[4.194]	[2.532]			[0.000]	[0.461]	[0.961]	[4.694]	[2.224]	
CADJPY	***−7.583	−0.057	0.013	**0.056	0.007	8.277	NZDUSD	***−9.648	0.018	0.000	***0.070	***0.004	8.406
	[6.181]	[0.608]	[0.792]	[2.145]	[0.911]			[14.374]	[0.400]	[0.244]	[7.378]	[4.795]	
EURAUD	***−6.925	−0.010	**0.010	***0.035	***0.014	8.255	USDCAD	0.000	−0.009	0.000	***0.012	*0.000	4.785
	[6.653]	[0.208]	[2.417]	[2.637]	[4.520]			[0.000]	[1.180]	[0.315]	[5.263]	[1.674]	
EURCAD	***−7.986	***−0.026	***−0.019	***0.104	***−0.027	8.728	USDCHF	0.000	−0.002	*0.002	***0.008	0.000	4.540
	[7.439]	[3.568]	[3.060]	[5.428]	[5.993]			[0.000]	[0.467]	[1.956]	[5.524]	[0.430]	
EURCHF	***−11.557	***−0.016	0.000	0.001	***−0.006	10.093	USDDKK	***−6.652	**−0.024	**0.008	0.003	0.002	8.009
	[2.853]	[4.630]	[0.015]	[0.480]	[4.149]			[7.389]	[2.450]	[2.045]	[0.281]	[0.625]	
EURDKK	0.000	0.001	***0.001	***0.001	***0.000	0.434	USDHKD	0.000	0.000	***0.001	0.001	0.000	0.375
	[0.000]	[0.863]	[5.745]	[3.077]	[4.037]			[0.000]	[0.132]	[4.589]	[1.632]	[1.522]	
EURGBP	***−9.205	***−0.009	0.000	***0.037	***−0.004	8.473	USDILS	***−21.796	−0.011	0.007	0.027	***0.011	12.599
	[11.680]	[3.092]	[0.236]	[4.876]	[3.638]			[26.352]	[0.356]	[1.422]	[1.098]	[3.885]	
EURJPY	***−7.526	−0.004	−0.003	***0.044	−0.001	8.682	USDJPY	0.000	0.000	**0.001	***0.014	***0.001	5.190
	[6.045]	[1.203]	[1.529]	[7.164]	[0.931]			[0.000]	[0.064]	[2.472]	[7.436]	[4.539]	
EURNOK	***−9.861	***−0.044	***0.016	***0.032	0.002	9.067	USDMXP	**−6.646	−0.001	−0.005	−0.017	***−0.009	8.239
	[10.765]	[2.903]	[3.693]	[3.123]	[0.474]			[2.259]	[0.067]	[1.628]	[1.560]	[3.920]	
EURSEK	***−9.990	−0.010	***0.009	***0.044	0.000	8.200	USDNOK	***−9.478	−0.019	0.000	***0.084	*0.003	9.084
	[12.427]	[1.100]	[2.742]	[4.411]	[0.107]			[10.432]	[1.190]	[0.183]	[5.426]	[1.919]	
EURUSD	0.000	***−0.003	**0.000	***0.013	***−0.001	1.914	USDSEK	***−8.400	−0.021	*0.005	***0.048	***0.004	8.267
	[0.000]	[3.911]	[2.057]	[8.164]	[6.200]			[10.058]	[1.613]	[1.865]	[4.452]	[3.772]	
GBPAUD	***−7.848	***0.079	***0.024	**0.045	*0.013	8.510	USDSGD	***−9.716	−0.007	0.002	***0.025	*−0.001	8.641
	[9.950]	[3.321]	[2.617]	[2.092]	[1.714]			[15.383]	[1.269]	[1.309]	[3.273]	[1.940]	
GBPCAD	***−9.132	0.002	0.009	***0.176	−0.007	8.442	USDZAR	***−9.467	0.020	*0.007	0.045	0.001	9.202
	[11.391]	[0.153]	[0.901]	[3.805]	[1.006]			[10.593]	[0.129]	[1.650]	[1.468]	[0.385]	
Expected sign	-	+	+	+	+		Expected sign	-	+	+	+	+	

Note: The linear regression coefficients are estimated by ordinary least squares on the full sample. All coefficients are in 100 millions % of the base currency, except for ρ_1 that is in %. The t-stats in square brackets are based on heteroscedasticity- and autocorrelation-consistent errors (Newey and West, 1987), and asterisks *, ** and *** denote significance at the 90%, 95% and 99% levels, respectively.

Table C.4: Order Flow Equation Coefficients Based on Mid-Quotes and Net Volume

The model is:

$$T_t = \zeta_{2,l} D_{l,t} + \sum_{i=1}^{10} \gamma_i r_{t-i} + \sum_{j \in C} \sum_{i=1}^{10} \delta_i^j T_{t-i}^j + \epsilon_{T,t},$$

where agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA), $D_{l,t}$ denotes a dummy variable matrix to account for time-fixed effects, and $C = \{CO, FD, NB, BA\}$. Transactions are indexed by t. r_t refers to the log-return in the mid-quote.

Eq. (4.3)	γ_1	δ_1^{CO}	δ_1^{FD}	δ_1^{NB}	δ_1^{BA}	$\bar{R}^2$ in %	Eq. (4.3)	γ_1	δ_1^{CO}	δ_1^{FD}	δ_1^{NB}	δ_1^{BA}	$\bar{R}^2$ in %
AUDJPY	0.627	0.086	***0.082	−0.018	***0.093	1.617	GBPCHF	**−0.181	**0.205	0.015	0.001	0.019	0.185
	[1.498]	[1.212]	[2.713]	[0.577]	[9.171]			[2.427]	[1.966]	[1.342]	[0.048]	[1.475]	
AUDNZD	***−1.246	1.456	**0.049	−0.016	***0.038	0.665	GBPJPY	***1.044	0.079	***0.068	*0.056	***0.107	2.452
	[5.799]	[1.430]	[2.190]	[0.446]	[3.129]			[4.661]	[1.065]	[2.698]	[1.674]	[6.093]	
AUDUSD	0.000	0.053	*−0.028	−0.001	***0.036	0.250	GBPUSD	0.000	−0.023	**0.032	0.052	***0.041	0.438
	[0.000]	[1.608]	[1.904]	[0.016]	[5.691]			[0.000]	[0.504]	[2.152]	[1.574]	[4.106]	
CADJPY	**−0.185	*0.368	−0.029	−0.068	0.018	0.354	NZDUSD	***−1.035	0.058	***−0.201	−0.042	***0.042	2.106
	[2.083]	[1.815]	[0.451]	[1.017]	[0.977]			[2.736]	[0.236]	[10.568]	[0.942]	[6.417]	
EURAUD	*−0.249	−0.001	−0.006	0.032	***0.022	0.097	USDCAD	0.000	***0.607	−0.003	0.021	***0.117	3.471
	[1.727]	[0.012]	[0.404]	[1.081]	[2.853]			[0.000]	[3.407]	[0.148]	[0.482]	[15.105]	
EURCAD	***−0.883	***0.041	**0.032	0.041	***0.050	0.718	USDCHF	0.000	*0.227	0.018	0.019	0.006	0.448
	[5.685]	[3.146]	[2.349]	[1.288]	[6.053]			[0.000]	[1.884]	[0.621]	[0.879]	[0.441]	
EURCHF	−2.642	*0.126	0.033	0.026	***0.061	1.260	USDDKK	*−0.300	0.011	***0.046	0.096	***0.050	0.773
	[1.585]	[1.700]	[1.505]	[1.084]	[4.432]			[1.683]	[0.539]	[2.999]	[1.450]	[3.276]	
EURDKK	0.000	−0.071	0.014	***0.084	***0.057	0.481	USDHKD	0.000	**0.126	**0.029	−0.031	***0.058	0.806
	[0.000]	[1.178]	[0.997]	[2.669]	[5.417]			[0.000]	[2.045]	[2.233]	[1.069]	[7.454]	
EURGBP	***−4.023	***0.074	−0.044	0.047	***0.044	1.261	USDILS	**0.446	***0.100	0.028	**0.144	***0.120	2.397
	[6.129]	[3.210]	[0.688]	[0.839]	[2.753]			[2.258]	[2.739]	[1.635]	[2.385]	[8.872]	
EURJPY	0.165	0.022	0.030	***0.093	***0.056	0.503	USDJPY	0.000	0.011	***0.050	**0.085	***0.054	0.427
	[0.580]	[0.697]	[1.347]	[2.819]	[4.334]			[0.000]	[0.251]	[3.511]	[2.352]	[4.815]	
EURNOK	***−2.016	0.041	***0.089	***0.090	***0.087	1.425	USDMXP	***−1.971	*0.200	***0.039	0.068	***0.055	0.989
	[6.837]	[0.567]	[3.100]	[3.268]	[9.029]			[4.181]	[1.957]	[3.125]	[1.081]	[6.136]	
EURSEK	***−2.758	***0.104	0.014	***0.229	*0.029	0.745	USDNOK	0.440	**0.110	*−0.028	0.010	*0.031	0.471
	[6.277]	[3.203]	[0.560]	[2.843]	[1.723]			[1.346]	[2.189]	[1.728]	[0.169]	[1.787]	
EURUSD	0.000	**0.064	***0.038	0.052	***0.069	1.566	USDSEK	0.044	0.042	−0.002	−0.030	***0.029	0.176
	[0.000]	[2.488]	[2.817]	[0.707]	[5.408]			[0.146]	[0.930]	[0.151]	[0.522]	[2.901]	
GBPAUD	***−0.172	***−0.067	**0.053	−0.024	**0.036	0.281	USDSGD	***−4.592	0.023	0.016	−0.066	***0.066	1.104
	[2.709]	[4.000]	[2.145]	[0.894]	[2.104]			[7.157]	[0.543]	[0.986]	[1.114]	[7.193]	
GBPCAD	−0.048	0.012	***0.052	0.031	***0.037	0.233	USDZAR	***−0.926	0.097	**0.026	0.039	***0.043	0.647
	[0.581]	[0.838]	[2.959]	[0.741]	[2.864]			[6.021]	[0.488]	[2.265]	[0.667]	[4.441]	
Expected sign	-	+	+	+	+		Expected sign	-	+	+	+	+	

Note: The linear regression coefficients are estimated by ordinary least squares on the full sample. γ_1 is in billions of the base currency. The t-stats in square brackets are based on heteroscedasticity- and autocorrelation-consistent errors (Newey and West, 1987), and asterisks *, ** and *** denote significance at the 90%, 95% and 99% levels, respectively.

Table C.5: Return Equation Coefficients Based on Transaction Prices and Net Volume

The model is:

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

where agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA), $D_{l,t}$ denotes a dummy variable matrix to account for time-fixed effects. $\Delta s_{k,t;t-\tau}$ and $\Delta s_{k,t;t-5\tau}$ account for the return over the prior day and week. Here, $\tau = 24$ and t is measured at hourly frequency and $C = \{CO, FD, NB, BA\}$. Transactions are indexed by t. r_t refers to the log-return in the price, which depends on the aggregate trade indicator variable T_t (+1 for a buy order and −1 for a sell order).

Eq. (4.2)	ρ_1	β_0^{CO}	β_0^{FD}	β_0^{NB}	β_0^{BA}	$\bar{R}^2$ in %	Eq. (4.2)	ρ_1	β_0^{CO}	β_0^{FD}	β_0^{NB}	β_0^{BA}	$\bar{R}^2$ in %
AUDJPY	***−8.369	**0.080	***0.034	***0.106	***0.047	9.153	GBPCHF	***−10.804	*−0.423	***−0.026	*0.050	***−0.039	9.564
	[7.810]	[2.073]	[3.923]	[4.238]	[9.635]			[4.423]	[1.730]	[2.772]	[1.808]	[3.356]	
AUDNZD	***−11.420	−0.129	0.000	0.007	***−0.007	8.423	GBPJPY	***−7.219	0.070	*0.020	***0.112	***0.030	9.256
	[17.486]	[0.662]	[0.048]	[0.558]	[2.766]			[3.727]	[0.850]	[1.887]	[5.963]	[3.010]	
AUDUSD	0.000	0.000	**0.001	***0.025	**0.001	5.017	GBPUSD	0.000	0.001	0.000	***0.005	**0.001	4.801
	[0.000]	[0.175]	[2.328]	[4.173]	[2.562]			[0.000]	[0.250]	[0.649]	[4.579]	[2.199]	
CADJPY	***−7.522	−0.046	0.013	**0.058	0.007	8.211	NZDUSD	***−9.300	0.021	0.000	***0.070	***0.004	8.233
	[5.906]	[0.499]	[0.783]	[2.214]	[0.956]			[13.850]	[0.467]	[0.256]	[7.408]	[4.689]	
EURAUD	***−6.983	−0.012	**0.009	***0.035	***0.014	8.270	USDCAD	0.000	−0.009	0.000	***0.012	**0.000	4.782
	[6.737]	[0.250]	[2.218]	[2.637]	[4.505]			[0.000]	[1.158]	[0.287]	[5.245]	[2.008]	
EURCAD	***−7.911	***−0.025	***−0.018	***0.105	***−0.027	8.627	USDCHF	0.000	0.000	*0.002	***0.008	0.000	4.514
	[7.218]	[3.478]	[2.997]	[5.503]	[5.892]			[0.000]	[0.081]	[1.736]	[5.524]	[0.329]	
EURCHF	***−11.899	***−0.016	0.000	0.001	***−0.006	10.158	USDDKK	***−6.495	**−0.024	**0.008	0.003	0.002	7.890
	[2.970]	[4.698]	[0.264]	[0.548]	[4.163]			[7.231]	[2.466]	[1.978]	[0.268]	[0.646]	
EURDKK	0.000	0.000	***0.001	**0.001	***0.001	0.240	USDHKD	0.000	−0.001	***0.001	*0.001	0.000	0.256
	[0.000]	[0.602]	[5.028]	[2.321]	[4.606]			[0.000]	[0.651]	[3.929]	[1.649]	[1.243]	
EURGBP	***−8.776	***−0.009	0.000	***0.037	***−0.004	8.366	USDILS	***−17.952	−0.016	0.000	0.018	***0.010	9.130
	[10.303]	[3.151]	[0.331]	[4.768]	[3.659]			[23.260]	[0.516]	[0.020]	[0.726]	[3.367]	
EURJPY	***−7.501	−0.005	−0.003	***0.044	−0.001	8.472	USDJPY	0.000	0.000	**0.001	***0.014	***0.001	5.179
	[6.723]	[1.291]	[1.483]	[7.155]	[0.969]			[0.000]	[0.097]	[2.206]	[7.351]	[4.499]	
EURNOK	***−9.829	***−0.042	***0.016	***0.030	0.001	8.792	USDMXP	**−6.351	−0.003	−0.004	−0.015	***−0.009	8.035
	[10.407]	[2.754]	[3.637]	[2.835]	[0.348]			[2.178]	[0.140]	[1.379]	[1.443]	[3.791]	
EURSEK	***−9.417	−0.010	***0.009	***0.045	0.000	7.730	USDNOK	***−9.317	−0.016	0.001	***0.088	*0.003	8.897
	[11.742]	[1.102]	[2.839]	[4.455]	[0.127]			[9.860]	[1.033]	[0.339]	[5.583]	[1.957]	
EURUSD	0.000	***−0.003	**0.000	***0.013	***−0.001	1.906	USDSEK	***−7.989	−0.022	**0.005	***0.050	***0.005	8.070
	[0.000]	[3.926]	[2.104]	[8.176]	[6.153]			[9.634]	[1.643]	[1.990]	[4.478]	[3.761]	
GBPAUD	***−7.915	**0.075	**0.023	**0.044	*0.013	8.427	USDSGD	***−9.998	−0.007	0.002	***0.025	**−0.002	8.917
	[10.115]	[2.520]	[2.427]	[2.067]	[1.786]			[14.703]	[1.306]	[1.365]	[3.240]	[2.275]	
GBPCAD	***−8.856	0.003	0.009	***0.180	−0.006	8.355	USDZAR	***−9.319	0.030	*0.008	*0.051	0.001	9.063
	[10.115]	[0.250]	[0.909]	[3.855]	[0.826]			[9.944]	[0.193]	[1.702]	[1.728]	[0.462]	
Expected sign	-	+	+	+	+		Expected sign	-	+	+	+	+	

Note: The linear regression coefficients are estimated by ordinary least squares on the full sample. All coefficients are in 100 millions % of the base currency, except for ρ_1 that is in %. The t-stats in square brackets are based on heteroscedasticity- and autocorrelation-consistent errors (Newey and West, 1987), and asterisks *, ** and *** denote significance at the 90%, 95% and 99% levels, respectively.

Table C.6: Order Flow Equation Coefficients Based on Transaction Prices and Net Volume

The model is:

$$T_t = \zeta_{2,l} D_{l,t} + \sum_{i=1}^{10} \gamma_i r_{t-i} + \sum_{j \in C} \sum_{i=1}^{10} \delta_i^j T_{t-i}^j + \epsilon_{T,t},$$

where agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA), $D_{l,t}$ denotes a dummy variable matrix to account for time-fixed effects, and $C = \{CO, FD, NB, BA\}$. Transactions are indexed by t. r_t refers to the log-return in the price, which depends on the aggregate trade indicator variable T_t (+1 for a buy order and −1 for a sell order).

Eq. (4.3)	γ_1	δ_1^{CO}	δ_1^{FD}	δ_1^{NB}	δ_1^{BA}	$\bar{R}^2$ in %	Eq. (4.3)	γ_1	δ_1^{CO}	δ_1^{FD}	δ_1^{NB}	δ_1^{BA}	$\bar{R}^2$ in %
AUDJPY	0.634	0.086	***0.082	−0.018	***0.093	1.617	GBPCHF	**−0.189	**0.205	0.015	0.001	0.019	0.185
	[1.555]	[1.211]	[2.711]	[0.586]	[9.165]			[2.559]	[1.966]	[1.341]	[0.052]	[1.476]	
AUDNZD	***−1.266	1.457	**0.049	−0.015	***0.038	0.670	GBPJPY	***1.054	0.078	***0.068	*0.056	***0.107	2.462
	[5.968]	[1.430]	[2.195]	[0.444]	[3.122]			[4.749]	[1.056]	[2.702]	[1.669]	[6.092]	
AUDUSD	0.000	0.053	*−0.028	−0.001	***0.036	0.250	GBPUSD	0.000	−0.023	**0.032	0.052	***0.041	0.438
	[0.000]	[1.608]	[1.904]	[0.016]	[5.691]			[0.000]	[0.504]	[2.152]	[1.574]	[4.107]	
CADJPY	**−0.187	*0.368	−0.029	−0.067	0.018	0.354	NZDUSD	***−1.035	0.058	***−0.201	−0.042	***0.042	2.108
	[2.107]	[1.816]	[0.452]	[1.016]	[0.978]			[2.741]	[0.236]	[10.569]	[0.941]	[6.413]	
EURAUD	*−0.242	−0.001	−0.006	0.032	***0.022	0.094	USDCAD	0.000	***0.607	−0.003	0.021	***0.117	3.471
	[1.676]	[0.012]	[0.405]	[1.079]	[2.851]			[0.000]	[3.407]	[0.148]	[0.482]	[15.106]	
EURCAD	***−0.884	***0.041	**0.032	0.041	***0.050	0.719	USDCHF	0.000	*0.227	0.018	0.019	0.006	0.448
	[5.696]	[3.151]	[2.354]	[1.290]	[6.057]			[0.000]	[1.883]	[0.622]	[0.878]	[0.440]	
EURCHF	−2.657	*0.126	0.032	0.026	***0.061	1.258	USDDKK	−0.292	0.011	***0.046	0.096	***0.050	0.773
	[1.610]	[1.700]	[1.499]	[1.085]	[4.431]			[1.627]	[0.541]	[2.998]	[1.449]	[3.276]	
EURDKK	0.000	−0.071	0.014	***0.084	***0.057	0.481	USDHKD	0.000	**0.126	**0.029	−0.031	***0.058	0.806
	[0.000]	[1.178]	[0.997]	[2.670]	[5.418]			[0.000]	[2.045]	[2.236]	[1.069]	[7.450]	
EURGBP	***−3.885	***0.074	−0.044	0.046	***0.044	1.247	USDILS	***0.494	***0.101	*0.029	**0.144	***0.120	2.406
	[5.959]	[3.213]	[0.688]	[0.824]	[2.762]			[2.839]	[2.785]	[1.680]	[2.380]	[8.886]	
EURJPY	0.188	0.022	0.030	***0.093	***0.056	0.503	USDJPY	0.000	0.011	***0.050	**0.085	***0.054	0.427
	[0.659]	[0.697]	[1.346]	[2.820]	[4.334]			[0.000]	[0.251]	[3.511]	[2.353]	[4.815]	
EURNOK	***−1.944	0.042	***0.089	***0.090	***0.087	1.414	USDMXP	***−1.952	*0.200	***0.040	0.068	***0.055	0.988
	[6.664]	[0.579]	[3.094]	[3.252]	[9.023]			[4.213]	[1.954]	[3.135]	[1.086]	[6.154]	
EURSEK	***−2.648	***0.104	0.014	***0.228	*0.029	0.733	USDNOK	0.424	**0.110	*−0.028	0.010	*0.031	0.466
	[6.201]	[3.197]	[0.561]	[2.843]	[1.726]			[1.311]	[2.186]	[1.730]	[0.167]	[1.788]	
EURUSD	0.000	**0.064	***0.038	0.052	***0.069	1.566	USDSEK	0.057	0.042	−0.002	−0.030	***0.029	0.177
	[0.000]	[2.488]	[2.817]	[0.707]	[5.407]			[0.191]	[0.931]	[0.153]	[0.526]	[2.901]	
GBPAUD	***−0.169	***−0.067	**0.053	−0.024	**0.036	0.276	USDSGD	***−4.407	0.024	0.016	−0.066	***0.066	1.086
	[2.685]	[4.019]	[2.145]	[0.891]	[2.106]			[6.911]	[0.544]	[0.993]	[1.123]	[7.196]	
GBPCAD	−0.050	0.012	***0.052	0.031	***0.037	0.236	USDZAR	***−0.895	0.099	**0.026	0.039	***0.043	0.637
	[0.605]	[0.841]	[2.958]	[0.739]	[2.864]			[5.936]	[0.501]	[2.272]	[0.671]	[4.447]	
Expected sign	-	+	+	+	+		Expected sign	-	+	+	+	+	

Note: The linear regression coefficients are estimated by ordinary least squares on the full sample. γ_1 is in billions of the base currency. T-stats in square brackets are based on heteroscedasticity- and autocorrelation-consistent errors (Newey and West, 1987), and asterisks *, ** and *** denote significance at the 90%, 95% and 99% levels, respectively.

C.1 Heterogeneous Contemporary Price Impact Across Agents

To assess if the contemporary price impact parameter β_0 significantly differs across agents, we conduct a two-sided t-test for every pairwise combination of agents:

$$H_0 : \text{agents have the same contemporary price impact parameter } \beta_0^{i,k}$$

$$H_1 : \beta_0^{i,k} \text{ differs across agents, i.e. } \beta_0^{i,k} \neq \beta_0^{j,k}$$

$$t\text{-stat} = \frac{|\beta_0^{i,k} - \beta_0^{j,k}|}{se_0^{i,k}}$$

where $i \neq j$, $k \in$ [currency pairs] and $se_0^{i,k}$ refers to HAC errors. For nearly every pairwise combination of agents we clearly reject the H_0 at a 5% confidence level. In particular, for almost every currency pair, the H_0 is rejected in four out of six pairwise combinations. The validity of this pairwise t-test is ensured by the general property of the log-level regression model, where the change in the independent variable by 1 unit can be approximately interpreted as an expected change by 10 000 $\times$ regression coefficient $\times$ BPS in the dependent variable.

Table C.7: Heterogeneous Contemporary Price Impact Across Agents Based on Mid-Quotes and Order Flow

	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB
FD	***0.0	-	**AUDJPY**	0.2	-	**AUDNZD**	***0.0	-	**AUDUSD**	0.3	-	**CADJPY**	***0.0	-	**EURAUD**
NB	***0.0	0.1	-	0.0	0.1	-	***0.0	***0.0	-	0.5	0.0	-	***0.0	0.4	-
BA	***0.0	***0.0	***0.0	***0.0	0.3	0.1	***0.0	0.3	***0.0	0.1	***0.0	0.1	***0.0	0.1	*0.0
FD	***0.0	-	**EURCAD**	***0.0	-	**EURCHF**	***0.0	-	**EURDKK**	***0.0	-	**EURGBP**	***0.0	-	**EURJPY**
NB	***0.0	***0.0	-	***0.0	0.0	-	0.3	***0.0	-	***0.0	0.3	-	***0.0	***0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.1	***0.0	***0.0	***0.0	***0.0	***0.0	0.1	***0.0
FD	***0.0	-	**EURNOK**	***0.0	-	**EURSEK**	***0.0	-	**EURUSD**	***0.0	-	**GBPAUD**	***0.0	-	**GBPCAD**
NB	***0.0	***0.0	-	***0.0	**0.0	-	***0.0	***0.0	-	***0.0	0.0	-	***0.0	0.1	-
BA	***0.0	***0.0	0.2	***0.0	***0.0	0.4	***0.0	0.1	***0.0	***0.0	0.4	**0.0	***0.0	0.3	***0.0
FD	***0.0	-	**GBPCHF**	***0.0	-	**GBPJPY**	***0.0	-	**GBPUSD**	***0.0	-	**NZDUSD**	***0.0	-	**USDCAD**
NB	***0.0	***0.0	-	***0.0	0.2	-	***0.0	***0.0	-	***0.0	0.1	-	***0.0	**0.0	-
BA	***0.0	**0.0	***0.0	***0.0	***0.0	***0.0	***0.0	**0.0	**0.0	***0.0	0.0	0.2	***0.0	0.1	***0.0
FD	***0.0	-	**USDCHF**	***0.0	-	**USDDKK**	***0.0	-	**USDHKD**	*0.0	-	**USDILS**	***0.0	-	**USDJPY**
NB	***0.0	***0.0	-	***0.0	***0.0	-	0.4	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	***0.0	0.2	***0.0	***0.0	0.1	***0.0	0.3	***0.0	0.5	***0.0	0.2	***0.0	***0.0	0.4	***0.0
FD	***0.0	-	**USDMXP**	***0.0	-	**USDNOK**	***0.0	-	**USDSEK**	***0.0	-	**USDSGD**	***0.0	-	**USDZAR**
NB	***0.0	***0.0	-	***0.0	0.2	-	***0.0	0.4	-	***0.0	0.2	-	***0.0	0.0	-
BA	***0.0	0.0	***0.0	***0.0	0.4	0.1	***0.0	0.1	0.3	***0.0	***0.0	***0.0	***0.0	0.3	***0.0

Note: The numbers correspond to p-values associated with the two-sided t-tests for equal price impact of the form: t-stat $= \frac{|\beta_0^{i,k} - \beta_0^{j,k}|}{se_0^{i,k}}$, where $i \neq j$, $k \in$ [currency pairs] and $se_0^{i,k}$ refers to heteroscedasticity- and autocorrelation-consistent errors and asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests. Agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA). Averages are calculated to account for both directions, i.e. $\beta_0^{i,k}$ vs. $\beta_0^{j,k}$ / $\beta_0^{j,k}$ vs. $\beta_0^{i,k}$.

Table C.8: Heterogeneous Contemporary Price Impact Across Agents Based on Transaction Prices and Order Flow

	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB
FD	***0.0	-	**AUDJPY**	0.1	-	**AUDNZD**	***0.0	-	**AUDUSD**	0.2	-	**CADJPY**	***0.0	-	**EURAUD**
NB	***0.0	0.1	-	**0.0	0.2	-	***0.0	***0.0	-	0.5	0.0	-	***0.0	0.4	-
BA	***0.0	***0.0	***0.0	***0.0	0.3	0.2	***0.0	0.2	***0.0	0.2	***0.0	0.1	***0.0	0.1	0.0
FD	***0.0	-	**EURCAD**	***0.0	-	**EURCHF**	***0.0	-	**EURDKK**	***0.0	-	**EURGBP**	***0.0	-	**EURJPY**
NB	***0.0	***0.0	-	***0.0	*0.0	-	0.1	*0.0	-	***0.0	0.4	-	***0.0	***0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.1	***0.0
FD	***0.0	-	**EURNOK**	***0.0	-	**EURSEK**	***0.0	-	**EURUSD**	***0.0	-	**GBPAUD**	***0.0	-	**GBPCAD**
NB	***0.0	***0.0	-	***0.0	**0.0	-	***0.0	***0.0	-	***0.0	0.0	-	***0.0	0.0	-
BA	***0.0	***0.0	0.1	***0.0	***0.0	0.4	***0.0	0.1	***0.0	***0.0	0.5	**0.0	***0.0	0.3	***0.0
FD	***0.0	-	**GBPCHF**	***0.0	-	**GBPJPY**	***0.0	-	**GBPUSD**	***0.0	-	**NZDUSD**	***0.0	-	**USDCAD**
NB	***0.0	***0.0	-	***0.0	0.3	-	***0.0	***0.0	-	***0.0	0.1	-	***0.0	**0.0	-
BA	***0.0	*0.0	***0.0	***0.0	***0.0	***0.0	***0.0	**0.0	*0.0	***0.0	*0.0	0.2	***0.0	0.1	***0.0
FD	***0.0	-	**USDCHF**	***0.0	-	**USDDKK**	***0.0	-	**USDHKD**	***0.0	-	**USDILS**	***0.0	-	**USDJPY**
NB	***0.0	***0.0	-	***0.0	***0.0	-	0.5	***0.0	-	0.1	***0.0	-	***0.0	***0.0	-
BA	***0.0	0.1	***0.0	***0.0	0.2	***0.0	0.4	***0.0	0.3	***0.0	0.2	***0.0	***0.0	0.4	***0.0
FD	***0.0	-	**USDMXP**	***0.0	-	**USDNOK**	***0.0	-	**USDSEK**	***0.0	-	**USDSGD**	***0.0	-	**USDZAR**
NB	***0.0	***0.0	-	***0.0	0.2	-	***0.0	0.3	-	***0.0	0.2	-	***0.0	0.0	-
BA	***0.0	*0.0	***0.0	***0.0	0.4	0.1	***0.0	0.1	0.3	***0.0	***0.0	***0.0	***0.0	0.3	***0.0

Note: The numbers correspond to p-values associated with the two-sided t-tests for equal price impact of the form: $t\text{-stat} = \frac{|\beta_0^{i,k} - \beta_0^{j,k}|}{se_0^{i,k}}$, where $i \neq j$, $k \in$ [currency pairs] and $se_0^{i,k}$ refers to heteroscedasticity- and autocorrelation-consistent errors and asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests. Agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA). Averages are calculated to account for both directions, i.e. $\beta_0^{i,k}$ vs. $\beta_0^{j,k}$ / $\beta_0^{j,k}$ vs. $\beta_0^{i,k}$.

Table C.9: Heterogeneous Contemporary Price Impact Across Agents Based on Mid-Quotes and Net Volume

	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB
FD	***0.0	-	**AUDJPY**	***0.0	-	**AUDNZD**	0.1	-	**AUDUSD**	**0.0	-	**CADJPY**	**0.0	-	**EURAUD**
NB	0.2	***0.0	-	***0.0	0.1	-	***0.0	***0.0	-	**0.0	0.0	-	*0.0	***0.0	-
BA	***0.0	0.0	***0.0	***0.0	0.0	**0.0	0.1	0.1	***0.0	***0.0	0.3	***0.0	***0.0	0.1	***0.0
FD	0.2	-	**EURCAD**	***0.0	-	**EURCHF**	0.1	-	**EURDKK**	***0.0	-	**EURGBP**	0.3	-	**EURJPY**
NB	***0.0	***0.0	-	***0.0	0.3	-	0.2	0.4	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	0.4	0.1	***0.0	***0.0	***0.0	***0.0	0.3	***0.0	*0.0	**0.0	***0.0	***0.0	0.0	0.1	***0.0
FD	***0.0	-	**EURNOK**	***0.0	-	**EURSEK**	***0.0	-	**EURUSD**	***0.0	-	**GBPAUD**	0.2	-	**GBPCAD**
NB	***0.0	**0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	0.1	0.1	-	***0.0	***0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.1	**0.0	0.2	0.0	***0.0
FD	***0.0	-	**GBPCHF**	**0.0	-	**GBPJPY**	0.4	-	**GBPUSD**	***0.0	-	**NZDUSD**	***0.0	-	**USDCAD**
NB	***0.0	***0.0	-	0.1	***0.0	-	**0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	***0.0	0.1	***0.0	*0.0	0.2	***0.0	0.4	0.3	***0.0	***0.0	***0.0	***0.0	***0.0	0.4	***0.0
FD	*0.0	-	**USDCHF**	***0.0	-	**USDDKK**	0.0	-	**USDHKD**	0.0	-	**USDILS**	0.1	-	**USDJPY**
NB	***0.0	***0.0	-	**0.0	0.2	-	0.2	0.2	-	0.1	*0.0	-	***0.0	***0.0	-
BA	0.0	***0.0	***0.0	***0.0	*0.0	0.4	0.0	***0.0	***0.0	***0.0	0.2	***0.0	*0.0	0.3	***0.0
FD	0.3	-	**USDMXP**	***0.0	-	**USDNOK**	***0.0	-	**USDSEK**	***0.0	-	**USDSGD**	0.1	-	**USDZAR**
NB	0.1	**0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	0.3	***0.0	-
BA	0.0	0.0	0.0	***0.0	0.1	***0.0	***0.0	0.4	***0.0	***0.0	***0.0	***0.0	***0.0	0.0	***0.0

Note: The numbers correspond to p-values associated with the two-sided t-tests for equal price impact of the form: $t\text{-stat} = \frac{|\beta_0^{i,k} - \beta_0^{j,k}|}{se_0^{i,k}}$, where $i \neq j$, $k \in$ [currency pairs] and $se_0^{i,k}$ refers to heteroscedasticity- and autocorrelation-consistent errors and asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests. Agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA). Averages are calculated to account for both directions, i.e. $\beta_0^{i,k}$ vs. $\beta_0^{j,k}$ / $\beta_0^{j,k}$ vs. $\beta_0^{i,k}$.

Table C.10: Heterogeneous Contemporary Price Impact Across Agents Based on Transaction Prices and Net Volume

	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB
FD	***0.0	-	**AUDJPY**	***0.0	-	**AUDNZD**	0.0	-	**AUDUSD**	*0.0	-	**CADJPY**	**0.0	-	**EURAUD**
NB	0.2	***0.0	-	***0.0	0.1	-	***0.0	***0.0	-	**0.0	*0.0	-	*0.0	***0.0	-
BA	***0.0	0.0	***0.0	***0.0	**0.0	***0.0	0.0	0.1	***0.0	***0.0	0.3	***0.0	***0.0	0.1	***0.0
FD	0.2	-	**EURCAD**	***0.0	-	**EURCHF**	0.0	-	**EURDKK**	***0.0	-	**EURGBP**	0.3	-	**EURJPY**
NB	***0.0	***0.0	-	***0.0	0.2	-	0.2	0.3	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	0.4	0.1	***0.0	***0.0	***0.0	***0.0	0.2	0.0	0.2	**0.0	***0.0	***0.0	0.0	0.1	***0.0
FD	***0.0	-	**EURNOK**	***0.0	-	**EURSEK**	***0.0	-	**EURUSD**	***0.0	-	**GBPAUD**	0.3	-	**GBPCAD**
NB	***0.0	*0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	0.1	0.1	-	***0.0	***0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.1	**0.0	0.2	0.0	***0.0
FD	***0.0	-	**GBPCHF**	**0.0	-	**GBPJPY**	0.5	-	**GBPUSD**	***0.0	-	**NZDUSD**	***0.0	-	**USDCAD**
NB	***0.0	***0.0	-	0.1	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	***0.0	0.1	***0.0	*0.0	0.2	***0.0	0.3	0.2	***0.0	***0.0	***0.0	***0.0	***0.0	0.3	***0.0
FD	0.1	-	**USDCHF**	***0.0	-	**USDDKK**	***0.0	-	**USDHKD**	0.1	-	**USDILS**	0.1	-	**USDJPY**
NB	***0.0	***0.0	-	**0.0	0.2	-	*0.0	0.2	-	0.1	0.0	-	***0.0	***0.0	-
BA	0.4	***0.0	***0.0	***0.0	0.0	0.4	***0.0	***0.0	***0.0	***0.0	**0.0	0.1	***0.0	0.2	***0.0
FD	0.4	-	**USDMXP**	***0.0	-	**USDNOK**	***0.0	-	**USDSEK**	***0.0	-	**USDSGD**	**0.0	-	**USDZAR**
NB	0.2	**0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	0.3	***0.0	-
BA	0.1	0.0	0.1	***0.0	0.1	***0.0	***0.0	0.3	***0.0	***0.0	***0.0	***0.0	***0.0	0.0	***0.0

Note: The numbers correspond to p-values associated with the two-sided t-tests for equal price impact of the form: $t\text{-stat} = \frac{|\beta_0^{i,k} - \beta_0^{j,k}|}{se_0^{i,k}}$, where $i \neq j$, $k \in$ [currency pairs] and $se_0^{i,k}$ refers to heteroscedasticity- and autocorrelation-consistent errors and asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests. Agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA). Averages are calculated to account for both directions, i.e. $\beta_0^{i,k}$ vs. $\beta_0^{j,k}$ / $\beta_0^{j,k}$ vs. $\beta_0^{i,k}$.

C.2 Heterogeneous Contemporary Price Impact Across Currency Pairs

The goal of this section is to investigate whether the FX spot market is fragmented in the sense that a particular agent i has a significantly different contemporary price impact parameter across currency pairs. In Tables C.7 to C.10 on pages 16–19 we have checked if the contemporary price impact parameter varies significantly across agents within a particular currency pair. Again we estimate Eq. (4.2) on the full sample and construct a pairwise two-sided t-test as follows:

$$H_0 : \text{agent } i \text{ has the same price impact parameter } \beta_0^{i,k} \text{ across currencies}$$

$$H_1 : \beta_0^{i,k} \text{ differs across currencies, i.e. } \beta_0^{i,k} \neq \beta_0^{i,q}$$

$$\text{t-stat} = \frac{|\beta_0^{i,k} - \beta_0^{i,q}|}{se_0^{i,k}}$$

where $k \neq q$, $k \in$ [currency pairs] and $se_0^{i,k}$ refers to HAC errors. Again, the validity of this t-test is warranted by the general properties of a log-level model. From Tables C.11 to C.14 on pages 21–24 we get the impression that corporates, funds, non-bank financials and banks acting as price takers have a contemporary price impact β_0 which varies heavily across currencies. Similar results hold for the remaining twenty currency pairs that we have excluded randomly from Tables C.11 to C.14 on pages 21–24.

Table C.11: Heterogeneous Contemporary Price Impact Across Currency Pairs Based on Mid-Quotes and Order Flow

CO	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	0.2								
EURCHF	0.1	0.1							
EURGBP	0.1	0.1	0.4						
EURNOK	0.5	0.0	0.0	0.0					
EURUSD	0.1	***0.0	0.0	0.0	0.0				
GBPCHF	0.1	0.0	***0.0	***0.0	0.0	***0.0			
GBPUSD	0.2	0.0	0.2	0.2	0.1	0.3	***0.0		
USDCHF	0.1	0.1	0.5	0.4	0.0	0.0	***0.0	0.2	
USDSEK	0.2	0.0	**0.0	**0.0	0.1	***0.0	0.1	0.0	*0.0

FD	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	0.0							
EURGBP	***0.0	**0.0	0.4						
EURNOK	0.2	***0.0	***0.0	***0.0					
EURUSD	***0.0	0.0	0.0	0.0	***0.0				
GBPCHF	***0.0	0.4	0.0	**0.0	***0.0	0.0			
GBPUSD	***0.0	***0.0	0.0	0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	0.0	0.4	0.5	***0.0	0.0	0.0	0.0	
USDSEK	*0.0	***0.0	0.0	0.0	*0.0	***0.0	***0.0	0.2	0.0

NB	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	**0.0							
EURGBP	***0.0	***0.0	**0.0						
EURNOK	***0.0	***0.0	0.0	0.2					
EURUSD	0.1	***0.0	***0.0	***0.0	***0.0				
GBPCHF	0.3	***0.0	***0.0	***0.0	***0.0	0.0			
GBPUSD	0.4	***0.0	***0.0	***0.0	***0.0	0.0	0.2		
USDCHF	**0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	
USDSEK	0.0	***0.0	***0.0	0.0	0.0	0.0	0.0	***0.0	***0.0

BA	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	0.1	0.0						
EURNOK	***0.0	***0.0	***0.0	***0.0					
EURUSD	***0.0	**0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	*0.0	0.2	0.1	***0.0	***0.0			
GBPUSD	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	***0.0	***0.0	
USDSEK	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	***0.0	*0.0	**0.0

Note: The numbers correspond to p-values associated with the two-sided t-tests for equal price impact of the form: $t\text{-stat} = \frac{|\beta_0^{i,k} - c_0^{i,q}|}{\beta_0^{i,k}}$, where $k \neq q$, $k \in$ [currency pairs] and $se_0^{i,k}$ refers to heteroscedasticity- and autocorrelation-consistent errors and asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests. Averages are calculated to account for both directions, i.e. $\beta_0^{i,k}$ vs. $\beta_0^{i,q}$ / $\beta_0^{i,q}$ vs. $\beta_0^{i,k}$.

Table C.12: Heterogeneous Contemporary Price Impact Across Currency Pairs Based on Transaction Prices and Order Flow

CO	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	0.2								
EURCHF	0.0	0.1							
EURGBP	0.0	0.1	0.5						
EURNOK	0.5	0.0	0.0	0.0					
EURUSD	0.0	***0.0	0.0	0.0	0.0				
GBPCHF	0.2	0.1	***0.0	***0.0	0.0	***0.0			
GBPUSD	0.1	0.1	0.2	0.2	0.1	0.2	***0.0		
USDCHF	0.0	0.2	0.3	0.3	0.0	0.0	***0.0	0.1	
USDSEK	0.3	0.0	**0.0	**0.0	0.2	***0.0	0.1	0.0	**0.0

FD	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	0.0							
EURGBP	***0.0	**0.0	0.4						
EURNOK	0.2	***0.0	***0.0	***0.0					
EURUSD	***0.0	0.0	0.0	0.0	***0.0				
GBPCHF	***0.0	0.5	0.0	**0.0	***0.0	0.0			
GBPUSD	***0.0	***0.0	0.0	0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	0.0	0.3	0.4	***0.0	0.0	*0.0	0.0	
USDSEK	0.0	***0.0	0.0	*0.0	0.0	***0.0	***0.0	0.1	0.0

NB	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	*0.0							
EURGBP	***0.0	***0.0	*0.0						
EURNOK	***0.0	***0.0	0.0	0.2					
EURUSD	0.1	***0.0	***0.0	***0.0	***0.0				
GBPCHF	0.3	***0.0	***0.0	***0.0	***0.0	0.0			
GBPUSD	0.4	***0.0	***0.0	***0.0	***0.0	0.0	0.2		
USDCHF	**0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	
USDSEK	0.0	***0.0	***0.0	0.0	0.0	0.0	0.0	**0.0	***0.0

BA	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	0.1	0.0						
EURNOK	***0.0	***0.0	***0.0	***0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	0.0	0.1	0.1	***0.0	***0.0			
GBPUSD	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	***0.0	0.0	**0.0	***0.0	***0.0	
USDSEK	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	***0.0	0.0	***0.0

Note: The numbers correspond to p-values associated with the two-sided t-tests for equal price impact of the form: $t\text{-stat} = \frac{|\beta_0^{i,k} - c_0^{i,q}|}{\beta_0^{i,k}}$, where $k \neq q$, $k \in$ [currency pairs] and $se_0^{i,k}$ refers to heteroscedasticity- and autocorrelation-consistent errors and asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests. Averages are calculated to account for both directions, i.e. $\beta_0^{i,k}$ vs. $\beta_0^{i,q}$ / $\beta_0^{i,q}$ vs. $\beta_0^{i,k}$.

Table C.13: Heterogeneous Contemporary Price Impact Across Currency Pairs Based on Mid-Quotes and Net Volume

CO	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	*0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	***0.0	0.0						
EURNOK	***0.0	*0.0	***0.0	***0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	0.1	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	***0.0	***0.0	***0.0	**0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	0.0	***0.0	0.2	***0.0	0.2	
USDSEK	***0.0	***0.0	0.2	0.0	0.0	***0.0	***0.0	***0.0	*0.0
FD	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	0.4							
EURGBP	***0.0	0.4	0.4						
EURNOK	*0.0	***0.0	***0.0	***0.0					
EURUSD	***0.0	0.4	0.1	0.3	***0.0				
GBPCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	0.1	0.2	0.1	***0.0	*0.0	***0.0		
USDCHF	***0.0	0.1	0.0	0.0	***0.0	***0.0	***0.0	0.0	
USDSEK	***0.0	0.0	0.0	**0.0	**0.0	***0.0	***0.0	***0.0	0.1
NB	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	0.1							
EURGBP	***0.0	**0.0	***0.0						
EURNOK	***0.0	0.0	***0.0	0.3					
EURUSD	***0.0	0.0	***0.0	***0.0	***0.0				
GBPCHF	0.0	0.0	***0.0	0.2	0.1	***0.0			
GBPUSD	***0.0	0.3	0.0	***0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	0.2	**0.0	***0.0	***0.0	***0.0	***0.0	0.0	
USDSEK	***0.0	***0.0	***0.0	0.1	0.1	***0.0	0.5	***0.0	***0.0
BA	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	0.4							
EURGBP	***0.0	0.1	0.1						
EURNOK	***0.0	0.0	***0.0	**0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	***0.0	***0.0	0.1	***0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	***0.0	0.0	**0.0	***0.0	0.0	
USDSEK	***0.0	***0.0	***0.0	***0.0	0.1	***0.0	***0.0	***0.0	***0.0

Note: The numbers correspond to p-values associated with the two-sided t-tests for equal price impact of the form: $t\text{-stat} = \frac{|\beta_0^{i,k} - c_0^{i,q}|}{\beta_0^{i,k}}$, where $k \neq q$, $k \in$ [currency pairs] and $se_0^{i,k}$ refers to heteroscedasticity- and autocorrelation-consistent errors and asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests. Averages are calculated to account for both directions, i.e. $\beta_0^{i,k}$ vs. $\beta_0^{i,q}$ / $\beta_0^{i,q}$ vs. $\beta_0^{i,k}$.

Table C.14: Heterogeneous Contemporary Price Impact Across Currency Pairs Based on Transaction Prices and Net Volume

CO	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	*0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	***0.0	0.0						
EURNOK	***0.0	0.0	***0.0	***0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	0.1	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	***0.0	***0.0	***0.0	*0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	0.0	***0.0	0.0	***0.0	0.4	
USDSEK	***0.0	***0.0	0.1	0.0	0.1	***0.0	***0.0	***0.0	**0.0

FD	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	0.4							
EURGBP	***0.0	0.4	0.5						
EURNOK	*0.0	***0.0	***0.0	***0.0					
EURUSD	***0.0	0.1	0.5	0.4	***0.0				
GBPCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	0.4	0.2	0.2	***0.0	0.0	***0.0		
USDCHF	***0.0	0.1	0.0	0.0	***0.0	***0.0	***0.0	0.0	
USDSEK	***0.0	0.0	0.0	***0.0	*0.0	***0.0	***0.0	***0.0	0.0

NB	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	0.1							
EURGBP	***0.0	*0.0	***0.0						
EURNOK	***0.0	0.0	***0.0	0.2					
EURUSD	***0.0	0.0	***0.0	***0.0	***0.0				
GBPCHF	0.0	0.0	***0.0	0.1	0.1	***0.0			
GBPUSD	***0.0	0.1	0.0	***0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	0.4	**0.0	***0.0	***0.0	***0.0	***0.0	0.0	
USDSEK	**0.0	***0.0	***0.0	0.1	0.0	***0.0	0.5	***0.0	***0.0

BA	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	0.3							
EURGBP	***0.0	0.0	0.1						
EURNOK	***0.0	0.0	**0.0	*0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	***0.0	***0.0	0.2	***0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	***0.0	0.0	
USDSEK	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	***0.0	***0.0	***0.0

Note: The numbers correspond to p-values associated with the two-sided t-tests for equal price impact of the form: $t\text{-stat} = \frac{|\beta_0^{i,k} - c_0^{i,q}|}{\beta_0^{i,k}}$, where $k \neq q$, $k \in$ [currency pairs] and $se_0^{i,k}$ refers to heteroscedasticity- and autocorrelation-consistent errors and asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests. Averages are calculated to account for both directions, i.e. $\beta_0^{i,k}$ vs. $\beta_0^{i,q}$ / $\beta_0^{i,q}$ vs. $\beta_0^{i,k}$.

C.3 Heterogeneous Permanent Price Impact Across Agents

In this section, we assess whether the permanent price impact varies across agents. Given that our measure of permanent price impact is able to disentangle temporary and permanent effects, it is superior to the notion of contemporaneous price impact of a trade. To assess if the permanent price impact parameter α_m significantly differs across agents, we test if all coefficients in Eq. (4.5) for a particular agent i are jointly significantly different from agent j's:

$$H_0 : \text{agents have the same permanent price impact parameter } \alpha_m^{j,k}, \text{ i.e. } R^i\theta^k = R^j\theta^k$$

$$H_1 : \alpha_m^{j,k} \text{ differs across agents, i.e. } R^i\theta^k \neq R^j\theta^k$$

$$F = (R^i\hat{\theta}_Q^k - R^j\hat{\theta}_Q^k)^\top [R^i(\hat{V}_Q/Q)(R^i)^\top)]^{-1}(R^i\hat{\theta}_Q^k - R^j\hat{\theta}_Q^k),$$

where $\hat{\theta}^k$ is a vector of parameter estimates with $||R^i\hat{\theta}^k||_1 = \sum_{l=0}^{10} |\hat{\beta}_l^{i,k}|$ and $||R^j\hat{\theta}^k||_1 = \sum_{l=0}^{10} |\hat{\beta}_l^{j,k}|$. F converges to a χ^2_Q distribution. R^i and R^j are $Q \times L$ matrices, where Q is the number of hypotheses being tested and L the number of coefficients. Let $\hat{V}_Q$ be an estimator of the covariance matrix. For each pairwise test, $i \neq j$ and $k \in$ [currency pairs] must hold. The validity of this pairwise F-test is ensured by the general property of the log-level regression model, where the change in the independent variable by one unit can be approximately interpreted as an expected change by 10 000 $\times$ regression coefficient $\times$ BPS in the dependent variable. For nearly every pairwise combination of agents we clearly reject the H_0 at a 5% global significance level. To overcome the curse of multiple testing, a Bonferroni correction is applied by testing each individual hypothesis at a significance level of $\frac{\alpha_g}{m}$, where α_g is the desired (global) overall significance level and m is the number of hypotheses. The Bonferroni correction is known to be more conservative than the Holm–Bonferroni method and the Šidák correction. Therefore, the former produces less false positives, a conservative property since we are seeking to show that the permanent price impact significantly alternates across agents.

Table C.15: Heterogeneous Permanent Price Impact Across Agents Based on Mid-Quotes and Order Flow

	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB
FD	***0.0	-	**AUDJPY**	***0.0	-	**AUDNZD**	***0.0	-	**AUDUSD**	***0.0	-	**CADJPY**	***0.0	-	**EURAUD**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	0.0	-	***0.0	0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.1	***0.0	***0.0	***0.0	***0.0	***0.0	0.1	***0.0
FD	***0.0	-	**EURCAD**	***0.0	-	**EURCHF**	***0.0	-	**EURDKK**	***0.0	-	**EURGBP**	***0.0	-	**EURJPY**
NB	***0.0	***0.0	-	***0.0	0.0	-	***0.0	***0.0	-	***0.0	**0.0	-	***0.0	***0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	*0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0
FD	***0.0	-	**EURNOK**	***0.0	-	**EURSEK**	***0.0	-	**EURUSD**	***0.0	-	**GBPAUD**	***0.0	-	**GBPCAD**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	0.0	-	***0.0	0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	**0.0	***0.0	***0.0	0.0	***0.0	***0.0	0.0	**0.0
FD	***0.0	-	**GBPCHF**	***0.0	-	**GBPJPY**	***0.0	-	**GBPUSD**	***0.0	-	**NZDUSD**	***0.0	-	**USDCAD**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	0.1	-	***0.0	***0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.4	0.4	***0.0	**0.0	***0.0
FD	***0.0	-	**USDCHF**	***0.0	-	**USDDKK**	***0.0	-	**USDHKD**	***0.0	-	**USDILS**	***0.0	-	**USDJPY**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	***0.0	0.2	***0.0	***0.0	0.1	***0.0	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	***0.0	0.2	***0.0
FD	***0.0	-	**USDMXP**	***0.0	-	**USDNOK**	***0.0	-	**USDSEK**	***0.0	-	**USDSGD**	***0.0	-	**USDZAR**
NB	***0.0	***0.0	-	***0.0	0.0	-	***0.0	***0.0	-	***0.0	0.0	-	***0.0	0.0	-
BA	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0

Note: The numbers correspond to p-values associated with the test statistic of a joint pairwise F-test:

$$F = (R^i\hat{\theta}^k_Q - R^j\hat{\theta}^k_Q)^\top [R^i(\hat{V}_Q/Q)(R^i)^\top]^{-1}(R^i\hat{\theta}^k_Q - R^j\hat{\theta}^k_Q),$$

where $\hat{\theta}^k$ is a vector of parameter estimates with $||R^i\hat{\theta}^k||_1 = \sum_{l=0}^{10}|\hat{\beta}^{i,k}_l|$ and $||R^j\hat{\theta}^k||_1 = \sum_{l=0}^{10}|\hat{\beta}^{j,k}_l|$. F converges to a χ^2_Q distribution. R^i and R^j are $Q \times L$ matrices, where Q is the number of hypotheses being tested and L the number of coefficients. Let $\hat{V}_Q$ be an estimator of the covariance matrix. For each pairwise test, $i \neq j$ and $k \in$ [currency pairs] must hold. Asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests. Agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA). Averages are calculated to account for both directions, i.e. $R^i\hat{\theta}^k_Q$ vs. $R^j\hat{\theta}^k_Q / R^j\hat{\theta}^k_Q$ vs. $R^i\hat{\theta}^k_Q$.

Table C.16: Heterogeneous Permanent Price Impact Across Agents Based on Transaction Prices and Order Flow

	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB
FD	***0.0	-	**AUDJPY**	***0.0	-	**AUDNZD**	***0.0	-	**AUDUSD**	***0.0	-	**CADJPY**	***0.0	-	**EURAUD**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	0.0	-	***0.0	0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.1	***0.0	***0.0	***0.0	***0.0	***0.0	0.1	***0.0
FD	***0.0	-	**EURCAD**	***0.0	-	**EURCHF**	***0.0	-	**EURDKK**	***0.0	-	**EURGBP**	***0.0	-	**EURJPY**
NB	***0.0	***0.0	-	***0.0	0.0	-	***0.0	***0.0	-	***0.0	**0.0	-	***0.0	***0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0
FD	***0.0	-	**EURNOK**	***0.0	-	**EURSEK**	***0.0	-	**EURUSD**	***0.0	-	**GBPAUD**	***0.0	-	**GBPCAD**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	0.0	-	***0.0	0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	**0.0	***0.0	***0.0	0.0	***0.0	***0.0	0.0	**0.0
FD	***0.0	-	**GBPCHF**	***0.0	-	**GBPJPY**	***0.0	-	**GBPUSD**	***0.0	-	**NZDUSD**	***0.0	-	**USDCAD**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	0.1	-	***0.0	***0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.2	0.4	***0.0	**0.0	***0.0
FD	***0.0	-	**USDCHF**	***0.0	-	**USDDKK**	***0.0	-	**USDHKD**	***0.0	-	**USDILS**	***0.0	-	**USDJPY**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	***0.0	0.1	***0.0	***0.0	0.1	***0.0	***0.0	***0.0	***0.0	***0.0	0.2	***0.0	***0.0	0.2	***0.0
FD	***0.0	-	**USDMXP**	***0.0	-	**USDNOK**	***0.0	-	**USDSEK**	***0.0	-	**USDSGD**	***0.0	-	**USDZAR**
NB	***0.0	***0.0	-	***0.0	0.0	-	***0.0	***0.0	-	***0.0	0.0	-	***0.0	0.1	-
BA	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0

Note: The numbers correspond to *p*-values associated with the test statistic of a joint pairwise *F*-test:

$$F = (R^i\hat{\theta}^k_Q - R^j\hat{\theta}^k_Q)^\top [R^i(\hat{V}_Q/Q)(R^i)^\top]^{-1}(R^i\hat{\theta}^k_Q - R^j\hat{\theta}^k_Q),$$

where $\hat{\theta}^k$ is a vector of parameter estimates with $||R^i\hat{\theta}^k||_1 = \sum_{l=0}^{10} |\hat{\beta}_l^{i,k}|$ and $||R^j\hat{\theta}^k||_1 = \sum_{l=0}^{10} |\hat{\beta}_l^{j,k}|$. F converges to a χ^2_Q distribution. R^i and R^j are $Q \times L$ matrices, where Q is the number of hypotheses being tested and L the number of coefficients. Let $\hat{V}_Q$ be an estimator of the covariance matrix. For each pairwise test, $i \neq j$ and $k \in$ [currency pairs] must hold. Asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests. Agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA). Averages are calculated to account for both directions, i.e. $R^i\hat{\theta}^k_Q$ vs. $R^j\hat{\theta}^k_Q$/$R^j\hat{\theta}^k_Q$ vs. $R^i\hat{\theta}^k_Q$.

Table C.17: Heterogeneous Permanent Price Impact Across Agents Based on Mid-Quotes and Net Volume

	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB
FD	***0.0	-	**AUDJPY**	***0.0	-	**AUDNZD**	***0.0	-	**AUDUSD**	***0.0	-	**CADJPY**	***0.0	-	**EURAUD**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	0.3	-	***0.0	***0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.1	***0.0	***0.0	*0.0	***0.0	***0.0	0.0	***0.0
FD	0.0	-	**EURCAD**	***0.0	-	**EURCHF**	***0.0	-	**EURDKK**	***0.0	-	**EURGBP**	0.0	-	**EURJPY**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	0.1	0.8	***0.0	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0
FD	***0.0	-	**EURNOK**	***0.0	-	**EURSEK**	***0.0	-	**EURUSD**	***0.0	-	**GBPAUD**	0.4	-	**GBPCAD**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	0.2	0.1	***0.0
FD	***0.0	-	**GBPCHF**	***0.0	-	**GBPJPY**	***0.0	-	**GBPUSD**	***0.0	-	**NZDUSD**	***0.0	-	**USDCAD**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	***0.0	0.2	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0
FD	***0.0	-	**USDCHF**	***0.0	-	**USDDKK**	***0.0	-	**USDHKD**	***0.0	-	**USDILS**	***0.0	-	**USDJPY**
NB	***0.0	***0.0	-	*0.0	***0.0	-	***0.0	***0.0	-	0.2	***0.0	-	***0.0	***0.0	-
BA	***0.0	***0.0	***0.0	***0.0	0.3	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.2	***0.0
FD	***0.0	-	**USDMXP**	***0.0	-	**USDNOK**	***0.0	-	**USDSEK**	***0.0	-	**USDSGD**	***0.0	-	**USDZAR**
NB	0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	***0.0	*0.0	***0.0	***0.0	0.6	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	**0.0	***0.0

Note: The numbers correspond to p-values associated with the test statistic of a joint pairwise F-test:

$$F = (R^i\hat{\theta}^k_Q - R^j\hat{\theta}^k_Q)^\top [R^i(\hat{V}_Q/Q)(R^i)^\top]^{-1}(R^i\hat{\theta}^k_Q - R^j\hat{\theta}^k_Q),$$

where $\hat{\theta}^k$ is a vector of parameter estimates with $||R^i\hat{\theta}^k||_1 = \sum_{l=0}^{10} |\hat{\beta}_l^{i,k}|$ and $||R^j\hat{\theta}^k||_1 = \sum_{l=0}^{10} |\hat{\beta}_l^{j,k}|$. F converges to a χ^2_Q distribution. R^i and R^j are $Q \times L$ matrices, where Q is the number of hypotheses being tested and L the number of coefficients. Let $\hat{V}_Q$ be an estimator of the covariance matrix. For each pairwise test, $i \neq j$ and $k \in$ [currency pairs] must hold. Asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests. Agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA). Averages are calculated to account for both directions, i.e. $R^i\hat{\theta}^k_Q$ vs. $R^j\hat{\theta}^k_Q / R^j\hat{\theta}^k_Q$ vs. $R^i\hat{\theta}^k_Q$.

Table C.18: Heterogeneous Permanent Price Impact Across Agents Based on Transaction Prices and Net Volume

	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB	CO	FD	NB
FD	***0.0	-	**AUDJPY**	***0.0	-	**AUDNZD**	***0.0	-	**AUDUSD**	***0.0	-	**CADJPY**	***0.0	-	**EURAUD**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	0.3	-	***0.0	***0.0	-
BA	***0.0	**0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	***0.0	**0.0	***0.0	***0.0	0.0	***0.0
FD	0.0	-	**EURCAD**	***0.0	-	**EURCHF**	***0.0	-	**EURDKK**	***0.0	-	**EURGBP**	0.0	-	**EURJPY**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	0.1	0.8	***0.0	***0.0	***0.0	***0.0	***0.0	0.1	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0
FD	***0.0	-	**EURNOK**	***0.0	-	**EURSEK**	***0.0	-	**EURUSD**	***0.0	-	**GBPAUD**	0.3	-	**GBPCAD**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.0	***0.0	0.2	0.1	***0.0
FD	***0.0	-	**GBPCHF**	***0.0	-	**GBPJPY**	***0.0	-	**GBPUSD**	***0.0	-	**NZDUSD**	***0.0	-	**USDCAD**
NB	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	***0.0	0.3	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0
FD	***0.0	-	**USDCHF**	***0.0	-	**USDDKK**	***0.0	-	**USDHKD**	***0.0	-	**USDILS**	***0.0	-	**USDJPY**
NB	***0.0	***0.0	-	0.0	***0.0	-	***0.0	***0.0	-	0.1	***0.0	-	***0.0	***0.0	-
BA	***0.0	***0.0	***0.0	***0.0	0.4	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.2	***0.0
FD	***0.0	-	**USDMXP**	***0.0	-	**USDNOK**	***0.0	-	**USDSEK**	***0.0	-	**USDSGD**	***0.0	-	**USDZAR**
NB	0.1	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-	***0.0	***0.0	-
BA	***0.0	0.0	***0.0	***0.0	0.3	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	*0.0	***0.0

Note: The numbers correspond to p-values associated with the test statistic of a joint pairwise F-test:

$$F = (R^i\hat{\theta}^k_Q - R^j\hat{\theta}^k_Q)^\top [R^i(\hat{V}_Q/Q)(R^i)^\top]^{-1}(R^i\hat{\theta}^k_Q - R^j\hat{\theta}^k_Q),$$

where $\hat{\theta}^k$ is a vector of parameter estimates with $||R^i\hat{\theta}^k||_1 = \sum_{l=0}^{10}|\hat{\beta}^{i,k}_l|$ and $||R^j\hat{\theta}^k||_1 = \sum_{l=0}^{10}|\hat{\beta}^{j,k}_l|$. F converges to a χ^2_Q distribution. R^i and R^j are $Q \times L$ matrices, where Q is the number of hypotheses being tested and L the number of coefficients. Let $\hat{V}_Q$ be an estimator of the covariance matrix. For each pairwise test, $i \neq j$ and $k \in$ [currency pairs] must hold. Asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests. Agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA). Averages are calculated to account for both directions, i.e. $R^i\hat{\theta}^k_Q$ vs. $R^j\hat{\theta}^k_Q / R^j\hat{\theta}^k_Q$ vs. $R^i\hat{\theta}^k_Q$.

C.4 Heterogeneous Permanent Price Impact Across Currency Pairs

The goal of this section is to investigate whether the FX spot market is fragmented in the sense that a particular agent i has a significantly different permanent price impact parameter across currency pairs. In Tables C.15 to C.18 on pages 26–29 we have checked if the permanent price impact parameter varies significantly across agents within a particular currency pair. As before, we estimate Eq. (4.2) on the full sample and construct a pairwise F-test where we test if all coefficients in Eq. (4.5) for a particular agent $i \in C = \{CO, FD, NB, BA\}$ are jointly significantly different in currency pair k than q:

$$H_0 : \text{agent } i \text{ has the same } \alpha_m^{j,k} \text{ across currencies, i.e. } R^i\theta^k = R^i\theta^q$$

$$H_1 : \alpha_m^{i,k} \text{ differs across currencies, i.e. } R^i\theta^k \neq R^i\theta^q$$

$$F = (R^i\hat{\theta}_Q^k - R^i\hat{\theta}_Q^q)^\top [R^i(\hat{V}_Q/Q)(R^i)^\top]^{-1}(R^i\hat{\theta}_Q^k - R^i\hat{\theta}_Q^q),$$

where $\hat{\theta}^k$ and $\hat{\theta}^q$ are vectors of parameter estimates with $||R^i\hat{\theta}^k||_1 = \sum_{l=0}^{10} |\hat{\beta}_l^{i,k}|$ and $||R^i\hat{\theta}^q||_1 = \sum_{l=0}^{10} |\hat{\beta}_l^{i,q}|$. F converges to a χ_Q^2 distribution. R^i is a $Q \times L$ matrix, where Q is the number of hypotheses being tested and L the number of coefficients. Let $\hat{V}_Q$ be an estimator of the covariance matrix. For each pairwise test $k \neq q$ and $k \in$ [currency pairs] must hold. Again, the validity of this pairwise F-test is warranted by the general properties of a log-level model.

Table C.19: Heterogeneous Permanent Price Impact Across Currency Pairs Based on Mid-Quotes and Order Flow

CO	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	***0.0	0.4						
EURNOK	***0.0	***0.0	0.1	0.5					
EURUSD	***0.0	***0.0	0.0	0.3	0.1				
GBPCHF	0.0	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	0.0	0.1	0.2	0.0	***0.0		
USDCHF	***0.0	***0.0	**0.0	***0.0	***0.0	***0.0	***0.0	***0.0	
USDSEK	***0.0	***0.0	0.0	0.0	0.9	***0.0	*0.0	0.1	***0.0
FD	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	***0.0	0.1						
EURNOK	**0.0	***0.0	***0.0	***0.0					
EURUSD	***0.0	***0.0	0.0	0.0	***0.0				
GBPCHF	***0.0	0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	*0.0	0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	***0.0	0.0	0.2	***0.0	0.3	**0.0	0.0	
USDSEK	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	**0.0
NB	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	0.0							
EURGBP	***0.0	***0.0	***0.0						
EURNOK	0.0	***0.0	***0.0	0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	0.2	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	0.0	***0.0	***0.0	***0.0	***0.0	0.1	0.0		
USDCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	*0.0	***0.0	
USDSEK	0.0	***0.0	***0.0	*0.0	0.0	***0.0	0.0	***0.0	***0.0
BA	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	*0.0							
EURGBP	***0.0	0.1	0.0						
EURNOK	***0.0	***0.0	***0.0	***0.0					
EURUSD	***0.0	**0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	0.0	0.0	0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	***0.0	0.1	**0.0	***0.0	***0.0	
USDSEK	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0

Note: The numbers correspond to p-values associated with the test statistic of a joint pairwise F-test:

$$F = (R^i\hat{\theta}^k_Q - R^i\hat{\theta}^q_Q)^\top [R^i(\hat{V}_Q/Q)(R^i)^\top]^{-1}(R^i\hat{\theta}^k_Q - R^i\hat{\theta}^q_Q),$$

where $\hat{\theta}^k$ and $\hat{\theta}^q$ are vectors of parameter estimates with $||R^i\hat{\theta}^k||_1 = \sum_{l=0}^{10}|\hat{\beta}^{i,k}_l|$ and $||R^i\hat{\theta}^q||_1 = \sum_{l=0}^{10}|\hat{\beta}^{i,q}_l|$. F converges to a χ^2_Q distribution. R^i is a $Q \times L$ matrix, where Q is the number of hypotheses being tested and L the number of coefficients. Let $\hat{V}_Q$ be an estimator of the covariance matrix. For each test, $k \neq q$ and $k \in$ [currency pairs] must hold. Asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied. Averages are calculated to account for both directions, i.e. $R^i\hat{\theta}^k_Q$ vs. $R^i\hat{\theta}^q_Q / R^i\hat{\theta}^q_Q$ vs. $R^i\hat{\theta}^k_Q$.

Table C.20: Heterogeneous Permanent Price Impact Across Currency Pairs Based on Transaction Prices and Order Flow

CO	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	***0.0	0.4						
EURNOK	***0.0	***0.0	0.0	0.4					
EURUSD	***0.0	***0.0	0.0	0.2	0.0				
GBPCHF	0.0	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	0.0	0.1	0.1	0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	
USDSEK	***0.0	***0.0	0.0	0.0	0.9	***0.0	0.0	0.1	***0.0

FD	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	***0.0	0.0						
EURNOK	**0.0	***0.0	***0.0	***0.0					
EURUSD	***0.0	***0.0	0.0	0.0	***0.0				
GBPCHF	***0.0	0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	**0.0	0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	***0.0	0.0	0.1	***0.0	0.2	**0.0	0.0	
USDSEK	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0

NB	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	0.0							
EURGBP	***0.0	***0.0	***0.0						
EURNOK	0.0	***0.0	***0.0	0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	0.2	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	0.0	***0.0	***0.0	***0.0	***0.0	0.1	0.0		
USDCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	**0.0	***0.0	
USDSEK	0.0	***0.0	***0.0	**0.0	0.0	***0.0	0.0	***0.0	***0.0

BA	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	0.0							
EURGBP	***0.0	0.2	0.0						
EURNOK	***0.0	***0.0	***0.0	***0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	0.0	0.0	0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	***0.0	0.1	**0.0	***0.0	***0.0	
USDSEK	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0

Note: The numbers correspond to *p*-values associated with the test statistic of a joint pairwise *F*-test:

$$F = (R^i\hat{\theta}^k_Q - R^i\hat{\theta}^q_Q)^\top [R^i(\hat{V}_Q/Q)(R^i)^\top]^{-1}(R^i\hat{\theta}^k_Q - R^i\hat{\theta}^q_Q),$$

where $\hat{\theta}^k$ and $\hat{\theta}^q$ are vectors of parameter estimates with $||R^i\hat{\theta}^k||_1 = \sum_{l=0}^{10}|\hat{\beta}^{i,k}_l|$ and $||R^i\hat{\theta}^q||_1 = \sum_{l=0}^{10}|\hat{\beta}^{i,q}_l|$. F converges to a χ^2_Q distribution. R^i is a $Q \times L$ matrix, where Q is the number of hypotheses being tested and L the number of coefficients. Let $\hat{V}_Q$ be an estimator of the covariance matrix. For each test, $k \neq q$ and $k \in$ [currency pairs] must hold. Asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied. Averages are calculated to account for both directions, i.e. $R^i\hat{\theta}^k_Q$ vs. $R^i\hat{\theta}^q_Q / R^i\hat{\theta}^q_Q$ vs. $R^i\hat{\theta}^k_Q$.

Table C.21: Heterogeneous Permanent Price Impact Across Currency Pairs Based on Mid-Quotes and Net Volume

CO	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	***0.0	0.0						
EURNOK	***0.0	***0.0	***0.0	***0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	*0.0	***0.0	***0.0	***0.0	***0.0	
USDSEK	***0.0	***0.0	***0.0	***0.0	0.1	***0.0	***0.0	***0.0	***0.0
FD	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	***0.0	0.0						
EURNOK	***0.0	***0.0	***0.0	***0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	0.0	0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	***0.0	0.1	***0.0	***0.0	***0.0	***0.0	***0.0	
USDSEK	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0
NB	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	***0.0	***0.0						
EURNOK	***0.0	*0.0	***0.0	*0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	***0.0	***0.0	**0.0	***0.0	0.0	
USDSEK	***0.0	0.0	***0.0	0.0	0.0	***0.0	***0.0	***0.0	***0.0
BA	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	***0.0	0.0						
EURNOK	***0.0	***0.0	***0.0	**0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.0	
USDSEK	***0.0	***0.0	***0.0	***0.0	**0.0	***0.0	***0.0	***0.0	***0.0

Note: The numbers correspond to *p*-values associated with the test statistic of a joint pairwise *F*-test:

$$F = (R^i\hat{\theta}^k_Q - R^i\hat{\theta}^q_Q)^\top [R^i(\hat{V}_Q/Q)(R^i)^\top]^{-1}(R^i\hat{\theta}^k_Q - R^i\hat{\theta}^q_Q),$$

where $\hat{\theta}^k$ and $\hat{\theta}^q$ are vectors of parameter estimates with $||R^i\hat{\theta}^k||_1 = \sum_{l=0}^{10}|\hat{\beta}^{i,k}_l|$ and $||R^i\hat{\theta}^q||_1 = \sum_{l=0}^{10}|\hat{\beta}^{i,q}_l|$. F converges to a χ^2_Q distribution. R^i is a $Q \times L$ matrix, where Q is the number of hypotheses being tested and L the number of coefficients. Let $\hat{V}_Q$ be an estimator of the covariance matrix. For each test, $k \neq q$ and $k \in$ [currency pairs] must hold. Asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied. Averages are calculated to account for both directions, i.e. $R^i\hat{\theta}^k_Q$ vs. $R^i\hat{\theta}^q_Q / R^i\hat{\theta}^q_Q$ vs. $R^i\hat{\theta}^k_Q$.

Table C.22: Heterogeneous Permanent Price Impact Across Currency Pairs Based on Transaction Prices and Net Volume

CO	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	***0.0	0.0						
EURNOK	***0.0	***0.0	***0.0	***0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	***0.0	**0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	*0.0	***0.0	***0.0	***0.0	***0.0	
USDSEK	***0.0	***0.0	***0.0	***0.0	0.1	***0.0	***0.0	***0.0	***0.0
FD	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	***0.0	0.0						
EURNOK	***0.0	***0.0	***0.0	***0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	0.0	0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	***0.0	0.0	**0.0	***0.0	***0.0	***0.0	***0.0	
USDSEK	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0
NB	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	***0.0	***0.0						
EURNOK	***0.0	0.0	***0.0	***0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	**0.0	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	***0.0	***0.0	**0.0	***0.0	0.0	
USDSEK	***0.0	0.0	***0.0	0.0	0.0	***0.0	*0.0	***0.0	***0.0
BA	AUDJPY	AUDNZD	EURCHF	EURGBP	EURNOK	EURUSD	GBPCHF	GBPUSD	USDCHF
AUDNZD	***0.0								
EURCHF	***0.0	***0.0							
EURGBP	***0.0	***0.0	0.0						
EURNOK	***0.0	***0.0	***0.0	**0.0					
EURUSD	***0.0	***0.0	***0.0	***0.0	***0.0				
GBPCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0			
GBPUSD	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0		
USDCHF	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	***0.0	0.0	
USDSEK	***0.0	***0.0	***0.0	***0.0	**0.0	***0.0	***0.0	***0.0	***0.0

Note: The numbers correspond to p-values associated with the test statistic of a joint pairwise F-test:

$$F = (R^i\hat{\theta}^k_Q - R^i\hat{\theta}^q_Q)^\top[R^i(\hat{V}_Q/Q)(R^i)^\top]^{-1}(R^i\hat{\theta}^k_Q - R^i\hat{\theta}^q_Q),$$

where $\hat{\theta}^k$ and $\hat{\theta}^q$ are vectors of parameter estimates with $||R^i\hat{\theta}^k||_1 = \sum_{l=0}^{10}|\hat{\beta}^{i,k}_l|$ and $||R^i\hat{\theta}^q||_1 = \sum_{l=0}^{10}|\hat{\beta}^{i,q}_l|$. F converges to a χ^2_Q distribution. R^i is a $Q \times L$ matrix, where Q is the number of hypotheses being tested and L the number of coefficients. Let $\hat{V}_Q$ be an estimator of the covariance matrix. For each test, $k \neq q$ and $k \in$ [currency pairs] must hold. Asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied. Averages are calculated to account for both directions, i.e. $R^i\hat{\theta}^k_Q$ vs. $R^i\hat{\theta}^q_Q$/$R^i\hat{\theta}^q_Q$ vs. $R^i\hat{\theta}^k_Q$.

Table C.23: Permanent Price Impact Across Agents: Joint F-test Based on Transaction Prices and Order Flow

in BPS	α_m^{CO}	α_m^{FD}	α_m^{NB}	α_m^{BA}	in BPS	α_m^{CO}	α_m^{FD}	α_m^{NB}	α_m^{BA}
AUDJPY	−5.302	1.021	***0.466	***1.767	GBPCHF	−1.250	0.817	*0.757	***0.278
	[1.235]	[1.954]	[4.063]	[31.875]		[1.182]	[1.086]	[2.400]	[4.412]
AUDNZD	**2.412	1.567	**−0.202	***0.458	GBPJPY	0.192	0.828	***−0.614	***1.399
	[2.649]	[1.355]	[2.635]	[5.553]		[0.760]	[1.495]	[3.635]	[18.734]
AUDUSD	1.127	***0.570	***0.928	***0.847	GBPUSD	***−1.738	***0.527	***0.532	***1.657
	[1.574]	[3.802]	[27.016]	[3.695]		[3.200]	[3.301]	[12.655]	[12.473]
CADJPY	2.818	0.814	0.250	***−0.143	NZDUSD	−1.156	***0.736	***1.343	***0.952
	[0.601]	[0.735]	[0.965]	[4.831]		[1.920]	[4.523]	[8.247]	[7.539]
EURAUD	−1.869	0.505	−0.198	***0.722	USDCAD	***−2.073	***0.466	***0.345	***0.571
	[1.257]	[1.318]	[1.368]	[4.316]		[3.545]	[2.865]	[8.250]	[3.535]
EURCAD	***−0.754	0.605	***0.603	***0.448	USDCHF	***−0.926	0.721	***0.428	0.675
	[4.207]	[1.028]	[4.028]	[3.427]		[3.058]	[1.477]	[23.141]	[2.131]
EURCHF	***−0.473	−0.018	−0.014	***0.119	USDDKK	***−1.995	0.082	0.683	−0.164
	[3.440]	[0.901]	[1.221]	[13.086]		[4.834]	[1.898]	[1.703]	[1.663]
EURDKK	0.045	0.054	**0.252	***0.051	USDHKD	−0.024	*0.020	0.011	**0.028
	[1.044]	[2.050]	[2.694]	[13.311]		[1.262]	[2.328]	[0.435]	[2.594]
EURGBP	***−0.642	0.329	***−0.007	***0.701	USDILS	−3.153	0.627	***−0.966	**0.631
	[3.779]	[1.402]	[3.256]	[7.712]		[1.230]	[1.009]	[4.617]	[2.555]
EURJPY	***−0.459	−0.712	***0.164	0.558	USDJPY	*0.031	***0.504	***−0.131	***0.860
	[4.524]	[1.288]	[6.159]	[1.998]		[2.345]	[4.963]	[25.651]	[7.655]
EURNOK	***−1.780	***0.921	0.212	***0.722	USDMXP	2.108	−0.014	***−0.503	0.849
	[3.169]	[6.031]	[2.111]	[3.889]		[0.966]	[1.055]	[5.496]	[1.833]
EURSEK	***−0.546	***1.138	0.583	***0.654	USDNOK	−0.459	0.970	***0.870	***0.105
	[3.313]	[8.569]	[2.122]	[3.465]		[1.621]	[2.121]	[3.621]	[4.593]
EURUSD	***−1.126	0.521	***0.058	***1.000	USDSEK	−2.493	***1.822	***1.153	***0.318
	[14.926]	[1.651]	[13.979]	[4.590]		[2.247]	[5.127]	[3.390]	[3.887]
GBPAUD	2.463	0.549	0.541	***1.339	USDSGD	***−0.488	***0.129	**0.325	***−0.054
	[1.042]	[1.237]	[1.618]	[5.453]		[3.132]	[2.992]	[2.735]	[3.108]
GBPCAD	*−0.347	0.534	1.514	0.473	USDZAR	−6.915	0.665	0.676	***3.462
	[2.419]	[1.044]	[1.731]	[0.859]		[0.787]	[1.424]	[1.651]	[10.945]

Note: The numbers in brackets correspond to the test statistic for a heteroscedasticity-consistent joint F-test, where the parameters in Eq. (4.5) are jointly different from zero. Asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests in the joint hypothesis. All numbers are in basis points (BPS). Agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA).

Table C.24: Permanent Price Impact Across Agents: Joint F-test Based on Mid-Quotes and Net Volume

in BPS	α_m^{CO}	α_m^{FD}	α_m^{NB}	α_m^{BA}	in BPS	α_m^{CO}	α_m^{FD}	α_m^{NB}	α_m^{BA}
AUDJPY	**2.053	**4.732	***10.366	***6.210	GBPCHF	−37.456	0.706	7.651	*−0.729
	[2.606]	[2.454]	[4.649]	[10.886]		[0.984]	[1.584]	[1.860]	[2.317]
AUDNZD	***0.362	2.438	3.555	***3.050	GBPJPY	28.129	5.216	***−5.976	***1.751
	[7.579]	[1.045]	[0.842]	[5.417]		[1.295]	[1.503]	[6.653]	[4.294]
AUDUSD	1.237	−0.061	***−0.375	0.226	GBPUSD	0.538	−0.250	**0.153	0.217
	[0.885]	[1.264]	[3.446]	[1.399]		[0.923]	[1.090]	[2.654]	[1.046]
CADJPY	6.789	−0.293	−0.037	−0.355	NZDUSD	14.720	0.421	***5.583	***0.609
	[0.542]	[1.802]	[1.049]	[0.635]		[0.855]	[0.857]	[6.826]	[3.195]
EURAUD	−3.317	1.034	−3.982	**0.111	USDCAD	−0.871	−0.059	***0.167	0.023
	[0.562]	[1.360]	[1.866]	[2.712]		[0.558]	[0.958]	[2.870]	[0.742]
EURCAD	**−1.514	0.696	***11.083	***−0.693	USDCHF	−0.191	0.551	***−0.243	0.169
	[2.514]	[1.691]	[3.498]	[4.889]		[1.447]	[1.239]	[3.580]	[1.577]
EURCHF	***−0.150	−0.007	0.445	***−0.356	USDDKK	−1.256	0.005	−0.863	−0.622
	[3.061]	[0.277]	[0.778]	[4.212]		[1.256]	[1.578]	[0.699]	[0.575]
EURDKK	0.095	***0.147	0.230	0.060	USDHKD	0.330	***0.001	−0.040	−0.012
	[1.118]	[3.348]	[2.095]	[1.763]		[1.957]	[2.930]	[1.635]	[1.510]
EURGBP	**0.776	0.051	***−0.377	***0.341	USDILS	−3.966	5.715	3.450	***1.912
	[2.510]	[1.326]	[3.649]	[3.212]		[1.148]	[1.289]	[0.609]	[2.881]
EURJPY	−1.791	0.334	***1.530	0.027	USDJPY	0.241	0.054	***−0.055	***0.125
	[0.688]	[1.815]	[5.722]	[0.920]		[0.395]	[0.799]	[6.286]	[3.468]
EURNOK	−5.115	***2.498	**3.610	0.687	USDMXP	1.547	0.592	−0.410	***−0.012
	[1.231]	[3.391]	[2.530]	[1.223]		[0.210]	[1.201]	[0.817]	[4.854]
EURSEK	−0.838	***2.219	***6.130	0.278	USDNOK	−2.299	−0.565	***14.373	−0.768
	[0.675]	[4.780]	[4.326]	[1.487]		[0.997]	[0.845]	[3.780]	[2.132]
EURUSD	***−0.277	−0.065	***1.148	***0.001	USDSEK	1.080	***2.206	**6.147	**−0.018
	[3.206]	[0.997]	[6.884]	[4.891]		[0.929]	[2.977]	[2.739]	[2.555]
GBPAUD	***17.460	5.601	14.314	***7.906	USDSGD	−3.133	0.344	***4.142	−0.051
	[16.363]	[1.259]	[1.350]	[3.086]		[1.787]	[1.952]	[2.942]	[0.663]
GBPCAD	1.704	3.856	**36.923	−0.300	USDZAR	−27.674	2.442	1.634	**2.206
	[1.470]	[0.458]	[2.533]	[0.601]		[1.174]	[2.122]	[1.047]	[2.620]

Note: The numbers in brackets correspond to the test statistic for a heteroscedasticity-consistent joint F-test, where the parameters in Eq. (4.5) are jointly different from zero. Asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests in the joint hypothesis. All numbers are in basis points (BPS). Agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA).

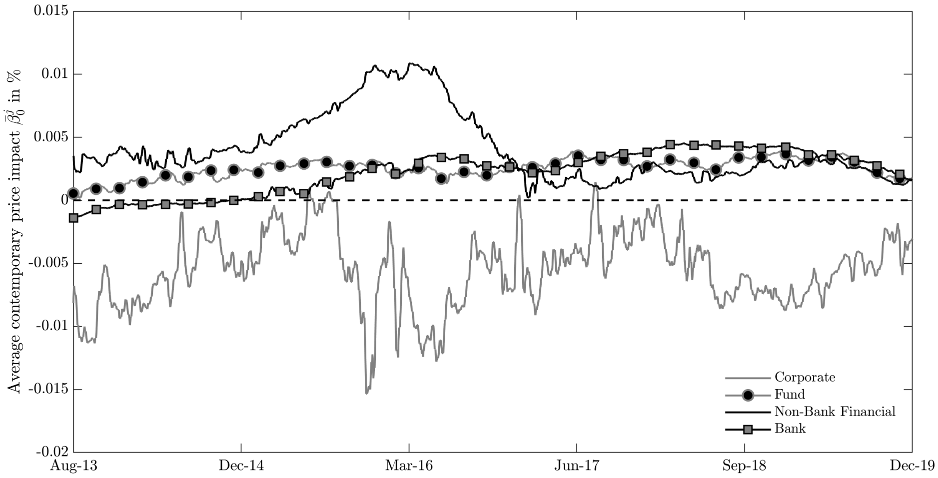
Table C.25: Permanent Price Impact Across Agents: Joint F-test Based on Transaction Prices and Net Volume

in BPS	α_m^{CO}	α_m^{FD}	α_m^{NB}	α_m^{BA}	in BPS	α_m^{CO}	α_m^{FD}	α_m^{NB}	α_m^{BA}
AUDJPY	**2.949	*4.601	***10.415	***6.208	GBPCHF	−38.977	0.522	8.227	*−0.789
	[2.586]	[2.391]	[4.544]	[11.202]		[0.895]	[1.554]	[1.692]	[2.287]
AUDNZD	***20.210	2.736	4.448	***3.031	GBPJPY	31.530	4.526	***−5.298	***1.668
	[8.024]	[1.051]	[0.849]	[5.417]		[1.307]	[1.305]	[6.372]	[4.201]
AUDUSD	1.263	−0.061	***−0.383	0.232	GBPUSD	0.479	−0.267	**0.174	0.224
	[0.977]	[1.295]	[3.344]	[1.447]		[0.772]	[0.984]	[2.586]	[1.074]
CADJPY	6.799	0.015	1.554	−0.252	NZDUSD	16.740	0.448	***6.037	***0.643
	[0.661]	[1.898]	[1.003]	[0.625]		[0.873]	[0.846]	[6.788]	[3.220]
EURAUD	−3.170	0.964	−4.054	**0.116	USDCAD	−0.817	−0.067	***0.136	0.028
	[0.651]	[1.309]	[1.869]	[2.656]		[0.521]	[0.950]	[2.856]	[0.872]
EURCAD	**−1.370	0.747	***11.489	***−0.666	USDCHF	−0.099	0.564	***−0.282	0.167
	[2.524]	[1.695]	[3.599]	[4.816]		[1.332]	[1.119]	[3.582]	[1.624]
EURCHF	***−0.372	−0.174	0.518	***−0.324	USDDKK	−1.279	−0.069	−0.419	−0.630
	[3.125]	[0.332]	[0.713]	[4.152]		[1.234]	[1.567]	[0.665]	[0.580]
EURDKK	0.188	***0.154	0.368	*0.069	USDHKD	*0.217	−0.009	−0.002	−0.006
	[1.221]	[2.854]	[2.241]	[2.427]		[2.400]	[1.980]	[1.515]	[1.371]
EURGBP	*0.640	0.112	***−0.821	***0.330	USDILS	−5.291	4.359	5.985	*1.459
	[2.359]	[1.357]	[3.630]	[3.183]		[0.954]	[0.936]	[0.401]	[2.402]
EURJPY	−2.048	0.287	***1.446	−0.006	USDJPY	0.168	0.048	***−0.082	***0.122
	[0.769]	[1.699]	[5.655]	[0.995]		[0.349]	[0.639]	[6.290]	[3.332]
EURNOK	−5.207	***2.821	*4.245	0.599	USDMXP	2.019	0.724	−0.596	***0.051
	[1.180]	[3.590]	[2.277]	[1.093]		[0.176]	[1.112]	[0.848]	[4.712]
EURSEK	−0.928	***2.548	***5.811	0.348	USDNOK	−1.594	−0.771	***14.761	*−0.859
	[0.522]	[4.005]	[4.037]	[1.342]		[0.968]	[0.948]	[4.047]	[2.271]
EURUSD	***−0.275	−0.063	***1.100	***0.007	USDSEK	0.906	***2.316	**6.508	**−0.122
	[3.121]	[1.030]	[6.856]	[4.905]		[0.833]	[3.110]	[2.759]	[2.707]
GBPAUD	***14.533	6.203	14.288	***8.371	USDSGD	−3.311	0.300	***4.302	−0.095
	[14.396]	[1.318]	[1.264]	[3.253]		[1.684]	[2.197]	[2.856]	[0.958]
GBPCAD	1.086	2.378	**38.235	−0.441	USDZAR	−25.981	2.740	2.765	**2.364
	[1.344]	[0.433]	[2.642]	[0.532]		[1.173]	[1.979]	[1.076]	[2.747]

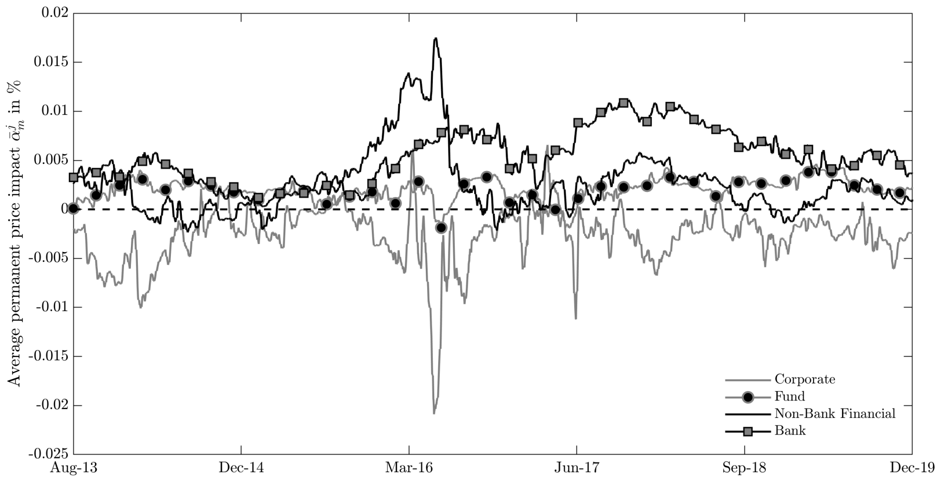
Note: The numbers in brackets correspond to the test statistic for a heteroscedasticity-consistent joint F-test, where the parameters in Eq. (4.5) are jointly different from zero. Asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests in the joint hypothesis. All numbers are in basis points (BPS). Agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA).

C.5 *Time Variation of $\bar{\beta}_0^j/\bar{\alpha}_m^j$: Trans. Prices and Order Flow*

Figure C.1: Twelve Months Rolling Window Regression for $\bar{\beta}_0^j / \bar{\alpha}_m^j$



(a) Contemporary Price Impact

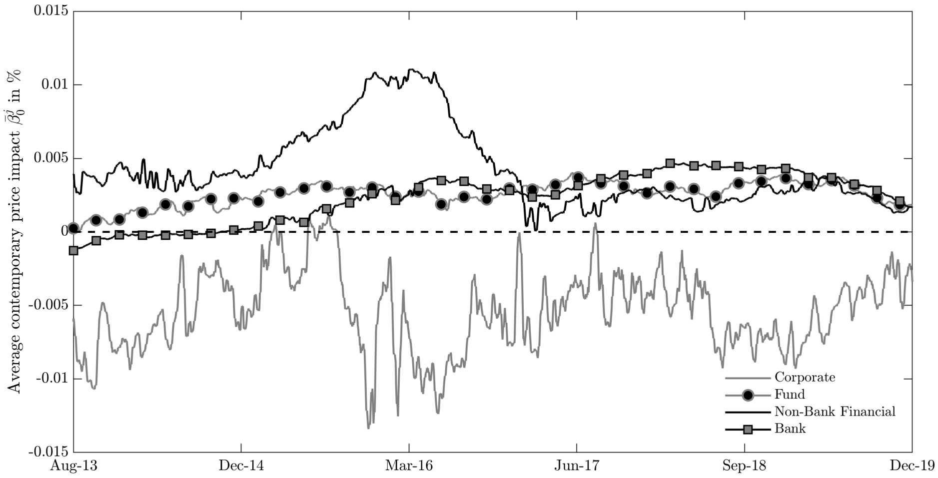


(b) Permanent Price Impact

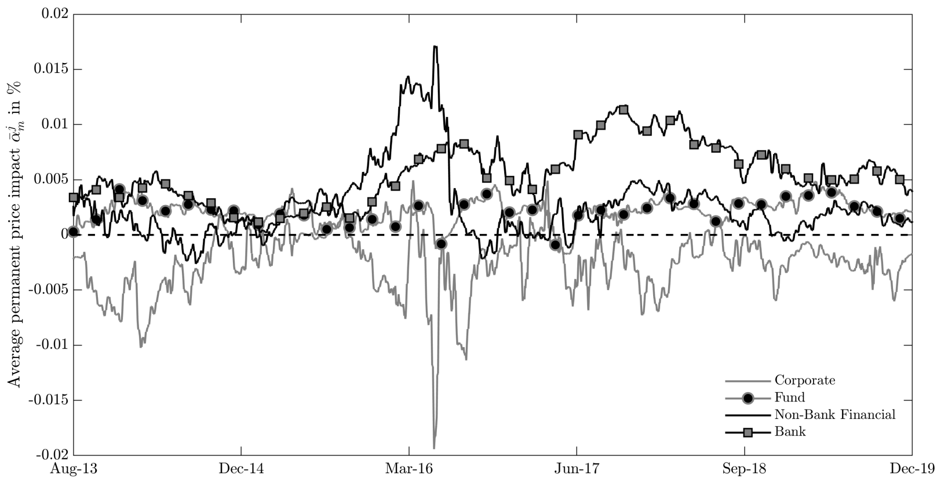
Note: The cross-sectional five-day-moving average contemporary ($\bar{\beta}_0^j$) and permanent ($\bar{\alpha}_m^j$) price impact are calculated after removing any coefficients that are heavy outliers with respect to the median.

C.6 *Time Variation of $\bar{\beta}_0^j/\bar{\alpha}_m^j$: Mid-Quotes and Order Flow*

Figure C.2: Twelve Months Rolling Window Regression for $\bar{\beta}_0^j / \bar{\alpha}_m^j$



(a) Contemporary Price Impact

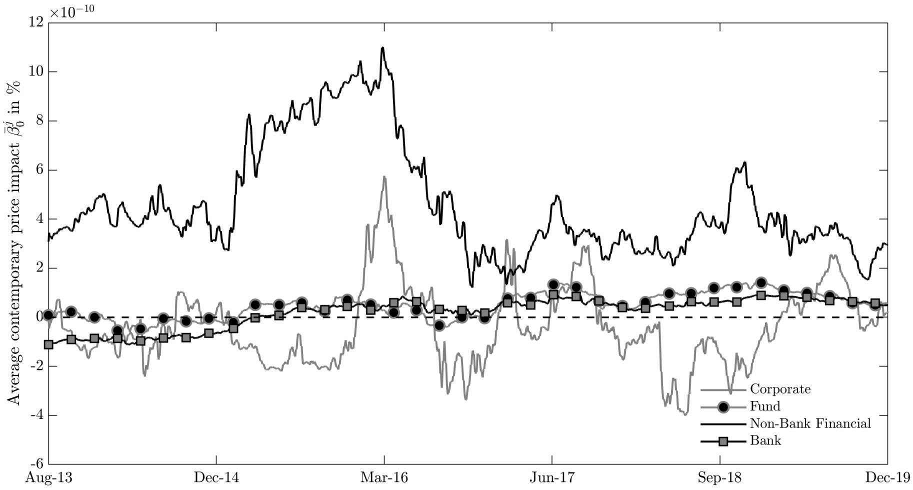


(b) Permanent Price Impact

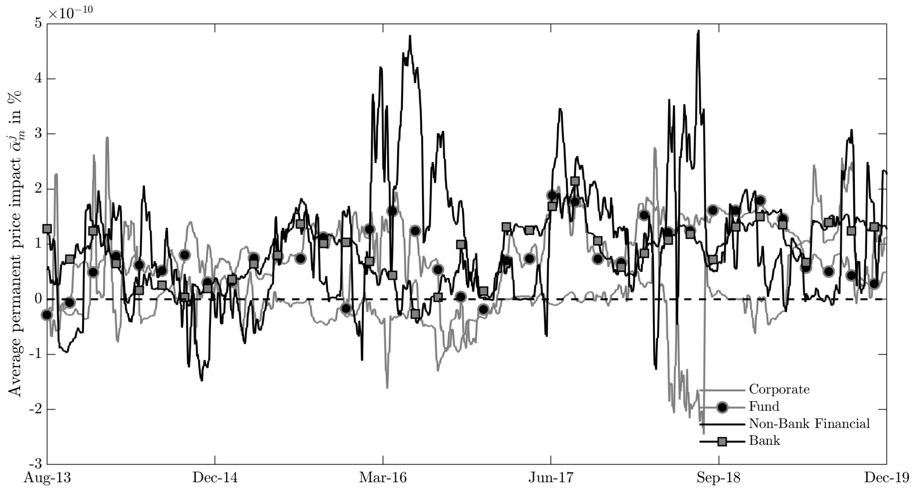
Note: The cross-sectional five-day-moving average contemporary ($\bar{\beta}_0^j$) and permanent ($\bar{\alpha}_m^j$) price impact are calculated after removing any coefficients that are heavy outliers with respect to the median.

C.7 *Time Variation of $\bar{\beta}_0^j/\bar{\alpha}_m^j$: Mid-Quotes and Net Volume*

Figure C.3: Twelve Months Rolling Window Regression for $\bar{\beta}_0^j / \bar{\alpha}_m^j$



(a) Contemporary Price Impact

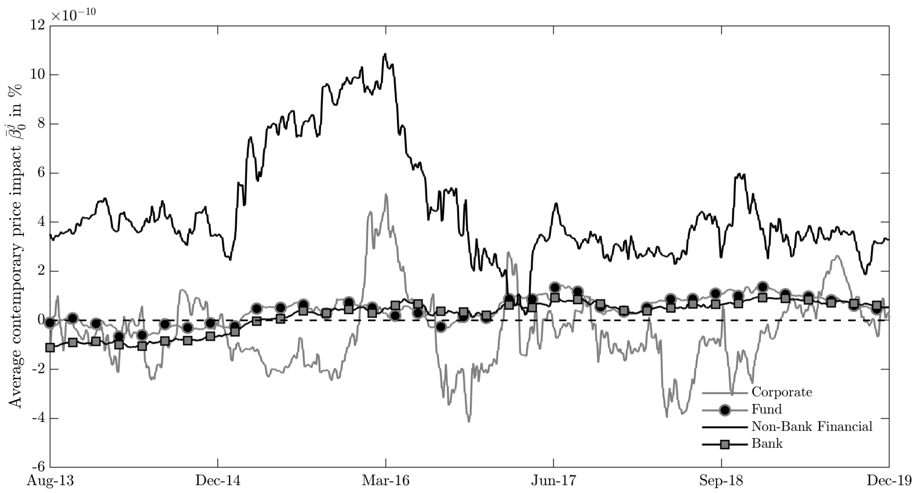


(b) Permanent Price Impact

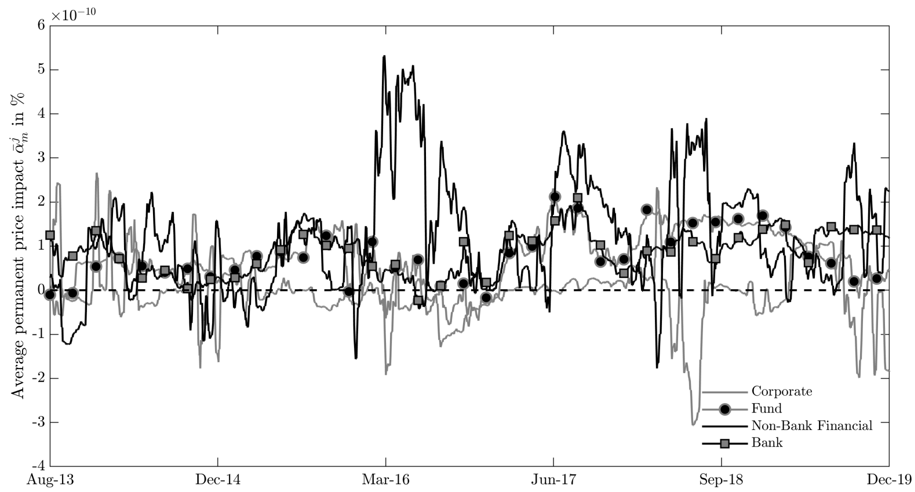
Note: The cross-sectional five-day-moving-average contemporary ($\bar{\beta}_0^j$) and permanent ($\bar{\alpha}_m^j$) price impact are calculated after removing any coefficients that are heavy outliers with respect to the median.

C.8 *Time Variation of $\bar{\beta}_0^j/\bar{\alpha}_m^j$: Trans. Prices and Net Volume*

Figure C.4: Twelve Months Rolling Window Regression for $\bar{\beta}_0^j/\bar{\alpha}_m^j$



(a) Contemporary Price Impact



(b) Permanent Price Impact

Note: The cross-sectional five-day-moving-average contemporary ($\bar{\beta}_0^j$) and permanent ($\bar{\alpha}_m^j$) price impact are calculated after removing any coefficients that are heavy outliers with respect to the median.

Table C.26: Economic Drivers of Net Order Volume (EUR-based)

	CO	FD	NB	BA
Net Order Volume				
CO_t		*−0.02	***−0.03	***−0.09
		[1.72]	[3.01]	[3.27]
FD_t	*−0.02		***−0.04	***−0.24
	[1.77]		[6.77]	[16.38]
NB_t	***−0.03	***−0.04		***−0.09
	[2.90]	[6.68]		[8.23]
BA_t	***−0.10	***−0.25	***−0.10	
	[3.33]	[14.45]	[7.87]	
CO_{t-1}	**0.05	0.00	**−0.02	0.01
	[2.20]	[0.39]	[2.27]	[0.43]
FD_{t-1}	−0.01	***0.10	0.00	**0.02
	[1.12]	[2.99]	[0.43]	[2.43]
NB_{t-1}	−0.01	*0.01	−0.03	0.00
	[1.00]	[1.95]	[1.32]	[0.53]
BA_{t-1}	0.01	0.01	0.00	***0.09
	[0.91]	[1.26]	[0.15]	[6.40]
Market Conditions				
$f_{t-1,t} - s_t$	−0.04	*−0.02	0.00	0.01
	[1.39]	[1.65]	[0.01]	[0.51]
r_t^{equity}	0.00	*−0.02	**−0.03	0.01
	[0.02]	[1.92]	[2.31]	[1.24]
y_t^{bond}	−0.01	*0.02	−0.01	0.00
	[1.16]	[1.73]	[0.57]	[0.53]
Trading Strategies				
ΔDOL	**0.02	0.00	***−0.07	***0.06
	[2.13]	[0.06]	[5.54]	[5.19]
ΔRER_{HML}	−0.01	0.00	0.01	−0.01
	[1.43]	[0.11]	[0.71]	[0.78]
ΔMOM_{HML}	0.00	0.00	0.00	0.00
	[0.60]	[0.11]	[0.17]	[0.01]
ΔCAR_{HML}	*0.01	0.01	0.00	0.01
	[1.92]	[1.52]	[0.37]	[1.11]
ΔVOL_{LMH}	−0.00	*0.01	0.01	***0.02
	[0.00]	[1.70]	[0.63]	[2.77]
R^2 in %	1.45	7.10	2.20	8.80
Adj. R^2 in %	1.29	6.95	2.05	8.66
Avg. #Time periods	1628	1628	1628	1628
#Exchange rates	9	9	9	9
Currency FE	yes	yes	yes	yes
Time-series FE	yes	yes	yes	yes

Note: This table collects results from fixed effects panel regressions of the form $NV_{k,t}^j = \lambda_t + \alpha_k + \beta' f_{k,t} + \varepsilon_{k,t}$, where $NV_{k,t}^j$ is daily standardised net volume, $f_{k,t}$ collects contemporaneous and lagged standardised net volume (the standard deviation of flows is computed via a 60-day rolling window), market conditions such as the interest rate differential ($f_{t-1,t} - s_t \approx i_t^* - i_t$), equity returns ($r_t^{equity}$) and changes in the 10-year government bond yield (y_t^{bond}) as well as the portfolio returns of common FX trading strategies. The superscript $j \in C = \{CO, FD, NB, BA\}$ denotes one of the market participants, namely, corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA). All specifications are based on standardised regressors and include both cross-sectional (α_k) and time fixed (λ_t) effects, hence the error term can be decomposed as $\epsilon_{k,t} = \lambda_t + \alpha_k + \varepsilon_{k,t}$. Δ stands for *relative* changes. The test statistics based on cross-sectionally clustered White standard errors (White, 1980) are reported in brackets. Asterisks *, ** and *** denote significance at the 90%, 95% and 99% levels.

C.9 Structural VAR

We estimate a *five-variate* structural VAR (SVAR) of *disaggregated* order flows in order to understand the lead-lag relation across price impacts of various customer segments. The SVAR is a variant of the model developed in Hasbrouck (1991a,b, 2007) and employed in Hendershott et al. (2011).[3] The approach is based on estimating the contribution of innovations and different sources of trading to the underlying efficient price. In particular, we estimate a model where only returns are contemporaneously affected by each group of market participants' order flows, whereas individual customer order flows are only affected by past flows (i.e. as in a standard VAR):

$$r_t = \phi_l D_{l,t} + \sum_{i=1}^{10} \alpha_i r_{t-i} + \sum_{j \in C} \left(\sum_{i=0}^{10} \beta_i^j T_{t-i}^j \right) + \epsilon_{r,t}, \tag{C1}$$

$$T_t^{CO} = \theta_{1,l} D_{l,t}^{CO} + \sum_{i=1}^{10} \gamma_i r_{t-i} + \sum_{j \in C} \left(\sum_{i=1}^{10} \delta_i^j T_{t-i}^j \right) + \epsilon_t^{CO}, \tag{C2}$$

$$T_t^{FD} = \theta_{2,l} D_{l,t}^{FD} + \sum_{i=1}^{10} \zeta_i r_{t-i} + \sum_{j \in C} \left(\sum_{i=1}^{10} \eta_i^j T_{t-i}^j \right) + \epsilon_t^{FD}, \tag{C3}$$

$$T_t^{NB} = \theta_{3,l} D_{l,t}^{NB} + \sum_{i=1}^{10} \lambda_i r_{t-i} + \sum_{j \in C} \left(\sum_{i=1}^{10} \nu_i^j T_{t-i}^j \right) + \epsilon_t^{NB}, \tag{C4}$$

$$T_t^{BA} = \theta_{4,l} D_{l,t}^{BA} + \sum_{i=1}^{10} \xi_i r_{t-i} + \sum_{j \in C} \left(\sum_{i=1}^{10} \rho_i^j T_{t-i}^j \right) + \epsilon_t^{BA}, \tag{C5}$$

where, as before, $D_{l,t}$ denotes a dummy variable matrix to account for time-fixed effects with $l = 24$ columns and $t = n$ rows, in which element l, t is 1 if there was a trade in that hour, and $C = \{CO, FD, NB, BA\}$ denotes one of the market participants, namely, corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA). Transactions are available as aggregated hourly flows and are indexed by t.[4] The error terms are given by $\epsilon_{r,t}$, ϵ_t^{CO}, ϵ_t^{FD}, ϵ_t^{NB} and ϵ_t^{BA} with the variances of $\sigma^2_{\epsilon,r}$, $\sigma^2_{\epsilon,CO}$, $\sigma^2_{\epsilon,FD}$, $\sigma^2_{\epsilon,NB}$ and $\sigma^2_{\epsilon,BA}$ (i.e. the variances of return shock and shocks to order flows of each trader type), respectively.

The only structural assumption in this model is that the order flows contemporaneously affect returns but flows themselves are only affected by past returns and flows. Technically, one could impose contemporaneous relationships across market

[3] The model is described in detail in Hasbrouck (2007, pp. 78-85).

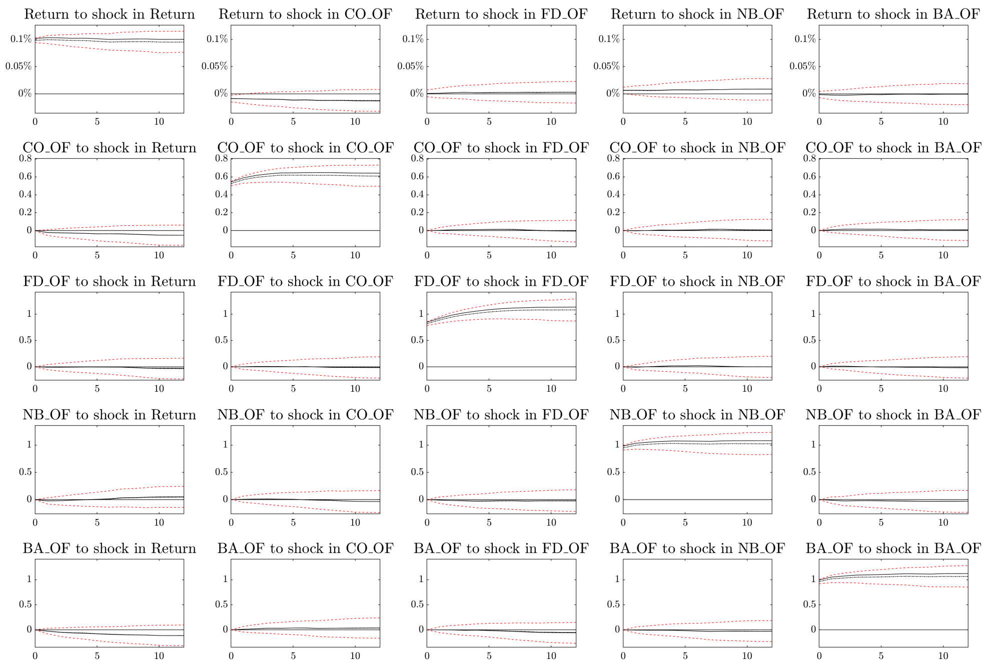
[4] A Dickey-Fuller unit root test on the time-series of regression variables confirms the stationarity of the time-series, including covariance stationarity. Hence, the VAR can be estimated consistently equation by equation using OLS.

participants' flows. We refrain from this for two reasons: First, ex ante it is not clear which trader type should be considered fastest. Second, the time granularity of the dataset is too low to identify meaningful lead-lag relationships across different customer groups. We estimate the VAR equation by equation consistently using OLS and compute (cumulative) impulse responses using the following structural shock matrix:

$$A = \begin{pmatrix} 1 & a_{1,2} & a_{1,3} & a_{1,4} & a_{1,5} \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix},$$

where the structural shock parameters $a_{1,2}$, $a_{1,3}$, $a_{1,4}$ and $a_{1,5}$ allow for order flows impacting returns contemporaneously.

Figure C.5: Cumulative Impulse Response - EURUSD



Note: These figures plot the mean and median cumulative impulse responses for the SVAR specified in Eq. (C1). The red dotted lines are 95% bootstrapped confidence bands. The x-axis depicts the forecasting horizon of the (cumulative) impulse response.

The results are similar using standard Cholesky decomposition. Given that the five-variate SVAR is overidentified, we estimate the structural parameters using the Full Information Maximimum Likelihood (FIML) scoring algorithm as it is described in Amisano and Giannini (1997, p.45). Figure C.5 is an illustrative example of how the cumulative impulse responses function looks like for a specific currency pair[5] (i.e. the EURUSD). Confidence bands have been calculated using standard Bootstrap procedures in the spirit of Efron (1979) and Efron and Tibshirani (1993) with 2 500 repetitions. The results are qualitatively in line with Payne (2003) and Hasbrouck (1991a). Given the general properties of the log-level model in the first VAR equation impulse response coefficients can be interpreted as percentage changes in returns for a one unit-shock in order flow.

From the SVAR analysis two key findings emerge, that are as follow: First, spill-over effects across agents' flows are negligible that is, individual agent's flows are contemporaneously affect by their own flows but less so by others. This result is consistent with the idea that FX markets are fragmented (Evans and Lyons, 2006). Second, FX returns tend to positively respond to shocks in non-bank financial and fund flows, whereas they do not react at all to shocks in corporate order flows. More precisely, the return impulse response to shocks in non-bank financial, fund, bank and corporate order flows are positive for 90%, 87%, 50% and 20% of all currency pairs, respectively.

C.10 *Diagnostic Tests*

To avoid misspecification in our regression analysis and to check the validity of our assumptions in the bivariate VAR model we conduct a battery of diagnostic tests. The consequences of misspecified models can be severe in terms of the adverse effects on the sampling properties of both estimators and tests. Therefore, the econometrics literature has developed a great variety of procedures for interrogating the quality of a model's specification. In Table C.27 we summarise all the diagnostic tests carried out on both the return (i.e. Eq. (4.2)) and order flow (i.e. Eq. (4.3)) equation, respectively.

Both the Ljung–Box and Durbin–Watson test confirm that the correlations in the population from which our sample is taken from are 0. Therefore, any observed correlations in the data result from randomness of the sampling process and do not lead to biased coefficient estimates. This holds for both the return (i.e. Eq. (4.2)) and order flow (i.e. Eq. (4.3)) equation, respectively, in case of the Durbin–Watson test, but only for the order flow equation when applying the Ljung–Box test. The White test for homoscedasticity suggests evidence of heteroscedasticity in the return equation. We correct for this by using heteroscedasticity and autocorrelation consistent standard errors. The Kwiatkowski–Phillips–Schmidt–Shin and Dickey–Fuller test are two im-

[5] Results for all other currency pairs are available upon request.

portant procedures to detect if the time series is (covariance) stationary or exhibits the properties of a unit root process. For the VAR model to be estimated consistently, it is necessary that the time series is covariance stationary with respect to the time index used. For both tests we either reject the H_0 of a unit root process in favour of a trend-stationary alternative or are not able to reject the H_0 of (covariance) trend-stationarity. To conclude, our econometric analysis does not suffer from any misspecification that could lead to biased coefficients or wrong inference.

Table C.27: Diagnostic Tests

Test	$\mathbf{H_0}$	**Return Equation**	**Order Flow Equation**
Ljung-Box	Independent distribution	✓	✗
Durbin-Watson	No First Order Autocorrelation	✗	✗
White	Homoscedasticity	✓	✗
Kwiatkowski-Phillips-Schmidt-Shin	(Covariance) Stationarity	✗	✗
Dickey-Fuller	Unit root	✓	✓

Note: For all tests we apply a significance level of 5%, except for the Durbin-Watson (DW) test, where the difference between the DW test statistic and its critical value 2 is $\leqslant 0.001$ for the entire cross-section. Check/Cross-marks are based on applicability to at least 85% of all currency pairs. A check-mark indicates that the null hypothesis (H_0) is rejected.

Appendix D Currency Portfolios

Before reporting some additional results related to the performance of our trading strategy we introduce our methodology of calculating dollar-neutral excess returns. To derive excess log returns we consider a US investor who invests the same amount into portfolios P_i and P_j, respectively:

Portfolio P_i:

- In t, enter a forward contract and put $F_{t,t+1}/(1+R_f)$ units of domestic currency on the bank account (this is the 'investment'), where R_f is the risk-free rate.
- In $t+1$, use the amount on the bank account to pay the forward price $F_{t,t+1}$ and get 1 unit of foreign currency, sell it and receive the spot rate S_{t+1}.

Portfolio P_j:

- In t, put $F_{t,t+1}/(1+R_f)$ units of domestic currency on the bank account (this is the 'investment'), where R_f is the risk-free rate.
- In $t+1$, there is the amount F_{t+1} on the bank account.

Intuitively, one can think of portfolio j as the (benchmark) amount an investors earns on her investment without entering the forward contract. As a result, the log ratio of the two portfolios (i.e. $log(P_i/P_j)$) must be equal to what is earned in excess of the benchmark portfolio j and is hence equal to the excess log return. Moreover, in the case of excess log returns it is straightforward to show that the initial investment happens to cancel out and thus, if we abstract from variation and maintenance margins at time t no capital is pledged to sustain this dollar-neutral position. Hence, the statement above is equivalent to saying that the investor goes long in currency pair *X/Y*, where X and Y are the base and quote currency of a non-USD currency pair, respectively, for example, GBPJPY or EURCHF. Therefore, she sells forward X for Y in t for delivery in $t+1$ and buys it back in the spot market in $t+1$. If we abstract from transaction cost, she sells at $F_{t,t+1}^{X/Y}$ and buys at $S_{t+1}^{X/Y}$. As she invests $S_{t+1}^{X/Y}$ in $t+1$ to sustain this position the gross return is

$$RX^{X/Y}_{\text{long spot/sell forward}} \equiv \frac{F_{t,t+1}^{X/Y}}{S_{t+1}^{X/Y}}.$$

Using no-arbitrage condition we can rewrite this as:

$$F_{t,t+1}^{X/Y} = F_{t,t+1}^{X/USD} \times F_{t,t+1}^{USD/Y} \quad \text{and} \quad S_{t+1}^{X/Y} = S_{t+1}^{X/USD} \times S_{t+1}^{USD/Y}. \tag{D1}$$

Note that for a USD base currency pair all terms including X are equal to 1 and therefore drop out from all expressions. Substituting we can write the gross return as follows:

$$RX^{X/Y}_{\text{long spot/sell forward}} = \frac{F^{X/USD}_{t,t+1} \times F^{USD/Y}_{t,t+1}}{S^{X/USD}_{t+1} \times S^{USD/Y}_{t+1}}. \tag{D2}$$

Taking logs we find that:

$$rx^{x/y}_{\text{long spot/sell forward}} = f^{X/USD}_{t,t+1} - s^{X/USD}_{t+1} + \left(f^{USD/Y}_{t,t+1} - s^{USD/Y}_{t+1}\right). \tag{D3}$$

We can express these returns using the USD as the base currency. In fact, prior transaction cost,

$$F^{X/USD}_{t,t+1} = \frac{1}{F^{USD/X}_{t,t+1}} \quad \text{and} \quad S^{X/USD}_{t+1} = \frac{1}{S^{USD/X}_{t+1}}. \tag{D4}$$

Therefore,

$$F^{X/Y}_{t,t+1} = \frac{F^{USD/Y}_{t,t+1}}{F^{USD/X}_{t,t+1}} \quad \text{and} \quad S^{X/Y}_{t+1} = \frac{S^{USD/Y}_{t+1}}{S^{USD/X}_{t+1}}. \tag{D5}$$

We conclude that

$$RX^{X/Y}_{\text{long spot/sell forward}} = \frac{F^{USD/Y}_{t,t+1} \times S^{USD/X}_{t+1}}{F^{USD/X}_{t,t+1} \times S^{USD/Y}_{t+1}}, \quad \text{so that in logs} \tag{D6}$$

$$rx^{X/Y}_{\text{long spot/sell forward}} = f^{USD/Y}_{t,t+1} - s^{USD/Y}_{t+1} - \left(f^{USD/X}_{t,t+1} - s^{USD/X}_{t+1}\right). \tag{D7}$$

We can repeat this argument taking into account bid–ask quotes. Thus, with the long spot/sell forward position, the investor sells at $F^{X/Y,b}_{t,t+1}$ and buys at $S^{X/Y,a}_{t+1}$. Hence, the gross return is now

$$RX^{X/Y}_{\text{long spot/sell forward}} \equiv \frac{F^{X/Y,b}_{t,t+1}}{S^{X/Y,a}_{t+1}}. \tag{D8}$$

Assuming triangular no-arbitrage restrictions apply to the bid–ask quotes,

$$F^{X/Y,b}_{t,t+1} = F^{X/USD,b}_{t,t+1} \times F^{USD/Y,b}_{t,t+1} \quad \text{and} \quad S^{X/Y,a}_{t+1} = S^{X/USD,a}_{t+1} \times S^{USD/X,a}_{t+1}, \tag{D9}$$

we conclude that

$$RX^{X/Y}_{\text{long spot/sell forward}} = \frac{F^{X/USD,b}_{t,t+1} \times F^{USD/Y,b}_{t,t+1}}{S^{X/USD,a}_{t+1} \times S^{USD/Y,a}_{t+1}}. \tag{D10}$$

Taking logs,

$$rx^{X/Y}_{\text{long spot/sell forward}} = f^{X/USD,b}_{t,t+1} - s^{X/USD,a}_{t+1} + \left(f^{USD/Y,b}_{t,t+1} - s^{USD/Y,a}_{t+1}\right). \tag{D11}$$

Again we can express these returns using the USD as the base currency. In fact,

$$F^{X/USD,b}_{t,t+1} = \frac{1}{F^{USD/X,a}_{t,t+1}} \quad \text{and} \quad S^{X/USD,a}_{t+1} = \frac{1}{S^{USD/X,b}_{t+1}}. \tag{D12}$$

Therefore,

$$F^{X/Y,b}_{t,t+1} = \frac{F^{USD/Y,b}_{t,t+1}}{F^{USD/X,a}_{t,t+1}} \quad \text{and} \quad S^{X/Y,a}_{t+1} = \frac{S^{USD/Y,a}_{t+1}}{S^{USD/X,b}_{t+1}}. \tag{D13}$$

We conclude that

$$RX^{X/Y}_{\text{long spot/sell forward}} = \frac{F^{USD/Y,b}_{t,t+1} \times S^{USD/X,b}_{t+1}}{F^{USD/X,a}_{t,t+1} \times S^{USD/Y,a}_{t+1}}, \quad \text{so that in logs} \tag{D14}$$

$$rx^{X/Y}_{\text{long spot/sell forward}} = f^{USD/Y,b}_{t,t+1} - s^{USD/Y,a}_{t+1} - \left(f^{USD/X,a}_{t,t+1} - s^{USD/X,b}_{t+1}\right). \tag{D15}$$

Under the restrictive assumption, that in t no capital is pledged to sustain the long spot/sell forward position this is a dollar-neutral position. Analogous reasoning can be applied to derive the log excess return from going short in currency pair *X/Y*:

$$RX^{X/Y}_{\text{sell spot/long forward}} = \frac{F^{USD/X,b}_{t,t+1} \times S^{USD/Y,b}_{t+1}}{F^{USD/Y,a}_{t,t+1} \times S^{USD/X,a}_{t+1}}, \quad \text{so that in logs} \tag{D16}$$

$$rx^{X/Y}_{\text{sell spot/long forward}} = -f^{USD/Y,a}_{t,t+1} + s^{USD/Y,b}_{t+1} + \left(f^{USD/X,b}_{t,t+1} - s^{USD/X,a}_{t+1}\right). \tag{D17}$$

In Tables D.1 and D.2 we present the annualised Sharpe ratio (SR), the annualised mean excess return (*Mean*), the maximum drawdown (MDD) and the Θ performance measure of Goetzmann et al. (2007) based on monthly rebalancing for both a US

(USD) and European (EUR) investor perspective, respectively. For both tables, Panel a) and b) tabulate the *prior* and *after* transaction cost performance of the first (Q_1) and third (Q_3) tertile portfolios, where AIP_{HML} is a linear combination of going short the first and long the third tertile. The reported portfolio returns take into account the effect of compounding as well as document the performance of common FX trading strategies (e.g. carry, momentum and value). To overcome the curse of heteroscedasticity and autocorrelation we apply heteroscedasticity- and autocorrelation-consistent standard errors (HAC errors) using the plug-in procedure for automatic lag selection by Andrews and Monahan (1992) and Newey and West (1994). An important finding emerges: our 'high minus low' portfolio AIP_{HML} is dollar-neutral, since both the US and European centric views yield identical returns.

An alternative approach would consist of subtracting $\Delta s^*_{t,t+1}$ from Eq. (4.2), that is, the change in the *USD/X* spot rate to account for the fact that a US investor has only US dollars. The intuition is as follows: a US investor starts with a certain finite amount of USD he wishes to invest and values non-USD returns at the spot rates s_t and s_{t+1}, respectively.[6]

In Table D.3 we document the deviations from triangular no-arbitrage for all non-USD currency pairs and find *no* evidence of systematic deviations both in the spot and the 1-day ahead forward domain. Results are similar for forward rates specifying delivery in 1-week or 1-month, respectively. Deviations from triangular no-arbitrage are close to zero, except for the AUDJPY, EURAUD and GBPAUD. The bottom line is that relying on triangular no-arbitrage is robust to FX market anomalies such as covered interest rate parity (*CIP*) deviations or failure of no-arbitrage conditions.

[6]Also, to save transaction cost, the US investor could open up multiple currency accounts in $t = 0$ or make an annual accounting valuation at the mid-quote of the multi currency portfolio. Our results are robust and qualitatively unchanged for both alternatives.

Table D.1: Performance Benchmarking: AIP_{HML} - USD

Panel a) Gross Returns	DOL	RER_{HML}	RER	MOM_{HML}	CAR_{HML}	BMS	VOL_{LMH}	Q_1	Q_3	AIP_{HML}
SR	−0.11	−0.22	−0.22	−0.13	0.05	0.68	−0.54	*0.65	0.23	**0.83
	[0.33]	[0.53]	[0.58]	[0.32]	[0.16]	[1.49]	[1.25]	[1.84]	[0.59]	[2.35]
Mean in %	−0.33	−1.08	−0.71	−0.91	0.39	2.79	−3.20	**3.01	1.04	***4.05
	[0.33]	[0.52]	[0.58]	[0.31]	[0.16]	[1.48]	[1.24]	[1.97]	[0.58]	[3.01]
MDD in %	6.48	14.26	10.14	28.56	19.31	8.30	29.30	8.05	11.24	7.19
Scaled MDD	7.40	9.40	10.22	12.19	8.34	6.71	15.00	5.78	8.23	4.95
Θ in %	−0.41	−1.32	−0.81	−1.41	−0.14	2.62	−3.55	2.79	0.84	3.81
Skewness	0.56	0.12	−0.02	−0.30	−0.70	0.16	0.11	−0.10	0.69	0.15
Kurtosis-3	1.55	−0.40	0.16	0.88	0.81	−0.31	−0.10	1.66	1.17	9.45

Panel b) Net Returns	DOL	RER_{HML}	RER	MOM_{HML}	CAR_{HML}	BMS	VOL_{LMH}	Q_1	Q_3	AIP_{HML}
SR	−0.24	−0.38	−0.38	−0.24	−0.07	0.47	−0.69	0.55	0.13	**0.65
	[0.69]	[0.91]	[1.02]	[0.61]	[0.19]	[1.04]	[1.59]	[1.59]	[0.33]	[1.96]
Mean in %	−0.70	−1.88	−1.24	−1.74	−0.48	1.95	−4.10	*2.57	0.59	**3.16
	[0.70]	[0.92]	[1.02]	[0.60]	[0.19]	[1.03]	[1.58]	[1.69]	[0.33]	[2.35]
MDD in %	7.67	17.51	12.01	31.57	21.24	10.19	35.65	8.58	12.35	7.57
Scaled MDD	8.71	11.38	12.03	13.29	9.07	8.20	17.83	6.13	9.01	5.18
Θ in %	−0.78	−2.12	−1.34	−2.24	−1.01	1.78	−4.45	2.36	0.39	2.92
Skewness	0.56	0.10	−0.03	−0.31	−0.70	0.14	0.09	−0.13	0.68	0.10
Kurtosis-3	1.53	−0.38	0.16	0.91	0.81	−0.34	−0.10	1.71	1.15	9.46

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

Table D.2: Performance Benchmarking: AIP_{HML} - EUR

Panel a) Gross Returns	EUR	RER_{HML}	RER	MOM_{HML}	CAR_{HML}	BMS	VOL_{LMH}	Q_1	Q_3	AIP_{HML}
SR	−0.47	−0.22	−0.22	−0.13	0.05	0.68	−0.54	*0.65	0.23	**0.83
	[1.12]	[0.53]	[0.58]	[0.32]	[0.16]	[1.49]	[1.25]	[1.84]	[0.59]	[2.35]
Mean in %	−2.58	−1.08	−0.71	−0.91	0.39	2.79	−3.20	**3.01	1.04	***4.05
	[1.13]	[0.52]	[0.58]	[0.31]	[0.16]	[1.48]	[1.24]	[1.97]	[0.58]	[3.01]
MDD in %	25.08	14.26	10.14	28.56	19.31	8.30	29.30	8.05	11.24	7.19
Scaled MDD	13.95	9.40	10.22	12.19	8.34	6.71	15.00	5.78	8.23	4.95
Θ in %	−2.89	−1.32	−0.81	−1.41	−0.14	2.62	−3.55	2.79	0.84	3.81
Skewness	0.25	0.12	−0.02	−0.30	−0.70	0.16	0.11	−0.10	0.69	0.15
Kurtosis-3	−0.11	−0.40	0.16	0.88	0.81	−0.31	−0.10	1.66	1.17	9.45
Panel b) Net Returns	EUR	RER_{HML}	RER	MOM_{HML}	CAR_{HML}	BMS	VOL_{LMH}	Q_1	Q_3	AIP_{HML}
SR	−0.54	−0.38	−0.38	−0.24	−0.07	0.47	−0.69	0.55	0.13	**0.65
	[1.30]	[0.91]	[1.02]	[0.61]	[0.19]	[1.04]	[1.59]	[1.59]	[0.33]	[1.96]
Mean in %	−3.02	−1.88	−1.24	−1.74	−0.48	1.95	−4.10	*2.57	0.59	**3.16
	[1.32]	[0.92]	[1.02]	[0.60]	[0.19]	[1.03]	[1.58]	[1.69]	[0.33]	[2.35]
MDD in %	27.96	17.51	12.01	31.57	21.24	10.19	35.65	8.58	12.35	7.57
Scaled MDD	15.38	11.38	12.03	13.29	9.07	8.20	17.83	6.13	9.01	5.18
Θ in %	−3.33	−2.12	−1.34	−2.24	−1.01	1.78	−4.45	2.36	0.39	2.92
Skewness	0.25	0.10	−0.03	−0.31	−0.70	0.14	0.09	−0.13	0.68	0.10
Kurtosis-3	−0.11	−0.38	0.16	0.91	0.81	−0.34	−0.10	1.71	1.15	9.46

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

Table D.3: Deviations from No-Arbitrage

AUDJPY	RMSE	MAE	MAPE	MASE	AUDNZD	RMSE	MAE	MAPE	MASE	CADJPY	RMSE	MAE	MAPE	MASE
LastMidquote	0.007	0.001	0.004	0.007	LastMidquote	0.000	0.000	0.004	0.014	LastMidquote	0.085	0.004	0.009	0.017
LastBid	0.012	0.006	0.009	0.017	LastBid	0.000	0.000	0.015	0.045	LastBid	0.086	0.007	0.011	0.022
LastAsk	0.013	0.008	0.010	0.020	LastAsk	0.000	0.000	0.015	0.046	LastAsk	0.086	0.000	0.012	0.023
ForwardMid	0.080	0.005	0.051	0.094	ForwardMid	0.001	0.000	0.053	0.161	ForwardMid	0.085	0.004	0.009	0.018
ForwardBid	0.093	0.016	0.056	0.102	ForwardBid	0.001	0.000	0.057	0.174	ForwardBid	0.086	0.003	0.010	0.019
ForwardAsk	0.116	0.005	0.060	0.110	ForwardAsk	0.002	0.000	0.062	0.189	ForwardAsk	0.085	0.004	0.010	0.019
EURAUD	RMSE	MAE	MAPE	MASE	EURCAD	RMSE	MAE	MAPE	MASE	EURCHF	RMSE	MAE	MAPE	MASE
LastMidquote	0.000	0.000	0.003	0.006	LastMidquote	0.000	0.000	0.004	0.010	LastMidquote	0.000	0.000	0.004	0.016
LastBid	0.000	0.000	0.009	0.022	LastBid	0.000	0.000	0.008	0.019	LastBid	0.000	0.000	0.013	0.057
LastAsk	0.000	0.000	0.009	0.020	LastAsk	0.000	0.000	0.007	0.018	LastAsk	0.000	0.000	0.012	0.057
ForwardMid	0.001	0.000	0.052	0.124	ForwardMid	0.000	0.000	0.004	0.011	ForwardMid	0.000	0.000	0.004	0.018
ForwardBid	0.002	0.000	0.060	0.145	ForwardBid	0.000	0.000	0.005	0.013	ForwardBid	0.000	0.000	0.005	0.025
ForwardAsk	0.002	0.000	0.057	0.136	ForwardAsk	0.000	0.000	0.004	0.011	ForwardAsk	0.000	0.000	0.005	0.024
EURDKK	RMSE	MAE	MAPE	MASE	EURGBP	RMSE	MAE	MAPE	MASE	EURJPY	RMSE	MAE	MAPE	MASE
LastMidquote	0.001	0.000	0.003	0.225	LastMidquote	0.000	0.000	0.003	0.008	LastMidquote	0.009	0.000	0.003	0.007
LastBid	0.002	0.001	0.013	0.830	LastBid	0.000	0.000	0.008	0.021	LastBid	0.016	0.010	0.009	0.020
LastAsk	0.002	0.001	0.013	0.827	LastAsk	0.000	0.000	0.007	0.019	LastAsk	0.016	0.009	0.008	0.019
ForwardMid	0.001	0.000	0.003	0.276	ForwardMid	0.000	0.000	0.003	0.009	ForwardMid	0.011	0.001	0.004	0.009
ForwardBid	0.001	0.000	0.004	0.342	ForwardBid	0.000	0.000	0.004	0.011	ForwardBid	0.014	0.001	0.005	0.012
ForwardAsk	0.001	0.000	0.004	0.355	ForwardAsk	0.000	0.000	0.004	0.012	ForwardAsk	0.013	0.000	0.005	0.011
EURNOK	RMSE	MAE	MAPE	MASE	EURSEK	RMSE	MAE	MAPE	MASE	GBPAUD	RMSE	MAE	MAPE	MASE
LastMidquote	0.002	0.000	0.006	0.018	LastMidquote	0.002	0.000	0.006	0.020	LastMidquote	0.000	0.000	0.003	0.007
LastBid	0.003	0.001	0.020	0.056	LastBid	0.003	0.001	0.017	0.056	LastBid	0.000	0.000	0.009	0.018
LastAsk	0.003	0.002	0.021	0.059	LastAsk	0.003	0.001	0.018	0.058	LastAsk	0.000	0.000	0.008	0.018
ForwardMid	0.002	0.000	0.007	0.019	ForwardMid	0.002	0.000	0.006	0.021	ForwardMid	0.002	0.000	0.052	0.110
ForwardBid	0.002	0.000	0.007	0.020	ForwardBid	0.004	0.000	0.008	0.027	ForwardBid	0.002	0.000	0.061	0.129
ForwardAsk	0.002	0.000	0.007	0.020	ForwardAsk	0.003	0.000	0.007	0.024	ForwardAsk	0.002	0.000	0.056	0.119
GBPCAD	RMSE	MAE	MAPE	MASE	GBPCHF	RMSE	MAE	MAPE	MASE	GBPJPY	RMSE	MAE	MAPE	MASE
LastMidquote	0.000	0.000	0.004	0.010	LastMidquote	0.000	0.000	0.003	0.007	LastMidquote	0.179	0.009	0.009	0.017
LastBid	0.000	0.000	0.008	0.018	LastBid	0.000	0.000	0.007	0.018	LastBid	0.178	0.000	0.014	0.026
LastAsk	0.000	0.000	0.007	0.017	LastAsk	0.000	0.000	0.008	0.019	LastAsk	0.180	0.018	0.014	0.026
ForwardMid	0.000	0.000	0.004	0.010	ForwardMid	0.000	0.000	0.003	0.007	ForwardMid	0.179	0.009	0.010	0.018
ForwardBid	0.000	0.000	0.004	0.010	ForwardBid	0.000	0.000	0.003	0.007	ForwardBid	0.179	0.010	0.010	0.019
ForwardAsk	0.000	0.000	0.004	0.010	ForwardAsk	0.000	0.000	0.003	0.007	ForwardAsk	0.179	0.009	0.010	0.019

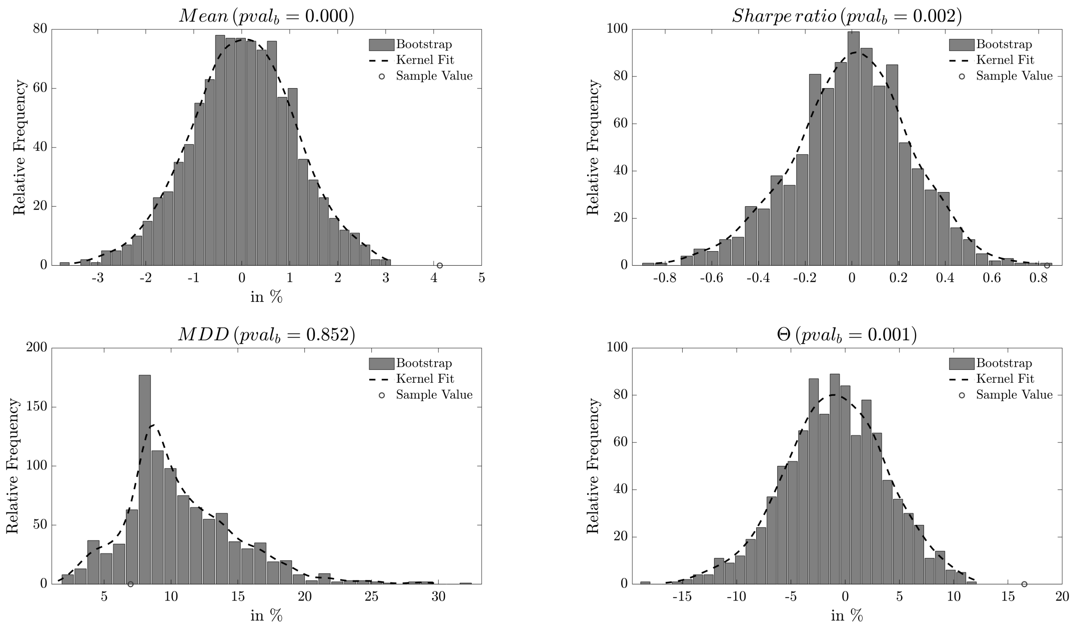
Note: This table tabulates the Root Mean Square Error (*RMSE*), Mean Absolute Error (*MAE*), Mean Absolute Percentage Error (*MAPE* in %), Mean Absolute Scaled Error (*MASE*) from replicating all non-USD currency pairs by imposing triangular no-arbitrage conditions and comparing the implied synthetic rate to the rates derived from Olsen and Bloomberg, respectively. All forward rates refer to a delivery in 1 day.

Table D.4: Performance Benchmarking: AIP_{HML} - Bootstrap

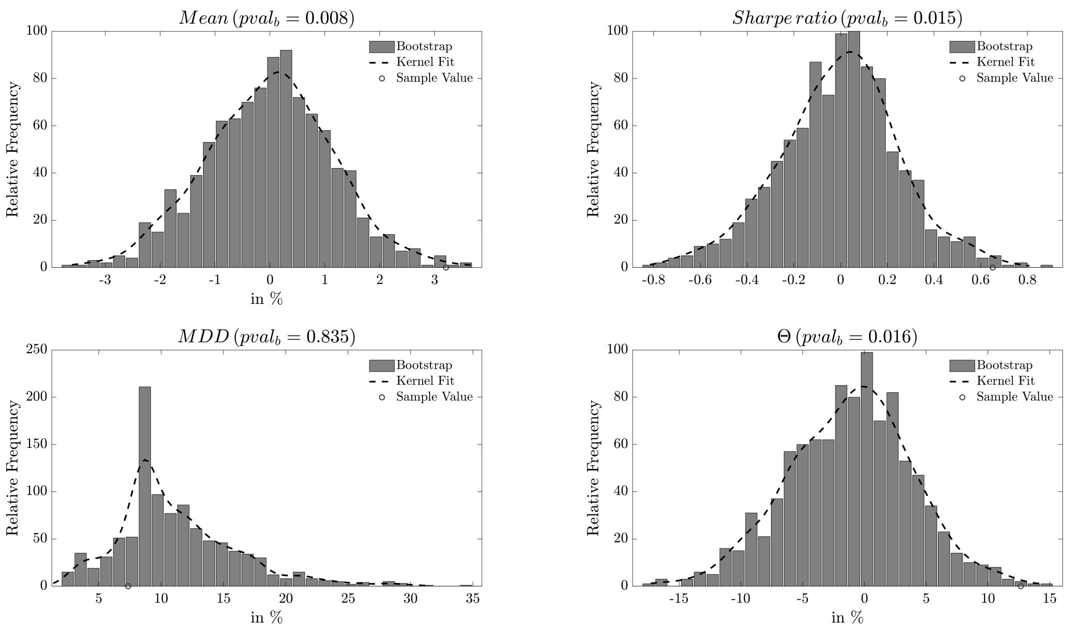
Panel a) Gross Returns	DOL	RER_{HML}	RER	MOM_{HML}	CAR_{HML}	BMS	VOL_{LMH}	Q_1	Q_3	AIP_{HML}
SR	−0.11	−0.22	−0.22	−0.13	0.05	0.68	−0.54	*0.65	0.23	**0.83
	[0.33]	[0.53]	[0.58]	[0.32]	[0.16]	[1.49]	[1.25]	[1.84]	[0.59]	[2.35]
Mean in %	−0.33	−1.08	−0.71	−0.91	0.39	2.79	−3.20	3.01	1.04	***4.05
	[0.04]	[0.26]	[0.24]	[0.71]	[1.16]	[0.95]	[0.71]	[1.57]	[0.21]	[3.16]
MDD in %	6.48	14.26	10.14	28.56	19.31	8.30	29.30	8.05	11.24	7.19
Scaled MDD	7.40	9.40	10.22	12.19	8.34	6.71	15.00	5.78	8.23	4.95
Θ in %	−0.41	−1.32	−0.81	−1.41	−0.14	2.62	−3.55	2.79	0.84	3.81
Skewness	0.56	0.12	−0.02	−0.30	−0.70	0.16	0.11	−0.10	0.69	0.15
Kurtosis-3	1.55	−0.40	0.16	0.88	0.81	−0.31	−0.10	1.66	1.17	9.45
Panel b) Net Returns	DOL	RER_{HML}	RER	MOM_{HML}	CAR_{HML}	BMS	VOL_{LMH}	Q_1	Q_3	AIP_{HML}
SR	−0.24	−0.38	−0.38	−0.24	−0.07	0.47	−0.69	0.55	0.13	**0.65
	[0.69]	[0.91]	[1.02]	[0.61]	[0.19]	[1.04]	[1.59]	[1.59]	[0.33]	[1.96]
Mean in %	−0.70	−1.88	−1.24	−1.74	−0.48	1.95	−4.10	2.57	0.59	**3.16
	[0.89]	[0.33]	[0.46]	[0.14]	[1.07]	[0.46]	[1.08]	[1.27]	[0.71]	[2.52]
MDD in %	7.67	17.51	12.01	31.57	21.24	10.19	35.65	8.58	12.35	7.57
Scaled MDD	8.71	11.38	12.03	13.29	9.07	8.20	17.83	6.13	9.01	5.18
Θ in %	−0.78	−2.12	−1.34	−2.24	−1.01	1.78	−4.45	2.36	0.39	2.92
Skewness	0.56	0.10	−0.03	−0.31	−0.70	0.14	0.09	−0.13	0.68	0.10
Kurtosis-3	1.53	−0.38	0.16	0.91	0.81	−0.34	−0.10	1.71	1.15	9.46

Note: This table presents the out-of-sample economic performance of the ALP_{HML} strategy *before* and *after* transaction cost based on monthly rebalancing. Panel a) reports the annualised Sharpe ratio (SR), the annualised average (simple) *gross* excess return (*Mean*), skewness, excess kurtosis (Kurtosis-3), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD) and the Θ performance measure of Goetzmann et al. (2007) for the tertile portfolios (Q_1, Q_2, Q_3) based on the uniform distribution. Panel b) lists the same measures as Panel a) but *after* transaction cost. DOL is based on an equally weighted long portfolio of all USD currency pairs, RER/RER_{HML} on the real exchange rate (cf. Menkhoff et al., 2017), MOM_{HML} on $f_{t-1,t} - s_t$ (cf. Asness et al., 2013), CAR_{HML} on the forward discount/premium ($f_{t,t+1} - s_t$, cf. Lustig et al., 2011), BMS is based on lagged standardised order flow (cf. Menkhoff et al., 2016) and VOL_{LMH} is based on currency pairs' exposure to the global volatility factor (cf. Menkhoff et al., 2012a). Significant findings at the 90%, 95% and 99% levels are represented by asterisks *, ** and ***, respectively. The numbers inside the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on bootstrapped p-values using 5 000 bootstrap repetitions.

Figure D.1: Bootstrapped Economic Performance of AIP_{HML}



(a) Before Transaction Cost



(b) After Transaction Cost

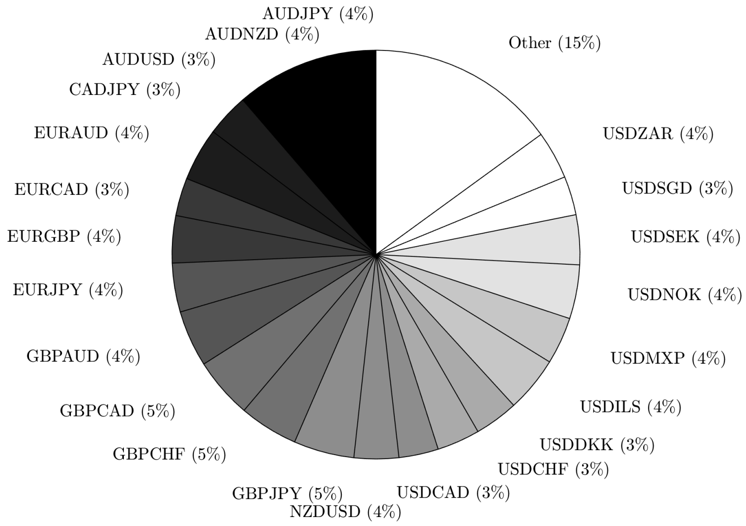
Note: Panels a) and b) depict bootstrapped p-values using 1000 bootstrap repetitions for AIP_{HML} before and after transaction cost, respectively. The upper-left plot displays the annualised mean excess return (*Mean*), the upper-right plot displays the annualised Sharpe ratio, the lower-left plot displays the maximum drawdown (*MDD*) and the lower-right plot displays the Θ performance measure of Goetzmann et al. (2007) based on monthly rebalancing. The bootstrapped p-values ($pval_b$) are reported in parenthesis in the titles.

Table D.5: Correlation with Common FX Risk Factors in %

	ΔVIX	ΔCDX	ΔTED	DOL	RER_{HML}	RER	MOM_{HML}	CAR_{HML}	BMS	VOL_{LMH}
ΔCDX	***71.41									
ΔTED	8.16	9.03								
DOL	−5.50	**−24.39	7.72							
RER_{HML}	6.08	−7.25	9.99	*21.89						
RER	−3.61	*−19.67	3.22	***59.26	***61.99					
MOM_{HML}	7.77	7.89	−0.72	−12.05	−6.13	−7.47				
CAR_{HML}	−11.72	−9.01	−7.32	*21.13	***−39.90	17.02	−17.25			
BMS	−7.47	−3.95	12.76	−6.47	−17.55	−16.60	*22.57	−8.13		
VOL_{LMH}	4.90	−14.00	−1.88	***87.59	**28.91	***63.53	−8.69	*19.45	−3.97	
AIP_{HML}	2.45	7.19	−9.62	**−24.75	−7.37	***−36.99	*20.96	***−43.60	1.08	**−25.09

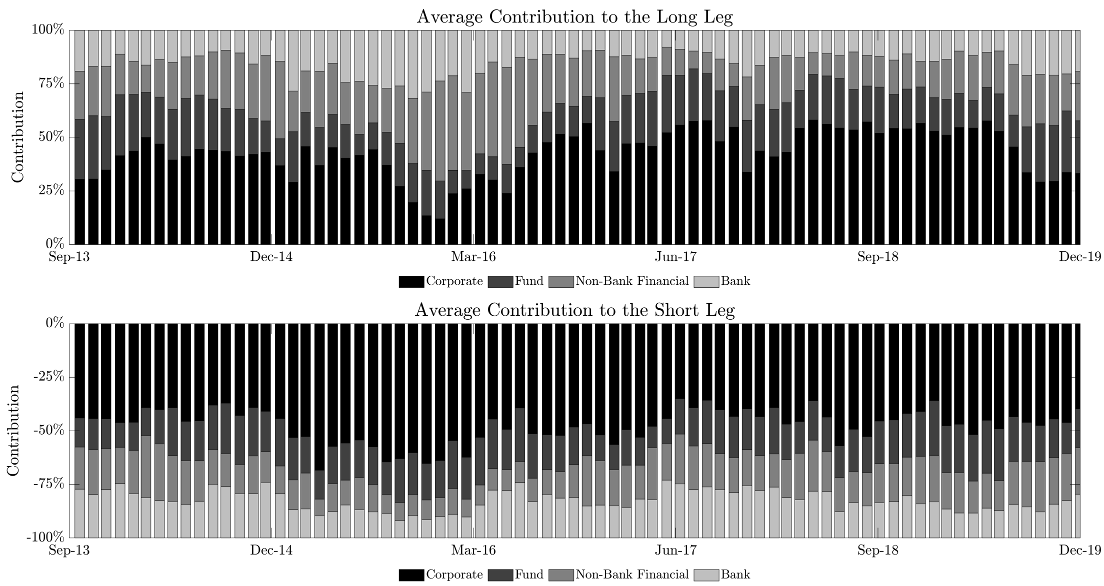
Note: This table shows the time series cross-correlation at lag 0 between the *gross* excess return of AIP_{HML} and the returns associated with different FX risk factors, where DOL is the return on the basket of USD currency pairs, RER/RER_{HML} are based on the real exchange rate (cf. Menkhoff et al., 2017), MOM_{HML} is based on $f_{t-1,t} - s_t$ (cf. Asness et al., 2013), CAR_{HML} is based on the forward discount/premium ($f_{t,t+1} - s_t$, cf. Lustig et al., 2011), BMS is based on lagged standardised order flow (cf. Menkhoff et al., 2016) and VOL_{LMH} is based on currency pairs' exposure to the global volatility factor (cf. Menkhoff et al., 2012a). ΔVIX is the return on the VIX index and ΔCDX and ΔTED are relative changes in the North American credit default swap index and the TED spread, respectively. Significant correlations at the 90%, 95% and 99% levels are represented by asterisks *, ** and ***, respectively.

Figure D.2: Distribution of Absolute Currency Exposure



Note: This figure shows the result of summing up the absolute exposure to each currency pair over time and then normalising to one. 'Other' comprise currency pairs with a relative share $\leqslant$ 3%: EURCHF, EURDKK, EURNOK, EURSEK, EURUSD, GBPUSD, USDCAD, USDHKD and USDJPY.

Figure D.3: Average Contribution to the *Long* and *Short* Leg



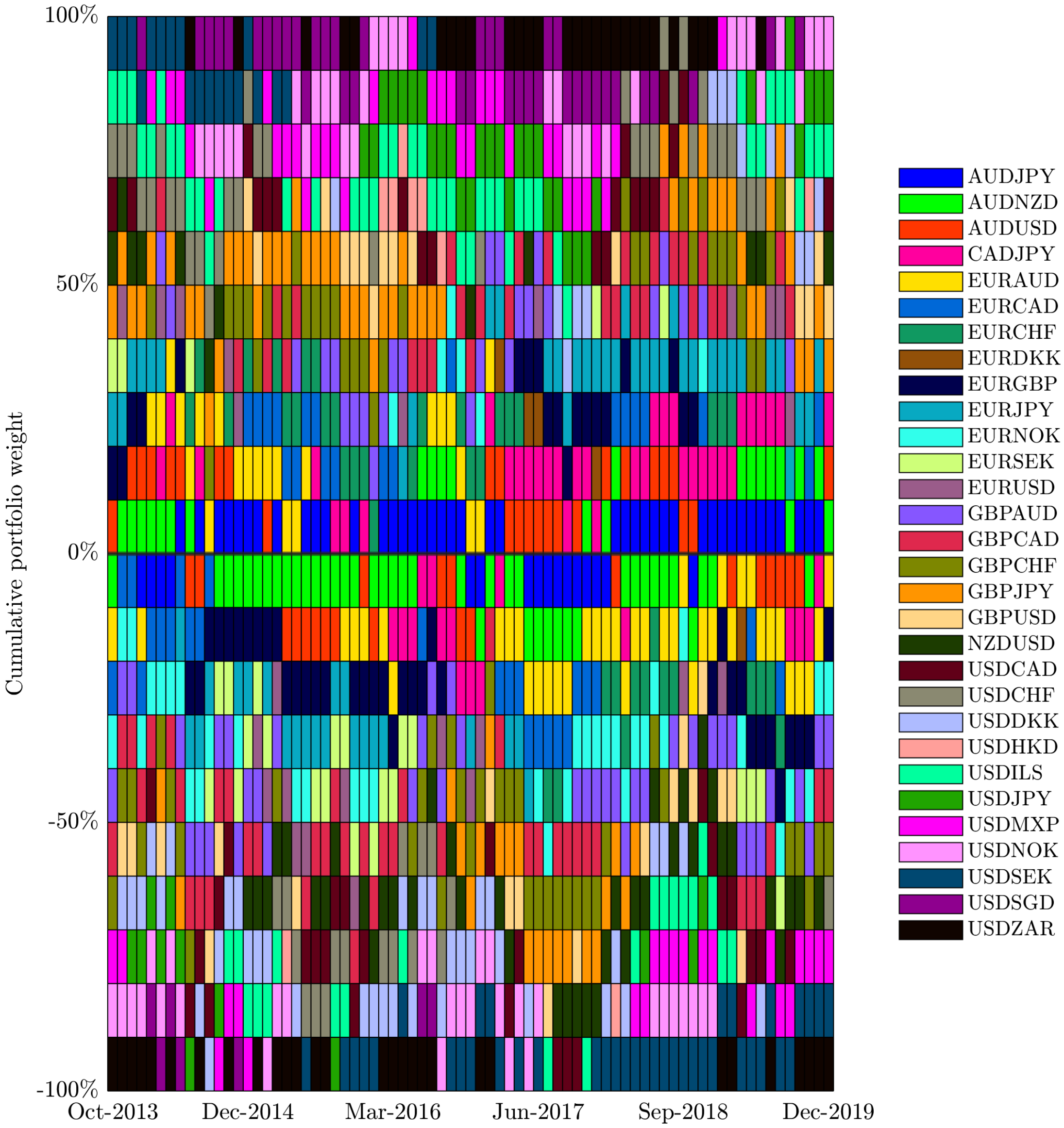
Note: For every currency pair k, the relative share of each agent's $\alpha_m^{j,k}$ to the average $\bar{\alpha}_m^k$ is computed, and eventually the mean is calculated across all currency pairs.

Table D.6: Exposure Regression Based on Monthly *Gross* Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept (α) in %	***4.05	**3.56	**3.54	**3.60	**3.70	***3.82	**3.52	**3.45	**4.03
	[3.09]	[2.46]	[2.40]	[2.45]	[2.42]	[2.88]	[2.26]	[2.31]	[2.55]
DOL		−0.20	−0.20	0.00	−0.19	−0.10	−0.20	0.01	0.08
		[1.46]	[1.35]	[0.03]	[1.48]	[0.91]	[1.40]	[0.08]	[0.66]
RER_{HML}			−0.04						
			[0.36]						
RER				***−0.37					***−0.36
				[2.61]					[2.77]
MOM_{HML}					0.20				
					[1.45]				
CAR_{HML}						**−0.41			**−0.40
						[2.21]			[2.27]
BMS							0.01		−0.06
							[0.11]		[0.55]
VOL_{LMH}								−0.24	
								[1.17]	
ΔVIX		−0.02	−0.01	0.02	−0.03	−0.09	−0.02	0.00	−0.06
		[0.13]	[0.08]	[0.12]	[0.19]	[0.57]	[0.12]	[0.03]	[0.37]
ΔTED		−0.10	−0.10	−0.10	−0.10	*−0.14	−0.10	−0.12	−0.12
		[1.17]	[1.09]	[0.94]	[1.07]	[1.67]	[1.26]	[1.29]	[1.31]
ΔCDS		0.04	0.03	−0.01	0.03	0.07	0.04	0.04	0.03
		[0.20]	[0.16]	[0.08]	[0.20]	[0.37]	[0.20]	[0.22]	[0.14]
R^2 in %	N/A	5.68	5.80	14.82	9.67	21.34	5.70	6.96	29.59
IR	0.24	0.22	0.22	0.23	0.23	0.26	0.21	0.21	0.28
#Obs	75	75	75	75	75	75	75	75	75

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

Figure D.4: Cumulative Portfolio Weights



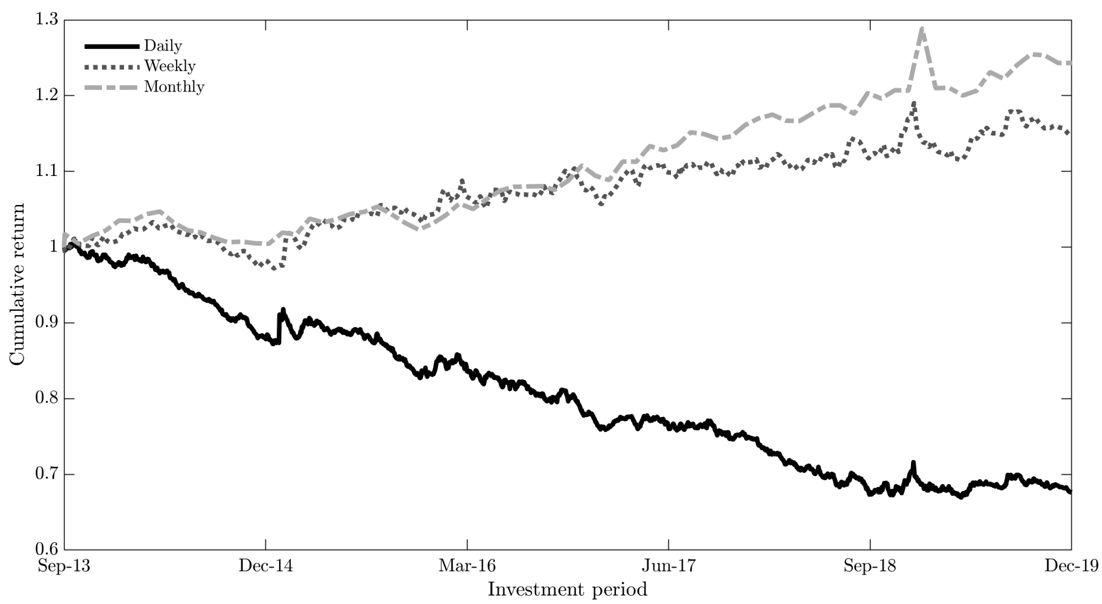
Note: This figure displays the time evolution of the cumulative portfolio weights of our baseline strategy (AIP_{HML}). For every month we document which currency pairs are gone short and long, respectively. Currency pairs that do not show up within a certain period are not invested at all in that particular period. By construction the cumulative weights of the long and short leg sum up to zero. Within each leg (long and short), every currency pair receives an equal weight of 10%.

Appendix E Transaction Cost

50% Rule. In recent works, Goyal and Saretto (2009), Gilmore and Hayashi (2011), Menkhoff et al. (2016) and Gargano et al. (2018) argue that the effective spread is less than 50% of the quoted bid–ask spread. Therefore, the goal of this chapter is twofold: First, analyse the distribution of transaction cost for daily, weekly and monthly rebalancing frequencies. Second, illustrate how the performance can be improved by optimising trading cost.

Despite being conservative in the way that we incorporate transaction cost into our analysis we are not able to fully incorporate all 'real world' trading cost. Additional costs can include price 'slippage' and spreads widening when transaction sizes are particularly large. In a real world setting, both of these effects that would typically lower returns should be incorporated by market participants when entering higher frequency strategies (daily/weekly). Therefore, our returns should be regarded as a benchmark to market participants who do not trade particularly large volumes and hence have smaller price impacts. However, following Goyal and Saretto (2009) and Menkhoff et al. (2016) our approach might be too conservative. Following Menkhoff

Figure E.1: Cumulative Returns After Transaction Cost - 50% Rule



Note: Cumulative returns are calculated applying only half of the bid–ask spread to every transaction. For non-daily rebalancing frequencies missing data points are interpolated linearly.

et al. (2016) and Gargano et al. (2018) we apply the 50% rule to our trading strategy. When paying only 50% of the actual spread per trade the annualised SR and return of AIP_{HML} raise to 0.74 and 3.51%, respectively. Figure E.1 shows the performance boost graphically for different rebalancing frequencies. As expected, the raise in cumulative returns is sharpest for daily rebalancing followed by weekly and monthly.

Rolling Over Forward Contracts. We follow the methodology outlined in Gilmore and Hayashi (2011) and build upon Appendix D to derive the after transaction cost excess returns for rolling over n successive periods for both a single currency pair and a portfolio of currency pairs.[7]

The spot bid–ask spread is $S_t^a - S_t^b$, where S_t^a (S_t^b) is the ask (*bid*) rate against the USD. The mid-quote is defined as $S_t \equiv \frac{(S_t^a + S_t^b)}{2}$ and we have that $S_t^a > S_t > S_t^b$. Forward rates can be expressed as the forward discount/premium (or forward points alternatively) plus the spot rate. Therefore the (outright) forward bid–ask rates are $F_t^b = S_t^b + P_t^b$ and $F_t^a = S_t^a + P_t^a$, respectively, where P_t^b and P_t^a denote the bid–ask values of forward points. Given that forward ask points are always larger than bid points and given $S_t^a > S_t^b$ we must have that the bid–ask spread should be wider for the forward outright rate than for the spot rate with $F_t^a > F_t > F_t^b$, where $F_t \equiv \frac{(F_t^a + F_t^b)}{2}$ is the mid forward quote.[8]

Ignoring bid–ask spreads and using mid-quotes the log excess return in USD from taking long positions on the 1-period forward contract over n consecutive periods from 0 to n is

$$rx_{0,\text{n}}^{\text{X/Y},(1)} \equiv \sum_{t=0}^{n} \left(f_{t,t+1}^{\text{USD/Y}} - s_{t+1}^{\text{USD/Y}} - \left(f_{t,t+1}^{\text{USD/X}} - s_{t+1}^{\text{USD/X}} \right) \right) , \tag{E1}$$

where lower case letters denote logarithmic variables and X and Y are the base and quote currency of a non-USD currency pair, respectively, to account for the possibility of investing into non-USD currency pair such as the *EURGBP*.

When incorporating bid–ask spreads for an investor who unwinds the forward position at the end of every period by going into the spot market and then at the same time reopens a new forward position, the net long excess return in Eq. (E1)

[7] Transaction cost in FX spot and future markets are studied, for example, in Bollerslev and Melvin (1994), Huang and Masulis (1999), Christiansen et al. (2011), Gilmore and Hayashi (2011) and Mancini et al. (2013).

[8] Forward points can be negative if the interest rate on the foreign currency is less than that on the home currency. In this case, the forward ask points will be larger (i.e. less negative) than the forward bid points.

becomes

$$rx_{0,\mathrm{n}}^{\mathrm{X/Y},(2.1)} \equiv \sum_{t=0}^{n} \left(f_{t,t+1}^{\mathrm{USD/Y},b} - s_{t+1}^{\mathrm{USD/Y},a} - \left(f_{t,t+1}^{\mathrm{USD/X},a} - s_{t+1}^{\mathrm{USD/X},b} \right) \right) . \tag{E2}$$

Since log returns are symmetric, the short excess return is simply the inverse of the long excess return

$$rx_{0,\mathrm{n}}^{\mathrm{X/Y},(2.2)} \equiv \sum_{t=0}^{n} \left(-f_{t,t+1}^{\mathrm{USD/Y},a} + s_{t+1}^{\mathrm{USD/Y},b} + \left(f_{t,t+1}^{\mathrm{USD/X},b} - s_{t+1}^{\mathrm{USD/X},a} \right) \right) . \tag{E3}$$

Therefore, after every period (i.e. day, week or month) the investor gets hit by the difference between the bid and the mid when opening a forward position and by the difference between offer and mid when unwinding. According to Gilmore and Hayashi (2011) most of these heavy transaction cost can be avoided if the position is rolled, that is, if the position is not unwound, but is instead extended over consecutive periods. Entering a FX swap allows the investor to roll a position immediately prior to maturity. The advantage is that the spot legs of the transaction cancel out and therefore the investor should save the bid–ask to be paid on the spot. Hence, long excess returns under rolling operation are given by

$$\begin{aligned} rx_{0,\mathrm{n}}^{\mathrm{X/Y},(3.1)} \equiv & \left(f_{0,1}^{\mathrm{USD/Y},b} - s_{1}^{\mathrm{USD/Y}} - \left(f_{0,1}^{\mathrm{USD/X},a} - s_{1}^{\mathrm{USD/X}} \right) \right) + \ldots \\ \ldots + & \sum_{t=1}^{n-1} \left[\tilde{f}_{t,t+1}^{\mathrm{USD/Y},l} - s_{t+1}^{\mathrm{USD/Y}} - \left(f_{t,t+1}^{\mathrm{USD/X},l} - s_{t+1}^{\mathrm{USD/X}} \right) \right] + \ldots \\ \ldots + & \left(\tilde{f}_{n-1,n}^{\mathrm{USD/Y},l} - s_{n}^{\mathrm{USD/Y},a} - \left(\tilde{f}_{n-1,n}^{\mathrm{USD/X},l} - s_{n}^{\mathrm{USD/X},b} \right) \right) , \end{aligned} \tag{E4}$$

where $\tilde{f}_t^l \equiv \log(S_t^b + P_t^b)$. By simple algebra we get that $\tilde{f}_t^l \equiv f_t + \log(1 - Z_t^l)$, where $Z_t^l = \frac{1}{2}\frac{(F_t^a - F_t^b) - (S_t^a - S_t^b)}{F_t}$. Hence, the investor pays the difference between the bid and mid upon entry (at the end of period 0), pays half times the bid–ask in the forward points in between, and then pays the difference between ask and mid when exiting (at the end of month n). Similar considerations lead to the short excess return

$$\begin{aligned} rx_{0,\mathrm{n}}^{\mathrm{X/Y},(3.2)} \equiv & \left(-f_{0,1}^{\mathrm{USD/Y},a} + s_{1}^{\mathrm{USD/Y}} + \left(f_{0,1}^{\mathrm{USD/X},b} - s_{1}^{\mathrm{USD/X}} \right) \right) + \ldots \\ \ldots + & \sum_{t=1}^{n-1} \left[-\tilde{f}_{t,t+1}^{\mathrm{USD/Y},s} + s_{t+1}^{\mathrm{USD/Y}} + \left(f_{t,t+1}^{\mathrm{USD/X},s} - s_{t+1}^{\mathrm{USD/X}} \right) \right] + \ldots \\ \ldots + & \left(-\tilde{f}_{n-1,n}^{\mathrm{USD/Y},s} + s_{n}^{\mathrm{USD/Y},b} + \left(\tilde{f}_{n-1,n}^{\mathrm{USD/X},l} - s_{n}^{\mathrm{USD/X},a} \right) \right) , \end{aligned} \tag{E5}$$

where $\tilde{f}_t^s \equiv \log(S_t^a + P_t^a)$ and by algebraic manipulation we get that $\tilde{f}_t^s \equiv f_t + log(1 - Z_t^s)$, where $Z_t^s = \frac{1}{2}\frac{(S_t^a - S_t^b) - (F_t^a - F_t^b)}{F_t}$. More precisely, the ratio of Eq. (E4) to Eq. (E1) and Eq. (E5) to Eq. (E1), respectively, reduces to

$$\left(f_{0,1}^{\text{USD/Y},b} - f_{0,1}^{\text{USD/X},a} - (f_{0,1}^{\text{USD/Y}} - f_{0,1}^{\text{USD/X}})\right) + \dots \tag{E6}$$
$$\dots + \left(s_n^{\text{USD/Y},a} - s_n^{\text{USD/X},b} - (s_n^{\text{USD/Y}} - s_n^{\text{USD/X}})\right) + \sum_{t=1}^{n-1} \log(1 - Z_t)\,,$$

for going long and to the opposite for going short

$$\left(-f_{0,1}^{\text{USD/Y},a} + f_{0,1}^{\text{USD/X},b} + (f_{0,1}^{\text{USD/Y}} - f_{0,1}^{\text{USD/X}})\right) + \dots \tag{E7}$$
$$\dots + \left(-s_n^{\text{USD/Y},b} + s_n^{\text{USD/X},a} + (s_n^{\text{USD/Y}} - s_n^{\text{USD/X}})\right) - \sum_{t=1}^{n-1} \log(1 - Z_t)\,,$$

Hence, according to Gilmore and Hayashi (2011) transaction cost reduce the geometric long (log) mean excess return per annum by approximately

$$R \times \left[\frac{1}{n}(\text{forward bid–ask spread} + \text{spot bid–ask spread})\right] + R \times \bar{Z}\,, \tag{E8}$$

and short (short) mean excess return by:

$$R \times \left[\frac{1}{n}(-\text{forward bid–ask spread} - \text{spot bid–ask spread})\right] - R \times \bar{Z}\,, \tag{E9}$$

respectively, where R is the number of trading days, weeks or months per year and $\bar{Z} \equiv \frac{1}{n-1}\sum_{t=1}^{n-1} Z_t$. The variable Z_t is the roll cost that has to be incurred every period, while the expression in square brackets in Eq. (E8) refers to the 'entry/exit' cost. Latter is divided by n since it only occurs once. When the number of periods n goes to infinity the bid–ask spreads are insignificant and the annual transaction cost is about roughly R times the annualised average roll cost. It is important to note that similar to Gilmore and Hayashi (2011) our historical transaction cost estimates should be viewed as providing only indicative orders of magnitude for the marginal cost faced by entities that have direct access to the OTC interbank foreign exchange market. There are at least three reasons why the effective costs faced by market participants who seek to implement this strategy might differ from our estimates. First, quoted Olsen spreads might not be accessible to every market participants due to insufficient credit lines or exclusive dealing relationships. According to Frankel and Poonawala (2010) this is particularly the case for emerging market currencies such as the USDILS, USDMXP, USDSGD or USDZAR. Second, larger trading volumes might not be available to be traded at the best bid–ask rates. Due to obvious reasons this is less of an issue for rolling over positions than direct sport transactions. Third, liquidity and time of the day influence spreads (see Ranaldo, 2009, Karnaukh et al., 2015). For example bid–ask spreads are wider on Latin American currencies in Asian hours or in European hours prior to the opening of the US markets.

So far, we have dealt with transaction cost for going long/short in a single currency pair. Now we turn our attention to portfolio excess returns. As before, by subscript k we denote the investment to currency $k \in$ [currency pairs]. Therefore, the notation is:

- $w_{k,t-1}$ is the position in currency k in units of the foreign currency, at the end of $t-1$ to be carried over to the next period t.
- $u_{k,t}$ is the amount, in units of foreign currency, to be unwind at the end of period t.
- $v_{k,t}$ is the amount, in units of foreign currency, to open at the end of period t.

Since *log* returns are *not* asset additive we use hereinafter simple returns rather than log returns. Given the notation above, the rolled position to be carried over to the next month $t+1$ is equal to $(w_{k,t-1} - u_{k,t})\frac{\tilde{F}_{k,t}}{S_{k,t}}$ and the value of the long position in every point in time is governed by

$$w_{k,t} = (w_{k,t-1} - u_{k,t})\frac{\tilde{F}_{k,t}}{S_{k,t}} + v_{k,t}, \tag{E10}$$

where $\tilde{F}_{k,t} \equiv F_{k,t}(1 - Z_{k,t})$ and $Z_{k,t} = \frac{1}{2}\frac{(F^a_{k,t} - F^b_{k,t}) - (S^a_{k,t} - S^b_{k,t})}{F_{k,t}}$. Due to symmetry the value of a short position is simply the inverse of the long position with bid–ask rates swapped around. We can rewrite this as

$$w_{k,t} = \left(\hat{w}_{k,t-1} - (\hat{u}_{k,t} - \hat{v}_{k,t})\right)\tilde{F}_{k,t}, \tag{E11}$$

where we define $\hat{w}_{k,t-1}$, $\hat{u}_{k,t}$ and $\hat{v}_{k,t}$ to be $\frac{w_{k,t-1}}{S_{k,t}}$, $\frac{u_{k,t}}{S_{k,t}}$ and $\frac{v_{k,t}}{\tilde{F}_{k,t}}$, respectively. This expression can be interpreted as the net deduction in units of domestic currency from investment in foreign currency k. $\hat{v}_{k,t}$ is the gross addition, while $\hat{u}_{k,t}$ is the gross deduction in domestic currency units. Assuming for simplicity that portfolio returns are reinvested continuously and no new funds are added to the portfolio, the following identity must hold for a long portfolio

$$\sum_{k=1}^{K} \frac{u_{k,t}}{S_{k,t}^{a}} = \sum_{k=1}^{K} \frac{v_{k,t}}{F_{k,t}^{b}}, \tag{E12}$$

and using 'hat' notation this self-sufficiency condition can be rewritten as

$$\sum_{k=1}^{K} \frac{S_{k,t}}{S_{k,t}^{a}} \hat{u}_{k,t} = \sum_{k=1}^{K} \frac{\tilde{F}_{k,t}}{F_{k,t}^{b}} \hat{v}_{k,t} \tag{E13}$$

Gilmore and Hayashi (2011) show algebraically that in order to maximise returns from rolling over the portfolio, it is necessary that $\hat{u}_{k,t} \times \hat{v}_{k,t} = 0$. However, the net portfolio deduction ($\sum_{k=1}^{K} \hat{u}_{k,t} - \hat{v}_{k,t}$) is positive, because

$$\sum_{k=1}^{K} \hat{u}_{k,t} - \sum_{k=1}^{K} \hat{v}_{k,t} > \sum_{k=1}^{K} \frac{S_{k,t}}{S_{k,t}^{a}} \hat{u}_{k,t} - \sum_{k=1}^{K} \frac{\tilde{F}_{k,t}}{F_{k,t}^{b}} \hat{v}_{k,t} = 0, \tag{E14}$$

where the inequality holds if for some currency pair k either $\hat{u}_{k,t} > 0$ or $\hat{v}_{k,t} > 0$. The last equality is due to Eq. (E13). This positive sum shall be interpreted as the cost of portfolio rebalancing. Theoretically, to minimise rebalancing costs we would need to identify for each t a set of constituent currencies such that $\hat{u}_{k,t} > 0$ and a disjoint set such that $\hat{v}_{k,t} > 0$. This could be done by solving the following optimisation problem:

$$\min \sum_{k=1}^{K} (\hat{u}_{k,t} - \hat{v}_{k,t}) \tag{E15}$$
$$s.t.$$
$$Eq.\ (\text{E12}), \hat{u}_{k,t} > 0, \hat{v}_{k,t} > 0,$$
$$\hat{w}_{k,t-1} - (\hat{u}_{k,t} - \hat{v}_{k,t}) = \omega_{k,t} \times \left(\sum_{i=1}^{K} \hat{w}_{i,t-1} - \sum_{i=1}^{K} (\hat{u}_{i,t} - \hat{v}_{i,t}) \right) \text{ for } k = 1, 2, ..., K,$$

where $\omega_{k,t}$ are the portfolio weights that shall sum up to unity. However, for our purposes we need to follow trading signals generated by the procedure described in *Currency Portfolios* (Section 6). Hence, we roll currency k over, *iff* the trading signal in t indicates that currency pair k shall be part of the same leg as it was in $t-1$. In this setting, the cumulative gross long excess return over a n period horizon is given by:

$$\frac{\sum_{k=1}^{K} w_{k,n-1} \times S_{k,0}^{\text{USD/X},b} \,/\, S_{k,n}^{\text{USD/Y},a}}{\sum_{k=1}^{K} w_{k,0} \times F_{k,n}^{\text{USD/X},a} / F_{k,0}^{\text{USD/Y},b}}, \tag{E16}$$

where the rolling over process is repeated until $t = n$ when the US-investor's position in foreign currency units is unwound and converted to USD at the spot ask rate. Considering transaction cost the cumulative excess return can be decomposed as:

$$\frac{\sum_{k=1}^{K} w_{k,0} \times S_{k,0}^{\text{USD/X}} \,/\, S_{k,1}^{\text{USD/Y}}}{\sum_{k=1}^{K} w_{k,0} \times F_{k,1}^{\text{USD/X},a} \,/\, F_{k,0}^{\text{USD/Y},b}} \times \prod_{t=1}^{n} \frac{\sum_{k=1}^{K} w_{k,t}/S_{k,t+1}}{\sum_{k=1}^{K} w_{k,t}/\tilde{F}_{k,t}} \times \dots \tag{E17}$$
$$\dots \times \frac{\sum_{k=1}^{K} w_{k,n-1} \times S_{k,n-1}^{\text{USD/X},b} \,/\, S_{k,n}^{\text{USD/Y},a}}{\sum_{k=1}^{K} w_{k,n-1} \times \tilde{F}_{k,n}^{\text{USD/X}} \,/\, \tilde{F}_{k,n-1}^{\text{USD/Y}}}.$$

This expression takes into account that when a new long (*short*) position was opened in period 0, the appropriate forward rate is the bid (*ask*) rate and the spot ask (*bid*) rate when the position is closed in period n. In addition to this, for a valid decomposition of Eq. (E16) we need to add the rebalancing cost $\sum_{k=1}^{K}(\hat{u}_{k,t} - \hat{v}_{k,t})$ to the denominator $\sum_{k=1}^{K} w_{k,t}/\tilde{F}_{k,t}$ in Eq. (E17):

$$\frac{\sum_{k=1}^{K} w_{k,0} \times S_{k,0}^{\text{USD/X}} \,/\, S_{k,1}^{\text{USD/Y}}}{\sum_{k=1}^{K} w_{k,0} \times F_{k,1}^{\text{USD/X},a} \,/\, F_{k,0}^{\text{USD/Y},b}} \times \prod_{t=1}^{n} \frac{\sum_{k=1}^{K} w_{k,t}/S_{k,t+1}}{\sum_{k=1}^{K} w_{k,t}/\tilde{F}_{k,t} + \sum_{k=1}^{K}(\hat{u}_{k,t} - \hat{v}_{k,t})} \times \dots \tag{E18}$$
$$\dots \times \frac{\sum_{k=1}^{K} w_{k,n-1} \times S_{k,n-1}^{\text{USD/X},b} \,/\, S_{k,n}^{\text{USD/Y},a}}{\sum_{k=1}^{K} w_{k,n-1} \times \tilde{F}_{k,n}^{\text{USD/X}} \,/\, \tilde{F}_{k,n-1}^{\text{USD/Y}} + \sum_{k=1}^{K}(\hat{u}_{k,n-1} - \hat{v}_{k,n-1})}.$$

In Table E.2 we summarise the performance of the AIP_{HML} strategy as well as benchmark it against common FX strategies, when long/short positions are rolled over instead of unwound and reopened. With monthly rebalancing performance improvement is small compared to daily or weekly rebalancing frequencies.

In Table E.3 we illustrate the surge in performance of trading with and without rolling over long/short positions. Overall, the performance improvement (both in terms of annualised excess returns and Sharpe ratios) is much more distinctive on a daily and weekly basis than on a monthly. Again, the reasons can be traced back to both the number of rebalancing points and the diversified currency exposure of the AIP_{HML} strategy. Strategies that rely on a smaller subset of currency pairs typically profit more from rolling over open positions, since the probability allocating the same weight to the same currency in two or more consecutive periods is naturally higher.

Table E.1 summarises transaction cost associated with different rebalancing frequencies for the AIP_{HML} strategy. In Figure E.5, we plot the empirical distribution of annual transaction cost for daily, weekly and monthly rebalancing frequencies. The histograms emphasise that transaction cost are largely innocuous on a monthly basis but kick in severely at higher rebalancing frequencies (daily/weekly).

Like Gargano et al. (2018), we find that transaction cost (i.e. roll costs) based on WM/Reuters data (see online appendix Gilmore and Hayashi, 2011) are higher than based on Olsen data (see Figure E.4) and in the ballpark of 1–2% per year.

Table E.1: Summary of Annual Trading Cost and Cost per Trade

Panel a) Annual Trading Cost in %	Daily	Weekly	Monthly
Mean	20.80	3.17	0.89
Median	16.97	2.95	0.76
Std	12.95	1.07	0.34
Panel a) Cost per Trade in %	**Daily**	**Weekly**	**Monthly**
Mean	0.08	0.06	0.07
Median	0.07	0.06	0.06
Std	0.05	0.02	0.03

Note: Panel a) shows the average, median and standard deviation of annualised trading cost in percentages for different rebalancing frequencies (daily, weekly and monthly). Annualised transaction cost are approximated by the cost per trade times the number of trading days, weeks and months per year. Panel b) lists the same measures as Panel a) but for the cost per trade associated with daily, weekly and monthly rebalancing. Transaction cost are calculated as the difference in log returns between excess returns based on mid-quote and bid–ask quotes.

Table E.2: Performance Benchmarking: Annualised Sharpe ratios and Returns with Rolling Over Long/Short Positions

Panel a) Gross Returns	*DOL*	RER_{HML}	*RER*	MOM_{HML}	CAR_{HML}	*BMS*	VOL_{LMH}	Q_1	Q_3	AIP_{HML}
SR	−0.11	−0.22	−0.22	−0.13	0.05	0.68	−0.54	*0.65	0.23	**0.83
	[0.33]	[0.53]	[0.58]	[0.32]	[0.16]	[1.49]	[1.25]	[1.84]	[0.59]	[2.35]
Mean in %	−0.33	−1.08	−0.71	−0.91	0.39	2.79	−3.20	**3.01	1.04	***4.05
	[0.33]	[0.52]	[0.58]	[0.31]	[0.16]	[1.48]	[1.24]	[1.97]	[0.58]	[3.01]
MDD in %	6.48	14.26	10.14	28.56	19.31	8.30	29.30	8.05	11.24	7.19
Scaled MDD	7.40	9.40	10.22	12.19	8.34	6.71	15.00	5.78	8.23	4.95
Θ in %	−0.41	−1.32	−0.81	−1.41	−0.14	2.62	−3.55	2.79	0.84	3.81
Skewness	0.56	0.12	−0.02	−0.30	−0.70	0.16	0.11	−0.10	0.69	0.15
Kurtosis-3	1.55	−0.40	0.16	0.88	0.81	−0.31	−0.10	1.66	1.17	9.45
Panel b) Net Returns	*DOL*	RER_{HML}	*RER*	MOM_{HML}	CAR_{HML}	*BMS*	VOL_{LMH}	Q_1	Q_3	AIP_{HML}
SR	−0.20	−0.35	−0.33	−0.23	−0.04	0.50	−0.65	0.56	0.13	**0.66
	[0.58]	[0.83]	[0.89]	[0.58]	[0.12]	[1.10]	[1.50]	[1.62]	[0.33]	[1.98]
Mean in %	−0.58	−1.70	−1.07	−1.64	−0.30	2.05	−3.82	*2.61	0.59	**3.20
	[0.59]	[0.83]	[0.89]	[0.56]	[0.12]	[1.09]	[1.48]	[1.72]	[0.33]	[2.38]
MDD in %	7.24	16.71	11.43	31.09	20.94	9.92	33.75	8.51	12.35	7.56
Scaled MDD	8.26	10.89	11.47	13.12	8.96	7.99	17.02	6.09	9.01	5.18
Θ in %	−0.67	−1.94	−1.18	−2.14	−0.83	1.88	−4.18	2.40	0.39	2.96
Skewness	0.59	0.11	−0.03	−0.31	−0.70	0.14	0.09	−0.12	0.68	0.10
Kurtosis-3	1.60	−0.38	0.16	0.88	0.82	−0.35	−0.11	1.70	1.15	9.44

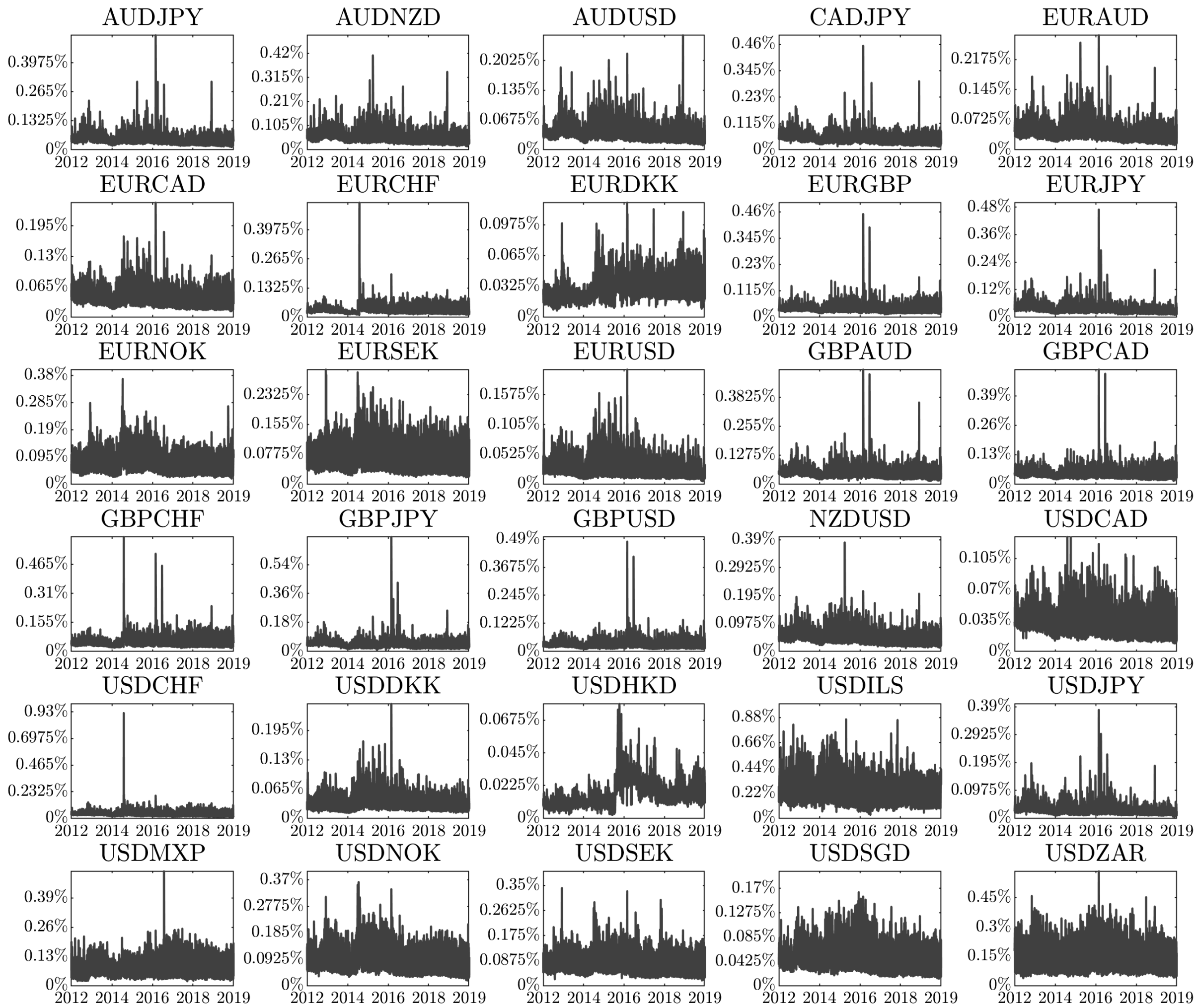
Note: This table presents the out-of-sample economic performance of the AIP_{HML} strategy *before* and *after* transaction cost based on monthly rebalancing. Panel a) reports the annualised Sharpe ratio (SR), the annualised average (simple) *gross* excess return (*Mean*), skewness, excess kurtosis (Kurtosis-3),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

Table E.3: Portfolio Summary Without (w/o) and With (w/) Rolling Over

	Daily		Weekly		Monthly	
	w/o roll	w/roll	w/o roll	w/roll	w/o roll	w/roll
SR	**−3.63	**−3.09	**0.14	**0.19	**0.65	**0.66
	[1.96]	[1.98]	[1.96]	[1.98]	[1.96]	[1.98]
Mean in %	***−16.45	***−14.00	0.67	0.90	**3.16	**3.20
	[8.95]	[7.65]	[0.41]	[0.56]	[2.35]	[2.38]
MDD in %	190.73	148.33	7.59	7.40	7.57	7.56
Scaled MDD	374.34	319.33	11.30	11.03	5.18	5.18
Θ in %	−16.66	−14.21	0.45	0.69	2.92	2.96
Skewness	2.31	2.29	0.75	0.75	0.10	0.10
Kurtosis-3	32.20	32.03	5.44	5.44	9.46	9.44

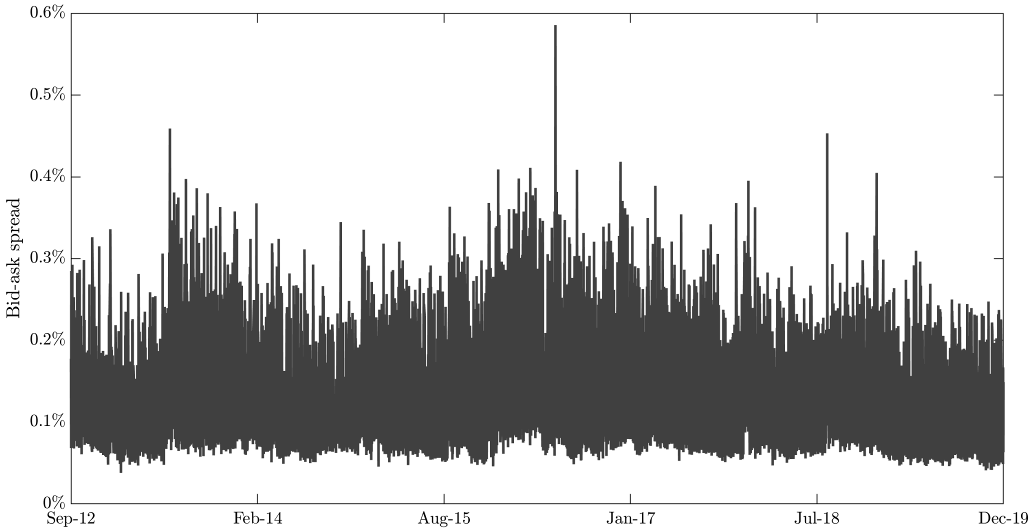
Note: This table compares the out-of-sample economic performance of the AIP_{HML} strategy for rolling over long/short positions when attaching the same weight to currency k in period $t-1$ and t against successive unwinding/opening of old/new positions. We report the annualised Sharpe ratio (SR), the annualised average (simple) *net* excess return (*Mean*), skewness, excess kurtosis (Kurtosis-3), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD) and the Θ performance measure of Goetzmann et al. (2007). Significant findings at the 90%, 95% and 99% levels are represented by asterisks *, ** and ***, respectively. The numbers inside the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroscedasticity- and autocorrelation-consistent errors correcting for serial correlation and the small sample size (using the plug-in procedure for automatic lag selection by Andrews and Monahan, 1992, Newey and West, 1994).

Figure E.2: Bid–Ask Spreads in the Cross-Section



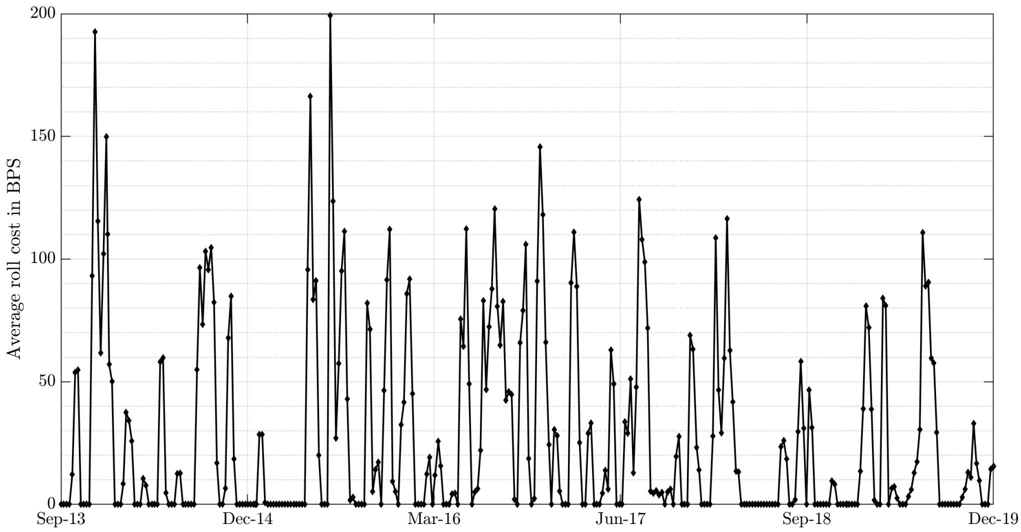
Note: Relative bid–ask spread as a fraction of the daily mid-quote for the entire cross-section of currency pairs.

Figure E.3: Cross-Sectional Average Bid–Ask Spread



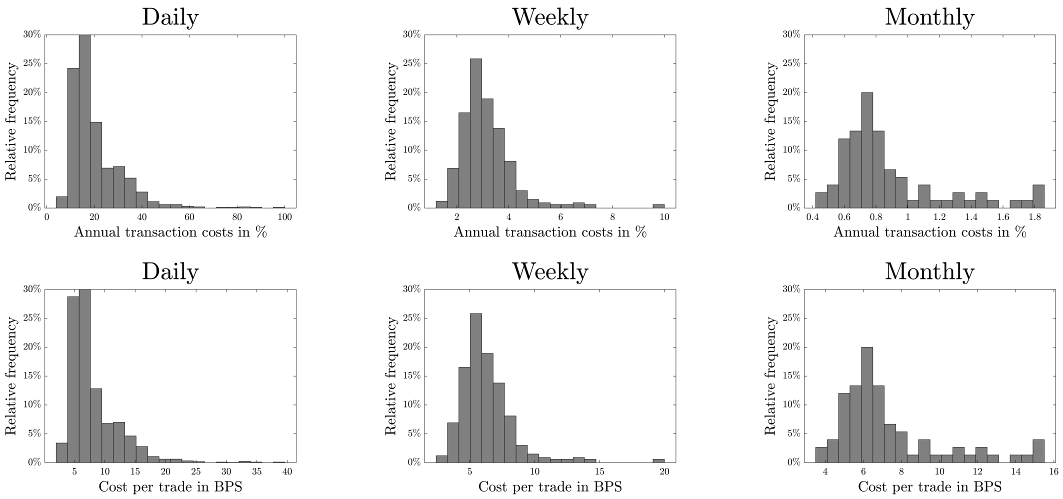
Note: Cross-sectional average relative bid–ask spread as a fraction of the daily mid-quote.

Figure E.4: Annualised Average Roll Costs in BPS



Note: Annualised (absolute) roll costs are displayed at a weekly frequency.

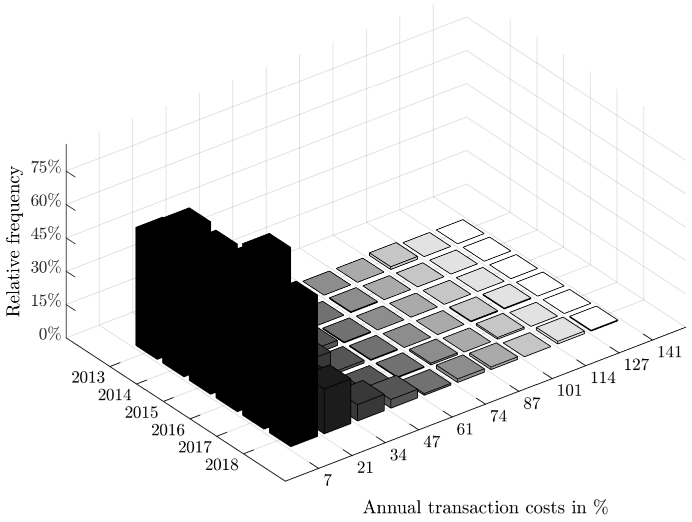
Figure E.5: Distribution of Annual Trading Cost and Cost Per Trade



Note: This figure shows the distribution of annual transaction cost and cost per trade for different rebalancing frequencies — daily, weekly and monthly. Annualised transaction cost are approximated by the cost per trade times number of trading days, weeks and months per year.

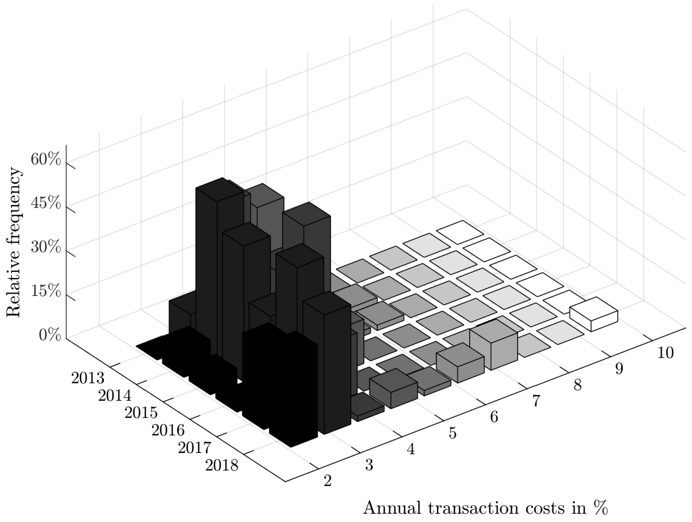
Figure E.6: Distribution of Annual Transaction Cost Over Time

Daily Rebalancing



Distribution of Annual Transaction Cost Over Time

Weekly Rebalancing



Distribution of Annual Transaction Cost Over Time

Monthly Rebalancing

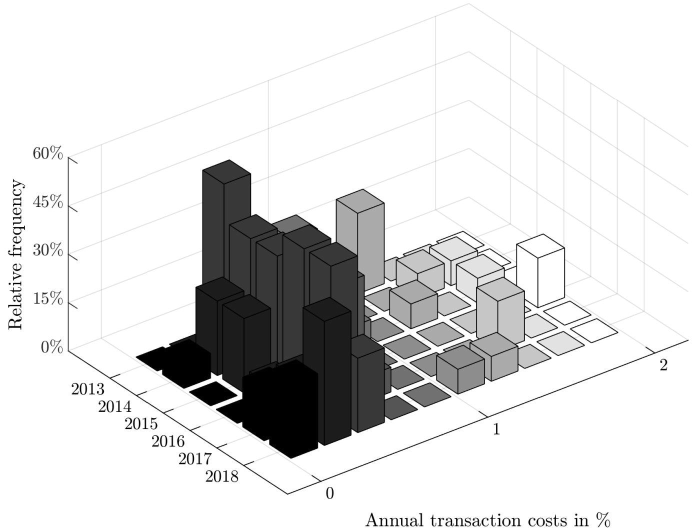
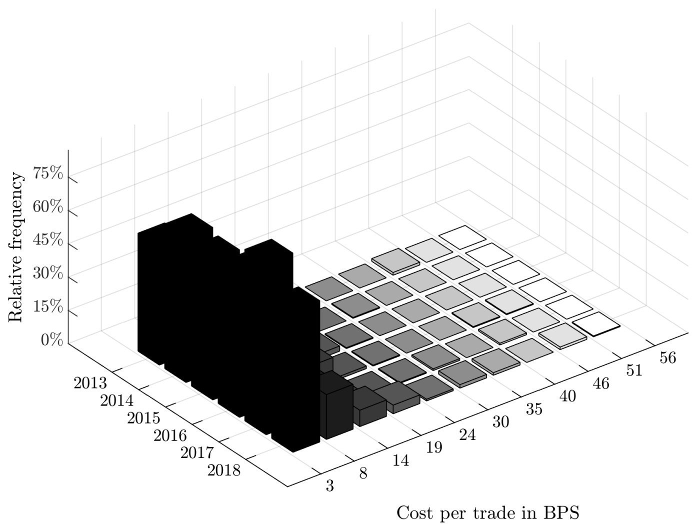


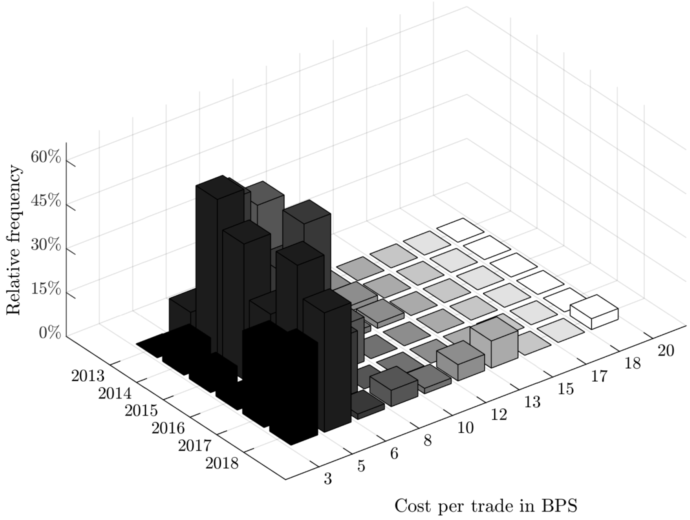
Figure E.7: Distribution of Cost per Trade

Daily Rebalancing



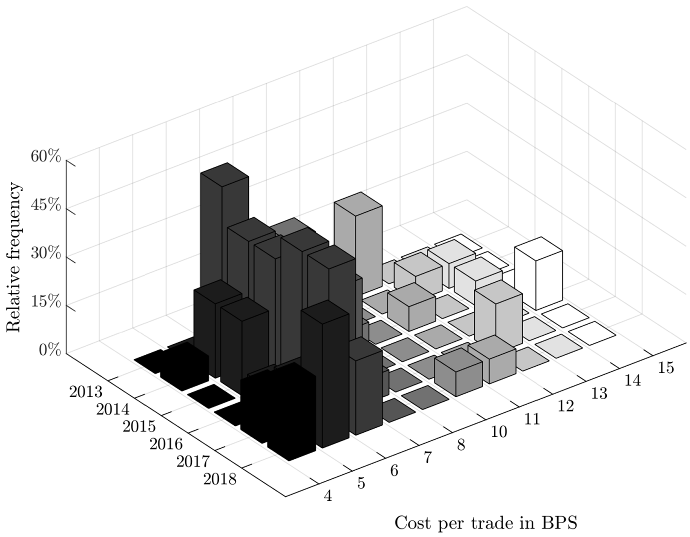
Distribution of Cost per Trade

Weekly Rebalancing



Distribution of Cost per Trade

Monthly Rebalancing

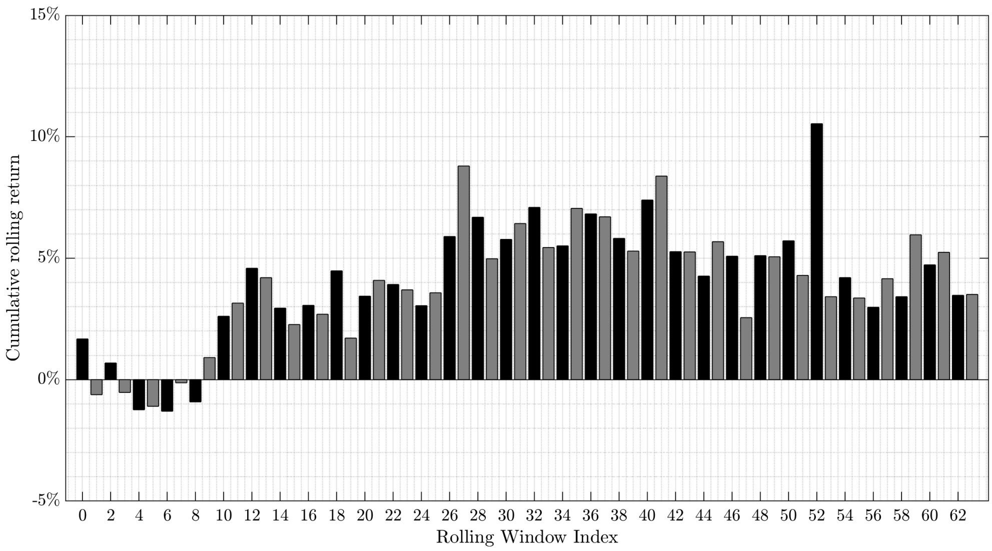


Appendix F Robustness Checks

We have performed a number of additional analyses and robustness checks that we summarise in this section. There are seven robustness tests in total.

Rolling One-year Returns. Figure F.1 demonstrates that our returns are robust to the length of investment period. Taking the *gross* returns from monthly rebalancing, we calculate the cumulative 12-month return in a rolling fashion. The cumulative annual returns are largely positive. The numbers on the horizontal axis designate the starting month of the rolling window period; that is, at tick 4, we measure the 12-month cumulative return for an investment from 11/ 2013 to 10/ 2014 (month 16).[9]

Figure F.1: Cumulative Rolling *Gross* Returns



Note: Rolling window *gross* returns for monthly rebalancing and 1-year investment horizon.

Subsampling Currencies. In the online appendix Section C, we have shown that the AIP_{HML} strategy exhibits a balanced exposure across currencies and over time. To alleviate any concerns that the economic profitability of AIP_{HML} is only driven by just a few currency pairs, we twist our analysis by considering a subset of the original 30 currency pairs. In Table F.1, we report the results for the annualised Sharpe ratio (SR), the annualised mean excess return (Mean), the maximum drawdown (MDD), the Θ performance measure of Goetzmann et al. (2007), skewness and excess kurtosis (Kurtosis-3) based on monthly rebalancing.

[9]Note that our results remain robust when randomly splitting the sample into two to three non-overlapping periods.

Table F.1: Subsample Performance Benchmarking

Panel a) Gross Returns	G10	EUR/ GBP	no EM	no CHF	AIP_{HML}
SR	**0.73	***0.96	**0.77	**0.76	**0.83
	[2.45]	[2.62]	[2.18]	[2.35]	[2.35]
Mean in %	**5.38	***6.37	**4.60	**3.65	***4.05
	[2.31]	[2.96]	[2.47]	[2.56]	[3.01]
MDD in %	7.11	7.67	8.56	5.88	7.19
Scaled MDD	3.26	3.86	4.77	4.14	4.95
Θ in %	4.84	5.92	4.24	3.42	3.81
Skewness	0.46	0.00	0.55	0.70	0.15
Kurtosis-3	2.24	3.09	5.85	6.93	9.45
Panel b) Net Returns	**G10**	**EUR/ GBP**	**no EM**	**no CHF**	**AIP_{HML}**
SR	**0.64	**0.85	*0.65	*0.57	**0.65
	[2.16]	[2.38]	[1.90]	[1.83]	[1.96]
Mean in %	**4.74	***5.70	**3.89	*2.73	**3.16
	[2.05]	[2.65]	[2.09]	[1.92]	[2.35]
MDD in %	7.51	7.91	9.15	6.70	7.57
Scaled MDD	3.43	3.97	5.07	4.70	5.18
Θ in %	4.21	5.25	3.53	2.50	2.92
Skewness	0.44	−0.02	0.52	0.65	0.10
Kurtosis-3	2.25	3.14	5.88	6.94	9.46

Note: In this table, in Panels a) and b), we report the *gross* and *net* performance measures, respectively, of AIP_{HML} based on four subsamples of currency pairs. These are as follows: i) G10 currency pairs plus the AUDJPY (10 in total), ii) EUR and GBP currency pairs only (14 in total), iii) all pairs excluding emerging market currencies (i.e. USDILS, USDMXP and USDZAR) and/or fixed pairs (i.e. EURDKK, USDDKK, USDHKD and USDSGD), iv) all pairs excluding the CHF crosses (27 in total). The performance measures are the annualised Sharpe ratio (SR), annualised average (simple) *gross* excess return (*Mean*), skewness, excess kurtosis (Kurtosis-3), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD) and Θ performance measure of Goetzmann et al. (2007). Significant findings at the 90%, 95% and 99% levels are represented by asterisks *, ** and ***, respectively. The numbers inside the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroscedasticity- and autocorrelation-consistent errors, correcting for serial correlation and the small sample size (using the plug-in procedure for automatic lag selection by Andrews and Monahan, 1992, Newey and West, 1994).

There are four cases to be distinguished, which are as follows: i) G10 currency pairs plus the most liquid Australasian currency cross i.e. AUDJPY (10 in total), ii) EUR and GBP currency pairs only (14 in total), iii) all pairs excluding emerging market currencies and/or fixed pairs, iv) all currency pairs excluding the CHF crosses (27 in total). For each subsample, the gross investment performance of AIP_{HML} remains economically and statistically significant at the 5% confidence level. In addition, the development of their performance across time is similar. The annualised *gross* and *net* excess returns and SRs range from 2.73–6.37% and 0.57–0.96, respectively. The lower performance in G10 is intuitive given that these are the most heavily traded and information efficient currency pairs and hence less subject to asymmetric information risk. Overall, the subsampling analysis alleviates two issues: First, our results are robust to the choice of currency pairs in the sample. Second, the AIP_{HML} performance does not seem to be driven by structural changes, such as the implementation of new regulations (e.g. capital and liquidity requirements of Basel III) or the temporary fixing of currencies (e.g. Swiss franc cap from 2011-2015). For instance, Du et al. (2018) show that *CIP* deviations concentrate at quarter ends and in some currencies.[10] Moreover, the performance steadily increases over time, and it is not originated by only a few currency pairs.

Excluding the Contemporary Price Impact. Next, we check whether our results are robust to including the (average) contemporary price impact ($\bar{\beta}_0$) in calculating the permanent price impact ($\bar{\alpha}_m$). To accomplish this, we replicate our trading strategy AIP_{HML} based on signals $\bar{\alpha}_n = \bar{\alpha}_m - \bar{\beta}_0$ ('reversal') and $\bar{\beta}_0$, respectively, and compare both to trading based on $\bar{\alpha}_m$. In line with our conjecture, Tables F.2 and F.3 document that both signals perform less well than trading on the permanent price impact. Therefore, we may conclude that trading on $\bar{\alpha}_m$, that is, $\bar{\beta}_0$ net of liquidity effects, maximises expected excess returns. However, our main results are robust to excluding $\bar{\beta}_0$ from $\bar{\alpha}_m$.

Rebalancing at Different Times of the Day. Instead of relying on the closing price (i.e. PX_{LAST}), we implement our trading strategy AIP_{HML} at different Bloomberg fixing times from 12 *am* to 8 *pm* GMT. The late evening hours (i.e. 9 *pm* to 23 *pm*) are excluded because during daylight saving time (i.e. from March–October), trading ends on Fridays at 9 *pm* GMT and during winter at 10 *pm* GMT, respectively. From Figure F.2, it is discernible that, for all fixing times both Sharpe ratios and mean returns are in line with the benchmark case of PX_{LAST} and their statistical significance is well beyond the 5% level.

[10] Du et al. (2018) document that high-interest-rate (low-interest-rate) currencies tend to exhibit a positive (negative) *CIP* basis, that is, the deviation from the *CIP* condition.

Table F.2: Performance Benchmarking: $(\bar{\beta}_0)_{HML}$

Panel a) Gross Returns	DOL	RER_{HML}	RER	MOM_{HML}	CAR_{HML}	BMS	VOL_{LMH}	Q_1	Q_3	$(\bar{\beta}_0)_{HML}$
SR	−0.11	−0.22	−0.22	−0.13	0.05	0.68	−0.54	0.44	−0.04	**0.54
	[0.33]	[0.53]	[0.58]	[0.32]	[0.16]	[1.49]	[1.25]	[1.17]	[0.10]	[2.05]
Mean in %	−0.33	−1.08	−0.71	−0.91	0.39	2.79	−3.20	2.03	−0.14	**1.89
	[0.33]	[0.52]	[0.58]	[0.31]	[0.16]	[1.48]	[1.24]	[1.20]	[0.10]	[2.08]
MDD in %	6.48	14.26	10.14	28.56	19.31	8.30	29.30	9.48	9.76	3.49
Scaled MDD	7.40	9.40	10.22	12.19	8.34	6.71	15.00	6.86	8.67	3.41
Θ in %	−0.41	−1.32	−0.81	−1.41	−0.14	2.62	−3.55	1.82	−0.28	1.77
Skewness	0.56	0.12	−0.02	−0.30	−0.70	0.16	0.11	−0.14	0.82	−0.15
Kurtosis-3	1.55	−0.40	0.16	0.88	0.81	−0.31	−0.10	−0.27	1.68	0.26
Panel b) Net Returns	DOL	RER_{HML}	RER	MOM_{HML}	CAR_{HML}	BMS	VOL_{LMH}	Q_1	Q_3	$(\bar{\beta}_0)_{HML}$
SR	−0.24	−0.38	−0.38	−0.24	−0.07	0.47	−0.69	0.34	−0.14	0.30
	[0.69]	[0.91]	[1.02]	[0.61]	[0.19]	[1.04]	[1.59]	[0.91]	[0.36]	[1.13]
Mean in %	−0.70	−1.88	−1.24	−1.74	−0.48	1.95	−4.10	1.56	−0.53	1.03
	[0.70]	[0.92]	[1.02]	[0.60]	[0.19]	[1.03]	[1.58]	[0.92]	[0.37]	[1.14]
MDD in %	7.67	17.51	12.01	31.57	21.24	10.19	35.65	10.53	10.72	5.26
Scaled MDD	8.71	11.38	12.03	13.29	9.07	8.20	17.83	7.56	9.49	5.09
Θ in %	−0.78	−2.12	−1.34	−2.24	−1.01	1.78	−4.45	1.35	−0.66	0.91
Skewness	0.56	0.10	−0.03	−0.31	−0.70	0.14	0.09	−0.16	0.82	−0.19
Kurtosis-3	1.53	−0.38	0.16	0.91	0.81	−0.34	−0.10	−0.26	1.66	0.23

Note: This table presents the out-of-sample economic performance of a strategy based on the contemporary price impact ($\bar{\beta}_0$) *before* and *after* transaction cost based on monthly rebalancing. Panel a) reports the annualised Sharpe ratio (SR), the annualised average (simple) *gross* excess return (*Mean*), skewness, excess kurtosis (Kurtosis-3), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD) and the Θ performance measure of Goetzmann et al. (2007) for the tertile portfolios (Q_1, Q_2, Q_3) based on the uniform distribution. Panel b) lists the same measures as Panel a) but *after* transaction cost. DOL is based on an equally weighted long portfolio of all USD currency pairs, RER/RER_{HML} on the real exchange rate (cf. Menkhoff et al., 2017), MOM_{HML} on $f_{t-1,t} - s_t$ (cf. Asness et al., 2013), CAR_{HML} on the forward discount/ premium ($f_{t,t+1} - s_t$, cf. Lustig et al., 2011), BMS is based on the lagged standardised order flow (cf. Menkhoff et al., 2016) and VOL_{LMH} is based on currency pairs' exposure to the global volatility factor (cf. Menkhoff et al., 2012a). Significant findings at the 90%, 95% and 99% levels are represented by asterisks *, ** and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroscedasticity- and autocorrelation-consistent errors correcting for serial correlation and the small sample size (using the plug-in procedure for automatic lag selection by Andrews and Monahan, 1992, Newey and West, 1994).

Restricting Order Flows to 'London hours'. In information models with risk aversion (e.g. Subrahmanyam, 1991) market makers want to limit their risk exposure stemming from large open FX positions. This might induce FX market makers to 'go home flat at night'.[11] Hence, we test the sensitivity of our results to risk aversion by

[11]We would like to thank an anonymous referee for pointing this out.

Table F.3: Performance Benchmarking: $(\bar{\alpha}_m - \bar{\beta}_0)_{HML}$

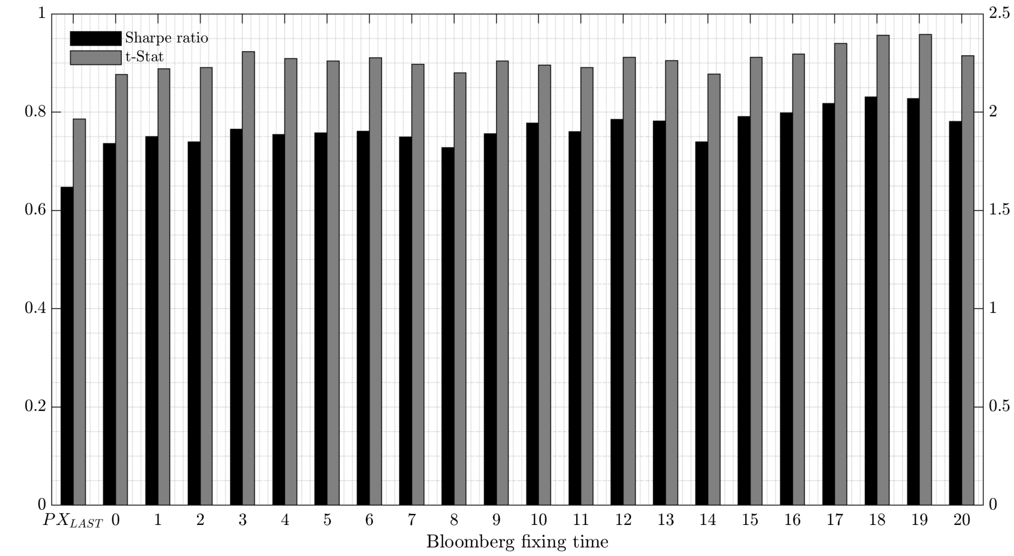
Panel a) Gross Returns	DOL	RER_{HML}	RER	MOM_{HML}	CAR_{HML}	BMS	VOL_{LMH}	Q_1	Q_3	$(\bar{\alpha}_m - \bar{\beta}_0)_{HML}$
SR	−0.11	−0.22	−0.22	−0.13	0.05	0.68	−0.54	*0.67	0.06	*0.68
	[0.33]	[0.53]	[0.58]	[0.32]	[0.16]	[1.49]	[1.25]	[1.90]	[0.16]	[1.86]
Mean in %	−0.33	−1.08	−0.71	−0.91	0.39	2.79	−3.20	**2.91	0.29	**3.20
	[0.33]	[0.52]	[0.58]	[0.31]	[0.16]	[1.48]	[1.24]	[2.03]	[0.15]	[2.09]
MDD in %	6.48	14.26	10.14	28.56	19.31	8.30	29.30	5.82	15.02	6.78
Scaled MDD	7.40	9.40	10.22	12.19	8.34	6.71	15.00	4.54	10.89	4.88
Θ in %	−0.41	−1.32	−0.81	−1.41	−0.14	2.62	−3.55	2.72	0.09	2.98
Skewness	0.56	0.12	−0.02	−0.30	−0.70	0.16	0.11	−0.21	0.27	−0.01
Kurtosis-3	1.55	−0.40	0.16	0.88	0.81	−0.31	−0.10	0.98	1.20	7.32
Panel b) Net Returns	DOL	RER_{HML}	RER	MOM_{HML}	CAR_{HML}	BMS	VOL_{LMH}	Q_1	Q_3	$(\bar{\alpha}_m - \bar{\beta}_0)_{HML}$
SR	−0.24	−0.38	−0.38	−0.24	−0.07	0.47	−0.69	0.58	−0.04	0.49
	[0.69]	[0.91]	[1.02]	[0.61]	[0.19]	[1.04]	[1.59]	[1.64]	[0.10]	[1.41]
Mean in %	−0.70	−1.88	−1.24	−1.74	−0.48	1.95	−4.10	*2.49	−0.18	2.31
	[0.70]	[0.92]	[1.02]	[0.60]	[0.19]	[1.03]	[1.58]	[1.74]	[0.10]	[1.51]
MDD in %	7.67	17.51	12.01	31.57	21.24	10.19	35.65	6.35	15.94	7.16
Scaled MDD	8.71	11.38	12.03	13.29	9.07	8.20	17.83	4.93	11.53	5.12
Θ in %	−0.78	−2.12	−1.34	−2.24	−1.01	1.78	−4.45	2.30	−0.37	2.10
Skewness	0.56	0.10	−0.03	−0.31	−0.70	0.14	0.09	−0.23	0.27	−0.05
Kurtosis-3	1.53	−0.38	0.16	0.91	0.81	−0.34	−0.10	1.04	1.18	7.42

Note: This table presents the out-of-sample economic performance of strategy based on the permanent price impact net of the contemporary effect ($(\bar{\alpha}_m - \bar{\beta}_0)_{HML}$) *before* and *after* transaction cost based on monthly rebalancing. Panel a) reports the annualised Sharpe ratio (SR), the annualised average (simple) *gross* excess return (*Mean*), skewness, excess kurtosis (Kurtosis-3), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD) and the Θ performance measure of Goetzmann et al. (2007) for the tertile portfolios (Q_1, Q_2, Q_3) based on the uniform distribution. Panel b) lists the same measures as Panel a) but *after* transaction cost. DOL is based on an equally weighted long portfolio of all USD currency pairs, RER/RER_{HML} on the real exchange rate (cf. Menkhoff et al., 2017), MOM_{HML} on $f^m_{t-1,t} - s^m_t$ (cf. Asness et al., 2013), CAR_{HML} on the forward discount/premium ($f^m_{t,t+1} - s^m_t$, cf. Lustig et al., 2011), BMS is based on the lagged standardised order flow (cf. Menkhoff et al., 2016) and VOL_{LMH} is based on currency pairs' exposure to the global volatility factor (cf. Menkhoff et al., 2012a). Significant findings at the 90%, 95% and 99% levels are represented by asterisks *, ** and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroscedasticity- and autocorrelation-consistent errors correcting for serial correlation and the small sample size (using the plug-in procedure for automatic lag selection by Andrews and Monahan, 1992, Newey and West, 1994).

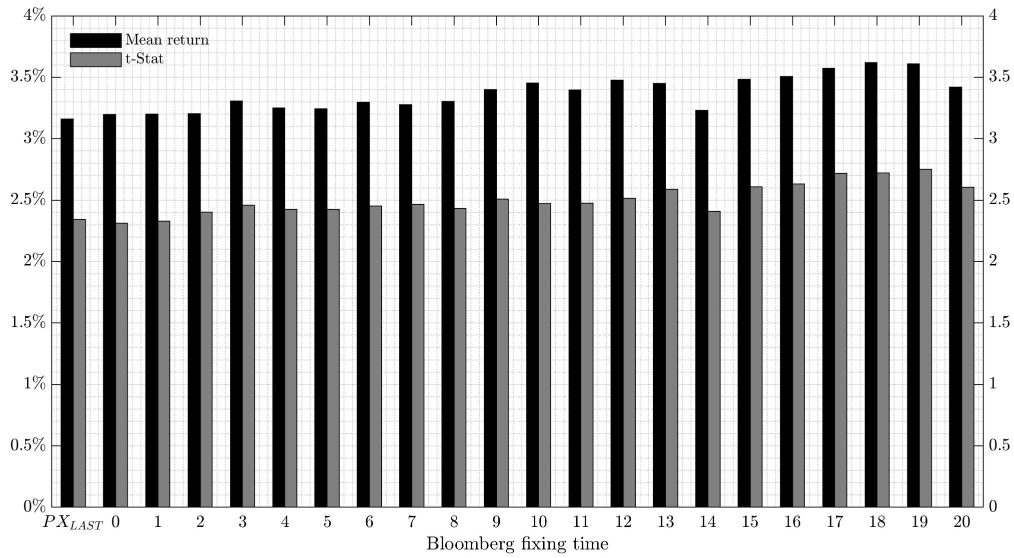
analysing order flows during (*outside*) the main stock market trading hours when risk aversion should be lower (*higher*).

To be more specific, we rerun our asset pricing analysis but only considering customer order flows during the main stock market trading hours (i.e. from 7 *am* to 9 *pm* GMT) when market makers are presumably acting as liquidity providers. In

Figure F.2: Trading at Different Bloomberg Fixing Times



(a) Sharpe ratios



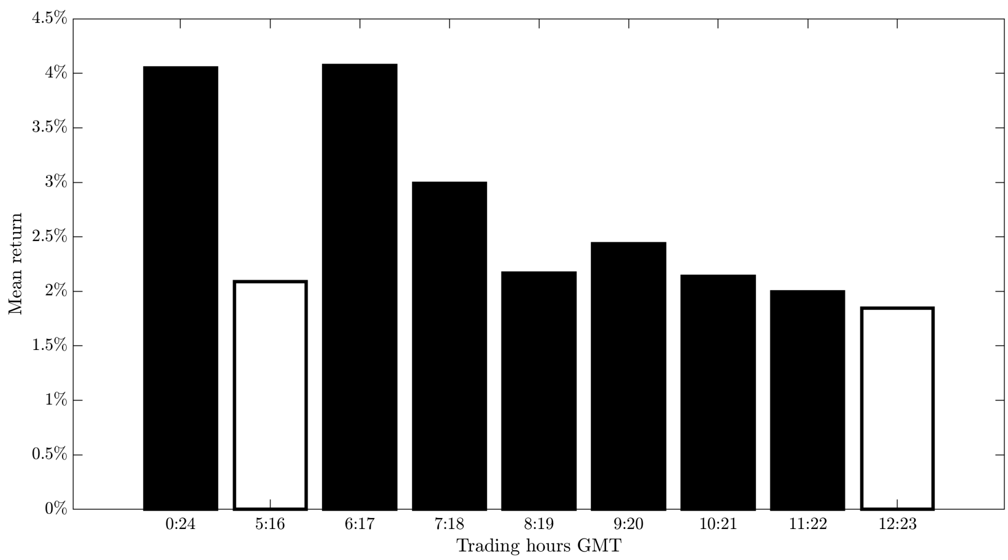
(b) Mean returns

Note: Figures a) and b) display the *Sharpe ratios* and *mean returns* as well as their respective *t*-stats (net of bid-ask spreads) for implementing AIP_{HML} at different Bloomberg fixing times (x-axis) based on monthly rebalancing and after transaction cost. The numbers on the horizontal axis denote the fixing time, for example, the bar denoted 17 refers to 5 *pm* (GMT, no BST adjustment). PX_{LAST} is the Bloomberg closing price.

Figure F.3 the first bar ('0 : 24') is the benchmark case that is based on unrestricted order flows around the clock. The other bars illustrate the performance of AIP_{HML} for restricting customer order flows to a 12-hour window. For instance, the bar at '7 : 18' indicates that daily customer flows have been calculated solely based on the order flows between 7 *am* and 6 *pm* (GMT). Black shaded bars correspond to average returns that are significant at the 10% level. The main takeaway is that AIP_{HML} consistently delivers both economically and statistically significant excess returns when pruning customer order flows based on the main stock market trading hours.

In addition to the above result, Figure 1 provides evidence that in our dataset market makers, and banks in general, are also active when the main stock markets are closed (i.e. London and New York). This empirical result is not in line with the idea that market makers *completely* 'close their books' over night (e.g. Evans and Lyons, 2002) but rather reflects the common practice to 'pass on the book' from one regional banking hub to another. As a result, and due to its OTC nature, the FX market operates 24/7. To conclude, our result are not materially impacted by the possibility that some of the order flows occurring during non-standard trading hours are induced by risk averse traders who want to off-load their positions to customers.

Figure F.3: Performance of AIP_{HML}: Pruned Order Flow



Note: This figure depicts the annualised mean return of AIP_{HML} based on pruned daily order flows. For instance, the bar at '7 : 18' indicates that daily customer order flows have been calculated solely based on the order flows between 7 *am* and 6 *pm* GMT. Black shaded bars are significant at the 10% level. The first bar '0 : 24' is the benchmark case that is based on unrestricted order flows around the clock.

Intraday Variation of $\bar{\beta}_0^j/\bar{\alpha}_m^j$. We estimate Eq. (4.2), but now filtering the time series for every hour of the day and running 24 single regressions. Two important findings emerge from Figure F.4, which are as follows: First, for sophisticated financial institutions (e.g. funds, non-bank financials and banks) both the contemporary and permanent price impacts tend to be higher during the more illiquid hours of the day, for example, during the European morning and evening. Second, corporates' contemporary price impact is largely negative, whereas their permanent price impact is virtually indistinguishable from zero for the better part of the trading day.

Optimising Transaction Cost. In Section E of the online appendix we have introduced the concept of rolling over long/short positions instead of opening a new position and unwinding the old one (Gilmore and Hayashi, 2011). The goal of this section is to illustrate how the performance of AIP_{HML} can be improved by optimising trading cost.

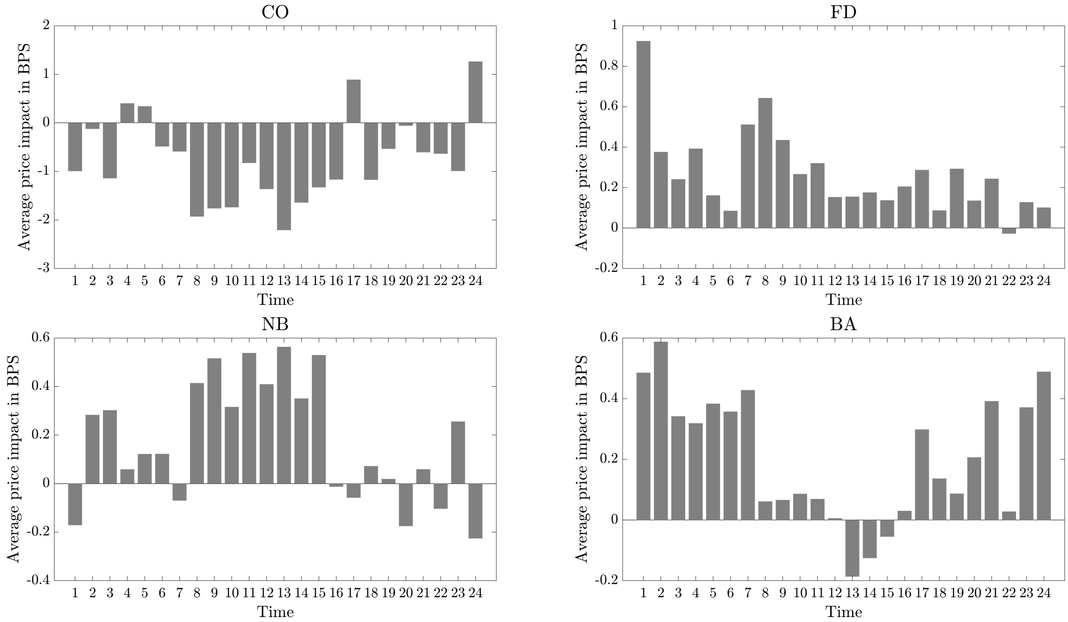
Gilmore and Hayashi (2011) introduce the concept of rolling over long/short positions. In other words, the investor opens a long position via a 1-period ahead forward contract in day 0, maintains the position for n successive periods via foreign exchange swaps and then unwinds in period n. Compared with the excess return prior transactions cost, the investor pays the difference between the bid and mid-rates when opening the position in period 0; the difference between the offer and mid-rates when unwinding the position in period n; and a daily 'roll cost' in between. The roll cost is the difference between the bid and mid of the FX forward points of foreign exchange swaps. Typically, this will be lower than the spread between the forward bid and mid rate. Similar reasoning applies to other time units (e.g. weekly and monthly rebalancing).

In the spirit of Gilmore and Hayashi (2011), we derive the transaction cost for rolling over n successive periods. For monthly rebalancing the performance improvement is relatively small compared to daily or weekly rebalancing frequencies. The reasons for this are twofold: First, on a monthly basis, we have 74 rebalancing points over the entire investment period, and therefore, transaction cost are less weighty. Figure 3 underlines this point. Second, given that our portfolio is well diversified across a large cross-section of currency pairs, the probability that the weights associated with currency pairs in period $t-1$ and t will coincide is low. Thus, when we limit our selection of investable currency pairs to a subset of all 30 currency pairs, the surge in performance is more pronounced, since the probability to attach the same weight to a currency pair in $t-1$ and t raises by construction. The annual average roll cost for our cross-section of currency pairs are in the ballpark of 0.1–0.2%, since the roll cost Z_t is effectively half of the forward points spread ($P_t^a - P_t^b$) multiplied by the number of trading days, weeks or months per investment period.

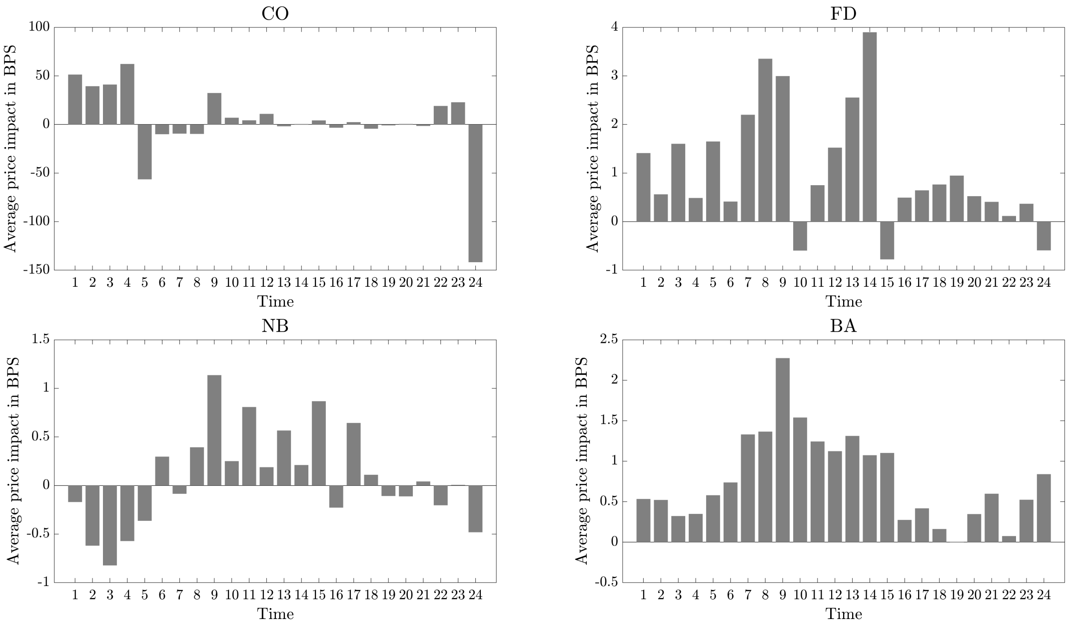
Beyond any doubt, the cost of rolling over different currencies can vary considerably. Nevertheless, this does not impinge on the goal of this section to prove that it is typically cheaper to roll a position over than to close it and then reopen it.

To conclude, despite the relatively short sample period, our asset pricing analysis highlights the economic importance of asymmetric information risk in global FX trading. Our results are robust to our choice of currencies and the length of investment periods. As a result, investors can effectively capitalise on the FX asymmetric information premium.

Figure F.4: Time-of-day Effect on $\bar{\beta}_0^j / \bar{\alpha}_m^j$



(a) Contemporary Price Impact



(b) Permanent Price Impact

Note: These figures show the average contemporary ($\bar{\beta}_0^j$) and permanent ($\bar{\alpha}_m^j$) price impacts across the entire cross-section of currency pairs for every group of market participants at different hours of the day. The cross-sectional averages are calculated after removing heavy outliers in terms of the median. The numbers on the horizontal axis denote the time of the day, for example, the bar denoted 17 refers to the price impact at 5 *pm* (London time, with British Summer Time (BST) adjustment).

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