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Asymmetric information risk in FX markets☆

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

1. Introduction

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

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

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possess distinct information sets and contribute differently to FX determination.

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

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

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

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

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

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

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

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

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

value (cf. Menkhoff et al., 2017). This behavior is in line with speculative trading motives and higher adverse selection risk when trading against such sophisticated speculators (Payne, 2003).

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

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

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

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

Second, our paper contributes to the asset pricing literature by building a novel long–short trading strategy capturing asymmetric information risk. This is an effective method of extracting superior information inherent in order flow that can be applied to other asset classes beyond FX. In the FX asset pricing literature, Lustig and Verdelhan (2007), Lustig et al. (2011), Menkhoff et al. (2012a,b), and Asness et al. (2013) identify common risk factors in currency markets based on the interest rate differential, real exchange rate, global FX volatility, and momentum. Other FX risk factors include macro-variables like global imbalances (e.g., Della Corte et al., 2016b) or volatility risk premiums (e.g., Della Corte et al., 2016a). Using data from a specific dealer bank, Menkhoff et al. (2016) analyze whether that bank can extract valuable information from its disaggregated customer FX order flow data to predict

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

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

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

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

the next day's FX rates. More specifically, they sort currency pairs into portfolios based on past order flows to assess the economic value as dealers' "smart money." To summarize, our paper makes two key contributions: first, we extend the methodology to isolate and analyze the information driven component of order flow with disaggregated customer flows. Second, we provide compelling empirical evidence that asymmetric information risk is priced in the global FX market.

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

2. Data

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

2.1. Heterogeneous FX order flow

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

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

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

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

Second, despite being the most comprehensive time-series data set on FX order flow, it does not cover the full FX (spot) market. The Bank for International Settlements (BIS) triennial survey reports an average daily trading volume of \$6.6 trillion.[11] Conversely, CLS settles approximately \$5.1 trillion per day, which translates to an average daily trading volume of \$1.9 trillion if one accounts for double-counting prime brokered trades. This is equivalent to covering 29% of the total FX volume based on the BIS triennial survey.[12] The reasons for this lack of coverage are manifold: first, FX options and nondeliverable forwards are not settled by CLS. Second, small banks with little FX turnover are seldom a settlement member. Third, CLS does not settle every currency for instance; the Chinese renminbi and Russian rubel are not yet eligible for settlement. Both Hasbrouck and Levich (2018) and

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

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

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

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

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

Cespa et al. (2020) demonstrate that the CLS coverage is underestimated compared to the BIS survey, since a large fraction of the volume reported by the BIS is related to interbank trading across desks and double-counts prime-brokered “give-up” trades.[13] Adjusting for these facts shrinks total FX volume to $3.8 trillion per day, and thus CLS covers at least 50% of it.[14]

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

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

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

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

2.2. Exchange rate returns

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

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

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

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

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

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

[16] Olsen data are filtered in real time by assigning a credibility tick (ranging from 0 to 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% to 3.0% per day.

3. Summary statistics

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

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

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

Fig. 1 fleshes out the idea that market participants behave heterogeneously during the day and provides prima facie evidence of market fragmentation. Notably, it shows that corporates trade at different times than funds or nonbank financials. For every market participant, we report the average aggregate hourly volume for each hour of the trading day based on London time. Investigating at which hours market participants are most active helps to identify time fixed effects in the trading behavior of FX market participants. Volume levels are closely related to stock market opening hours around the world. Specifically, volume is lowest during the night when only the Australian market is open and is highest when both European and North American markets are operating in the afternoon. This pattern persists across market participants. Banks, nonbank financials, and funds all trade more around the clock. Banks are the largest subsection of the aggregate, with an average contribution of 30–50%. They reduce their activity by about two-thirds outside of the London stock market trading hours[18] to limit inventory risk (Evans and Lyons, 2002).

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

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

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

Table 1
Summary statistics for hourly spot returns.

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

in BPS	AUDJPY	AUDNZD	AUDUSD	CADJPY	EURAUD	EURCAD
Mean(Δ_r)	0.00	−0.04	−0.08	0.02	0.07	0.04
Std(Δ_r)	15.38	9.34	12.53	14.11	12.16	11.14
Min(Δ_r)	−540.61	−120.73	−228.41	−407.53	−140.71	−146.40
Max(Δ_r)	175.69	162.48	137.07	159.59	184.65	169.51
Avg. spread	4.00	4.33	3.25	4.10	3.50	3.48
AC(1) in %	0.24	−3.40	−0.41	0.74	1.16	0.55
in BPS	EURCHF	EURDKK	EURGBP	EURJPY	EURNOK	EURSEK
Mean(Δ_r)	−0.02	0.00	0.02	0.06	0.07	0.06
Std(Δ_r)	9.96	0.52	10.60	12.69	10.47	8.57
Min(Δ_r)	−1355.15	−10.03	−174.75	−502.24	−349.16	−101.96
Max(Δ_r)	248.53	11.37	434.97	203.05	282.01	184.08
Avg. spread	2.71	2.61	3.24	3.10	6.00	5.30
AC(1) in %	−3.36	−19.32	−1.07	0.98	−1.42	−2.43
in BPS	EURUSD	GBPAUD	GBPCAD	GBPCHF	GBPJPY	GBPUSD
Mean(Δ_r)	−0.02	0.05	0.03	−0.03	0.05	−0.03
Std(Δ_r)	10.26	12.87	11.95	13.76	14.98	11.18
Min(Δ_r)	−183.95	−369.35	−503.66	−1362.38	−895.73	−588.25
Max(Δ_r)	147.86	199.27	218.81	249.81	327.34	225.99
Avg. spread	2.27	4.16	3.96	4.15	3.79	2.66
AC(1) in %	1.43	0.52	−0.93	−3.13	1.77	1.72
in BPS	NZDUSD	USDCAD	USDCHF	USDDKK	USDHKD	USDILS
Mean(Δ_r)	−0.03	0.07	0.01	0.03	0.00	−0.03
Std(Δ_r)	13.71	9.64	12.72	10.25	0.84	9.54
Min(Δ_r)	−204.26	−142.93	−1377.04	−145.23	−30.93	−178.48
Max(Δ_r)	174.39	187.09	250.23	182.45	16.35	187.19
Avg. spread	3.95	2.62	3.11	2.88	1.69	24.72
AC(1) in %	−2.22	−0.31	−4.01	1.18	−9.66	−11.71
in BPS	USDJPY	USDMXP	USDNOK	USDSEK	USDSGD	USDZAR
Mean(Δ_r)	0.08	0.09	0.10	0.09	0.02	0.14
Std(Δ_r)	11.46	15.41	13.79	12.65	6.26	20.41
Min(Δ_r)	−318.89	−356.76	−379.52	−164.75	−113.95	−249.15
Max(Δ_r)	156.68	572.61	367.60	300.75	108.06	558.23
Avg. Spread	2.51	5.82	6.85	6.00	3.47	11.11
AC(1) in %	1.11	1.85	−0.66	−0.45	−1.64	−0.50

Table 2
Summary statistics for hourly (net) volume.

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

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

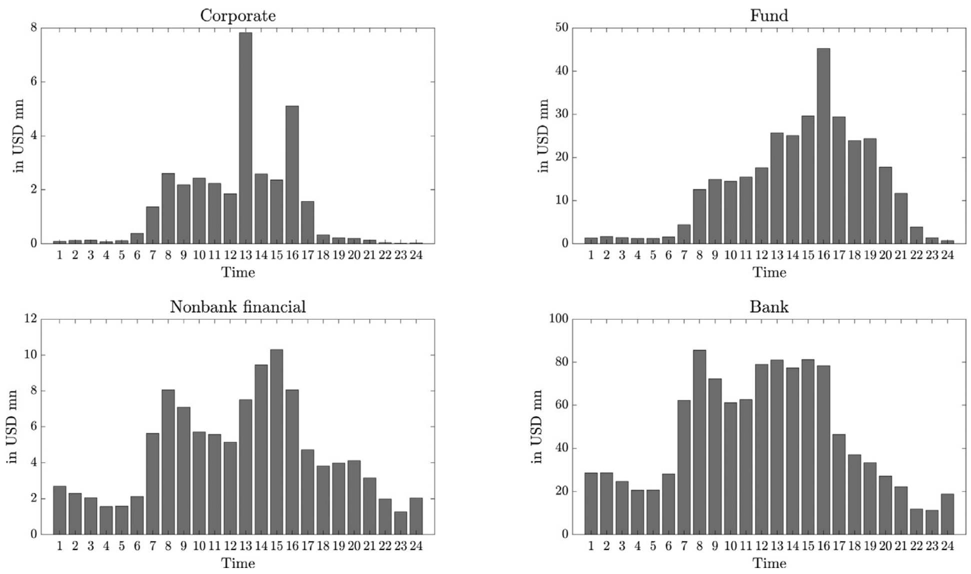

Fig. 1. Distribution of (net) trading volume over a day. This figure plots the average intraday hourly net volume (in USD mn). The average is computed across all 1885 trading days and 30 currency pairs. The horizontal axis denotes the closing time; for example, 17 refers to the volume between 4 and 5 pm (London time, GMT). The sample covers the period from September 2, 2012 to December 31, 2019.

4. Methodology

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

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

Consistent with this framework, we build an encompassing model that allows for heterogeneous order flows and controls for short-term mean reversion as well as hourly seasonalities. Especially, (4.2) describes the trade-by-trade evolution of the quote midpoint, while (4.3) refers to the persistent effect of order flow. We define T_t to be the buy-sell indicator (+1 for buys, −1 for sells) for trade t in a specific currency pair k.[19] Furthermore, we define r_t as the log FX rate return based on the midquote. Easley and O'Hara (1987) present a theoretical asymmetric information model in which private information revealed by an order and the consequent change in quotes are positively related to order flow size. We account for these effects by introducing an order size variable (cf. Hasbrouck, 1988) into the VAR specifications. Logarithms of the signed net volume (z_t) are taken to control for the effect of presumed nonlinearities between order size and quote revisions:

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

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.[20] Hourly dummies are included to control for daily seasonalities affecting FX rates and order flows. More importantly, the VAR accommodates both lagged returns and order flow in both the return (i.e., (4.2)) and order flow equations (i.e., (4.3)), since many microstructure imperfections, such as price discreteness, inventory effects, lagged adjustment to information, noncompetitive behaviors, and order splitting, are thought to cause lagged effects. The number of lags is

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

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

selected to be ten based on the Akaike/Bayesian information criteria and the theoretical arguments in Hasbrouck (1991a,b):

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

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

where $D_{l,t}$ denotes a dummy variable matrix to account for time fixed effects with $l = 24$ columns and $t = n$ rows, in which element l, t is 1 if there was a trade in that hour; and $C = \{CO, FD, NB, BA\}$ denotes disaggregated order flow categories. Moreover, the regression considers the lagged exchange rate changes over the previous day $\Delta s_{t;t-\tau}$ and over the prior week $\Delta s_{t;t-5\tau}$. Here, $\tau = 24$, and t is measured hourly. For convenience of exposition, currency specific subscripts (i.e., k) have been suppressed in (4.2) and (4.3). The error terms $\epsilon_{r,t}$ and $\epsilon_{T,t}$ can be interpreted as the (unexpected) public and private information components (Hasbrouck, 1991a). This dichotomy ensures that the permanent price impact $\alpha_m^{j,k}$ in (4.5) can be interpreted as a measure of asymmetric/private information.[21] Since we include contemporaneous T_t in (4.2) but not in (4.3), the system is exactly identified, and hence the error terms shall have a zero mean and be jointly and serially uncorrelated:

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

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

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

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

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

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

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

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

5. Heterogeneous asymmetric information

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

5.1. Estimation method and the contemporaneous price impact

First, we estimate (4.2), (4.3) using standard ordinary least squares (OLS) on the full sample, controlling for seasonal time-of-the day effects, lagged returns, and order

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

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

Table 3
Return equation coefficients.
This table reports estimates of the following regression model

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

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

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

size.[23] Second, we apply a 12-month rolling window for measuring the time variation of both the contemporary β_0^j and permanent price impact α_m^j, respectively. The main advantage of the VAR approach lies in its potential for generalization to gain a more nuanced view of the trade–quote interactions.[24] For the sake of clarity, we only present the results for lagged return equation coefficients ρ_1 and γ_1, the contemporary price impact β_0^j and lagged order flow δ_1^j, where $j \in C$ denotes one group of market participants. Table 3 shows the regression coefficients of the bivariate VAR estimated through ten lags. The most important ones are those of T_0^j in (4.2) that measure the contemporary price impact of a trade.

For the great majority of currency pairs, regression coefficients bear the expected signs summarized in Table 3: here, ρ_1 coefficients are negative and entail short-term mean reversion, while β_0^j coefficients are positive and in line with market microstructure theory (e.g., Kyle, 1985; Glosten and Milgrom, 1985). This is especially true for the most liquid and frequently traded currency pairs.[25] The true beauty of the log-level model in Table 3 is its interpretability: coefficients can be interpreted as percentage changes in the dependent variable for a one-unit change of the independent variable.[26] The coefficients at longer

[23] To avoid misspecification in our regression analysis and to check the validity of our assumptions in (4.4), we conduct a battery of diagnostic tests that are summarized in the Online Appendix.

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

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

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

lags (i.e., beyond lags seven and eight) frequently alternate in sign, are seldom significant, and quickly decay to zero. From these results, it is apparent that, on average, all agents except corporates have a significantly positive contemporary price impact.

For some currency pairs (e.g., EURGBP, EURNOK, EURUSD), corporates experience significantly negative contemporary price impact parameters. The negative β_0^{CO} is consistent with earlier work by Bjønnes et al. (2005), Lyons (2006), Carpenter and Wang (2007), Cerrato et al. (2011), Evans and Lyons (2012), and Menkhoff et al. (2016) and indicates that corporates often buy (sell) in a falling (rising) market.[27] Rather than from informational motives, a negative relation between order flow and return arises from liquidity needs (Grossman and Miller, 1988) and dealers' inventory features (Stoll, 1978). Thus, corporate trading seems to be driven by risk sharing, hedging, and liquidity issues as well as by additional costs unrelated to adverse selection. This idea squares well with the different timing in their trading behavior (see Fig. 1). Whereas banks and other financial institutions access a richer information set by trading around the clock, the trading activity of corporates is more segmented and limited within a few hours.[28]

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

Table 4 summarizes the order flow equation coefficients, which also bear the expected signs: here, γ_1 is negative and highly significant, while δ_1^j coefficients are positively significant for most currency pairs and reflect the positive autocorrelation in trades. This is consistent with the findings in the stock market literature, for example, Hasbrouck and Ho (1987), Hasbrouck (1988), and Madhavan et al. (1997), and it shows that purchases tend to follow purchases and similarly for sales. Rather than with inventory control mechanisms, the short-run predominance of positive autocorrelation can be reconciled with delayed price adjustments to new information. Again, γ_1 implies negative autocorrelation in the quote revisions. In the order flow equation estimation, this implies Granger–Sims causality running from quote revisions to trades. This causality is in line with microstructure theory, where a negative relation between trades and lagged quote revisions is consistent with inventory control effects and/or the price experimentation hypothesis formulated by Leach and Madhavan (1992), in which the market maker sets quotes to extract information optimally from traders.

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

5.2. Analysis of the permanent price impact

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

5.2.1. Heterogeneous price impact across agents

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

To assess whether the permanent price impact parameter α_m^j significantly differs across groups of agents, we test

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

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

Table 4
Order flow equation coefficients.
This table reports estimates of the following regression model

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

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

(4.3)	γ_1	δ_1^{CO}	δ_1^{FD}	δ_1^{NB}	δ_1^{BA}	$\bar{R}^2$ in %
AUDJPY	***34.453	−0.014	***0.041	0.001	***0.061	1.672
	[8.661]	[0.208]	[2.694]	[0.107]	[12.407]	
AUDNZD	***−35.226	0.124	0.009	0.001	***0.051	0.585
	[6.714]	[0.690]	[0.490]	[0.216]	[10.712]	
AUDUSD	**−8.763	0.010	0.008	***0.020	***0.039	0.507
	[2.276]	[0.328]	[1.426]	[4.102]	[8.036]	
CADJPY	−2.469	0.036	0.007	0.008	***0.030	0.209
	[0.718]	[0.395]	[0.328]	[0.828]	[6.156]	
EURAUD	***−14.415	0.023	0.003	0.003	***0.022	0.226
	[3.626]	[0.493]	[0.306]	[0.458]	[4.523]	
EURCAD	***−27.702	***0.146	−0.005	**0.018	***0.037	0.620
	[6.512]	[4.850]	[0.578]	[2.464]	[7.529]	
EURCHF	*−41.130	***0.079	***0.028	0.004	***0.064	1.791
	[1.739]	[3.636]	[3.609]	[0.537]	[12.341]	
EURDKK	133.740	−0.036	***0.026	***0.082	***0.074	1.070
	[1.578]	[0.946]	[2.641]	[2.812]	[13.460]	
EURGBP	***−37.084	**0.029	***0.022	−0.004	***0.045	1.035
	[8.007]	[1.972]	[3.366]	[0.630]	[9.419]	
EURJPY	0.970	0.004	**0.018	***0.025	***0.039	0.993
	[0.261]	[0.190]	[2.178]	[4.777]	[8.076]	
EURNOK	***−38.956	***0.053	***0.038	***0.034	***0.075	1.376
	[7.544]	[2.836]	[4.524]	[4.492]	[15.042]	
EURSEK	***−44.468	***0.054	***0.035	***0.024	***0.081	1.392
	[8.165]	[3.875]	[4.707]	[3.149]	[16.525]	
EURUSD	***−35.157	0.010	***0.030	0.001	***0.051	1.815
	[7.576]	[1.179]	[5.421]	[0.270]	[10.439]	
GBPAUD	−5.831	−0.191	0.016	0.012	***0.022	0.128
	[1.576]	[1.022]	[1.605]	[1.533]	[4.616]	
GBPCAD	***13.404	**0.224	0.008	***0.028	***0.034	0.258
	[3.102]	[2.123]	[0.739]	[3.211]	[6.852]	
Expected sign	-	+	+	+	+	

(4.3)	γ_1	δ_1^{CO}	δ_1^{FD}	δ_1^{NB}	δ_1^{BA}	$\bar{R}^2$ in %
GBPCHF	***−28.160	**0.145	0.001	0.006	***0.023	0.377
	[4.300]	[2.029]	[0.121]	[0.612]	[4.671]	
GBPJPY	***42.777	−0.001	***0.029	0.006	***0.054	1.389
	[6.283]	[0.024]	[2.679]	[0.891]	[10.653]	
GBPUSD	**−10.448	0.018	0.008	0.005	***0.048	0.836
	[2.525]	[1.142]	[1.350]	[0.894]	[9.976]	
NZDUSD	***−15.227	−0.059	**0.015	0.004	***0.056	0.694
	[4.343]	[0.896]	[2.039]	[0.819]	[11.678]	
USDCAD	1.868	0.005	0.009	0.003	***0.054	1.117
	[0.383]	[0.177]	[1.377]	[0.557]	[11.158]	
USDCHF	***−15.953	***0.076	***0.025	0.001	***0.041	0.551
	[3.741]	[3.205]	[3.730]	[0.161]	[8.454]	
USDDKK	**−8.360	0.008	*0.014	0.004	***0.020	0.543
	[1.967]	[0.199]	[1.669]	[0.196]	[3.528]	
USDHKD	***−301.884	**0.232	**0.015	0.021	***0.058	0.749
	[4.764]	[2.228]	[2.461]	[1.215]	[11.823]	
USDILS	4.110	0.165	***0.028	0.007	***0.075	1.369
	[0.917]	[1.419]	[2.592]	[0.495]	[13.396]	
USDJPY	−2.790	*0.023	***0.027	***0.016	***0.028	0.503
	[0.681]	[1.698]	[4.699]	[3.235]	[5.819]	
USDMXP	***−24.825	*0.067	0.007	**0.014	***0.048	0.530
	[6.273]	[1.884]	[0.917]	[2.115]	[9.791]	
USDNOK	***8.968	0.079	***0.021	0.005	***0.071	0.924
	[2.670]	[1.541]	[2.663]	[0.616]	[14.005]	
USDSEK	**−7.691	***0.090	***0.026	0.006	***0.048	0.557
	[2.080]	[3.351]	[3.648]	[0.822]	[9.833]	
USDSGD	***−73.324	−0.014	0.011	−0.005	***0.049	0.705
	[9.593]	[0.310]	[1.547]	[0.557]	[10.229]	
USDZAR	***−16.545	0.032	***0.022	**−0.016	***0.050	0.679
	[6.707]	[0.785]	[2.828]	[2.171]	[10.238]	
Expected sign	-	+	+	+	+	

if all coefficients in (4.5) for a specific agent category i are jointly significantly different from that of agent j. In line with asymmetric information theory (see Glosten and Milgrom, 1985; Grossman and Miller, 1988; Lyons, 2006), we find that order flows have a different effect on prices depending on the market participant behind them. For nearly every pairwise combination of agents, the F-test clearly rejects the null hypothesis of equal price impacts.[29] All in all, we provide evidence that superior information is pervasive and systematically varies across market participants. For asset pricing, this also implies that each market participant is exposed to asymmetric information and adverse selection risk, which should be priced in FX rates.

5.2.2. Fragmentation in the FX market across currencies

In traditional market microstructure models (e.g., Kyle, 1985), the price impact depends on the precision of the private signal, variation in liquidity trades, and risk aversion coefficients of informed traders and liquidity providers (Subrahmanyam, 1991). All these factors vary across currencies and time, creating systematically different price impacts across FX rates. Overall, currency pairs that are more affected by asymmetric information should reveal a larger permanent price impact. Table 5 shows that every currency pair is affected by multiple categories of agents' permanent price impact, suggesting that asymmetric information risk is pervasive across FX rates. This result holds for both the most (e.g., EURUSD and USDJPY) and least (e.g., EURCAD and USDSEK) liquid currency pairs. Generally, more (less) risk-averse investor should be more (less) reluctant to invest in illiquid assets. However, our estimates seem to have general validity and are not biased toward less liquid FX rates potentially being more affected by risk aversion. As an additional test, we reiterate our analysis by estimating the permanent price impact during the main stock markets trading hours (i.e., from 7 am London open to 9 pm New York close, GMT), that is, when risk aversion should be less pronounced. We find a similar picture reinforcing the idea that asymmetric information risk is ubiquitous across FX rates.

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

Table 5
Permanent price impact across agents: joint *F*-test.
This table reports estimates of the permanent price impact that are retrieved from estimating (4.5) on the full sample. All regression coefficients are in basis points (BPS). The numbers in brackets correspond to the test statistic for a heteroskedasticity-consistent joint *F*-test, where the parameters in (4.5) are jointly different from zero. The sample covers the period from September 2, 2012 to December 31, 2019. Asterisks *, **, and *** denote significance at the global 90%, 95%, and 99% levels (α_g), respectively. For each individual test, a Bonferroni correction is applied such that the local significance level is $\frac{\alpha_g}{m}$, where m is the number of multiple tests in the joint hypothesis. Agents are abbreviated as follows: corporates (CO), funds (FD), nonbank financials (NB), and banks acting as price takers (BA).

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

Empirically, we find the global FX market to be fragmented in the sense that a specific agent i has a significantly different price impact parameter (both β_0^j/α_m^j) across currency pairs. As before, we estimate (4.2) on the full sample and construct a pairwise F-test, where we test whether all the coefficients in (4.5) for a particular agent category $i \in C = \{CO, FD, NB, BA\}$ are jointly significantly different in currency pair k compared with currency pair q.[30] The main result that emerges from this analysis is that corporates, funds, nonbank financials, and banks acting as price takers have a permanent price impact α_m^j, which varies heavily across currencies. Overall, our empirical analysis extends earlier research on customer order flows (e.g., Evans and Lyons, 2006; Osler et al., 2011; Menkhoff et al., 2016) at a global scale. An avenue for future research would be to understand the effect of regulation on the local nature of FX price discovery.

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

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

5.2.3. Time varying information flows

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

In Fig. 2, we plot the average permanent price impact (α_m^j) across currency pairs over time. Importantly, the α_m^j is present at all times and does not cluster in distressed periods. Furthermore, the α_m^j appears to be larger and more dispersed across agents during the European sovereign debt crisis (2010–2014), that is, when risk aversion was presumably high. Across agents, corporates seem to have the strongest time variation, consistent with the idea that their trades are driven by uninformative reasons (e.g., market risk, hedging, or liquidity shocks) rather than by a systematic processing of superior information.[31]

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

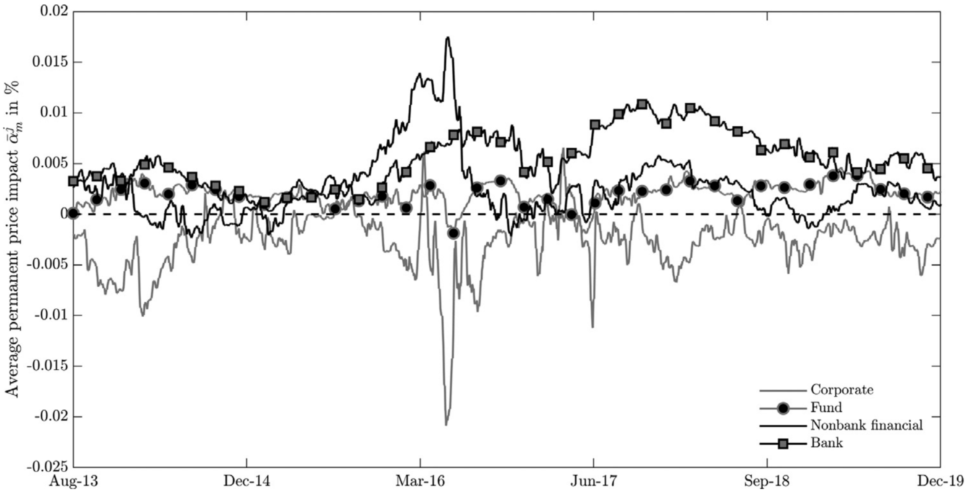

Fig. 2. Five-day moving average permanent price impact ($\bar{\alpha}_m^j$). This figure plots the average permanent price impact across 30 currency pairs for corporates, funds, nonbank financials, and banks after removing any permanent price impact estimates that are more than three scaled median absolute deviations away from the sample median. The currency pair specific permanent price impact coefficients are retrieved from estimating (4.5) in a twelve month rolling window fashion. The sample covers the period from August 26, 2013 to December 31, 2019.

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

5.3. Drivers of customer order flows

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

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

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

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

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

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

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

Table 6
Economic drivers of net order volume (USD-based currency pairs).

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

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

currency when foreign equity markets are doing well and do the opposite for bond markets. This finding is in line with a general risk-taking attitude in upward markets inducing investments abroad (i.e., buy foreign currency and sell domestic currency) and an opposite pattern during flight-to-quality episodes (Ranaldo and Söderlind, 2010). Such a behavior is also in line with the role of financial intermediaries absorbing global imbalances in the FX markets (Gabaix and Maggiori, 2015).

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

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

6. Asymmetric information risk premium

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

6.1. Trading strategy

From an asset pricing perspective, a coherent method to capture asymmetric information risk is to construct a long–short portfolio based on the systematic level of asymmetric information across currency pairs. In the context of global FX trading, we consistently apply this idea by introducing a novel and readily implementable trading strategy based on a simple idea: order flows of agents and currencies impounding a persistent price impact convey superior information. Put differently, holding currency pairs with higher informational asymmetries (i.e., high average permanent price impact) requires a positive risk premium for taking the risk of trading against informed investors. Thus, if a currency's return responds permanently (weakly) to order flows in the same direction, it belongs to the long (short) basket.[35]

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

Trading signals are generated from estimating (4.2) in a 12-month rolling window fashion at a daily frequency based on binary order flow and midquotes with the number of lags equal to ten days.[38] To avoid any look-ahead bias, we use yesterday's trading signals ($t-1$) to create portfolio weights today (t). The advantage of running this regression at daily rather than hourly frequency is twofold: first, it is computationally less expensive and hence is easily replicable in a real-world setting.[39] Second, forward rates are usually not available at an hourly frequency, and therefore using daily data ensure that signals are extracted at the same frequency as excess returns.

Hence, investment starts in September 2013 after one year of formation period. This leaves us more than six years for testing out-of-sample performance. For every rolling window index and currency pair k, we obtain the average permanent price impact $\bar{\alpha}_m^k$ (see (4.6)). Next, we sort currency pairs by $\bar{\alpha}_m^k$ in ascending order.[40] The AIP_{HML} portfolio is long (short) currency pairs in the top (bottom) tertile that exhibit the highest (lowest) $\bar{\alpha}_m^k$. Portfolio rebalancing takes place at the beginning of every month.

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

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

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

To account for the possibility of investing in a non-USD currency pair such as the *EURGBP*, we modify (6.1) such that, instead of one forward contract,[41] the US investor enters two forward contracts based on triangular no-arbitrage conditions:

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

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

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

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

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

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

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

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

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

6.2. Trading performance

In Table 7, we present the annualized Sharpe ratio (SR); the annualized mean excess return (Mean); the maximum drawdown (MDD); and the Θ performance measure of Goetzmann et al. (2007), skewness, and excess kurtosis (Kurtosis-3) based on monthly rebalancing, respectively.[44] The Θ performance measure of Goetzmann et al. (2007) is only slightly lower than the mean return, indicating that

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

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

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

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

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

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

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

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

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

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

Table 7
Performance benchmarking AIP_{HML}.
This table presents the out-of-sample economic performance of the AIP_{HML} trading strategy before and after transaction cost based on monthly rebalancing. Panel A reports the annualized Sharpe ratio (SR), annualized average (simple) gross excess return (*Mean*), skewness, excess kurtosis (Kurtosis-3), maximum drawdown (MDD), MDD divided by volatility (Scaled MDD), and Θ performance measure of Goetzmann et al. (2007) for the tertile portfolios (Q_1, Q_2, Q_3) based on the uniform distribution. Panel B lists the same measures as Panel A but after transaction cost. *DOL* is based on an equally weighted long portfolio of all USD currency pairs, RER/RER_{HML} on the real exchange rate (cf. Menkhoff et al., 2017), MOM_{HML} on $f_{t-1,t} - s_t$ (cf. Asness et al., 2013), and CAR_{HML} on the forward discount/premium ($f_{t,t+1} - s_t$, cf. Lustig et al., 2011). *BMS* is based on the lagged standardized order flow (cf. Menkhoff et al., 2016) and VOL_{LMH} is based on currency pairs' exposure to the global volatility factor (cf. Menkhoff et al., 2012a). Significant findings at the 90%, 95%, and 99% levels are represented by asterisks *, **, and ***, respectively. The numbers in the brackets are the corresponding test statistics for the mean return and SR being equal to zero, respectively, based on heteroskedasticity- and autocorrelation-consistent errors correcting for serial correlation and the small sample size (using the plug-in procedure for automatic lag selection by Andrews and Monahan, 1992; Newey and West, 1994). The sample covers the period from September 9, 2013 to December 31, 2019.

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

neither outliers nor nonnormality are driving the superior performance.[45] Panel A and B of Table 7 tabulates the before and after transaction cost performances of the first (Q_1) and third (Q_3) tertile portfolios, where AIP_{HML} is a linear combination of going short in Q_1 and long in Q_3. The same table also considers the performance of common FX trading strategies.[46]

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

Fig. 3 depicts the cumulative (simple excess) returns of different rebalancing frequencies before and after transaction cost. Gross returns are based on midquotes for both the spot and forward rates. The investment period is the entire sample period (September 2012 to December 2019) minus 12 months of the formation period to retrieve the first trading signal; thus, it spans from September 2013 to January 2019. Two merits arise from Fig. 3: first, daily rebalancing is substantially less profitable than monthly rebalancing due to higher transaction cost, but it bears similar cumulative returns prior to transaction cost. Second, the equity curves steadily increase over time and do not experience any regime switches. Note that the cumulative returns are also increasing after October 2018 (i.e., the first

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

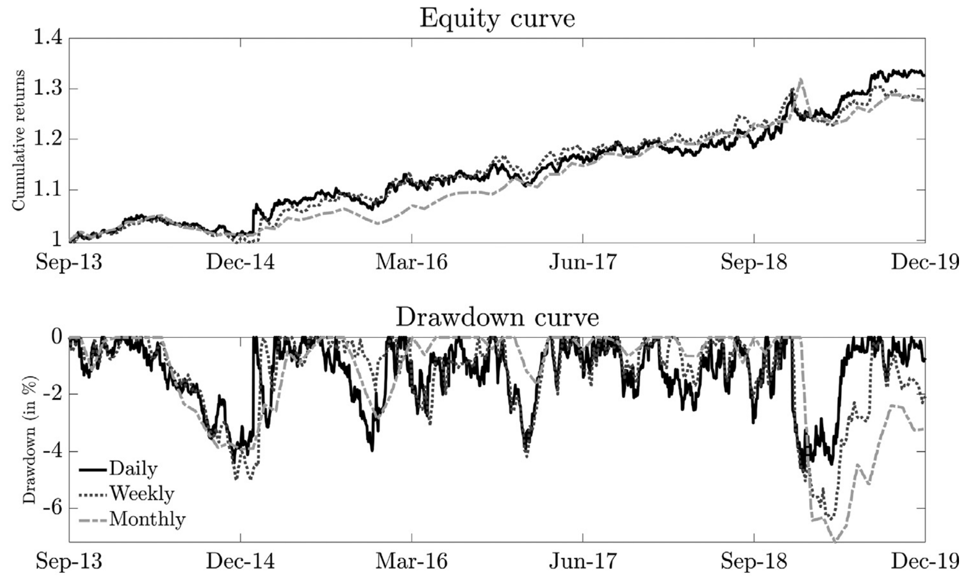
[46] The summary statistics for these benchmark strategies differ from those in Cespa et al. (2020). Our correspondence with the authors revealed three potential reasons for the differences: first, different time period with only four overlapping years. Second, the authors use three-month averages to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

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

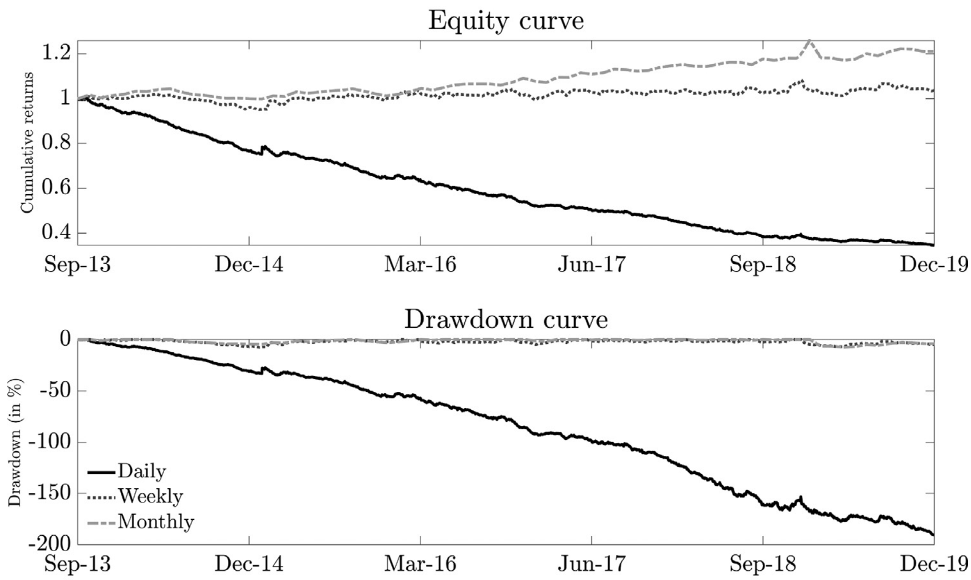
[48] The *RER* and RER_{HML} are constructed based on Menkhoff et al. (2017), where currency pairs are sorted based on their real exchange rate. *HML* stands for "high-minus-low."

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

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



(a) Before transaction cost



(b) After transaction cost

Fig. 3. Equity and drawdown curves AIP_{HML}. Panel a) of this figure plots the before transaction cost cumulative equity curve of a one dollar investment into the AIP_{HML} trading strategy as well as the drawdown curve in percent (%) for daily, weekly, and monthly rebalancing. Panel b) shows the same performance measures as Panel a) but after accounting for transaction cost. For nondaily rebalancing frequencies, missing data points are interpolated linearly. The sample covers the period from September 6, 2013 to December 31, 2019.

dissemination of the working paper version), reinforcing the risk premium hypothesis rather than some unexploited trading opportunity or other forms of market inefficiency.

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

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

Table 8
Exposure regression based on monthly gross returns.

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

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

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

6.3. Exposure regression

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

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

Consistent with the asymmetric information hypothesis, AIP_{HML} returns are more correlated (see Table 8) with factors related to (currency) fundamental values, that is, the real exchange rate (RER_{HML}) and carry (CAR_{HML}). As expected, AIP_{HML} is unrelated to the standardized total order flow (BMS), global volatility (VOL_{LMH}), and momentum (MOM_{HML}). All these results hold after controlling for relative changes in the VIX index, JP Morgan Global FX Volatility index (VXY), the North American credit default swap index (CDX), and the TED spread, respectively. In addition, we decompose the VXY into an "uncertainty" and "risk aversion" component (Bekaert et al., 2013). The regression coefficient of "risk aversion" bears the expected (negative) sign but is generally statistically insignificant and does not affect the abnormal returns (α) generated by AIP_{HML}. This corroborates the overall validity of our results and highlights that they seem to hold in both a risk-neutral

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

and risk-averse framework, respectively. Overall, none of the control variables has a material impact on our trading strategy's superior performance.[53]

6.4. Explaining the asymmetric information risk premium

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

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

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

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

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

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

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

6.5. Robustness tests and limitations

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

7. Conclusion

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

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

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

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

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