HETEROGENEOUS INFORMATION CONTENT OF GLOBAL FX TRADING

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Heterogeneous Information Content of Global FX Trading∗

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Abstract

This work studies the information content of trades in the world’s largest over-the-counter (OTC) market, the foreign exchange (FX) market. It analyses a novel, comprehensive order flow dataset, distinguishing amongst different groups of market participants and covering a large cross-section of currency pairs. Both the contemporary and permanent price impact are heterogeneous 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 superior information, generates high returns even after accounting for risk, transaction costs and other common risk factors documented in the FX literature.

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

Keywords: Asymmetric information, Currency portfolios, Heterogeneity, Order flow, OTC, Price discovery

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Abstract

This work studies the information content of trades in the world’s largest over-the-counter (OTC) market, the foreign exchange (FX) market. It analyses a novel, comprehensive order flow dataset, distinguishing amongst different groups of market participants and covering a large cross-section of currency pairs. Both the contemporary and permanent price impact are heterogeneous 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 superior information, generates high returns even after accounting for risk, transaction costs 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 $5.4 trillion (see BIS, 2016). Since it is almost entirely an over-the-counter (OTC) market, FX trading activity is relatively opaque and fragmented.\(^1\) Without a centralised trading mechanism, information is dispersed across various types of market participants (e.g. commercial banks, investment management firms, international corporations, hedge funds and central banks), which maintain heterogeneous relationships with another. All these participants possess distinct information sets and may contribute differently to FX determination.

This paper sheds new light on how different market participants determine currency values in the global FX market and on the information content of their trades. To do this, we utilise a consistent methodology to analyse a novel, comprehensive dataset that has three main advantages: First, it 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). Second, it includes identity-based order flow data broken down into types of market participants such as corporates, funds, non-bank financial firms and banks acting as price takers. The order flow represents the net of buy volume by price takers minus the sell volume by market maker FX transactions. Third, it provides hourly order-flow time series, which is the finest time granularity that has ever been studied for the global FX market. In this framework, we address two key questions, which are as follows: Does order flow impact FX prices heterogeneously across market participants, time and currency pairs? Does the heterogeneous information content of global FX trading provide significant economic value to be revealed in a profitable trading strategy?

Answering these questions is important for both regulators and academics, who have sought to better understand how asset prices are determined and how (fundamental) information is processed in financial markets. The asymmetric information paradigm first formalised by Glosten and Milgrom (1985) and Kyle (1985) prescribes, that when some agents have superior information about the fundamental value of an asset, their trades convey 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

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\(^1\)The FX market microstructure is explained in detail in Lyons (2006), King et al. (2012). More recent developments of the FX markets are discussed, for example, in Rime and Schrmpf (2013), Moore et al. (2016).
content. Another body of the literature shows that the non-informative ‘frictions’, such as transaction costs (Roll, 1984), liquidity shocks (Grossman and Miller, 1988) and inventory effects (Stoll, 1978), generate temporary price impacts and reversals. Therefore, the information content of trades is an important issue that calls for further research. Our work provides novel insights into price formation and asymmetric information issues by dissecting order flow into end-user segments of the global FX market and investigating which of them contain superior information for predicting future FX rates.

In recent years, structural changes of the FX market, such as the rise of electronic and (high-frequency) automated trading, have exacerbated market fragmentation and asymmetric information across market participants (BIS, 2018). Together with its OTC nature, all these issues can create adverse selection, illiquidity and other frictions, such as search costs and bargaining power, especially in distressed times, for example, during the financial crisis of 2008 (Duffie, 2012). Consequently, regulators have implemented global regulatory reforms, for increasing transparency and market quality, such as the Dodd-Frank Act (USA, 2010), EMIR (Europe, 2012), and MiFID II (Europe, 2014). Shedding light on dispersed information and fragmentation in global FX markets would support these regulations that have direct implications on financial stability, price effectiveness and fairness. Furthermore, our study hopes to be relevant to global investors for gauging heterogeneous information contents of FX order flow data.

Our paper proceeds in two parts. In the first part, we empirically address the question of whether global order flow impacts FX prices heterogeneously across market participants, time and currency pairs. To accomplish this, we use 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 analysis builds on the empirical methodology that decomposes the order-flow price impact into transitory and permanent components. The transient component arises from non-information factors, such as inventory control effects (see Hasbrouck, 1988), price discreteness, order fragmentation, price pressure and smoothing (see Hasbrouck, 1991a).
In contrast, a trade can also convey fundamental information bearing a persistent impact on the security price. Econometrically, this paradigm is implemented using a bivariate vector auto-regression (VAR) system in which price return and order flow both evolve endogenously and the latter is allowed to contemporaneously impact the former. This framework provides the following two key advantages: First, it captures the persistent price impact of the trade innovation (using impulse-response analyses), which is a more precise estimate of processing superior fundamental information than the immediate price impact — the latter being contaminated by transient (liquidity) effects. Second, it is a general 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 from inventory control, price pressure effects and order fragmentation as well as other ‘frictions’, such as price discreteness, non-competitive behaviours or transaction cost components.

We refine this VAR system by allowing for heterogeneous price impacts of different agents. More specifically, we estimate a bivariate VAR model that controls for order size, short-term mean reversion and hourly seasonalities in a rolling fashion for studying the time variation of both contemporary and permanent price impact impounded by the order flow of different market participants. We find compelling evidence that order flow impacts FX spot prices heterogeneously across agents, time and currency pairs. Across agents, we find that corporates have a significantly lower contemporaneous and permanent price impact than funds, non-bank financials or banks do. Moreover, order flows by market participants follow divergent patterns. For instance, corporates’ order flow is negatively correlated with that of other categories, including banks; this is consistent with the idea that corporates largely reflect uninformed trading (see Menkhoff et al., 2016), as well as with two common practices applied by FX dealers — discount fees to beg for customers’ liquidity provision and offsetting an informative order flow with a non-informative one to reduce their exposure to asymmetric information risk. 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’ trading tops at midday and concentrates during the London trading hours, that is, from 8 am to 4 pm GMT. This finding suggests, that in addition to banks, funds and non-bank financials gain more access to superior information by trading all around the clock, and this squares well with their permanent price impact. Rolling-window regressions and sub-sampling analysis reveal that the order flow price impact is time varying and heterogeneously distributed across time. Across currency pairs, we find that both the contemporary and permanent price impacts vary heavily across currencies,
suggesting (time-varying) asymmetric information in the cross-section of FX rates. Overall, our findings indicate that order flow impacts FX spot prices heterogeneously across agents, time and currency pairs, supporting the asymmetric information hypothesis and maintaining consistency with the fragmented and opaque nature of the global FX market.

In the second part of the paper, we analyse the economic value of order flow heterogeneity. To accomplish this, we introduce a novel long–short trading strategy based on a simple idea that is consistent with the information asymmetry hypothesis: Order flows of agents and currencies impounding a persistent price impact convey superior information, leading to better predictions of future evolutions of FX rates. Put differently, a higher informational advantage (i.e. a high permanent price impact) goes hand in hand with higher excess returns. The intuition behind this strategy relies on well-documented deviations from the uncovered interest rate parity (UIP) condition and the forward premium puzzle: When regressing FX returns on interest rate differentials, the slope coefficient is typically not equal to one; rather it is negative. In other words, the forward premium points into the ‘wrong’ direction of the expected price movement. Given that our measure of persistent price impact captures order flows conveying superior information, it is naturally well suited to identifying trading that correctly predicts currency values or conversely, that is more biased by UIP deviations. 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.

For assessing the economic value of heterogeneous information content of global FX trading, we take the perspective of a US investor who engages in timely transactions using this information. Our strategy, which we call ALPHML, is an equally weighted long–short portfolio that it is rebalanced on a daily, weekly and monthly basis. Trading signals are generated from a bivariate rolling window VAR model. For every currency pair the permanent price impact is summed up across agents to derive the (aggregate) informative price impact. The ALPHML portfolio then consists of the 33.33% highest (lowest) aggregate permanent price impact currency pairs in the long (short) leg. In this context, going long (short) means buying (selling) a foreign currency in the forward market and selling (buying) it in the spot market next period. Transaction costs are implemented using accurate quoted bid–ask rates for both forward contracts and spot transactions. At the monthly rebalancing, ALPHML generates a both economically and statistically significant annualised return of 5.72% (4.82%) and a Sharpe ratio (SR) of

\footnote{For extensive surveys and regression results on UIP deviations, see, for example, Hansen and Hodrick (1980), Fama (1984), Lustig and Verdelhan (2007).}
1.27 (1.08) before (after) transaction costs. Furthermore, we show that these returns cannot be explained by the main common FX risk factors, such as momentum, carry and value (see Asness et al., 2013, Lustig et al., 2011, Menkhoff et al., 2012b, 2017).

To summarise, two important findings emerge from our analysis: First, both the contemporary and permanent price impacts systematically differ across agents, time and currency pairs, supporting the asymmetric information hypothesis and conforming to the fragmentation and opacity prevalent in OTC markets. Second, there is a significant economic value in the informative part of order flow measured by the permanent price impact in the sense that it is possible to exploit their time series and cross-sectional variation to build a simple long-short strategy.

**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 asymmetry across market participants (e.g. Kyle, 1985, Glosten and Milgrom, 1985, Easley and O’Hara, 1987, 1991, Holden and Subrahmanyam, 1992). Prior research has already shown indirect evidence of heterogeneous behaviours in FX markets by looking at intra-day patterns of volatility (Engle et al., 1990), FX rates (Ito et al., 1998) or surrounding special moments, such as central bank interventions (e.g. Peiers, 1997) and prior to sovereign debt downgrades (e.g. Michaelides et al., 2018).

Starting from the key contributions of Evans (2002), Evans and Lyons (2002, 2005), several papers provide more direct evidence of information asymmetry by investigating how aggregate order flow determines FX rates. 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 (e.g. Moore and Payne, 2011, Chaboud et al., 2014, Breedon et al., 2018) or on customers’ order flow for a specific bank (e.g. Evans and Lyons, 2006, Carpenter and Wang, 2007, Breedon and Vitale, 2010, Cerrato et al., 2011, Osler et al., 2011, Breedon and Ranaklo, 2013, Menkhoff et al., 2016). However, these findings are not generalisable to the entire FX market. 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 (compared to the previous microstructure

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3For an excellent recent survey of this research, see Vayanos and Wang (2013).

4This 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).

5For 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 different market impact in different currency markets (Lyons, 2006).
literature). Building on the seminal work by Hasbrouck (1988, 1991a,b), we propose a general model for heterogeneous price impacts across agents, disentangling permanent (informative) and temporary (uninformative) effects. Thus, our findings provide empirical evidence of information asymmetry in the world's largest OTC market and support prior theoretical research on FX determination with heterogeneous contributions from different agents by Bacchetta and van Wincoop (2005) and Evans and Lyons (2006).

Second, our paper contributes to the asset pricing literature by building a long-short strategy based on the permanent price impact. 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) are the first to build cross-sections of currency portfolios to show that consumption growth risk explains why UIP fails to hold. Lustig et al. (2011), Menkhoff et al. (2012a,b) and Asness et al. (2013) identify common risk factors in currency markets based on the real exchange rate, global FX volatility and momentum. Other factors explaining carry trade returns include macro-variables like global imbalances (e.g. Della Corte et al., 2016b) or volatility risk premia (e.g. Della Corte et al., 2016a). We add to this literature by investigating whether the heterogeneity in global FX order flows provides significant economic value for building a profitable trading strategy. Menkhoff et al. (2016) perform a thorough analysis that also studies FX order flow and dissects customer currency trades into end-user segments. However, two key improvements of our work extend beyond this paper: We employ a sounder methodology and more granular data. On the methodological side, Menkhoff et al. (2016) construct currency portfolios using lagged, total order flow, which confounds transient (uninformative) and persistent (informative) effects of trades. The methodology used in our paper is more accurate and consistent because it isolates the informative component of order flow, which genuinely generates superior predictions of FX evolutions. As we show empirically, our methodology is more effective in extracting superior information from order flow and thus delivering higher excess returns. On the data side, the dataset studied in our paper is representative for the global FX market and can be accessible to anyone, whereas their work relies on an anonymous bank-specific source. Furthermore, we use a comprehensive intra-day (hourly) dataset encompassing 30 currency pairs (instead of 15 daily FX rates).

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. Section 5 estimates a simple trade/quote revision model and analyses price impact heterogeneity across agents, time and currency pairs. Section 6 exploits the price impact
heterogeneity by a profitable long–short trading strategy. 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, which is publicly available from Quandl.com, a financial and economic data provider. CLS Group operates the world’s largest multi-currency cash settlement system, handling over 50% of global spot, swap and forward FX transaction volume. After each and every FX transaction, settlement members of CLS are entitled to submit the details of the order for authentication and matching by CLS. 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 (2018). To the best of our knowledge, this is the first paper to study CLS order flow data.

2.1 Heterogeneous FX Information Content

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 on most of trade instructions from settlement members within 2 minutes of trade execution. Most of the currently 66 current settlement members are large multinational banks. Furthermore, there are over 20000 ‘third party’ clients of the settlement members, including other banks, funds, non-bank financial institutions and corporations. On the settlement date, CLS mitigates counterparty risk by simultaneously settling both sides of the FX transaction. The FX spot market works on a $t+2$ settlement schedule, unless both parties are in North America (e.g. $t + 1$). That is, when a spot trade occurs at time $t$, the settlement instructions are submitted to CLS, specifying that the real transfer should occur two days later (see Pajarliev and Levich, 2012, Levich, 2012 for further studies on CLS).

This dataset has several features that make it suitable to investigating the information content of FX order flow and its statistical and economic value. First, CLS records the trading volume in the base currency, as well as the number of transactions on an hourly

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basis from Sunday 9 pm to Friday 9 pm (London time, GMT with 7 months using British Summer Time (BST)), and thus, it matches the whole FX trading week from the opening in Sydney on Monday morning to the closing in New York on Friday evening. 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 as well as the access to price-relevant information across the four 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 and buy trade count, referring to how much of the buy currency was purchased by the price takers from the market makers. The sell volume and sell trade count indicate the amount of the sell currency sold by the same price takers to the same market makers.

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 pairings between price takers and market makers: corporate/bank, fund/bank and non-bank financial/bank.\(^8\)

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 are then separated into two groups based on their coreness in the network. 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

\(^7\)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.

\(^8\)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’.
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 are excluded from this dataset.

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

Our full sample period spans from 2 September 2012 to 31 January 2019 and includes data for 16 major currencies and 30 currency pairs.9 This large cross-section of FX rates is important for evaluating the economic value of order flow and deriving a profitable trading strategy from the inherent information fragmentation across currencies.

The order flow dataset is limited to spot transactions. Three characteristics of the dataset merit being discussed in more detail: First, it contains around 6 years of data, which is a relatively long compared with previous studies on FX microstructure. Using a high-frequency dataset raises the statistical value of order flow in a time series setting by

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9The 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 USD/KRW due to insufficient amount of trades per price taker category. The remaining 30 currency pairs are: AUD/JPY, AUD/NZD, AUD/USD, CAD/JPY, EUR/AUD, EUR/CAD, EUR/CHF, EUR/DKK, EUR/GBP, EUR/JPY, EUR/NOK, EUR/SEK, EUR/USD, GBP/AUD, GBP/CAD, GBP/CHF, GBP/JPY, GBP/USD, NZD/USD, USD/CAD, USD/CHF, USD/DKK, USD/HKD, USD/ILS, USD/JPY, USD/MXN, USD/NOK, USD/SEK, USD/SGD, and USD/ZAR.
mitigating endogeneity and reverse causality issues and allowing us to measure the price impact of the order flow over rolling windows.

Second, despite being the most comprehensive time-series dataset on FX order flow, it does not cover the full FX (spot) market. The 2016 BIS triennial survey (see BIS, 2016) reports an average daily trading volume of $5.1 trillion. Conversely, CLS settles approximately $1.5 trillion, or 30% of the total FX volume. 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 avoid becoming a settlement member. Third, CLS does not settle some of the high-volume currencies, namely the Chinese renminbi and Russian rubel. 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 BIS is related to inter-bank trading across desks and double-counts prime brokered ‘give-up’ trades. Adjusting for these facts shrinks total FX volume to $3.0 trillion per day, and thus CLS covers 50% of the FX market.

Third, this dataset does not cover all transactions originated by one of the three price taker categories. More precisely, if a corporation settles a trade via a prime broker who is member of CLS, then this trade would show up as a bank/bank transaction. 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 the latter is behaving 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, which we define 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,

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

\[\text{In the 2016 BIS report (cf. p. 9), ‘related party trades’ and ‘prime brokers’ generated $0.94 trillion and $0.89 trillion in turnover, respectively.}\]

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

\[\text{This can be also true for algo traders who should be classified funds when directly dealing with CLS.}\]

\[10\]

\[11\]

\[12\]
where a positive $T_t$ indicates the net buying pressure in the counter currency against the base 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. Thus, the FX order flow and exchange rate return are both measured hourly. The exchange rate return is calculated as the log difference in the mid-quote FX rate over a trading hour:

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

(2.2)

where natural logarithms are denoted by lowercase letters. Returns are always calculated based on 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 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 reasonable in the range of 10-21 basis points (BPS). Third, the average relative spread varies substantially 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 (USD441 mn), USDJPY (USD240 mn) and USDCAD (USD225 mn). Our ranking is largely in line with both the BIS Triennial Surveys and Gargano et al. (2018). Across currencies, we observe a mild first order autocorrelation of

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13 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.
9–17% that is consistent with prior research on stock markets, for example, Hasbrouck and Ho (1987).\textsuperscript{14} Funds and non-bank financials are the largest categories after banks acting as price takers, whilst corporates form the smallest group. There are at least two potential reasons why corporates show up less frequently in this dataset: First, corporates are known to use swap rather than spot transactions to hedge their currency exposure. Second, large, multinational corporations are more likely to trade via CLS, whereas smaller, regional corporates access the FX spot market indirectly through prime brokers/banks. Hence, we cannot rule out a potential bias towards large corporations in the data.

Figure 1 fleshes out the idea that market participants behave heterogeneously during the day and provides \textit{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 (no BST adjustment). Investigating at which hours market participants are most active helps in identifying time-fixed effects in the trading behaviour of FX market participants. In the European morning, when only Asian markets are open, volume levels are relatively low. The FX volume rises when European and London markets open at 6 am and 7 am London time, respectively. Around lunchtime, trading drops, and it picks up again when New York traders enter the market around 1 pm. Volume is lowest during the night, between 10 pm and 11 pm, when only the Australian market is open. 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%. As expected, corporate trading is more concentrated in European working hours, i.e. 7 am to 5 pm.\textsuperscript{15}

In line with prior research on equity markets (see Jain and Joh, 1988, Gerety and Mulherin, 1992), we extend our analysis to the FX order flow and find that (absolute) net volume is concentrated in the early and later parts of the trading day in London and New York, suggesting heterogeneous information flows across (intra-day) time.\textsuperscript{16}

To conclude the descriptive analysis, we address two possible problematic issues on order flow data segregated by market participants groups, which were 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 2 plots the average correlation coefficients between customer order flows for horizons of 1, 2, ..., and 60 trading days (see the online appendix for signed net volume). 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. The shaded areas correspond to 95% confidence bands based on a moving-block bootstrap with 1000 repetitions. We find global evidence that all correlations between financial (FD and BA) and non-financial customers (CO and NB) are significantly negative at all horizons, while there is hardly any significant correlation between flows of the non-financial customer groups. 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 across the entire cross-section of currencies, serial autocorrelation is not an issue, since the difference between the Durbin–Watson test statistic and its critical value $2 \times 0.001$ is $< 0.001$ for all the currency pairs. The Ljung–Box test for residual autocorrelation renders similar results: For more than 90% of currency pairs we do not reject the null of no residual autocorrelation in order flow up to lag 24.

4 Methodology

In this section, we describe the methodology used for investigating whether market participants exhibit a heterogeneous price impact in the FX market. The approach builds on the framework developed by Hasbrouck (1988, 1991a), who introduces a VAR that makes almost no structural assumptions about the nature of information or order flow, but instead, infers the nature of information and trading from the observed sequence of quotes and trades. In the general setting of Hasbrouck (1991b), stock price movements
are either related or unrelated to a recent trade. More specifically, trade-related price moves may convey superior private information, although the model itself does not make any structural assumptions on information. However, for the VAR model to be estimated consistently, it is necessary that the time series is covariance stationary in terms of the time index used. Jones et al. (1994) and Barclay and Hendershott (2003) argue that trades based on ‘public information’ lead to orthogonal price moves to recent trades.

Hasbrouck (1988) provides a useful model for separating the permanent (information) effects and temporary (inventory) effects of a trade, but this 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 decompose into trade-related and trade-unrelated components. 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 seasonality. Especially, Eq. (4.2) describes the trade-by-trade evolution of the quote midpoint, whilst Eq. (4.3) refers to the persistence 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.\(^{17}\) 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 are taken to control for presumed non-linearities between order size and quote revisions:

\[
\begin{align*}
 v_t &= \begin{cases} 
 +\log(z_t) & \text{if } z_t > 0 \\
 0 & \text{if } z_t = 0 \\
 -\log(-z_t) & \text{if } z_t < 0 
\end{cases},
\end{align*}
\]  

(4.1)

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 \( T_t \).\(^{18}\) Hourly dummies are

\(^{17}\)\( T_{CO}^t \) for corporate, \( T_{FD}^t \) for fund, \( T_{NB}^t \) for non-bank financial and \( T_{BA}^t \) 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.

\(^{18}\)It is important to note that our main results remain qualitatively unchanged when excluding the order-size variable from our baseline VAR model.
included to control for daily seasonalties 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 and Bayesian information criteria, as well as theoretical foundations postulated by Hasbrouck (1991a,b). Our findings remain qualitatively unchanged when using more lags (+/−5) but become computationally expensive. Especially, the regression coefficients $\beta^j_i$ at lags 8/9 and beyond are mostly statistically insignificant:

\[
\begin{align*}
 r_t &= \zeta_{1,t}D_{l,t} + \sum_{i=1}^{10} \alpha_i r_{t-i} + \sum_{j \in C} \left( \sum_{i=0}^{10} \beta^j_i T^j_{t-i} + \sum_{i=1}^{10} \phi^j_i S^j_{t-i-1} \right) + v_1 \Delta s_{k,t,t-\tau} + v_2 \Delta s_{k,t,t-10r} + \epsilon_{r,t}, \\
 T_t &= \zeta_{2,t}D_{l,t} + \sum_{i=1}^{10} \gamma_i r_{t-i} + \sum_{j \in C} \left( \sum_{i=1}^{10} \delta^j_i T^j_{t-i} + \sum_{i=1}^{10} \omega^j_i S^j_{t-i-1} \right) + \epsilon_{T,t},
\end{align*}
\]

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 $C = \{CO, FD, NB, BA\}$. Transactions are indexed by $t$. Moreover, the regression considers the lagged exchange rate changes over the previous day $\Delta s_{k,t,t-\tau}$ and over the prior week $\Delta s_{k,t,t-10r}$. Here, $\tau = 24$, and $t$ is measured hourly. The error terms $\epsilon_{r,t}$ and $\epsilon_{T,t}$ can be interpreted as an expected (public information) and unexpected (private information) component, respectively. This dichotomy ensures that the impulse response function $\alpha^j_m$ in Eq. (4.6) can be interpreted as a measure of asymmetric/private information. Hasbrouck (1991a) thoroughly discusses some of the imperfections which might disturb this dichotomy in practice.

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:

\[
\begin{align*}
 E(\epsilon_{T,t}) &= E(\epsilon_{r,t}) = 0, \\
 E(\epsilon_{T,t}\epsilon_{T,s}) &= E(\epsilon_{r,t}\epsilon_{r,s}) = E(\epsilon_{T,t}\epsilon_{r,s}) = 0, \text{ for } s \neq t.
\end{align*}
\]

Next, to make Eqs (4.2) and (4.3) more intuitive, the VAR shall be inverted to its vector moving average (VMA) representation. Hereby, we follow the methodologies in Hasbrouck
(1991b) and Hendershott et al. (2011), and thus derive:

\[
y_t = \begin{bmatrix} r_t \\ y_t \\ T_t \end{bmatrix} = \Theta(L)\epsilon_t = \begin{bmatrix} a_r D_t & b_r(L) & c_r(L) & d_r(L) & s_r \\ a_T D_t & b_T(L) & c_T(L) & d_T(L) & 0 \end{bmatrix} \begin{bmatrix} \epsilon_{D,t} \\ \epsilon_{r,t} \\ \epsilon_{T,t} \\ \epsilon_{S,t} \\ \epsilon_{v,t} \end{bmatrix}, \tag{4.5}
\]

where \(b_r(L), c_r(L), d_r(L), b_T(L), c_T(L)\) and \(d_T(L)\) are lag polynomial operators. In this case, \(c_r, c_T, d_r, d_T\) represents a row vector equal to \([\beta^C, \beta^F, \beta^N, \beta^B], [\phi^C \delta^F \delta^N \delta^B], [\phi^C \phi^F \phi^N \phi^B]\) and \([\omega^C \omega^F \omega^N \omega^B]\), respectively. Moreover, \(s_r\) refers to a row vector consisting of \([v_1, v_2]\) from the return equation. \(\epsilon_{D,t}, \epsilon_{r,t}, \epsilon_{T,t}, \epsilon_{S,t}\) and \(\epsilon_{v,t}\) denote the innovation terms associated with dummies, returns, order flow, volume control and cumulative daily and weekly returns, respectively.

A possible concern about our VAR setting is that some endogeneity may originate from the contemporaneous log return with a simultaneous effect on order-flow.\(^{19}\) There are two ways of mitigating this issue empirically, which are as follows, i) increasing the sampling frequency to approach ‘quasi-event’ time, and, ii) introducing feedback trading, as proposed in Danielsson and Love (2006). The former remedy cannot be applied with this aggregated dataset. We have attempted various ways of implementing the latter solution but the following issues arise: First, the instruments are too weak when applying the Danielsson and Love (2006) methodology to frequencies greater than 5 minutes; second, it is not clear how to choose strong instruments that are both highly correlated with the endogenous variable and economically meaningful. 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 methodology that can be applied in this setting.

**Permanent Price Impact.** From Eqs (4.2) and (4.3) we can derive the permanent price impacts at the individual agent level and aggregated across agents. Following Hasbrouck (1991a), the permanent price impact of agent \(j \in C\), with \(C = \{CO, FD, NB, BA\}\),

\(^{19}\)The argument why causality runs from quantities to prices is related to order flow being correlated with information that is not known by all market participants. Thus, order flow is a proximate cause of exchange rate changes, with the underlying dispersed information being the primitive cause (Lyons, 2006).
can be calculated as follows:

$$\alpha^j_m(\epsilon_{T_j,t}) = \sum_{t=0}^{m} E[r_t | \epsilon_{T_j,t}] = \sum_{t=0}^{m} \beta^j_t, \quad (4.6)$$

where $m$ indicates the number of lags, which is 10 in our case. Since $\alpha^j_m$ is cumulative over several hours (even weak effects can add up), VAR estimates of a lower order ($t \leq 10$) are likely to overstate the long-run price impact. 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 cumulative impulse response (permanent price impact) aggregated across agents is given by

$$\alpha_m(\epsilon_{T_j,t}) = \sum_{j \in C} \sum_{t=0}^{m} c^j = \sum_{j \in C} \alpha^j_m. \quad (4.7)$$

In this framework, the cumulative impulse response function of the quoted price to a one-unit shock in the order flow equation 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. Since $\alpha_m$ lies at the heart of the subsequent asset pricing analysis, it is important to underline that $\alpha_m$ possesses a natural interpretation as the information content of the innovation net of transient effects inherent in global FX trading. To summarise, the approach of Hasbrouck (1991a,b) is the most suitable econometric methodology for capturing the permanent price impact conveyed by trade innovations robust to transitory effects, such as price discreteness, inventory effects, information cascades and lagged adjustment to trades.

5 Heterogeneous Information Content of Global FX Trading

In this section, we analyse whether the price impact in the global FX spot market is heterogeneous 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 Estimating a Simple Trade/Quote Revision Model

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. Second, we apply a 12-month rolling window for measuring the time variation of both the contemporary $c_{t}^{j,r}$ and permanent price impact $\alpha_{t}^{j}$. The main advantage of the VAR approach lies in its potential for generalisation to gain a more nuanced view of the trade-quote interactions. For the sake of clarity, we only present the results for lagged return equation coefficients $b_{t}^{r} (\alpha_{1})$ and $b_{t}^{T} (\gamma_{1})$, the contemporary price impact $c_{t}^{j,r} (\beta_{0}^{j})$ and lagged order flow $c_{t}^{j,T} (\delta_{1}^{j})$, where $j \in C$ denotes one of the market participants.

Table 3 shows the regression coefficients of the bivariate VAR estimated through 10 lags. The most important ones are those of $T_{0}^{j,r}$ that measure the contemporary price impact of a trade. Coefficients beyond lag eight and nine are seldom significant. To overcome the curse of heteroscedasticity and autocorrelation we apply heteroscedasticity- and autocorrelation-consistent standard errors (HAC errors) based on the Newey and West (1987) estimator of the covariance matrix (10 lags).

For the great majority of currency pairs, regression coefficients bear the expected signs summarised in Table 3: Here, $b_{t}^{r}$ coefficients are negative and entail short-term mean reversion, while $c_{t}^{j,r}$ coefficients are positive and in line with market microstructure theory. This is especially true for the most liquid and frequently traded currency pairs.

The true beauty of the log-level model in Table 3 is its interpretability: Coefficients can be interpreted as percentage changes in the dependent variable for a one-unit change of the independent variable. The coefficients at longer lags alternate in sign and decay to zero after a few lags. From these results, it is apparent that all agents except corporates have a significantly positive contemporary price impact.

For some currency pairs (e.g. EURGBP, EURNOK, EURUSD), corporates experience significantly negative contemporary price impact parameters. The negative $\beta_{0}^{CO}$ is consistent with earlier work by Bjønnes et al. (2005), Lyons (2006), Carpenter and Wang.

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20 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.

21 As in Hasbrouck (1991a), $T_{t}$ is defined as a limited dependent variable. If $T_{t}$ and $r_{t}$ are jointly covariance stationary and invertible, a VAR model as in Eq. (4.5) exists. However, while the error terms are serially uncorrelated, they are not serially independent in general. The disturbance properties in Eq. (4.4) further ensure that the coefficients in Eq. (4.5) are estimated consistently by OLS. Nonetheless, estimation errors can lead to non-zero disturbance terms for certain out-of-sample data points (see Hasbrouck, 1991b).

22 One of these basic ideas is that quantities both clear markets and convey information (see Kyle, 1985, Grossman and Miller, 1988, Glosten and Milgrom, 1985).

23 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 for further results.
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. 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 seem to be driven by risk sharing, hedging and liquidity issues (i.e. implicitly paying an insurance premium), 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 few hours.

The negative $\beta_{CO}^{\beta}$ is also consistent with two common practices applied by FX dealers to fulfill their liquidity needs: First, dealers may apply discount fees to beg customers’ liquidity provisions. Second, dealers offset 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. 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 ($\upsilon_1$) is negative and highly significant for all currency pairs, whilst the return over the prior week ($\upsilon_2$) is negative but insignificant for the majority of currency pairs.

Table 4 summarises the order flow equation coefficients, which also bear the expected signs: Here, $b_{1T}$ is negative and highly significant, while $c_{j,T}^{\beta}$ coefficients are positively significant and reflect a strong positive autocorrelation in trades. For most currency pairs, $c_{j,T}^{\beta}$ is positive but statistically not always significant. 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, $b_{1T}^{\beta}$ implies negative autocorrelation in the quote revisions.

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

25 Alternatively, the negative coefficient for the contemporaneous price impact of corporate order flow may be interpreted on the basis of Lyons (1997) and Bjønnes and Rime (2005): As market makers unwind their inventories onto non-financial customers, order flow may be wrongly signed. Moreover, Breedon and Vitale (2010) argue that, while liquidity effects of order flow are transient, a trade imbalance may have a long-lived impact via a portfolio-balance effect when the order flow is not informative.
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 the traders.

For both the return and order flow equation, hourly dummies 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 are mostly positive and significant, but around a fraction of a BPS. Thus, larger trades subsequently lead to a larger price impact, increasing the spread and the level of asymmetric information.

So far, we have centred our analysis on the contemporary price impact. We now turn to the permanent component. The sums of $c^j_t$ and $d^j_t$ measure the persistent effects of the trade indicator $T^j_t$ and trade size variables $\tilde{S}^j_t$. A positive $d^j_t$ indicates that order size, in addition to trade direction, conveys information. Furthermore, in the model of Hasbrouck (1991a), $\alpha^j_m$ 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 price arises from asymmetric information signalled by that trade. This intuition is reflected in Eq. (4.5), which identifies all public information with the quote revision innovation ($\epsilon^r_{r,t}$) and all private information with the trade innovation ($\epsilon^T_{T,t}$). The dichotomy above ensures that $\epsilon^T_{T,t}$ reflects no public information, and hence, the impulse response function $\alpha^j_m$ can be interpreted as a measure of asymmetric/private information. In Table 5 we summarise the estimates of permanent price impact for every agent and currency pair. In general, we find that the permanent (cumulative) price impact parameters are positive and significant across agents (with a handful of exceptions), except for corporates for the above-mentioned reasons. Hence, the positive (negative) $\alpha^j_m$ again reflects that order flows coming from financial firms (corporates) are informative (non-informative).

The permanent (cumulative) price impact parameters appear to be positive and significant across agents (with a handful of exceptions), except for corporates for the above-mentioned reasons. Hence, the negative $\alpha^j_m$ again reflects that their order flow is non-informative. In this framework, the sums of $c^j_t$ and $d^j_t$ measure the persistent effects of the trade indicator $T^j_t$ and trade size variables $\tilde{S}^j_t$. A positive $d^j_t$ indicates that order size, in addition to trade direction, conveys information. Furthermore, in the model of Hasbrouck (1991a) $\alpha^j_m$ can be interpreted as the measure of asymmetric/private in-
formation 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 price must arise from asymmetric information signalled by that trade.

5.2 Heterogeneous Price Impact Across Agents

The question we address here is whether the estimates of price impact are significantly different across agents. In this and all subsequent sections, we focus solely on the permanent price impact parameter $\alpha_m$ as it was defined in Section 4. The following results are de facto identical for both the contemporary and permanent price impacts. Thus, the online appendix collects the output tables and all the technical details.

To assess whether the permanent price impact parameter $\alpha^i_m$, significantly differs across agents, we test if all coefficients in Eq. (4.6) for a specific agent $i$ 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. 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. For overcoming the curse of multiple testing, a Bonferroni correction is applied.

5.3 Fragmentation in the FX Market Across Currencies

Another important question is whether the price impact varies across currency pairs. 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 $\epsilon^{i,r}_0/\alpha^i_m$) 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. (4.6) for a particular agent $i \in C = \{CO, FD, NB, BA\}$ are jointly significantly different in currency pair $k$ compared with $q$. Again, the validity of this $F$-test is warranted by the general properties of a log-level model. For technical details and output tables, see the online appendix. The main result that emerges from this analysis is that corporates, funds, non-bank financials and banks

\[\text{See Tables B.7 to B.15 on pages 13-23 in the online appendix.}\]
\[\text{See Tables B.11 to B.19 on pages 18-28 in the online Appendix.}\]
acting as price takers have a permanent price impact $\alpha^j_m$, which varies heavily across currencies. However, this type of market segmentation appears to be less pronounced for corporates than for funds or non-bank financials. The reasons for this are twofold: First, corporates are mostly active in the swap rather than spot market. Second, funds and non-bank financials are more sophisticated and specialised investors that frequently trade on superior information, which may well vary across currencies. Overall, our empirical analysis confirms earlier research on customer order flow (e.g. Evans and Lyons, 2006, Osler et al., 2011, Menkhoff et al., 2016). Furthermore, our results provide evidence that non-financial customers do not trade strategically, but rather, they are hedging. A prosperous avenue for future research would be understanding the effect of regulation on the local nature of FX price discovery.

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

5.4 Time-Varying Information Flows

In this section, we introduce time as a third dimension of heterogeneity and study the time variation of both the contemporary and permanent price impacts. Again we estimate Eq. (4.5) 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 3, we plot both the average $c^j_r$ and $\alpha^j_m$ across currency pairs over time. The plotted averages exclude any coefficients that are either heavy outliers with respect to the median or not significant at a 95% confidence level, applying a simple two-sided t-test and the same joint F-test as in Table 5, respectively. Corporates seem to have the strongest time variation, consistent with the idea that their trades are driven by uninformative reasons (market risk, hedging or liquidity shocks) rather than a systematic processing of superior information. We use the Brown-Forsythe test for verifying whether corporates’ price impact parameter exhibits 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’ contemporary or permanent price impact parameter at a 95% confidence level for all pairwise combinations.

The main difference across market participants is that the permanent price impact of sophisticated agents, such as funds and banks, is stable on average across time, while
financially less literate agents (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.\footnote{Some hedge funds and high-frequency traders 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 maximise their impact in certain times.}

As a robustness check, 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, which are as follows: First, price impacts tend to be higher during the more illiquid hours of the day, for example, during the European morning and evening. Second, corporate price impact is many times higher (although it is negative during the most liquid hours of the day) than the price impact related to sophisticated financial institutions (e.g. funds, banks and non-bank financials). See the online appendix Section B for output tables and figures.

6 Currency Portfolios

In the foregoing sections, we have studied how order flow impacts FX spot prices heterogeneously. In the remaining part of this paper we address the question of whether this heterogeneity provides significant economic value. To accomplish this, we introduce a simple yet innovative trading strategy based on UIP deviations that exploits the (persistent) price impact heterogeneity.

6.1 Trading Strategy

Hasbrouck (1991a) demonstrates that any permanent price impact of a trade must arise from superior information about the future evolution of the security price. To capitalise on asymmetric information, a coherent trading strategy should apply this method to detect order flows conveying superior information across agents and assets in a timely manner. In the context of global FX trading, we consistently apply this idea by introducing a novel long-short trading strategy based on a simple idea: Order flows of agents and currencies impounding a persistent price impact convey superior information, leading to better predictions of future evolutions of FX rates. Put differently, a higher informational advantage (i.e. a high permanent price impact) goes hand in hand with higher excess returns. The intuition behind this strategy relies on well-documented deviations from the
UIP condition and forward premium puzzle: When regressing FX returns on interest rate differentials, the slope coefficient is typically below 1 and even negative. In other words, the forward premium points into the ‘wrong’ direction of the expected price movement.

Following the empirical work by Lustig and Verdelhan (2007) and Lustig et al. (2011), a straightforward interpretation of our trading strategy arises: Given that our measure of persistent price impact captures order flows conveying superior information (net of temporary liquidity effects), it is naturally well suited for identifying trading that correctly predicts currency values, or conversely, that is more biased by UIP deviations. Consequently, currency pairs with a high (low or negative) aggregate permanent price impact are more likely to gain positive (negative) excess returns, that is, deviate from the UIP in the sense that $f_{t,t+1} \geq s_{t+1}$ ($f_{t,t+1} \leq s_{t+1}$). With this intuition in mind, the excess returns of this trading strategy are sourced by asymmetric (private) information and are not driven by temporary liquidity effects.

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

Trading signals are generated from estimating Eq. (4.2) 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. The advantage of running this regression at daily rather than hourly frequency is twofold: First, it is computationally less expensive, and hence, easily

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30Results are robust to investing with a lag of 1 day up to a week.

31All our results are qualitatively unchanged when we use a rank or value based weighting scheme.

32Lustig and Verdelhan (2007) were the first to build cross-sections of currency portfolios. Tertile portfolios are known to be less prone to be driven by outliers in smaller cross-sections ($N \leq 30$) than quartile or quintile portfolios are (see Bali et al., 2016).

33The 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 $\tilde{S}_i$ in Eq. (4.2), we do not have to weight the (permanent) price impact coefficients by their trading volume. Our main results are qualitatively unchanged if we remove the order size variable from Eq. (4.2) and multiply each market participant’s permanent price impact by its trading volume aggregated over $m = 10$ lags.
replicable for global investors. Second, forward rates are usually not readily available at an hourly frequency, and therefore, using daily data ensures that signals are extracted at the same frequency as excess returns are.

Hence, investment starts in August 2013 after 1 year of formation period. This leaves us 5.5 years for testing out-of-sample performance. For every rolling window index and currency pair $k$, we obtain the aggregate permanent price impact $\alpha^k_m$ (see Eq. (4.7)). Next, we sort $\alpha^k_m$ currency pairs by size and in ascending order. The $ALP_{HML}$ portfolio consists of the 33.33% highest (lowest) $\alpha^k_m$ currency pairs in the long (short) leg. Portfolio rebalancing takes place at the beginning of every day, week or month.

Following the FX asset pricing literature, going long or short in a specific currency pair involves forward positions. Therefore, the log excess return $r_x$ of buying a foreign currency in the forward market and selling it in the spot market after one day, week or month is

$$r_x^{t+1} = f_{t,t+1} - s_{t+1}, \quad (6.1)$$

assuming forward rates satisfy the CIP condition in normal times. Here, $f_{t,t+1}$ 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 non-USD currency pair such as the EURGBP, we modify Eq. (6.1) such that, instead of one forward contract, the US investor enters two forward contracts based on triangular no-arbitrage conditions:

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

where $X$ and $Y$ are the base and quote currency of a non-USD currency pair, respectively.

For a detailed derivation and discussion on alternative methods, see the online appendix.

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34 The order flow dataset is released hourly by CLS and is publicly accessible through Quandl with a 30-minute lag. FX quotes by Olsen are readily available to investors at a 1-minute frequency.

35 At this stage, it is important to point out that a trading strategy based on the permanent price impact derived from 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 Akram et al. (2008) study high-frequency deviations from Covered Interest rate Parity (CIP). They conclude that CIP holds at daily and lower frequencies.

37 Daily, weekly and monthly forward bid–ask points are obtained from Bloomberg. Forward rates can be expressed as the forward discount/premium (or forward points) plus the spot rate. Therefore, the simple (outright) forward bid–ask rates are $F^b = S_t + P^b_t$ and $F^a = S_t + P^a_t$, respectively, where $P^b_t$ and $P^a_t$ denote the bid–ask values of forward points, respectively, and $S_t$ is the mid-quote, defined as $S_t = (S^b_t + S^a_t) / 2$. Our results are robust to using spot bid ($S^b_t$) and ask ($S^a_t$) quotes instead of the mid-quote for calculating forward rates.
Section C on page 40. The main advantage of this approach is that we do not have to distinguish between different investors (e.g. European, Japanese, etc.), since all returns are dollar-neutral.

Since we have bid–ask quotes for spot and forward contracts\textsuperscript{38}, we can compute the investor’s true realised excess return net of transaction costs in the spirit of Lustig et al. (2011). The net log currency excess return for an investor who goes long in foreign currency $y$ is

$$r_{X/Y, t+1} = f_{t,t+1} - s_{t+1} - (f_{t,t+1} - s_{t+1})$$  \hspace{1cm} (6.3)

where the investor buys the foreign currency or equivalently sells the dollar forward at the bid price $f_{t,t+1}$ in period $t$ and sells the foreign currency, or equivalently, buys USD at the ask price $s_{t+1}$ in the spot market in period $t+1$. Similarly, for an investor who is long in the USD (and thus, short in the foreign currency) the net log currency excess return is given by

$$r_{X/Y, t+1} = -f_{t,t+1} + s_{t+1} + (f_{t,t+1} - s_{t+1})$$  \hspace{1cm} (6.4)

and the (simple) portfolio return $RX_p$ is given by

$$RX_{p,t+1} = \sum_{k=1}^{K_t} w_{k,t+1} RX_{k,t+1},$$  \hspace{1cm} (6.5)

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

6.2 Trading Performance

In Table 6, we present the annualised Sharpe ratio (SR), the annualised mean excess return (Mean), the maximum drawdown (MDD) and the $\Theta$ performance measure of

\textsuperscript{38}The bid–ask spread data are available for quoted spreads and not effective spreads. To be conservative, unlike the researchers in earlier work (e.g. Goyal and Saretto, 2009, Gilmore and Hayashi, 2011, Menkhoff et al., 2016 and Gargano et al., 2018), we do not employ 50\% of the quoted bid–ask spread as the actual spread. Thus, from a real-world implementation point of view, we can think of our after transaction cost estimates as a lower bound. The online appendix shows the trivial increase in performance when applying the 50\% rule to proxy effective spreads.
Goetzmann et al. (2007) based on monthly rebalancing, respectively.\footnote{Prior transaction costs, trading performance remains similar for weekly and daily returns, but it erodes significantly on a daily basis when transaction costs are taken into consideration.} Despite being commonly used, the SR exhibits an important drawback—the effect of non-normalities (see Jondeau and Rockinger, 2011) is not taken into account, which may be important in a small-sample setting. The \( \Theta \) performance measure of Goetzmann et al. (2007) overcomes this issue by re-estimating the sample mean while putting less weight on outlier returns. Both prior and post transaction costs \( \Theta \) is only slightly lower than the mean return, indicating that neither outliers nor non-normality are driving the superior performance.

Panel a) and b) of Table 6 tabulate the before and after transaction cost performances of the first (\( Q_1 \)) and third (\( Q_3 \)) tertile portfolios, where \( ALP_{HML} \) is a linear combination of going short in \( Q_1 \) and long in \( Q_3 \) that considers the effect of compounding, as well as the performance of common FX trading strategies. To overcome the curse of heteroscedasticity and autocorrelation, we apply HAC errors using the plug-in procedure for automatic lag selection by Andrews and Monahan (1992) and Newey and West (1994).

First, we wish to compare performance to a pure order flow-based strategy. Hence, following the identical methodology as in Menkhoff et al. (2016), we construct a trading strategy (‘Buying Minus Selling’ pressure, \( BMS \)) based on aggregate standardised total order flow and compare it with \( ALP_{HML} \). We claim that the advantage of using a VAR model for measuring the permanent price impact is its ability to separate temporary liquidity effects of order flow from persistent ones based on informational motives. Consequently, the predictive power of the permanent price impact on exchange rate changes should be higher, and thereby outperform a pure order flow-based strategy (i.e. \( BMS \)).

From Table 6, it is discernible that \( ALP_{HML} \) clearly outperforms \( BMS \), mainly because \( \alpha_m \) measures the long-lived (ultimate) information effect of a trade net of temporary liquidity effects, while the order flow itself can arise from both informational and non-informational motives. Given that the dataset analysed in Menkhoff et al. (2016) is different and inaccessible, a direct one-to-one comparison is not permissible.\footnote{The differences are twofold: First, our data come from a non-bank-specific source that dissects the aggregate (signed) net volume into different customer end-user segments for a different, non-overlapping period in time. Second, Menkhoff et al. (2016) focus on daily rebalancing, whereas we perform monthly rebalancing due to significant transaction costs.}

Second, in Panel b) we concentrate on the post-transaction cost performance of \( ALP_{HML} \). Two main results emerge, which are as follows: First, an economically and statistically high performance of the \( ALP_{HML} \) strategy is observed. Second, our strategy clearly outperforms common FX risk factor strategies based on USD-based currency
pairs (i.e. $DOL$), the real exchange rate (i.e. $RER/RER_{HML}$), or momentum (i.e. $MOM_{HML}/CAR_{HML}$).

Note that both $MOM_{HML}$ and $CAR_{HML}$ are momentum-based strategies, where the latter is the ‘classic’ carry trade. In line with empirical research, for example, Lustig and Verdelhan (2007), $CAR_{HML}$ generates negative excess returns and Sharpe ratios after transaction costs. This is presumably due to the negative relationship between exchange rate changes and the interest rate differential/forward premium or discount.

Figure 4 depicts the cumulative (simple excess) returns of different rebalancing frequencies before and after transaction costs. Gross returns are based on mid-quotes for both the spot and forward rates. The equity curves show a steadily increasing pattern and visually confirm that our returns are not driven by a few outliers. Daily rebalancing is substantially less profitable than monthly rebalancing due to the high transaction costs, but it bears similar cumulative returns prior to transaction costs. The investment period is the entire sample period (September 2012 to January 2019) minus 12 months of the formation period to retrieve the first trading signal; thus, it spans from August 2013 to January 2019. As discernible in Figure 4, cumulative returns seem to increase steadily over time and do not experience any regime switches.

In general, our results show that less frequently rebalancing investors are rewarded by higher returns both before and after transaction costs. In addition to the cumulative returns, the maximum drawdown curves are constructed. This drawdown measure corresponds to the cumulative return of the $ALP_{HML}$ portfolio relative to the last peak. With monthly rebalancing, the $ALP_{HML}$ strategy can beat itself over extended periods of time and exhibits a maximum drawdown of 4.33% (5.01%) prior (post) transaction costs.

Finally, for overcoming the statistical limitations of a relatively short out-of-sample

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41 The $DOL$ portfolio consists of equally weighted long USD currency pairs. The portfolio return is given by Eq. (6.5).
42 The $RER$ and $RER_{HML}$ are constructed based on Menkhoff et al. (2017), where currencies with a real exchange rate above (below) the cross-sectional average are gone long (short). These weights are scaled such that their absolute sum equals unity. For $RER_{HML}$ we rank the currency pairs based on the real exchange rate and form a ‘high minus low’ portfolio in the sense that the top (bottom) tertile currencies receive a positive (negative) weight.
43 The $MOM_{HML}$ strategy involves a currency sorting based on the realised CIP deviation $(f_{m,t-1}^m - s_t^m)$, where $m$ stands for mid-quote and goes long (short) currencies in the top (bottom) tertile; see Asness et al. (2013). For $CAR_{HML}$ (see Lustig et al., 2011), currency pairs are sorted based on the forward discount/premium $(f_{m,t+1}^m - s_t^m)$ and again a ‘high minus low’ portfolio is formed where the long (short) leg consists of the 33.33% currency pairs with the highest forward premium (discount).
44 $MOM_{HML}$ assigns a positive (negative) weight to currencies that undershot (overshot) the future spot rate implied by CIP in the past period and bets that the direction of this deviation will persist over the next period. $CAR_{HML}$ assigns a positive (negative) weight to currencies experiencing a forward premium (discount), hoping that they appreciate (depreciate) over the next period.
period, we use standard bootstrap techniques. Figure 7 presents bootstrapped \( p \)-values for \( ALP_{HML} \) before and after transaction costs, respectively, using 1000 bootstrap repetitions. Each of the four quarters displays one of the performance measures introduced at the beginning of this section. Taken together, these distributions underline the statistical significance of \( ALP_{HML} \) and confirm the appropriate use of asymptotic \( p \)-values. See the online appendix for further distribution figures and outputs equivalent to Table 6 but based on bootstrapped \( p \)-values.

### 6.3 Portfolio Weights

This subsection sheds light on the currency exposure of \( ALP_{HML} \) and analyses the decomposition of the long and short legs. As illustrated in Figure 5, this analysis delivers two main findings: First, our trading strategy exhibits a balanced exposure across currency pairs, where all the currency pairs receive an average absolute weight of 3–5%.

Second, in Figure 6, we calculate the relative contribution of every agent’s \( \alpha_{ijm}^k \) to the aggregate permanent price impact \( \alpha^k_m \) per currency pair and then take the average across all currencies for \( ALP_{HML} \) with monthly rebalancing. This figure clearly shows that all the groups of market participants are represented providing further evidence of heterogeneous information across market participants. This picture is in line with our empirical finding that corporate trading is largely uninformative for predicting the evolution of FX rates but this informativeness can be used to for sourcing the short leg. Moreover, both the long and short legs appear to be equally balanced across agents. This result is not surprising if compared with Figure 3: Both sophisticated agents (funds, non-bank financials, and banks acting as price takers) and financially less literate agents (corporates) experience significant time variation of their permanent price impact.

### 6.4 Exposure Regression

Here, we address the question of whether gross returns of \( ALP_{HML} \) can be explained by any of the common FX risk factors presented in Lustig et al. (2011), Asness et al. (2013) and Menkhoff et al. (2016, 2017). In Table 8, we regress the monthly portfolio returns of the \( ALP_{HML} \) strategy on the monthly net excess returns associated with the following common risk factors: \( DOL, RER_{HML}, RER, MOM_{HML}, CAR_{HML} \) and \( BMS \); we also do this for the return on the VIX index and the change in the iTraxx Europe CDS index. The regressions are based on simple gross excess returns, that is, Eq. (6.5).
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 $ALP_{HML}$ cannot be explained by the traditional FX momentum ($MOM_{HML}$) and is negatively related to carry trade ($CAR_{HML}$ à la Lustig et al., 2011). The trading strategy generates a significant Jensen’s alpha ($\alpha$) of about 40–50 BPS per month and information ratios (IRs) of c. 30–39%, where the IR is defined as $\alpha$ divided by the residual standard deviation.

The relatively low correlations (see Table 7) between the monthly returns of $ALP_{HML}$ and other common risk factors underpin our findings in Table 8. The correlation is negligible/negative for momentum-based ones ($MOM_{HML}$ and $CAR_{HML}$). Consistent with the asymmetric information hypothesis, $ALP_{HML}$ returns are more correlated to factors related to (currency) fundamental values, that is, the real exchange rate ($RER_{HML}$, $RER$). As expected, $ALP_{HML}$ is positively related to the standardised total order flow ($BMS$). In addition, $ALP_{HML}$ relates negatively to both returns on the VIX index and to changes in the CDS spread.

6.5 Transaction Costs

Transaction costs are defined as the difference in the excess return per annum over $n$ successive days, weeks or months without and with bid-ask spreads. Both average and median transaction costs are substantially higher and more volatile when rebalancing occurs more frequently. However, the differences on a cost-per-transaction basis are negligible. In the online appendix Section C we collect further tables and histograms that plot the empirical distribution of annual transaction costs for daily, weekly and monthly rebalancing frequencies.

Gilmore and Hayashi (2011) introduce the concept of rolling over an open long/short position instead of opening a new position and unwinding the old one. In other words, the investor opens a long position via a 1-day forward contract in day 0, maintains the position for $n$ successive days via foreign exchange swaps and then unwinds in day $n$. Compared with the excess return prior transactions costs, the investor pays the difference between the bid and mid-rates when opening the position in day 0; the difference between the offer and mid-rates when unwinding the position in day $n$; 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 far lower than the difference between the bid and mid of the forward 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 costs for rolling over \( n \) successive periods. For technical details and derivations, refer to the online appendix Section D, where we summarise the performance of the \( ALP_{HML} \) strategy, when long/short positions are rolled over. Here, monthly rebalancing performance improvement is small compared with daily or weekly rebalancing frequencies. The reasons for this are twofold: First, on a monthly basis, we have 64 rebalancing points over the entire investment period, and therefore, the transaction costs are less weighty. Figure 4 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. The annual average roll costs for our cross-section of currency pairs are in the ballpark of 1–2\%, since the roll cost \( Z_t \) is effectively half of the forward points spread \((P^a_t - P^b_t)\) 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 than to close it and then reopen it. Finally, in this section, we have paid tribute to the importance of transaction costs and introduced the notion of rolling over long and short positions.

6.6 Robustness Tests

We performed a number of additional analyses and robustness checks that we briefly summarise in this section. To conserve space, we focus on five of them and more detailed results are reported in the online appendix.

**Rolling One-year Returns.** Figure 8 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 persistently positive. The numbers on the x-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).\(^{45}\)

**Subsampling Currencies.** In Section 6.3, we showed that the \( ALP_{HML} \) strategy exhibits a balanced exposure across currencies and over time. To alleviate any concerns that the economic profitability of \( ALP_{HML} \) is only driven by just a few currency pairs,

\(^{45}\)Note that our results remain robust when randomly splitting the sample into two to three non-overlapping periods.
we twist our analysis by considering a subset of the original 30 currency pairs. In Table 9, we report the results for the annualised SR, the annualised mean excess return (Mean), the MDD and the Θ performance measure based on monthly rebalancing.

There are four cases to be distinguished, which are as follows: i) G10 currency pairs plus the most liquid EUR cross pairs (14 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 investment performance of $ALP_{HML}$ 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 4.46–7.30% and 0.87–1.27, respectively. Overall, the subsampling analysis alleviates three issues: First, our results are robust to the choice of currency pairs in the sample. Second, the $ALP_{HML}$ 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). For instance, Du et al. (2018) show that CIP deviations concentrate at quarter ends and in some currencies. Moreover, the performance steadily increases over time, and it is not originated by only a few currency pairs. Third, the $ALP_{HML}$ performance is not affected by specific events.

**Excluding the Contemporary Price Impact.** Next, we check whether our results are robust to including the contemporary price impact ($c_0$) in calculating the permanent price impact ($\alpha_m$). To accomplish this, we replicate our trading strategy $ALP_{HML}$ based on signals $\alpha_n = \alpha_m - c_0$ (‘reversal’) and $c_0$, respectively, and compare both to trading based on $\alpha_m$. In line with our conjecture, we find that both signals perform less well than trading on the permanent price impact. Therefore, we may conclude that trading on $\alpha_m$, that is, $c_0$ net of liquidity effects, maximises expected excess returns. However, excluding $c_0$ from $\alpha_m$ leaves our main results qualitatively unchanged.

**Using Bid–Ask Quotes from Electronic Broking Service (EBS).** Instead of using indicative quotes from Olsen we use directly tradeable bid–ask quotes from EBS. However, EBS spot quotes are only available for the whole year 2016. Thus, the sample size is too small to draw a clear conclusion but renders an accurate proxy for market depth. The goal is showing that our trading strategy is profitable and easy to implement.

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46Du 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.

47Bid–ask quotes from Olsen are generally considered to be a good proxy for the cost of trading that non-inter-dealer market participants are expected to face.

48Ideally, future research can replicate our results on a longer sample of forward and spot bid–ask quotes.
from a large institutional client point of view. Historically, EBS has been the primary trading venue for EURUSD, USDJPY, EURJPY, USDCHF and EURCHF while Thomson Reuters Matching has primarily traded commonwealth (AUDUSD, NZDUSD, USD-CAD) and emerging market currency pairs. Therefore, we exclude infrequently traded currency pairs based on our goal of constructing an hourly time series of tradeable bid-ask quotes. For each hour, we pick the first best bid-ask quotes and calculate the volume weighted average price if we wish to trade an amount greater than what is offered at the best bid-ask. In the online appendix Section D we tabulate the SRs at daily rebalancing and after transaction costs for trading at different hours of the day, as well as dollar amounts. As expected, annualised SRs are higher for smaller trade sizes and peak during the most liquid hours of the day, that is, from 10 am to 4 pm GMT.

**Rebalancing at Different Times of the Day.** Instead of relying on the closing price (i.e. $PX_{LAST}$), we implement our trading strategy $ALP_{HML}$ 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 9, it is discernible that, for all fixing times SRs are close to 1 and their statistical significance is far beyond the 5% level.

To conclude, despite the relatively short sample period, our asset pricing analysis highlights the economic value of heterogeneous information contents of 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 asymmetric information across agents.

7 Conclusion

In this paper, we analysed the heterogeneous information content of global FX trading in an effort to improve our understanding of the world’s largest OTC market, the FX market. We address the following two questions: Given that the FX market hosts various types of market participants, does order flow impact FX prices heterogeneously? Do asymmetric information contents in global FX trading lead to a profitable trading strategy?

To answer these questions, we analysed a new and representative 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 and fragmentation in OTC markets. Especially, corporates have a significantly lower contemporaneous and
permanent price impact than funds, non-bank financials or banks do, suggesting (time-varying) asymmetric information across market participants and in the cross-section of FX rates.

For assessing the economic value of order flow heterogeneity, we introduced a novel long-short trading strategy based on UIP deviations that exploits the persistent price impact. Given that our measure of permanent price impact captures the persistent effect of order flow net of temporary liquidity effects, it is naturally well suited to identifying superior information that correctly predicts the evolution of FX rates and puzzling out the forward premium bias. Put differently, a higher informational advantage (i.e. a high permanent price impact) goes hand in hand with higher excess returns. As a consequence, currency pairs with a large positive (small or negative) permanent price impact, that is, a high (small) informational advantage, gain positive (negative) excess returns. Overall, the strategy generates an annualised excess return and a SR that are both economically and statistically significant, even after accounting for transaction costs. Furthermore, the returns generated by our strategy are unrelated to other common currency strategies and risk factors.

Our paper should be relevant for both academics and policymakers. For academics, our method for detecting superior 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, such as an increase of transparency, price efficiency and fairness, have yet to be achieved or have produced the suited effects in only some market segments.
References


Table 1: Summary Statistics for Hourly Spot Returns

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<td>-0.03</td>
<td>0.05</td>
<td>-0.04</td>
</tr>
<tr>
<td>Std(Δₜ)</td>
<td>10.68</td>
<td>13.08</td>
<td>12.06</td>
<td>14.09</td>
<td>15.33</td>
<td>11.23</td>
</tr>
<tr>
<td>Min(Δₜ)</td>
<td>-183.95</td>
<td>-369.35</td>
<td>-503.66</td>
<td>-1,362.38</td>
<td>-895.73</td>
<td>-588.25</td>
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<tr>
<td>Max(Δₜ)</td>
<td>147.86</td>
<td>183.43</td>
<td>190.47</td>
<td>249.81</td>
<td>327.34</td>
<td>153.96</td>
</tr>
<tr>
<td>Avg. Spread</td>
<td>2.35</td>
<td>4.27</td>
<td>4.03</td>
<td>4.21</td>
<td>3.88</td>
<td>2.67</td>
</tr>
<tr>
<td>AC(1) in %</td>
<td>1.09</td>
<td>0.80</td>
<td>-0.70</td>
<td>-3.37</td>
<td>1.95</td>
<td>2.40</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>in BPS</th>
<th>NZDUSD</th>
<th>USDCAD</th>
<th>USDCIF</th>
<th>USDKKK</th>
<th>USDKHKD</th>
<th>USDLHS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean(Δₜ)</td>
<td>-0.03</td>
<td>0.08</td>
<td>0.02</td>
<td>0.03</td>
<td>0.00</td>
<td>-0.02</td>
</tr>
<tr>
<td>Std(Δₜ)</td>
<td>14.14</td>
<td>10.01</td>
<td>13.32</td>
<td>10.68</td>
<td>0.79</td>
<td>9.84</td>
</tr>
<tr>
<td>Min(Δₜ)</td>
<td>-204.26</td>
<td>-142.93</td>
<td>-1,377.04</td>
<td>-145.23</td>
<td>-30.93</td>
<td>-178.48</td>
</tr>
<tr>
<td>Max(Δₜ)</td>
<td>174.39</td>
<td>187.09</td>
<td>250.23</td>
<td>182.45</td>
<td>16.35</td>
<td>187.19</td>
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<tr>
<td>Avg. Spread</td>
<td>4.14</td>
<td>2.72</td>
<td>3.25</td>
<td>2.90</td>
<td>1.69</td>
<td>24.29</td>
</tr>
<tr>
<td>AC(1) in %</td>
<td>-2.26</td>
<td>-0.20</td>
<td>-4.15</td>
<td>1.40</td>
<td>-9.72</td>
<td>-12.02</td>
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<table>
<thead>
<tr>
<th>in BPS</th>
<th>USDJPY</th>
<th>USDJXP</th>
<th>USDNOK</th>
<th>USDSEK</th>
<th>USDSGD</th>
<th>USDZAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean(Δₜ)</td>
<td>0.09</td>
<td>0.11</td>
<td>0.11</td>
<td>0.09</td>
<td>0.02</td>
<td>0.14</td>
</tr>
<tr>
<td>Std(Δₜ)</td>
<td>11.94</td>
<td>15.85</td>
<td>14.26</td>
<td>13.00</td>
<td>6.52</td>
<td>20.84</td>
</tr>
<tr>
<td>Min(Δₜ)</td>
<td>-318.89</td>
<td>-356.76</td>
<td>-379.52</td>
<td>-164.75</td>
<td>-113.95</td>
<td>-249.15</td>
</tr>
<tr>
<td>Max(Δₜ)</td>
<td>156.68</td>
<td>572.61</td>
<td>367.60</td>
<td>300.75</td>
<td>108.06</td>
<td>558.23</td>
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<tr>
<td>Avg. Spread</td>
<td>2.62</td>
<td>5.99</td>
<td>7.16</td>
<td>6.21</td>
<td>3.65</td>
<td>11.37</td>
</tr>
<tr>
<td>AC(1) in %</td>
<td>1.14</td>
<td>2.50</td>
<td>-0.31</td>
<td>-0.13</td>
<td>-1.50</td>
<td>0.08</td>
</tr>
</tbody>
</table>

**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(Δₜ)), standard deviation (Std(Δₜ)), minimum (Min(Δₜ)) and maximum (Max(Δₜ)) 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>
<thead>
<tr>
<th>Currency Pair</th>
<th>USD mn</th>
<th>CO</th>
<th>FD</th>
<th>NB</th>
<th>BA</th>
<th>USD mn</th>
<th>CO</th>
<th>FD</th>
<th>NB</th>
<th>BA</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUDJPY</td>
<td>0.02</td>
<td>0.96</td>
<td>1.25</td>
<td>14.73</td>
<td></td>
<td>GBPCHF</td>
<td>0.01</td>
<td>1.47</td>
<td>0.64</td>
<td>5.82</td>
</tr>
<tr>
<td>AUDNZD</td>
<td>0.00</td>
<td>0.77</td>
<td>1.32</td>
<td>12.94</td>
<td></td>
<td>GBPJPY</td>
<td>0.09</td>
<td>1.73</td>
<td>2.36</td>
<td>16.46</td>
</tr>
<tr>
<td>AUDUSD</td>
<td>0.81</td>
<td>25.49</td>
<td>10.18</td>
<td>91.01</td>
<td></td>
<td>GBPUSD</td>
<td>3.45</td>
<td>44.60</td>
<td>14.71</td>
<td>135.38</td>
</tr>
<tr>
<td>CADJPY</td>
<td>0.02</td>
<td>0.30</td>
<td>0.55</td>
<td>4.95</td>
<td></td>
<td>NZDUSD</td>
<td>0.04</td>
<td>8.06</td>
<td>3.50</td>
<td>35.24</td>
</tr>
<tr>
<td>EURAUD</td>
<td>0.07</td>
<td>2.51</td>
<td>1.99</td>
<td>16.60</td>
<td></td>
<td>USDCAD</td>
<td>1.17</td>
<td>29.89</td>
<td>12.35</td>
<td>181.86</td>
</tr>
<tr>
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<td>0.98</td>
<td>2.10</td>
<td>1.74</td>
<td>12.57</td>
<td></td>
<td>USDCHF</td>
<td>1.00</td>
<td>10.88</td>
<td>10.25</td>
<td>66.26</td>
</tr>
<tr>
<td>EURCHF</td>
<td>0.64</td>
<td>7.67</td>
<td>4.21</td>
<td>35.27</td>
<td></td>
<td>USDKK</td>
<td>0.77</td>
<td>3.39</td>
<td>0.12</td>
<td>7.61</td>
</tr>
<tr>
<td>EURDKK</td>
<td>0.17</td>
<td>4.48</td>
<td>0.58</td>
<td>18.55</td>
<td></td>
<td>USDHKD</td>
<td>0.06</td>
<td>11.82</td>
<td>1.23</td>
<td>42.01</td>
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<tr>
<td>EURGBP</td>
<td>2.85</td>
<td>17.15</td>
<td>4.32</td>
<td>47.55</td>
<td></td>
<td>USDILS</td>
<td>0.03</td>
<td>1.12</td>
<td>0.21</td>
<td>10.80</td>
</tr>
<tr>
<td>EURJPY</td>
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<td>6.83</td>
<td>7.15</td>
<td>38.59</td>
<td></td>
<td>USDJPY</td>
<td>3.38</td>
<td>49.88</td>
<td>18.10</td>
<td>169.13</td>
</tr>
<tr>
<td>EURNOK</td>
<td>0.98</td>
<td>5.03</td>
<td>2.43</td>
<td>19.17</td>
<td></td>
<td>USDMXP</td>
<td>0.27</td>
<td>10.07</td>
<td>2.21</td>
<td>31.55</td>
</tr>
<tr>
<td>EUREK</td>
<td>2.18</td>
<td>8.26</td>
<td>2.60</td>
<td>24.07</td>
<td></td>
<td>USDNOK</td>
<td>0.22</td>
<td>4.77</td>
<td>1.52</td>
<td>18.81</td>
</tr>
<tr>
<td>EURUSD</td>
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<td>122.94</td>
<td>26.96</td>
<td>272.32</td>
<td></td>
<td>USDSEK</td>
<td>0.32</td>
<td>7.43</td>
<td>1.73</td>
<td>22.80</td>
</tr>
<tr>
<td>GPBAUD</td>
<td>0.02</td>
<td>1.43</td>
<td>1.04</td>
<td>7.85</td>
<td></td>
<td>USD SGD</td>
<td>0.19</td>
<td>5.75</td>
<td>1.25</td>
<td>35.75</td>
</tr>
<tr>
<td>GBPCAD</td>
<td>0.11</td>
<td>0.90</td>
<td>0.81</td>
<td>6.19</td>
<td></td>
<td>USDZAR</td>
<td>0.07</td>
<td>4.86</td>
<td>1.36</td>
<td>21.77</td>
</tr>
</tbody>
</table>

**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:

\[ r_t = \zeta_0 D_{t,t} + \sum_{i=1}^{10} \alpha_i r_{t-i} + \sum_{j \in C} \left( \sum_{i=0}^{10} \beta_j T_{i,t} + \sum_{i=0}^{10} \phi_i S_{i,t-1} \right) + u_1 \Delta s_{k,t-1} + u_2 \Delta s_{k,t-10} + \epsilon_{r,t}, \]

where \( \alpha \)s are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA), \( D_{t,t} \) denotes a dummy variable matrix to account for time-fixed effects. In addition, \( \Delta s_{k,t-1} \) and \( \Delta s_{k,t-10} \) account for the return over the prior day and week. Here, \( t = 24 \) 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. \( S_{i,t} \) controls for order size and refers to the residuals of regressing signed log volume against current and lagged values of the trade indicator variable \( T_t \).

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>( m )</th>
<th>( \beta_i )</th>
<th>( \alpha_i )</th>
<th>( \phi_j )</th>
<th>( \beta_j )</th>
<th>( \phi_j )</th>
<th>( \beta_j )</th>
<th>( \phi_j )</th>
<th>( \phi_j )</th>
<th>( \beta_j )</th>
<th>( \phi_j )</th>
<th>( \phi_j )</th>
<th>( \beta_j )</th>
<th>( \phi_j )</th>
</tr>
</thead>
<tbody>
<tr>
<td>EUR/JPY</td>
<td>9.23</td>
<td>0.03</td>
<td>0.02</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>USD/CHF</td>
<td>1.54</td>
<td>0.02</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>USD/ZAR</td>
<td>0.34</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

**Note:** The regression coefficients are estimated by ordinary least squares on the full sample. All coefficients are in %. T-stats in square brackets are based on heteroscedasticity- and autocorrelation-consistent errors, and asterisks *, ** and *** denote significance at the 90%, 95% and 99% levels, respectively.
Table 4: Order Flow Equation Coefficients

The model is:

$$T_t = \sum_{i=1}^{10} \gamma_i r_{t-i} + \sum_{j \in C} \left( \sum_{i=1}^{10} \delta_j T^j_{t-i} + \sum_{i=1}^{10} \omega_j S^j_{t-i} \right) + \epsilon_{T,t},$$

where agents are abbreviated as follows: corporates (CO), funds (FD), non-bank financials (NB) and banks acting as price takers (BA), $D_{i,t}$ 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. $S^j_t$ controls for order size and refers to the residuals of regressing signed log volume against current and lagged values of the trade indicator variable $T_t$.

<table>
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<th>$r_{t-1} \times (3)$</th>
<th>$\gamma_1$</th>
<th>$\gamma_2$</th>
<th>$\gamma_3$</th>
<th>$\gamma_4$</th>
<th>$\gamma_5$</th>
<th>$\gamma_6$</th>
<th>$\gamma_7$</th>
<th>$\gamma_8$</th>
<th>$\epsilon_{T,t}$</th>
<th>$\Delta \gamma_1$</th>
<th>$\Delta \gamma_2$</th>
<th>$\Delta \gamma_3$</th>
<th>$\Delta \gamma_4$</th>
<th>$\Delta \gamma_5$</th>
<th>$\Delta \gamma_6$</th>
<th>$\Delta \gamma_7$</th>
<th>$\Delta \gamma_8$</th>
<th>$\Delta \epsilon_{T,t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUDJPY</td>
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<td>0.004</td>
<td>0.004</td>
<td>0.002</td>
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</tr>
<tr>
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<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
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<td>0.001</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>USDSEK</td>
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<td>0.001</td>
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<td>0.001</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>EURJPY</td>
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<td>0.001</td>
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<td>0.001</td>
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<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
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<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td></td>
</tr>
</tbody>
</table>

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

| Expected sign | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + | + |
Table 5: Permanent Price Impact Across Agents: Joint F-test

<table>
<thead>
<tr>
<th>in BPS</th>
<th>( \alpha_{CO}^{m} )</th>
<th>( \alpha_{FD}^{m} )</th>
<th>( \alpha_{NB}^{m} )</th>
<th>( \alpha_{BA}^{m} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUD/JPY</td>
<td>(-10.551)</td>
<td>(0.824)</td>
<td>***</td>
<td>**</td>
</tr>
<tr>
<td>[1.263]</td>
<td>[1.650]</td>
<td>[4.899]</td>
<td>[12.107]</td>
<td>[32.107]</td>
</tr>
<tr>
<td>AUD/NZD</td>
<td>(0.451)</td>
<td>(1.404)</td>
<td>***</td>
<td>**0.384</td>
</tr>
<tr>
<td>[1.594]</td>
<td>[1.709]</td>
<td>[3.653]</td>
<td>[4.773]</td>
<td>[9.398]</td>
</tr>
<tr>
<td>AUD/USD</td>
<td>(2.073)</td>
<td>***</td>
<td>**0.545</td>
<td>**0.164</td>
</tr>
<tr>
<td>[1.970]</td>
<td>[3.746]</td>
<td>[25.374]</td>
<td>[3.906]</td>
<td>[5.424]</td>
</tr>
<tr>
<td>CAD/JPY</td>
<td>(2.080)</td>
<td>(1.176)</td>
<td>(0.114)</td>
<td>**0.144</td>
</tr>
<tr>
<td>[0.734]</td>
<td>[0.542]</td>
<td>[1.222]</td>
<td>[4.079]</td>
<td>[4.314]</td>
</tr>
<tr>
<td>EURAUD</td>
<td>(-1.048)</td>
<td>(0.573)</td>
<td>**0.278</td>
<td>**0.781</td>
</tr>
<tr>
<td>[0.747]</td>
<td>[1.308]</td>
<td>[1.662]</td>
<td>[4.477]</td>
<td>[2.434]</td>
</tr>
<tr>
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<td>**0.069</td>
<td>**0.285</td>
</tr>
<tr>
<td>[7.541]</td>
<td>[0.824]</td>
<td>[4.530]</td>
<td>[3.784]</td>
<td>[1.985]</td>
</tr>
<tr>
<td>EUR/CHF</td>
<td>(0.104)</td>
<td>**0.019</td>
<td>**0.020</td>
<td>**0.053</td>
</tr>
<tr>
<td>[1.154]</td>
<td>[0.681]</td>
<td>[0.626]</td>
<td>[10.223]</td>
<td>[9.822]</td>
</tr>
<tr>
<td>EUR/JPY</td>
<td>***</td>
<td>**0.627</td>
<td>**0.207</td>
<td>**0.658</td>
</tr>
<tr>
<td>[4.579]</td>
<td>[1.539]</td>
<td>[5.923]</td>
<td>[2.533]</td>
<td>[2.463]</td>
</tr>
<tr>
<td>EUR/NOK</td>
<td>***</td>
<td>**1.803</td>
<td>**1.057</td>
<td>**0.086</td>
</tr>
<tr>
<td>[8.019]</td>
<td>[8.376]</td>
<td>[2.914]</td>
<td>[3.062]</td>
<td>[2.561]</td>
</tr>
<tr>
<td>EUR/SEK</td>
<td>***</td>
<td>**0.677</td>
<td>**0.188</td>
<td>**0.650</td>
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<td>[3.500]</td>
<td>[2.130]</td>
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<td>***</td>
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<td>**0.229</td>
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<td>0.368</td>
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</table>

Note: The numbers in brackets correspond to the test statistic for a joint F-test, where the parameters in Eq. (4.6) are jointly different from zero. Asterisks *, ** and *** denote significance at the global 90%, 95% and 99% levels (\(\alpha_g\)), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is \(\frac{\alpha_g}{m}\), where \(m\) is the number of multiple tests in the joint hypothesis. 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: Performance Benchmarking: $ALP_{HML}$

<table>
<thead>
<tr>
<th>Panel a) Gross Returns</th>
<th>$DOL$</th>
<th>$RER_{HML}$</th>
<th>$RER$</th>
<th>$MOM_{HML}$</th>
<th>$CAR_{HML}$</th>
<th>$BMS$</th>
<th>$Q_1$</th>
<th>$Q_2$</th>
<th>$Q_3$</th>
<th>$ALP_{HML}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SR</td>
<td>-0.22</td>
<td>*0.78</td>
<td>0.66</td>
<td>0.06</td>
<td>0.04</td>
<td>0.25</td>
<td>***-1.02</td>
<td>0.23</td>
<td>***1.27</td>
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<tr>
<td></td>
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<td>[0.10]</td>
<td>[0.61]</td>
<td>[2.63]</td>
<td>[0.55]</td>
<td>[3.74]</td>
<td></td>
</tr>
<tr>
<td>Mean in %</td>
<td>-0.72</td>
<td>*4.00</td>
<td>1.85</td>
<td>0.20</td>
<td>0.03</td>
<td>0.90</td>
<td>***-4.61</td>
<td>0.96</td>
<td>***5.72</td>
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<tr>
<td></td>
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<td>[1.69]</td>
<td>[1.59]</td>
<td>[0.15]</td>
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<tr>
<td>MDD in %</td>
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<td>6.19</td>
<td>3.61</td>
<td>15.73</td>
<td>16.64</td>
<td>9.50</td>
<td>6.12</td>
<td>13.25</td>
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<tr>
<td>Θ in %</td>
<td>-1.15</td>
<td>3.03</td>
<td>1.28</td>
<td>-0.86</td>
<td>-1.10</td>
<td>0.00</td>
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Panel b) Net Returns

<table>
<thead>
<tr>
<th>$DOL$</th>
<th>$RER_{HML}$</th>
<th>$RER$</th>
<th>$MOM_{HML}$</th>
<th>$CAR_{HML}$</th>
<th>$BMS$</th>
<th>$Q_1$</th>
<th>$Q_2$</th>
<th>$Q_3$</th>
<th>$ALP_{HML}$</th>
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</thead>
<tbody>
<tr>
<td>SR</td>
<td>-0.34</td>
<td>0.63</td>
<td>0.48</td>
<td>-0.06</td>
<td>-0.07</td>
<td>0.04</td>
<td>***-0.92</td>
<td>0.14</td>
<td>***1.08</td>
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<tr>
<td></td>
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<td>[0.13]</td>
<td>[0.16]</td>
<td>[0.09]</td>
<td>[2.36]</td>
<td>[0.33]</td>
<td>[3.12]</td>
</tr>
<tr>
<td>Mean in %</td>
<td>-1.08</td>
<td>3.18</td>
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<td>-0.80</td>
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<td>[1.36]</td>
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<td>[0.14]</td>
<td>[0.16]</td>
<td>[0.09]</td>
<td>[2.14]</td>
<td>[0.31]</td>
<td>[2.62]</td>
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<tr>
<td>MDD in %</td>
<td>7.67</td>
<td>6.64</td>
<td>3.81</td>
<td>16.90</td>
<td>18.51</td>
<td>11.03</td>
<td>6.48</td>
<td>14.28</td>
<td>5.01</td>
</tr>
<tr>
<td>Θ in %</td>
<td>-1.15</td>
<td>3.03</td>
<td>1.28</td>
<td>-0.86</td>
<td>-1.10</td>
<td>0.00</td>
<td>-4.01</td>
<td>0.44</td>
<td>4.67</td>
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</table>

**Note:** This table presents the out-of-sample economic performance of the $ALP_{HML}$ strategy before and after transaction costs based on monthly rebalancing. Panel a) reports the annualised Sharpe ratio (SR), annualised average (simple) gross excess return ($Mean$), maximum drawdown (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 costs. $DOL$ 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 $f_{t+1}^m - s_t^m$ (cf. Asness et al., 2013), $CAR_{HML}$ on the forward discount premium $(f_{t+1}^m - s_t^m$, cf. Lustig et al., 2011) and $BMS$ is based on the lagged standardised order flow (cf. Menkhoff et al., 2016). 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 7: Correlation with Common FX Risk Factors in %

<table>
<thead>
<tr>
<th></th>
<th>ΔVIX</th>
<th>ΔCDS</th>
<th>DOL</th>
<th>RER_{HML}</th>
<th>RER</th>
<th>MOM_{HML}</th>
<th>CAR_{HML}</th>
<th>BMS</th>
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<tbody>
<tr>
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<tr>
<td>RER_{HML}</td>
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<td>24.48</td>
<td>21.73</td>
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<td>RER</td>
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<td>1.22</td>
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<td>***63.06</td>
<td>***73.60</td>
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<tr>
<td>MOM_{HML}</td>
<td>26.50</td>
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<td>3.68</td>
<td>−10.52</td>
<td>−22.24</td>
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<tr>
<td>CAR_{HML}</td>
<td>−38.12</td>
<td>−33.60</td>
<td>9.31</td>
<td>***−60.86</td>
<td>−22.70</td>
<td>−10.60</td>
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<tr>
<td>BMS</td>
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<td>35.65</td>
<td>−15.93</td>
<td>−7.76</td>
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<td>ALP_{HML}</td>
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<td>−2.84</td>
<td>13.20</td>
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</tbody>
</table>

Note: This table shows the time series cross-correlation at lag 0 between the gross excess return of HML and the returns associated with different FX risk factors, where DOL is based on USD currency pairs, RER/RER_{HML} are based on the real exchange rate (cf. Menkhoff et al., 2017), MOM_{HML} is based on f_{it}^{m} − s_{it}^{m} (cf. Asness et al., 2013), CAR_{HML} is based on the forward discount/premium (f_{it+1}^{m} − s_{it}^{m}, cf. Lustig et al., 2011) and BMS is based on lagged standardised order flow (cf. Menkhoff et al., 2016). ΔVIX is the return on the VIX index, and ΔCDS the change in the iTraxx Europe CDS index. Significant correlations at the 90%, 95% and 99% levels are represented by asterisks *, ** and ***, respectively.
<table>
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<td>-0.066</td>
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<td>CARHML</td>
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</table>

**Note:** This table shows the results of regressing monthly gross excess returns by \( ALPH_{HML} \) on monthly excess returns associated with common risk factors, where \( DOL \) is based on USD currency pairs; \( RER/RER_{HML} \) are based on the real exchange rate (cf. Menkhoff et al., 2017), \( MOM_{HML} \) is based on \( f_{t-1,t}^m - s_t^m \) (Asness et al., 2013, cf.), \( CAR_{HML} \) is based on the forward discount/premium (\( f_{t,t+1}^m - s_t^m \), cf. Lustig et al., 2011) and \( BMS \) is based on the lagged standardised order flow (cf. Menkhoff et al., 2016). \( ΔVIX \) is the return on the VIX index and \( ΔCDS \) the change in the iTraxx Europe CDS index. The information ratio (IR) is defined as \( \alpha \) divided by the residual standard deviation. Significant findings at the 90%, 95% and 99% levels are represented by asterisks *, ** and ***, respectively. The numbers inside the brackets are the corresponding test statistics based on 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: Subsample Performance Benchmarking

<table>
<thead>
<tr>
<th>Panel a) Gross Returns</th>
<th>G10</th>
<th>EUR/GBP</th>
<th>no EM</th>
<th>no CHF</th>
<th>ALP_{HML}</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SR</strong></td>
<td><strong>1.10</strong></td>
<td><strong>1.05</strong></td>
<td><strong>0.99</strong></td>
<td><strong>1.09</strong></td>
<td><strong>1.27</strong></td>
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<td>[2.86]</td>
<td>[2.87]</td>
<td>[3.17]</td>
<td>[3.74]</td>
</tr>
<tr>
<td>Mean in %</td>
<td><strong>5.94</strong></td>
<td><strong>7.30</strong></td>
<td><strong>5.85</strong></td>
<td><strong>5.40</strong></td>
<td><strong>5.72</strong></td>
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<td>[2.42]</td>
<td>[2.58]</td>
<td>[3.08]</td>
</tr>
<tr>
<td>MDD in %</td>
<td>12.02</td>
<td>6.16</td>
<td>6.52</td>
<td>6.37</td>
<td>4.33</td>
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<tr>
<td>MPPM in %</td>
<td>4.96</td>
<td>6.18</td>
<td>4.88</td>
<td>4.30</td>
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</table>

<table>
<thead>
<tr>
<th>Panel b) Net Returns</th>
<th>G10</th>
<th>EUR/GBP</th>
<th>no EM</th>
<th>no CHF</th>
<th>ALP_{HML}</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SR</strong></td>
<td><strong>0.97</strong></td>
<td><strong>0.86</strong></td>
<td><strong>0.87</strong></td>
<td><strong>0.91</strong></td>
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<td>[2.59]</td>
<td>[3.12]</td>
</tr>
<tr>
<td>Mean in %</td>
<td><strong>5.17</strong></td>
<td><strong>6.59</strong></td>
<td><strong>5.11</strong></td>
<td><strong>4.46</strong></td>
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<tr>
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<td>[2.16]</td>
<td>[2.62]</td>
</tr>
<tr>
<td>MDD in %</td>
<td>12.73</td>
<td>6.51</td>
<td>7.16</td>
<td>7.08</td>
<td>5.01</td>
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<tr>
<td>MPPM in %</td>
<td>4.96</td>
<td>6.18</td>
<td>4.88</td>
<td>4.30</td>
<td>4.67</td>
</tr>
</tbody>
</table>

Note: In this table, in Panels a) and b), we report the gross and net performance measures, respectively, of ALP_{HML} based on four subsamples of currency pairs. These are as follows: i) G10 currency pairs plus the most liquid EUR cross pairs (14 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). 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 1: Distribution of Trading Volume Over a Day

Note: This figure shows the average hourly volume (in USD million) during the entire trading day. The average is computed across all the trading days and currency pairs using the entire sample period from September 2012 to January 2019. The numbers on the horizontal axis denote the closing time, for example, the bar labelled 17 refers to the volume between 4 pm and 5 pm (GMT, no British Summer Time (BST) adjustment).
Figure 2: 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 3: Twelve Months Rolling Window Regression for $c_{0r,k}/\alpha_{mk}^{k}$

Note: The cross-sectional average contemporary ($\bar{c}_{0r}$) and permanent ($\bar{\alpha}_{mk}$) price impacts are calculated after removing any coefficients that are either heavy outliers in terms of the median or not significant at a 95% confidence level, applying a simple two-sided $t$-test and joint $F$-test, respectively.
Figure 4: Equity and Drawdown Curves

(a) Before Transaction Costs

(b) After Transaction Costs

Note: For non-daily rebalancing frequencies, missing data points are interpolated linearly.
Figure 5: 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 ≤ 3%: AUDUSD, EURCHF, EURDKK, EURNOK, EURSEK, EURUSD, GBPUSD, USDCAD, USDKD and USDJPY.

Figure 6: Average Contribution to the Long and Short Leg

Note: The relative share of each agent’s \( \alpha^{j,k}_m \) to the aggregate \( \alpha^k_m \) is computed, and the mean is calculated across all currency pairs.
Figure 7: Bootstrapped Economic Performance of $ALP_{HML}$

Note: Panels a) and b) depict bootstrapped $p$-values using 1000 bootstrap repetitions for $ALP_{HML}$ before and after transaction costs, 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 $\Theta$ performance measure of Goetzmann et al. (2007) based on monthly rebalancing. The bootstrapped $p$-values ($pval_b$) are reported in parenthesis in the titles.
Figure 8: Cumulative Rolling Gross Returns

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

Figure 9: Sharpe ratios and T-stats for Different Bloomberg Fixing Times: Net Returns

Note: This figure displays the Sharpe ratios and their T-stats for implementing $ALP_{HML}$ at different Bloomberg fixing times (x-axis) based on monthly rebalancing and after transaction costs. 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.