What is the value of retail order flow?

Abstract

We assess the value of retail order flow by studying the performance of specialized retail market makers (RMMs) in the German equity market. RMMs earn an average (gross) Sharpe ratio of 17.85, which is more than twice as large as that earned by proprietary trading firms active in public limit order markets. A simple calculation suggests that RMMs' willingness to pay for retail order flow is around 60% of their revenues, or 1.76 bps of their trading volume. The profitability of retail market making is rooted in reduced exposure to adverse selection and inventory risk.

Keywords: Equity markets, retail trading, market making, internalization, payment for order flow.

JEL Codes: G10, G12.

1 Introduction

Retail trading in equity markets has grown strongly over recent years, fuelled by the rise of commission-free trading and the combination of low interest rates, large-scale fiscal stimulus and the COVID-19 pandemic. While there is evidence that retail investors on aggregate have performed well (Welch, 2022) and helped to improve market liquidity (Ozik et al., 2021), economists and regulators have become increasingly concerned about the "gamification" of trading (Barber et al., 2022) and conflicts of interest in the brokerage industry (Egan, 2019).

Much of the debate has centered around the market structure for retail trading, including the practice of "internalization" and "payment for order flow" (PFOF). While not a new phenomenon, the events surrounding the meme-stock frenzy of January 2021 and the decision of brokerage firm Robinhood to halt trading in affected securities led to a wave of public outrage.[1] In the aftermath, the US Securities and Exchange Commission called for an overhaul of US retail equity market structure and an investigation into the implications of PFOF. In Europe, lawmakers went further and recently decided to ban PFOF altogether from 2026 onwards.[2]

In this paper, we contribute to the debate on retail equity market structure by providing a comprehensive assessment of the value of retail order flow. The key premise of PFOF is that the internalization of retail order flow is profitable, which enables brokers to charge a fee for directing their customers' orders towards specialized intermediaries. If brokers can exert at least some market power, the size of the "kickback" they can extract

[1] See "This is the way: the Reddit traders who took on Wall Street's elite", Financial Times, 29 January 2021.

[2] See "SEC aims to stem trading practice of payment for order flow", Financial Times, 8 June 2022, and "EU agrees deal on securities rules that includes ban on broker commission", Reuters Newswire, 29 June 2023. During our sample period, PFOF was already illegal in several EU countries, but common practice in others.

should depend on the profitability of retail market making.

We use detailed regulatory data on the trading activity of five specialized retail market makers (RMMs) in the German equity market. They jointly account for more than half of all retail order flow, which is internalized via a set of RMM-affiliated trading venues. We assess their trading activity and profitability (on a gross basis) and contrast it with a large group of proprietary trading firms (PTFs) active in the German equity market. Our findings are as follows.

First, we show that RMMs exhibit a trading behaviour that is broadly similar to that of PTFs as documented in the literature (e.g., Kirilenko et al., 2017). They handle significant trading volume (122 million EUR per RMM-day) and maintain very low inventory positions (less than 1% of total volume). While the bulk of their trading occurs in affiliated trading venues against retail investors, a significant share of this order flow ultimately ends up in public limit order markets (PLOMs) where RMMs re-balance their inventories.[3] We also show that about 85% of RMM volume is executed during regular trading hours (RTH), with the remaining share traded before the open or after the close.

We then evaluate RMMs' performance. Overall, retail market making is vastly profitable, especially on a risk-adjusted basis. The average RMM earns a daily return of 20.11 bps and exhibits a Sharpe ratio of 17.85. Interestingly, we find that almost half of their profits are generated outside regular trading hours (OTH), even though it only accounts for only around 15% of trading volume. However, the increased profitability of

[3]We use the term "public limit order market" (PLOM) as an umbrella term for all multilateral trading venues with i) transparent limit order books that ii) cater to a broad base of market participants and iii) are not dominated by a single liquidity provider. These markets are responsible for price discovery. In our context, this includes Xetra, the electronic limit order book of the German stock exchange, as well as a number of multilateral trading facilities (MTFs) that act as direct competitors (e.g. CBOE, Turquoise, Acquis), but do not have official exchange status. It is important to distinguish these venues from RMM-affiliated venues, some of which are technically also classified as exchanges or MTFs (other operate as "systematic internalisers"). Their business model is entirely focused on retail investors, and thus fundamentally different.

OTH trading also comes with higher risk, so that it offers a similar Sharpe ratio than RTH trading.

Next, we contrast RMMs' activity with that of 21 PTFs active in the German equity market. While these PTFs trade similar volumes, their activity is concentrated in the 100 most liquid stocks. They keep somewhat larger overnight inventory positions (around 10%), and trade almost exclusively in PLOMs. While PTFs generate significant trading revenues, they perform less well than RMMs on a risk-adjusted basis. We estimate an average Sharpe ratio of 7.42 across our 21 PTFs, and an average daily return of 6.03 bps.

We then provide a simple back-of-the-envelope calculation that aims to quantify the value of retail order flow. We do so by assuming that a trading firm can either i) act as PTF in PLOMs, or ii) become an RMM. Since RMMs earn higher risk-adjusted returns than PTFs, the value of retail order flow is equal to the trading firm's willingness to pay for becoming an RMM. Using our profitability estimates, we find that RMMs would be willing to give up 27.1 million EUR per year (1.76 bps of total trading volume), or close to 60% of their trading revenues. Scaled to the size of the U.S. stock market, this corresponds to 1.56 billion USD/year. Overall, these numbers compare rather well to those reported in recent literature (Ernst and Spatt, 2022; Schwarz et al., 2022; Bryzgalova et al., 2022) and the financial press.

Finally, we explore the sources of the differential profitability of retail and wholesale order flow. First, we examine the role of adverse selection by decomposing the effective spread into a short-term price impact and the realized spread. Our results suggest that the retail order flow absorbed by RMMs is completely uninformed and does not generate any price impact. This enables RMMs to provide some price improvement, and at the same time earn significantly higher realized spreads.

Second, we look at differences in inventory risk. We show that RMMs' inventories exhibit a significantly faster mean reversion than those of PTFs (with half-lifes of 15.9 and 41.8 minutes, respectively). We then decompose the mean reversion speed into a passive and an active component, and find that the result is driven by i) retail order flow being relatively more balanced, and ii) RMMs being more aggressive in offloading any non-zero inventory positions in PLOMs.

Our findings can inform the regulatory debate on retail equity market structure. The internalization of retail flow is profitable because it exposes intermediaries to a significantly lower level of risk compared to the order flow in PLOMs. Overall, this finding is consistent with the cream-skimming view of internalization (Easley et al., 1996), and gives rise to concerns about the possible negative effects on overall market liquidity. Moreover, the "excess profits" arising from retail market making provide a yardstick that can help policy makers to assess the extent to which the benefits of order flow segmentation accrue to retail investors, for example in the form of price improvements and reduced commissions.

Related Literature. Our paper contributes to the fast-growing literature on the microstructure of retail equity markets. While its origins date back to the rise of internalization in the 1990s (e.g. Röell, 1990; Easley et al., 1996; Battalio et al., 1997), this literature has attracted renewed attention in recent years as a result of the retail investor boom triggered by the COVID-19 pandemic and public controversies surrounding the rise of commission-free brokerage accounts, trading halts in "meme stocks" and the controversy surrounding PFOF.

In this context, several recent papers study the execution quality of small retail orders under PFOF arrangements relative to the benchmark of exchange-based trading (Adams et al., 2021; Schwarz et al., 2022; Levy, 2022; Dyhrberg et al., 2022). Overall, the evidence is consistent with i) retail investors receiving price improvement and ii) significant variation in investors' trading costs. Ernst et al. (2024) study the relationship between brokers' routing decisions and internalizers past performance. Some of this literature focuses on retail trading in equity options, which has exploded recently and now accounts for about half of the total market (Bryzgalova et al., 2022). Ernst and Spatt (2022) show that PFOF in options is large and argue that this incentivizes brokers to tilt their clients towards options trading. Hendershott et al. (2022) study auctions in options markets through which wholesalers internalize retail order flow. While they find evidence for price improvements, they also argue that wholesalers engage in cream-skimming.

The growth of PFOF has also led to new theoretical work that examines why such arrangements can be profitable for market makers. Parlour and Rajan (2003) develop a model where PFOF creates rents for liquidity providers by softening competition (see also Lescourret and Robert, 2011). Barardehi et al. (2021) show that wholesalers decide which retail flow to internalize and which to send on to the exchanges in response to liquidity demand by institutional investors. Accordingly, they use retail flow as a source for inventory management. Baldauf et al. (2023) develop a model consistent with this view, where the internalization of retail order flow helps to reduce inventory risk at the portfolio level. Finally, van Kervel and Yueshen (2023) develop a model where the possibility to execute order flow off-exchange induces intermediaries to scale back on-exchange liquidity provision. In line with a recent SEC proposal, Ernst et al. (2022) develop a theoretical model to shed light on the merits of a move from PFOF to competitive order-by-order auctions. They argue that, under some conditions, auctions may give rise to a winner's curse that could harm retail investor welfare.

A third strand of the literature analyzes the performance of retail investors and their impact on overall market quality. Some authors provide evidence that retail investors do well on average and their trading predicts future returns and helps to stabilize markets (Boehmer et al., 2021; Ozik et al., 2021; Welch, 2022). However, other point towards "attention-induced trading" by first-time investors (Barber et al., 2022), increased inventory risk from herding behaviour (Eaton et al., 2022) and negative volatility spillovers from retail options trading (Lipson et al., 2023). These developments were likely fuelled by the widespread removal of trading commissions (Even-Tov et al., 2022).

Finally, our paper is also related to several papers examining the returns to intermediation activity and their determinants. Most notably, Menkveld (2013) and Baron et al. (2019) analyze the profitability of PTFs in Dutch and Swedish equities and point to the role of speed for managing adverse selection risk and inventory control. Anand and Venkataraman (2016) show that the profitability of market making on the Canadian equity market exhibits significant commonality, and counterintuitively increases with volatility. Van Kervel and Menkveld (2019) and Korajczyk and Murphy (2019) examine the effects of PTFs on the execution costs of other market participants. Overall, PTFs appear to impose some costs on large institutional investors, but benefit smaller investors.

2 The retail trading landscape in Germany

The laboratory for our analysis is the German equity market. Despite a lower level of stock market participation (see, e.g. Giannetti and Koskinen, 2010), the structure of the German market for retail trading in equities closely resembles that of the United States.[4]

[4]There are some differences to other European countries. Notably, PFOF is illegal in the Netherlands and the United Kingdom. See Aramian and Comerton-Forde (2023) for a recent overview of retail trading mechanisms in Europe.

Retail customers in Germany typically access the stock market via a brokerage account held at a bank or a standalone broker. Following the success of Robinhood in the United States, a number of so-called "neo-brokers" entered the market starting in 2019 in order to capitalize from a retail trading boom spurred by low interest rates and amplified by the COVID-19 pandemic. Their business model is largely built on ultra-low commissions financed through PFOF and easy-to-use trading apps aimed at a younger generation of investors. Examples for neo-brokers include Trade Republic, Scalable Capital, Smartbroker, JustTrade, Finanzen.net, BUX Zero, among others.

While critical for the neo-broker community, the internalization of retail order flow in the German equity market goes back to at least the peak of the dot.com bubble in the late 1990s.[5] Today, the market is dominated by five retail market makers (RMMs) which operate specialized trading venues. Several of these firms have emerged around Germany's former regional stock exchanges, which had become largely redundant with the advent of electronic trading. Unlike the large US wholesalers (Citadel, Susquehanna, Virtu), RMMs in Germany typically do not act as market makers on PLOMs and their proprietary trading activity is focused on retail order flow.[6] This simple business model enables us to cleanly identify the profitability of retail making making.

Traditionally, German retail brokers offer their customers a choice between sending their orders to PLOMs (exchanges or multilateral trading facilities) or RMM-affiliated venues. This does not mean that they do not receive any PFOF, since they may obtain compensation for nudging clients towards particular venues, for example through the

[5]For example, the German retail broker DAB began offering off-exchange trading with Lang & Schwarz in 1998. See https://en.wikipedia.org/wiki/DAB_BNP_Paribas.

[6]Some RMMs also provide execution services to smaller institutional clients in an agency capacity. However, these activities are very small.

default settings of their order entry forms.[7] However, several neo-brokers route their entire order flow to a single RMM, which implies significantly higher revenues from PFOF and enables them to charge low commissions.[8] This has put pressure on incumbent brokers to increase their reliance on PFOF and route more order flow to RMMs (see Section 3.2).

3 Data and descriptive statistics

We first describe the data and then provide an overview of aggregate developments over the sample period.

3.1 Data

We obtain supervisory transaction-level data collected under the EU's MiFID II framework from the "Research Data and Service Centre" (RDSC) at Deutsche Bundesbank. Our sample period is July 2018 - June 2021 and thus spans exactly three years. In the following, we describe the essential features of these data. Additional details can be found in the "Regulatory technical and implementing standards" published by the European Securities Markets Authority.[9]

The data cover all equity transactions for which the German securities markets regulator BaFin is the relevant "competent authority", irrespectively of where the transaction takes place. This includes the near-universe of German stocks as well as a small number of foreign stocks that are listed and actively traded in Germany.[10] In addition, the dataset

[7]See "Wie Banken beim Aktienhandel doppelt abkassieren", Wirtschaftswoche, 23 April 2015 (available in German only).

[8]These brokers typically designate a backup venue in case the RMM faces an outage. However, there were no significant RMM outages during our sample period.

[9]These are available at: https://www.esma.europa.eu/sites/default/files/library/2015/11/2015-esma-1464_annex_i_-_draft_rts_and_its_on_mifid_ii_and_mifir.pdf

[10]One example for a foreign stock in the supervisory remit of Bafin is Qiagen N.V., a Dutch company originally founded in Germany that is part of the DAX30 blue chip index and predominantly traded on

also contains information on all equity transactions executed by legal entities registered in Germany, including trading in foreign stocks on foreign markets. Taken together, our dataset covers all trading in German stocks as well as all trading by German entities.

Each transaction record contains the key variables typically found in equity market datasets such as the ISIN code, price, quantity, currency, execution timestamp (rounded to the nearest second), and execution venue. In addition, the data also contain confidential information about the identity of the buyer and the seller for each transaction. While institutional counterparties are identified via their legal entity identifier (LEI), the identity of natural persons was masked by the RDSC before making the data available to us. Accordingly, we can only identify whether a counterparty is a natural person, but it is not possible to follow individuals across stocks or over time.

We restrict our sample to the most liquid German stocks. Importantly, this ensures that our data cover the entire trading activity across all venues, and therefore enables a meaningful comparison of RMMs' and PTFs' activity in these securities. To this end, we retrieve the historical constituents of the CDAX Index, which contains all German stocks from the two most liquid market segments ("General Standard" and "Prime Standard"). Throughout our sample period, a total of 457 stocks were part of this index at some point in time. We also download data for daily opening and closing prices as well as trading volume from Refinitiv Eikon. Finally, we obtain intraday quote data for a subset of these stocks (members of the DAX and MDAX indices) from Refinitiv Datascope.

All five RMMs active in Germany internalize retail order flow through affiliated trading venues. We link trading venues (identified by a market identifier code, or MIC) and market makers based on public information on their websites. Moreover, we run cross-checks to

Xetra, Germany's main stock market.

verify that the vast majority of the underlying order flow stems from natural persons or from retail brokers.

Before turning to the analysis, it is important to stress that the use of RSDC micro-data is subject to a set of rules and principles aimed at preserving data confidentiality. This includes provisions concerning the minimum number of observation units (e.g. legal entities) and thresholds on concentration ratios. Given our small sample size of only five RMMs, this at times prevents us from providing more detailed summary statistics than the mean and standard deviation.[11]

3.2 Aggregate developments

We first illustrate the aggregate developments of retail trading activity in the German equity market. Figure 1 depicts the time series of retail trading volume and contrasts it with the activity on Deutsche Boerse's Xetra platform, the primary market for German stocks. We observe that retail trading in Germany increases significantly over the sample period, and spikes during the Covid-19 lockdown periods in spring 2020 and winter 2020/21. Overall, retail trading has been edging up from around 400 million EUR per day at the beginning of the sample period to around 600 million EUR per day towards the end. At the same time, trading on Xetra has stayed largely constant (albeit a few swings) at close to 5 billion EUR per day. This means that the share of retail activity has increased from around 7% to more than 12%. The overall pattern in consistent with the widely-documented retail trading boom in the United States (Ozik et al., 2021).

[Insert Figure 1 here.]

[11]The detailed set of rules and guidelines is available at: https://www.bundesbank.de/resource/blob/826176/ffc6337a19ea27359b06f2a8abe0ca7d/mL/2021-02-gastforschung-data.pdf

Next, we look at the distribution of retail order flow across RMM-affiliated trading venues and other trading venues.[12] Figure 2 shows that the share of retail volume handled by RMMs has increased steadily over our sample period, from slightly below 40% at the beginning to close to 60% towards the end. This is consistent with the growing importance of neo-brokers over the sample period and increased attempts by incumbents to fend off competition by nudging their clients towards these venues in exchange for PFOF.

[Insert Figure 2 here.]

One feature of RMM-affiliated venues is their extended trading hours. Trading on Xetra, which dominates trading in German equities, takes place from 9:00-17:35 CET. We henceforth refer to this time window as "regular trading hours" (RTH). By contrast, the RMM-affiliated venues are typically open 8:00-22:00, which means they offer both pre-market (8:00-9:00) and after-hours trading (17:35 - 22:00).[13] We henceforth label the union of these two time periods as "outside regular trading hours" (OTH). Figure 3 provides a decomposition of RMMs' trading activity into RTH and OTH. We can see that OTH trading is an economically significant phenomenon, as it oscillates around 15% of RMMs' total trading during the sample. However, there is no clear trend over time.

[Insert Figure 3 here.]

4 Retail market making

This Section contains our analysis of retail market making. We first describe RMMs' trading activity, and then examine their performance. Finally, we cross-check our results

[12] For this comparison, we exclude retail trades that are marked as "XOFF", since these cannot be attributed to a particular trading venue. These are typically so-called "give-up" trades between brokers and their retail clients, where the original trade was executed either with an RMM or in PLOMs.

[13] One RMM-affiliated venue operates even longer hours, from 7:30-23:00.

with public disclosures for plausibility.

4.1 RMM trading activity

Table 1 provides a comprehensive overview of RMMs' trading activity. Since RMMs trade in a broad array of securities, their activity and performance is best assessed from a portfolio perspective. For each variable, we report the mean and standard deviation, and whenever possible (i.e. in line with the Bundesbank's confidentiality rules) also the median. To ensure robustness against outliers, we winsorize measures of trading volume, revenue, and capital usage.[14]

Panel A shows that the average RMM-day is characterized by a trading volume of 122 million EUR, which is spread out over around 270 stocks. The average inventory ratio is below 1 percent, which suggests that RMMs carry very little overnight inventory, consistent with their focus on retail liquidity provision. More generally, RMMs tend to take relatively limited positions. Their capital usage, defined as the maximum intraday inventory position at the portfolio level, averages 4 million EUR, or less than 4% of their average trading volume.

OTH trading accounts for close to 15% of the average RMM-day, and the number of traded stocks is significantly lower at around 186. Since PLOMs are closed by definition, RMMs are not able to engage in active inventory management when trading OTH. Accordingly, they exhibit an average inventory ratio of around 4.24%, compared to 0.91% during RTH. Note that there are some diversification effects between RTH and OTH trading due imperfectly correlated order flow.

[14]Variables with support over the real line are winsorized at the 1st and 99th percentile, while those with only positive support are winsorized at the 99th percentile. For variables that are the sum of two components (RTH + OTH), we first winsorize the individual components and then take the sum.

[Insert Table 1 here.]

Panel B details how RMMs' trading activity is distributed across different trading venues. Slightly more than half of their trading volume is executed on their own venues, while lit exchanges account for 26.5% and off-exchange deals ("XOFF") sum up to 14.8%. Other trading venues (e.g. dark pools and systematic internalizers) account for less than five percent of RMMs' trading.

Taken together, these numbers suggest that RMMs frequently resort to other trading venues for managing the inventory risk that arises from the internalization of retail orders. The fact that lit exchange volume accounts for more than a quarter of RMMs' trading is consistent with retail order flow not being perfectly balanced, with the resulting imbalance ultimately ending up in PLOMs.

4.2 RMM performance

We next turn to examining RMMs' performance. As is customary in the literature (Menkveld, 2013; Baron et al., 2019), we compute trading revenues as the net cash flows accumulated during trading plus the mark-to-market value of the final position. Assuming a zero starting inventory, the revenue π from a total of N trades in a given stock is

$$\pi = \sum_{n=1}^{N} v_n (p^* - p_n), \tag{1}$$

where v_n denotes the signed quantity of the n-th trade, p_n is the corresponding transaction price, and p^* is the price at which any non-zero final position is marked to market. This equation can be interpreted as the market value of a position of $\sum_{n=1}^{N} v_n$ shares minus the cost of acquisition.

To deal with the fact that some of RMMs' activity falls outside regular trading hours, we compute their total daily revenue as the sum of revenues accruing during pre-market trading, regular trading hours, and after-hours trading. In the spirit of equation (1), we mark end-of-period positions to market using the next available exchange-determined price. That means we mark pre-market trading positions to the opening price, RTH trading to the closing price, and after-hours trading to the next day's opening price. Formally, trading revenues are given by

$$\pi^{total} = \underbrace{\sum_{k=1}^{K} v_k(p^o - p_k)}_{\pi^{pre}} + \underbrace{\sum_{l=1}^{L} v_l(p^c - p_l)}_{\pi^{RTH}} + \underbrace{\sum_{m=1}^{M} v_m(p^{o'} - p_m)}_{\pi^{after}}, \tag{2}$$

where K, L and M are the number of trades during pre-market, RTH, and after-hours trading, respectively, p^o and p^c denote the opening and closing price on the same day, and $p^{o'}$ is the next day's opening price. Finally, we define the trading revenue outside trading hours (OTH) as the sum of revenues from pre-market and after hours trading, $\pi^{OTH} = \pi^{pre} + \pi^{after}$.

[Insert Table 2 here.]

We compute RMMs' revenues for each stock-day, and then sum over all traded stocks to obtain their revenues at the portfolio level. These are reported in Table 2. The average RMM-day generates trading revenues of 36,710 EUR, with a standard deviation of approximately 48,600 EUR.

When looking at the breakdown into RTH and OTH trading, we can see that OTH revenues account for approximately half of the total. Figure 4 shows that this is a very persistent phenomenon, with relatively little time-series variation. Since OTH trading only accounts for about 15% of trading, this implies that it generates signficantly higher revenues per EUR traded. On the average RMM-day, RMMs earn 2.55 cents per 100 EUR traded, with a standard deviation of 2.01 cents. Unlike for revenues expressed in EUR, this distribution is quite symmetric, with the median equal to 2.47 bps. While RTH yields an average revenue of 1.62 cents, OTH trading earns 9.99 cents. However, OTH trading is also considerably more risky with a standard deviation of 7.13 cents, relative to only 1.89 cents for RTH trading. This is consistent with the differences in inventory ratios reported in Table 1 (Panel B). As RMMs cannot resort to other marketplaces for inventory management, OTH liquidity provision is more risky and thus gives rise to more volatile revenues.

[Insert Figure 4 here.]

We also compute daily returns. These are obtained by dividing revenues by an estimate for the employed capital. We follow Baron et al. (2019) and approximate capital conservatively with an RMM's maximum inventory position (at the portfolio level) over the entire sample period. Based on this, we obtain an average daily return of 20.11 bps, with a standard deviation of 26.73 bps. Consistent with our results on revenues, we observe similar returns for OTH and RTH trading.

We examine the risk-return trade-off more closely in Panel B of Table 2, where we compute Sharpe ratios at the firm level. We assume a zero risk-free rate, which has the advantage that the Sharpe ratio is independent of our measure of capital usage.[15] Due to the low number of observations, we only report the cross-sectional mean and standard deviation. Based on their trading revenue, RMMs are extremely profitable,

[15] As in Baron et al. (2019), this assumption is innocuous because short-term interest rates were slightly negative and essentially flat over the sample period.

with an average Sharpe ratio of 17.85. Moreover, we find that OTH and RTH trading offer similar Sharpe ratios, which are equal to 17.16 and 14.37, respectively. Accordingly, the differences in terms of revenues per EUR traded across these different subperiods are almost entirely explained by differences in risk.

Finally, Table 3 presents some key metrics for RMM activity and profitability at the RMM-stock-day level. Contrasting these to their portfolio-level equivalents in Table 1 and Table 2 provides some insights regarding i) diversification effects as well as ii) differences across more and less active stocks.

[Insert Table 3 here.]

For example, the average inventory ratio at the RMM-stock-day level is 30%, compared to less than 1% at the portfolio level. This implies that RMMs are carrying significant inventory positions at the individual stock level (relative to stock-level trading volume), but these wash out almost completely at the portfolio level. We see similar effects in terms of capital usage. The average RMM-stock-day exhibits a capital usage of 50,310 EUR, which would sum up to almost 14 million EUR for an average of 270 stocks. This contrasts with less than 4 million of actual capital used for the average RMM-day at the portfolio level (Table 1).

We also find that the revenues from OTH trading exceed those from RTH trading, but they are reaped less frequently at the individual stock-level since there is a significant number of days with no OTH trading in less liquid securities. Moreover, we observe that the average revenue per EUR traded at the RMM-stock-day level is 25.51 cents, or ten times the average at the portfolio level. This indicates that trading in smaller stocks generates significantly larger revenues.

4.3 Cross-check with public data sources

We end this section by cross-checking our data on RMMs' trading revenues with information from their public filings. All five RMMs are publicly listed companies, which allows us to compare our estimates with numbers from their annual reports. While this comparison is bound to be imperfect for reasons detailed below, it still helps to gauge the overall plausibility of our findings based on microdata.

We hand-collect information on RMMs' trading revenues ("Handelsergebnis") from their publicly available annual reports. Figure 5 plots the aggregate results, which shows that the five firms together generate average annual trading revenues of 271.89 million EUR over the sample period.[16] Consistent with the retail investor boom during the COVID-19 pandemic, income for the years 2020 and 2021 significantly exceeded that for 2018 and 2019.

[Insert Figure 5 here.]

For comparison, we aggregate our estimates from Table 2, which yields annual RMM trading profits of 46.25 million EUR ($36,710$ EUR $\times$ 5 firms $\times$ 252 trading days). However, these numbers are not directly comparable because trading in our sample stocks covers only part of RMMs' business. This is illustrated in Figure 6, which contrasts RMMs' trading volume in CDAX securities with their total trading volume, including foreign stocks, bonds, ETFs/ETPs, warrants, and other products. Overall, our sample stocks account for 29.98% of RMM trading during July 2018 - June 2021.

[Insert Figure 6 here.]

[16] The detailed firm-level data are provided in Table OA.1 in the Online Appendix.

Moreover, there is evidence that RMMs' trading activity beyond our sample stocks is significantly more profitable. A complete assessment of RMMs' trading revenues is unfortunately difficult due to a lack of reliable prices for the bulk of the instruments they trade. However, to gain some insight, we compute revenues relative to trading volume for the Nasdaq 100 index constituents, which averages 3.34 cents per 100 EUR traded.[17] Relative to the estimate for our sample stocks (2.55 bps), this suggests that trading in the most liquid U.S. stocks generates 31% higher revenues.

If we conservatively assume that all of RMMs' trading activity outside our sample stocks yields a similar level of profitability than Nasdaq 100 securities, it would generate revenues of 141.35 million EUR (46.25 million EUR $\times \frac{0.7}{0.3} \times \frac{3.34}{2.55}$). Summing up, we thus arrive at an estimate for RMMs' total annual trading revenues of 187.60 million EUR ($46.25 + 141.35$), which represents around 69% of the numbers derived from their annual reports. We therefore conclude that our estimates derived from microdata are highly plausible.

5 Non-retail market-making: a benchmark

In this section, we examine the trading activity and performance of non-RMM proprietary trading firms (PTFs) in the German equity market. The purpose is to obtain a benchmark for RMMs based on a simple idea. RMMs are proprietary trading firms who pay brokers for the "privilege" of executing their retail order flow. Without these PFOF agreements, RMMs would alternatively have to operate similar to other PTFs and intermediate trades

[17] The mean (median) revenue per 100 EUR across 3,024 RMM-days is 3.34 (3.02) cents, with a standard deviation of 4.44 cents. There are only four RMMs active in Nasdaq 100 securities, and the market is more concetrated than in German stocks. Therefore, a more detailed analysis of trading in Nasdaq 100 securities is unfortunately hampered by our data confidentiality rules.

in PLOMs.

Our identification of PTFs closely follows Baron et al. (2019). We first search the data for members of the European Principal Traders Association (EPTA).[18] We then manually screen the 200 most active entities for additional proprietary trading firms based on information provided on their webpage. We discard a small number of firms that self-report as being solely focused on derivatives trading.[19] Moreover, we drop one firm due to data quality concerns because it reports a large number of off-exchange block trades with unrealistic transaction prices. This leaves us with a total of 21 PTFs.

Table 4 provides an overview of PTFs' trading activity. Panel A shows that trading volume on the average PTF-day is 156 million EUR, which is only slightly larger than the numbers for RMMs reported in the previous section. By contrast, the standard deviation is considerably higher, suggesting more significant variation across firms and/or over time. On average, PTFs trade 101 stocks per day, which is significantly lower than the 270 stocks traded by RMMs. This is natural because most PTFs are likely to be focused on high-frequency trading strategies that can only implemented in sufficiently liquid securities. The average inventory ratio is 9.6 percent. While higher than what we find for RMMs, it is considerably lower that the numbers reported by Baron et al. (2019). PTFs' capital usage also corroborates the view that they take larger positions than RMMs. It average 8.40 million EUR, which is about twice that of RMMs, while both groups exhibit comparable trading volumes. Overall, these numbers are consistent with PTFs acting as intermediaries.

[18] See `https://www.fia.org/epta/articles/fia-epta-membership`.

[19] Market making in derivatives naturally involves entering offsetting positions in the cash market. However, the resulting revenues from these positions are not necessarily representative of the firm's profitability, so that we prefer to exclude these entities. Adding them to the sample of PTFs does not affect our conclusions.

[Insert Table 4 here.]

Panel B reports a breakdown of PTFs' activity across different types of trading venues. More than 85% of their trading activity occurs in PLOMs. Off-exchange trading accounts for slightly more than 6%, with other venues (including dark pools and systematic internalisers) accounting for the remainder. In sum, this is consistent with PTFs trading almost exclusively in transparent limit order markets.

We next turn to measures of PTFs' performance, which we report in Table 5. Since PTFs trade almost exclusively on PLOMs, we do not provide a breakdown into RTH and OTH (when those markets are closed by definition). Accordingly, any inventory is marked to the daily closing price. On average, PTFs earn 17.79 million EUR per trading day, which is about half of what RMMs earn on average. The standard deviation is 50.92 million EUR, suggesting that there is considerable variation across firms and/or over time.

[Insert Table 5 here.]

When scaling revenues by trading volume, we find an average revenue of 3.82 cents per 100 EUR traded with a standard deviation of 22.38 cents. While this exceeds RMMs' average revenue per EUR traded 2.55 cents by about 60%, this effect is essentially driven by a long right tail. The median revenue per 100 EUR traded is only 1.39 cents for PTFs, which is substantially lower than the median for RMMs (2.47 cents), and even lower than what RMMs earn during RTH trading (1.55 cents).

The average daily PTF return is 6.03 bps, which is considerably lower than the 20.11 bps earned by RMMs over the entire day, or the 9.81 bps earned during RTH. PTFs exhibit lower revenues and higher capital usage, which both work towards relatively lower returns.

Panel B looks more closely at the risk-return trade-off for the 21 PTFs in our sample. The average annualized Sharpe ratio is 7.42, with a cross-sectional standard deviation of 7.72. This suggests that PTFs are highly profitable on a risk-adjusted basis, and our numbers are broadly consistent with findings reported elsewhere. For comparison, Baron et al. (2019) report an average Sharpe ratio of 4.16 (with a standard deviation of 6.58) for 16 PTFs in the Swedish equity market, and Menkveld (2013) finds a Sharpe ratio of 7.62 for a large market maker in Dutch equities.

While PTFs earn very attractive Sharpe ratios, they pale in comparison with those earned by RMMs (Table 2), who are more than twice as profitable on a risk-adjusted basis. This even continues to be true when restricting RMMs to their revenues earned during RTH. Accordingly, retail market making is vastly more profitable (on a gross basis) than similar activity in PLOMs.

[Insert Table 6 here.]

As in the previous section, we also report some of the key activity and profitability metrics at the PTF-stock-day level. These are summarized in Table 6, and the resulting insights are similar to the case of RMMs. On average, PTFs exhibit individual stock-level inventories of around 32%, compared to around 10% at the portfolio level. We see qualitatively similar effects in terms of capital usage. Similarly, the stock-level revenue by trading volume average 8.19 cents per 100 EUR traded, which is more than double the number when aggregating across all stocks. The fact that the difference is significantly less pronounced than for RMMs is not surprising, since we have already shown that PTFs only trade a more limited sets of stocks, so that cross-sectional variation in terms of liquidity is less pronounced.

6 The value of retail order flow

In this section, we provide a simple back-of-the-envelope calculation that aims to quantify the value of retail order flow. To this end, we take the perspective of a trading firm that can either i) act as PTF in PLOMs, or ii) be an RMM. Since RMMs' earn higher risk-adjusted returns than PTFs, the value of retail order flow is then equal to the trading firm's willingness to pay for becoming an RMM.

Since we assume a zero risk-free rate, the level of capital drops out from the Sharpe ratio. Hence, a trading firm's willingness to pay for retail order flow, ϕ, must satisfy

$$\sqrt{252}\frac{\mu_{RMM} - \phi}{\sigma_{RMM}} = \sqrt{252}\frac{\mu_{PTF}}{\sigma_{PTF}} \tag{3}$$

or

$$\phi = \mu_{RMM} - \frac{\sigma_{RMM}}{\sigma_{PTF}} \times \mu_{PTF}, \tag{4}$$

where μ_i and σ_i denote the mean and standard deviation of daily revenues for trader group $i \in \{RMM, PTF\}$. Using the numbers in Table 2 and Table 5 (Panel B), we get

$$\phi = 36,710 - \frac{27,100}{30,630} \times 17,190 = 21,500 \tag{5}$$

Hence, a trading firm would be willing to pay up to 21,500 EUR per day for access to retail order flow. This amounts to almost 60% of RMMs' revenues. Given the average RMM-day trading volume of 121.63 million EUR, it corresponds to roughly 1.76 bps. With five RMMs and 252 trading days, it sums up to 27.1 million EUR per year on aggregate.

In principle, ϕ represents the cash lump sum that a monopolistic broker could extract from competitive RMMs as PFOF. However, since there is a significant level of concentration among both RMMs and brokerage firms in Germany, it appears reasonable that neither side has complete bargaining power. Accordingly, our estimate is more likely to represent an upper bound.

Unfortunately, there are no disclosures for PFOF in Germany. Accordingly, we can only compare our estimates to public data from the United States under SEC Rule 606. Bryzgalova et al. (2022) report that PFOF in US equities was 2.4 billion USD for the period 2020-2021, or 1.2 billion USD/year. While these numbers are very large compared to our estimate, data on stock market trading volumes helps to put things into perspective. According to the World Federation of Exchanges, on-book trading volume for NYSE, Nasdaq and CBOE Global Markets averaged 62.1 trillion USD/year over the period 2019-2021, compared to 1.6 trillion EUR for Deutsche Boerse (see Table OA.2). Hence, trading in US equities is about 33 times larger than in German stocks, based on an average EUR-USD exchange rate of 1.15. Moreover, the share of retail trading relative to the market total in the US appears to be significantly larger than in Germany. A recent Forbes article estimates it to be almost one quarter of US stock trading, while our estimates for Germany (Figure 1) are only about half of that.[20] This would imply a multiple of 66, and thus correspond to $\phi = 1.56$ billion USD/year (based on the above exchange rate). This is reasonably close to the publicly available PFOF data mentioned above.

In the Online Appendix (Table OA.3), we illustrate how our findings very with the outlier treatment. Our results are based on a relatively conservative approach where we winsorize the data at the 1% level. If we tighten our criteria (i.e. winsorize fewer observations), our findings become stronger. For example, winsorization at the 0.1% level implies an estimate for ϕ of 29,360 EUR per MM-day, an increase of around 37 percent.

[20] See "Retail Trading Just Hit An All-Time High. Here's What Stocks Are The Most Popular", Forbes Magazine, 3 Feb 2023 (online).

Conversely, a loosening of the criteria leads to lower estimates for ϕ. However, since the mean revenues are largely unaffected by applying different winsorization levels, looser criteria may be difficult to justify.

7 Dissecting profitability differences - adverse selection

In this section, we dissect the profitability differences between RMMs and PTFs. We focus on the two traditional sources of dealer risk highlighted in the literature, namely adverse selection (Kyle, 1985; Glosten and Milgrom, 1985) and inventory risk (Stoll, 1978; Amihud and Mendelson, 1980).

7.1 Adverse selection risk

A widespread argument is that internalization is profitable because retail order flow exposes market makers to little adverse selection risk. To shed light on this issue, we analyze the effective spread and its decomposition for RMMs' and PTFs' passive orders. We focus on stocks that are part of the DAX and MDAX indices because they are traded by essentially all RMMs and PTFs, unlike the less liquid stocks. We obtain quote data for Deutsche Boerse's Xetra platform from Refinitiv Datascope and compute the midquote for each order book update. We then match each trade in our database to the most recent midquote.

The effective (half) spread for the τ-th order is given by

$$ES_\tau = d_\tau \cdot \frac{p_\tau - m_\tau}{m_\tau} \tag{6}$$

where $d_\tau \in, \{-1, 1\}$ is the trade-direction indicator, p_τ is the transaction price, and m_τ is the prevailing midquote. Trades are signed using the Lee and Ready (1991) algorithm. The effective spread can be rewritten as the sum of the price impact and the realized spread, which are given by

$$PI_\tau = d_\tau \cdot \frac{m_{\tau+\Delta} - m_\tau}{m_\tau} \tag{7}$$

$$RS_\tau = d_\tau \cdot \frac{p_\tau - m_{\tau+\Delta}}{m_\tau}, \tag{8}$$

where $m_{\tau+\Delta}$ denotes the midquote after a time interval Δ has elapsed. We use an interval of 10 seconds, following the recent literature (Baron et al., 2019).

The price impact aims to capture the adverse selection risk that the market maker is exposed to, whereas the realized spread is an estimate of the market maker revenue (see Foucault et al., 2013). The underlying assumption is that the market maker closes out his position after 10 seconds at the then-prevailing midquote. While this a simplistic setting that is unlikely to reflect reality accurately, a higher price impact is indicative for market makers being subject to more adverse price movements following passive trades.

We compute all three measures for RMMs' passive executions on affiliated trading venues and all of PTFs' passive executions, and then compute equal-weighted averages for each MM-stock-day. We then regress each of these variables on two dummy variables that are equal to one if the market maker is a RMM (PTF), and zero otherwise. Table 7 contains the resulting regression coefficients with standard errors double-clustered at the market maker and stock level and increasingly stringent versions of fixed effects. For illustration, Figure 7 depicts quarterly averages for all measures (and differences across groups) over time. Panel A reveals that PTFs post wider effective spreads, which is consistent with RMMs providing price improvements to retail investors. In our preferred specification with stock-day fixed effects, RMMs charge an equal-weighted spread of 4.44 bps, which is about 25% lower than the 5.94 bps charged by PTFs (column 4). While the difference is highly economically significant, it is only marginally statistically significant with a t-statistic of 1.89.[21]

[Insert Table 7 and Figure 7 here.]

So while there is some evidence of RMMs providing price improvement in the German equity market, it is rather weak. This is perhaps not too surprising. On the one hand, brokers have an incentive to ensure that their customers obtain execution quality that is no worse than what is available on PLOMs. On the other hand, brokers have an incentive to maximize PFOF, and the ability of RMMs to provide price improvement mechanically declines with the size of their PFOF to brokers (as discussed in Levy, 2022).

Importantly, best execution under MiFID remains principles-based and is not enforced on a trade-by-trade basis. This means that RMMs can execute individual trades at prices that are worse than the currently prevailing best bid and offer. From this perspective, the fact that there is at least some weak evidence for price improvement is perhaps even surprising.

When turning to the decomposition in Panels B and C, we can see immediately that PTFs are subject to significant adverse selection risks, while RMMs are not. After controlling for stock-day fixed effects, the price impact of orders executing against RMM quotes is not distinguishable from zero.[22] By contrast, PTFs suffer a price impact of 4.54

[21] In the Online Appendix (Table OA.4), we present the results for value-weighted measures. In this case, the price improvement is no longer statistically significant.

[22] This result somewhat differs from Dyhrberg et al. (2022), who report small, but positive small price impacts for internalized retail orders in the U.S. equity market. One reason for this difference could be differences in retail investor sophistication across the Atlantic.

bps (Panel B, column 4). As a result, RMMs are able to earn significantly higher realized spreads (Panel C).

Since these static measures assume a uniform and fixed investment horizon, one cannot map them directly to our estimates for intermediary revenues in Table 2 and Table 5. Nevertheless, they provide strong evidence that RMMs are not exposed to the risk of adverse selection, but at the same time offer comparable bid-ask spreads. This readily explains why their revenues exhibit a much more favourable risk-return trade-off than those of PTFs.[23]

7.2 Inventory risk

Next, we analyze differences in inventory risk across RMMs and PTFs. Following Hansch et al. (1998) and Korajczyk and Murphy (2019), we estimate the speed of mean reversion in dealer inventories. For each stock i, day t and market maker m, we estimate the regression

$$\Delta I_\tau = \alpha + \kappa(I_{\tau-1} - \bar{I}) + \epsilon_\tau, \tag{9}$$

where I_τ is the market maker's inventory position (in shares) at the end of the τ-th intra-daily 15-minute interval, and $\Delta I_\tau \equiv I_\tau - I_{\tau-1}$. Thus, the estimate $\hat{\kappa}$ has an associated inventory half-life of $15\frac{ln(1/2)}{ln(1+\hat{\kappa})}$ minutes. In line with our analysis of trading revenues, we assume that market makers start the day with a zero inventory, which is also the assumed target (i.e. we set $\bar{I} = 0$). Moreover, to ensure comparability across intermediaries, we restrict the analysis to DAX and MDAX stocks traded during regular trading hours.

The behaviour of market maker inventories arises from two components: i) the imbal-

[23] In the Online Appendix (Table OA.5), we show that we obtain consistent results for different levels of stock liquidity.

ance that arises from the absorption of customer order flow, and ii) the sum of offsetting trades that are used to prevent inventory positions from becoming too large. Accordingly, it is interesting to analyze whether any potential disparities in mean reversion between RMMs and PTF are driven by differences in i), ii), or both.

To shed light on this question, we decompose changes in market maker inventories into their passive and active components, i.e. $\Delta I_\tau = \Delta I_\tau^P + \Delta I_\tau^A$. We proceed in the same way as for our analysis of adverse selection. For RMMs, we compute ΔI_τ^P as the net trading volume arising from passive executions in affiliated trading venues (i.e. passively absorbed retail order flow), whereas for PTFs it is computed as the net trading volume from all passive executions. We then estimate

$$\Delta I_\tau^P = \alpha^P + \kappa^P (I_{\tau-1} - \bar{I}) + \epsilon_\tau^P \tag{10}$$

$$\Delta I_\tau^A = \alpha^A + \kappa^A (I_{\tau-1} - \bar{I}) + \epsilon_\tau^A. \tag{11}$$

Notice that linearity implies $\kappa = \kappa^P + \kappa^A$.

We estimate equations (9) - (11) for each market maker-stock-day by OLS and then proceed as in the previous subsection. We regress the resulting coefficient estimates, winsorized at the 1% level, on two dummy variables that are equal to one if the market maker is a RMM (PTF), and zero otherwise. Table 8 contains the results, with standard errors double-clustered at the market maker and stock level and increasingly stringent versions of fixed effects. Our discussion focuses on the numbers in column (4). For illustration, Figure 8 plots quarterly averages of the group-specific coefficients and their differences over time.

[Insert Table 8 and Figure 8 here.]

Panel A shows that RMMs' inventories exhibit a significantly faster mean reversion ($\hat{\kappa} = -0.48$) than those of PTFs ($\hat{\kappa} = -0.22$). The coefficient estimates imply an inventory half-life of 15.9 minutes for RMMs, compared to 41.8 minutes for PTFs. These results indicate that inventory risk is a key reason for PTFs' significantly more volatile trading revenues documented in Section 5.

Panel B shows that part of the faster mean-reversion in PTF inventories is due to the different nature of customer order flows. The estimate for the passive component of mean reversion is $\hat{\kappa}^P = -0.16$ for RMMs, compared to $\hat{\kappa}^P = -0.09$ for PTFs. The difference is statistically significant at the 1% level. These results are consistent with retail order flow being significantly more balanced on average than the rest of the market, which contributes to a faster mean-reversion of RMMs' inventories.

Finally, Panel C shows that also the active component of inventory mean reversion is significantly stronger for RMMs ($\hat{\kappa}^A = -0.32$) than for PTFs ($\hat{\kappa}^A = -0.13$). This suggests that RMMs are substantially more aggressive in offloading any imbalances in their customer order flow. These results may reflect a lower risk appetite or a lower level of capital (risk-bearing capacity). It is difficult to gauge whether this is the result of preferences, or rather due to less sophisticated business models that aim at minimizing the overall exposure to inventory risk.

Taken together, RMMs exhibit a significantly lower exposure to inventory risk than PTFs, consistent with our results on trading revenues in Sections 4 and 5. This stems from the combination of more balanced customer order flow and more active inventory risk management.[24]

[24] In the Online Appendix (Table OA.6), we additionally show that these results are very similar across groups of stocks with different levels of liquidity.

7.2.1 Meme stocks and noise trader risk

The "meme stock" frenzy surrounding Gamestop (GME) suggests that the typically benign nature of retail order flow may change under extraordinary circumstances. In January 2021, buying pressure from retail investors coordinating via the Reddit community "r/WallStreetBets" caused a run-up in GME's stock price, which culminated in a short-squeeze with large losses for several hedge funds.[25] Controversially, Robinhood and several retail brokers suspended new stock purchases purchases in GME and several other meme stocks on January 28. While prices fell sharply in subsequent weeks, a second frenzy in GME took place in late Febuary/early March.

While these events occurred in U.S. stocks, their impact sweeped across the Atlantic. Notably, GME was the most actively traded stock among German retail investors on a total of seven trading days in the period January-March 2021, which means that German RMMs were also subject to heightened investor demand for meme stocks. The coordination of retail investor trading suggests that their order flow was no longer balanced, but rather a source of "noise trader risk" (De Long et al., 1990; Eaton et al., 2022). This forced RMMs to either build up larger inventories or alternatively become more aggressive in laying off positions in PLOMs.

[Insert Figure 9 here.]

Figure 9 provides an illustration of RMMs exposure to inventory risk in GME from November 2020 to June 2021. Consistent with increasingly one-sided demand from retail investors, we find that the passive component of RMMs inventories in GME ceases to be mean-reverting (i.e. $\hat{\kappa}^P$ is no longer negative) during the last week of January and

[25] See, e.g. "Hedge fund Melvin closes bet against GameStop after Reddit trader onslaught", Financial Times, 27 January 2021.

then again during late Febuary/early March (Panel B). However, RMMs do not passively absorb the order imbalance by taking on larger inventories, but instead respond by scaling up their active inventory management (Panel C), giving rise to a more negative $\hat{\kappa}^A$. As a result, the overall mean-reversion speed of RMM inventories in GME actually increased during these trading frenzies, which is reflected in a lower estimate $\hat{\kappa}$ (Panel A). Notice that the overall pattern in Panel B of Figure 8 is also consistent with this "case study", since the estimate κ^P for RMMs is steadily creeping up after 2020Q1.

8 Conclusion

We have analyzed the activity of specialized RMMs in the German equity market. Retail market making is vastly profitable, and exhibits a very favourable risk-return trade-off, especially when benchmarked against other PTFs that act as intermediaries on PLOMs. The intermediation of retail order flow is as a low-risk business because of reduced adverse selection and inventory risk.

We provide a simple back-of-the envelope calculation to assess the economic value of retail order flow. Our estimate is the lump-sum payment that equates the Sharpe ratio of RMMs and PTFs, which can be interpreted as intermediaries' willingness to pay for access to retail orders. Scaled appropriately, the resulting estimates are reasonably close to public disclosures on PFOF in the U.S. equity market.

Our findings can help to inform policy. In particular, our estimate of the "excess profitability" of internalization could be used as a yardstick to evaluate whether the full benefits of order flow segmentation accrue to retail investors in the form of price improvements and reduced commissions.

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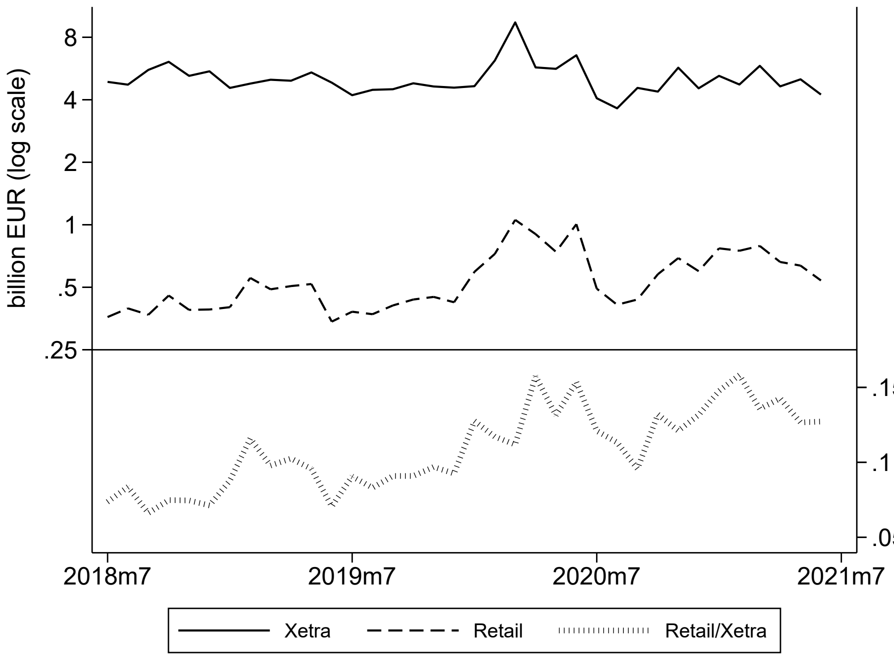
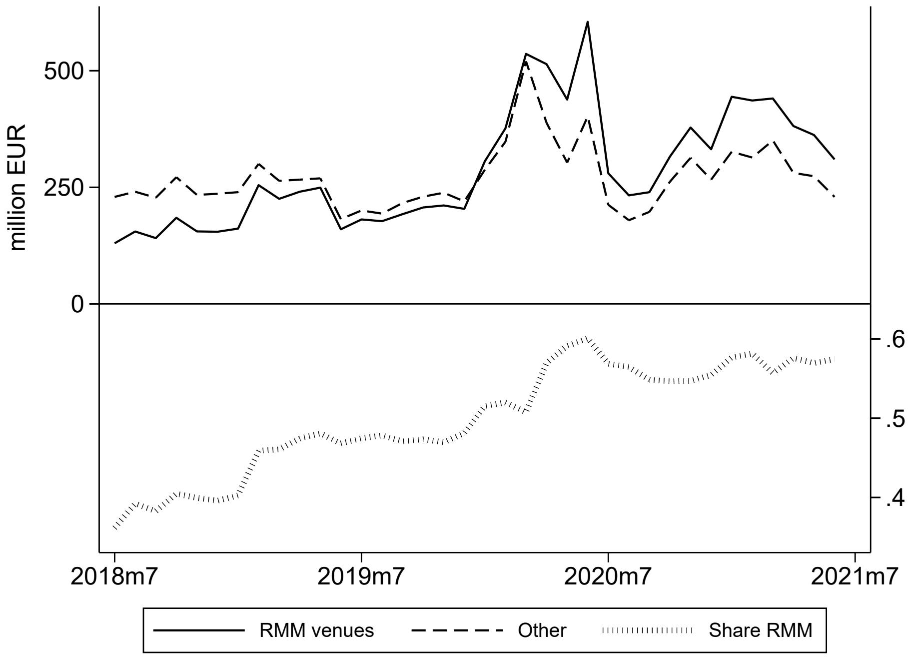
9 Tables and Figures

Figure 1: Growth in retail trading



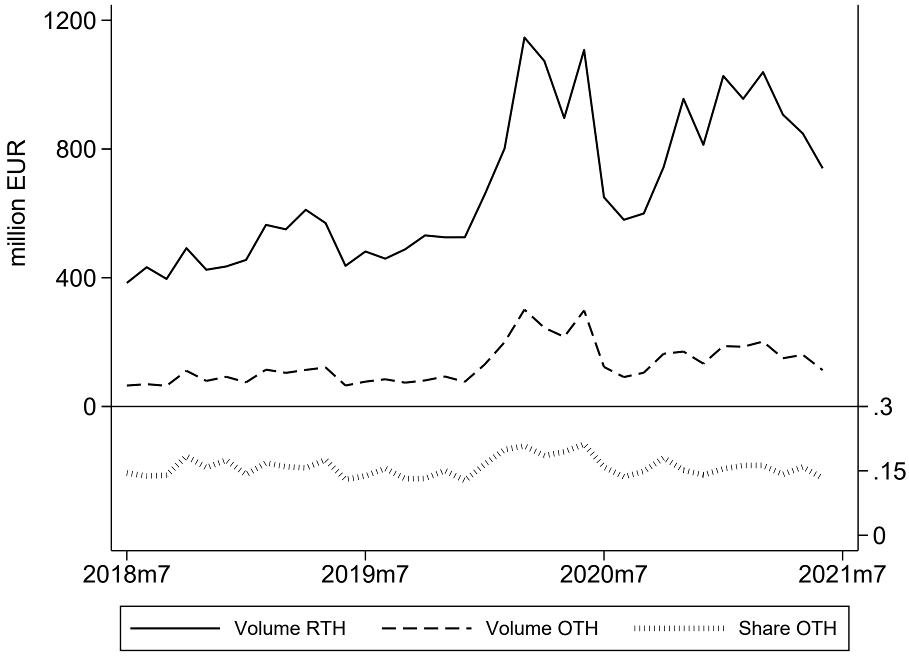
This figure illustrates the growth of retail trading in the German equity market over the sample period (July 2018 - June 2021). The solid line (*Xetra*) plots the evolution of daily average trading volume (in billion EUR, left axis) on the Xetra platform, the main market for trading German equities. The dashed line (*Retail*) represents the daily average trading volume (in billion EUR, left axis) by retail investors across all trading venues other than “XOFF”. The dotted line (right axis) depicts their ratio.

Figure 2: Growth in internalization



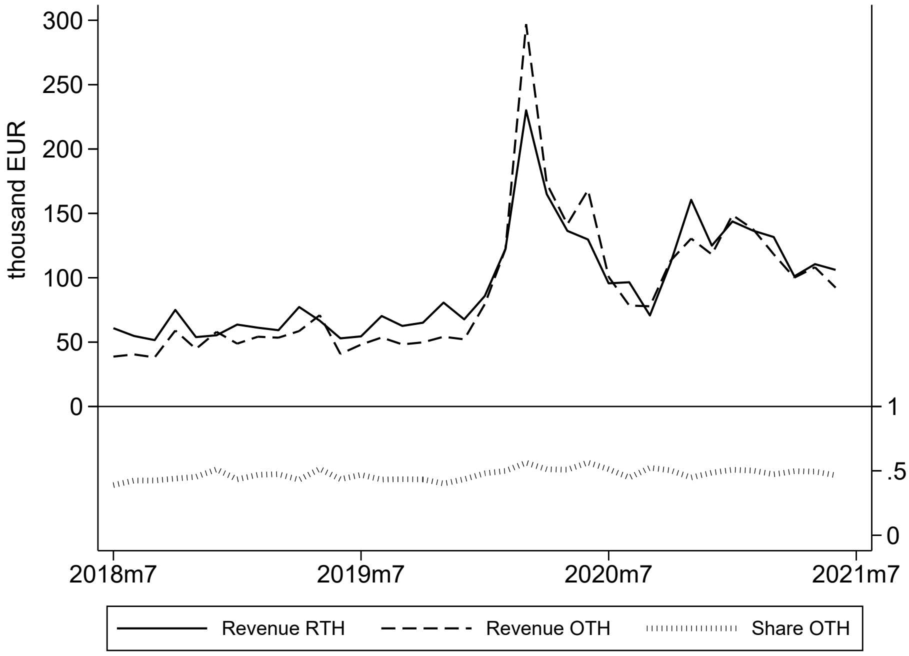
This figure illustrates the growth of retail order flow internalization in the German equity market over the sample period (July 2018 - June 2021). The solid line (*RMM venues*, left axis) represents the sum of retail trading volume (in million EUR, daily average for each month) executed in RMM-affiliated venues. The dashed line (*Other*, left axis) is the contemporaneous retail trading volume executed in other trading venues excluding “XOFF”. The dotted line (right axis) represents the share of RMM-affiliated venues.

Figure 3: RMM trading volume - RTH vs. OTH trading



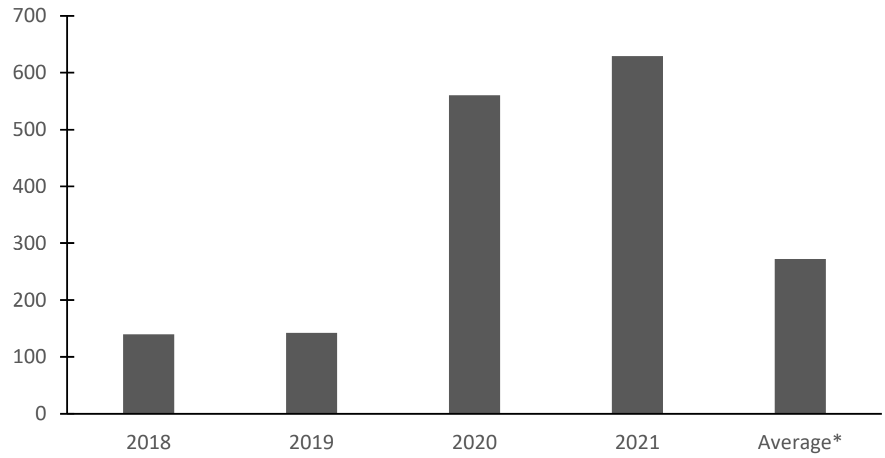
This figure depicts the evolution of RMM trading volume in the German equity market during regular trading hours (*Volume RTH*, solid line, left axis) and outside trading hours (*Volume OTH*, dashed line, left axis) for the sample period July 2018 - June 2020. Both series represent daily averages during the respective months. The dotted line (right axis) represents the relative share of OTH trading volume.

Figure 4: RMM trading revenues - RTH vs. OTH trading



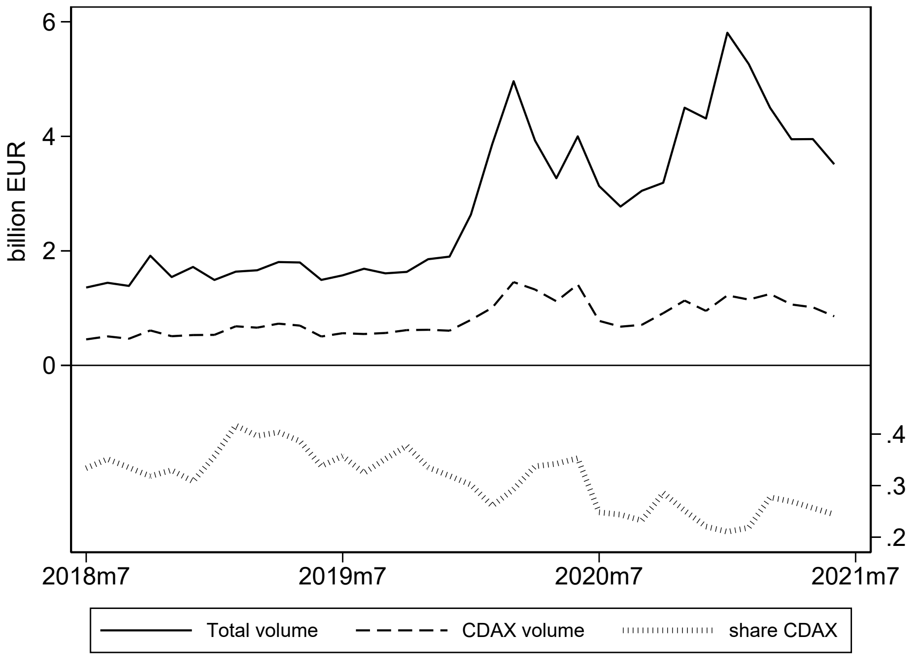
This figure depicts the evolution of aggregate RMM trading revenues in the German equity market during regular trading hours (*Revenue RTH*, solid line) and outside trading hours (*Revenue OTH*, dashed line) for the sample period July 2018 - June 2020. Trading revenues are computed following equation (2). Both series represent daily averages during the respective months and are expressed in thousand EUR (left axis). The dotted line (right axis) represents the relative share of OTH trading revenues.

Figure 5: Aggregate annual RMM revenue



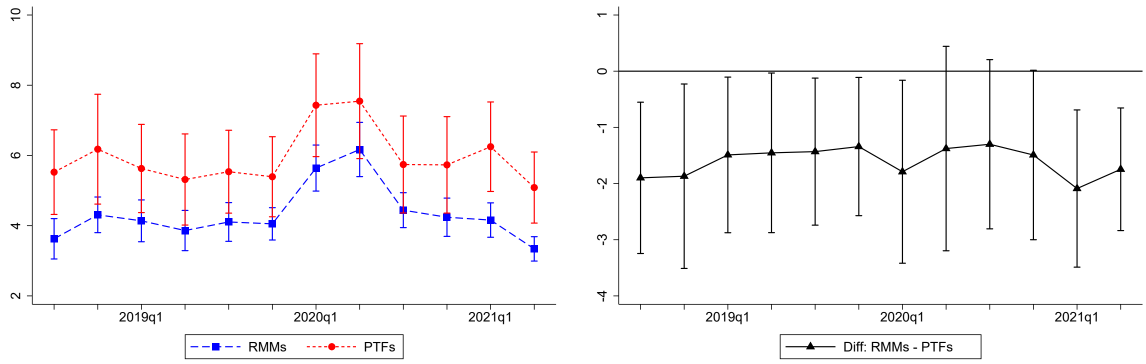
This figure depicts the evolution of annual aggregate trading revenues for the five German RMMs. Numbers are in million EUR. Since our sample period spans from July 2018 to June 2021, the average is computed by weighting the numbers for 2018 and 2021 with a factor of 0.5. Numbers for 2018 and 2019 are based on only four RMMs, but the missing RMM accounts for less than 3% of aggregate trading revenues in 2020 and 2021. See Table OA.1 for the underlying data.

Figure 6: Share of sample stocks in overall RMM activity

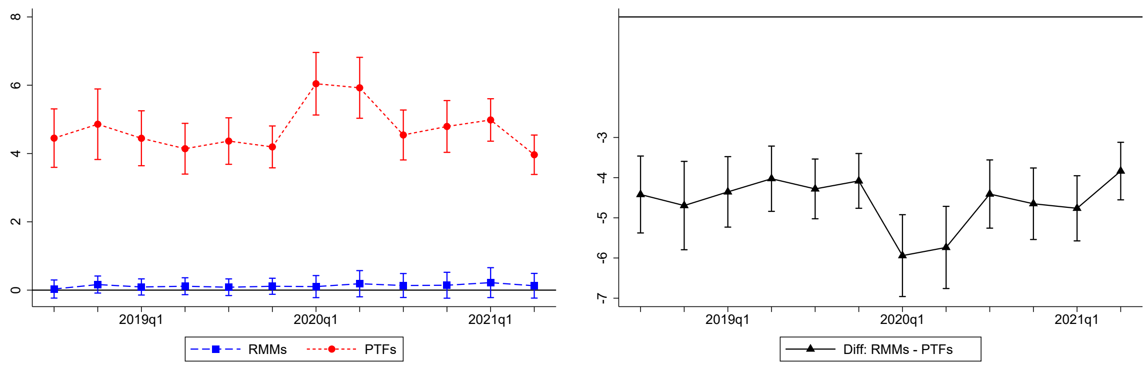


This figure depicts the evolution of RMMs' monthly trading volume across all assets (solid line, left axis) as well as their monthly trading volume in CDAX secruties (dashed line, left axis). The dotted line (right axis) depicts the share of CDAX volume securities relative to the total.

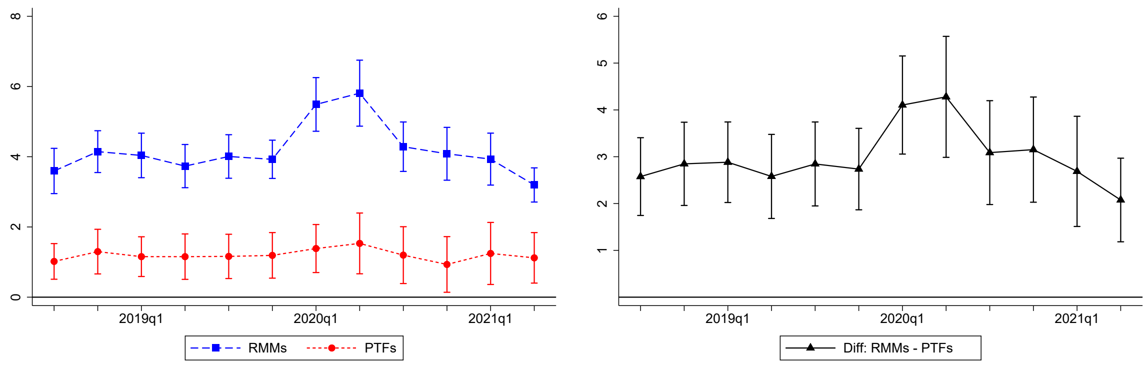
Figure 7: Adverse selection over time



Panel A: Effective spread



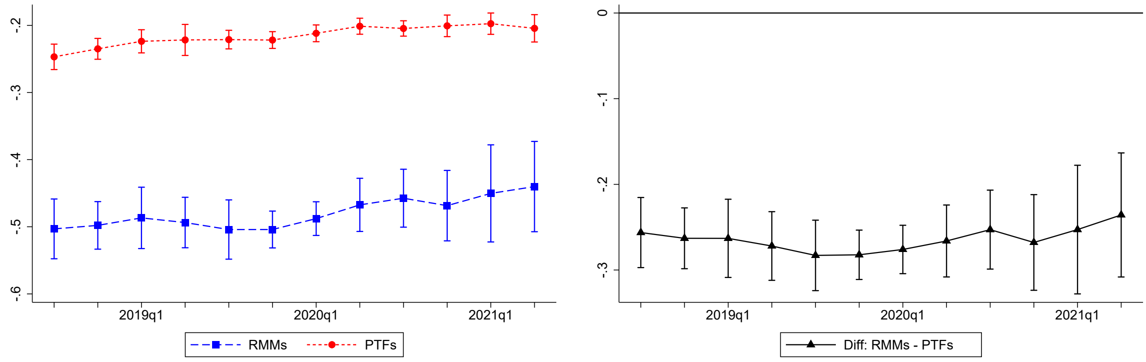
Panel B: Price Impact



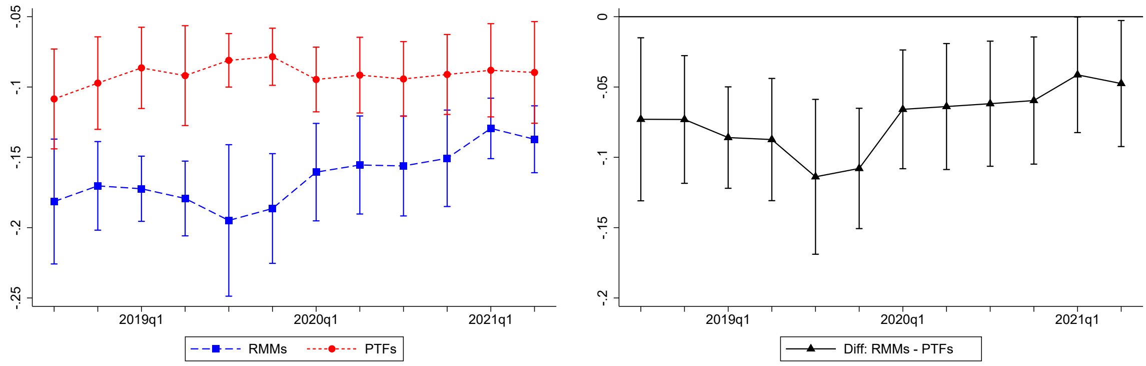
Panel C: Realized Spread

This figure depicts the quarterly evolution of average effective spreads (Panel A), price impacts (Panel B) and realized spreads (Panel C). In each Panel, the left graph presents the averages for RMMs (long-dashed line, squared markers) and PTFs (short-dashed line, round markers), while the right graph shows their difference (solid line, triangular markers). The capped bars indicate 90% confidence bands.

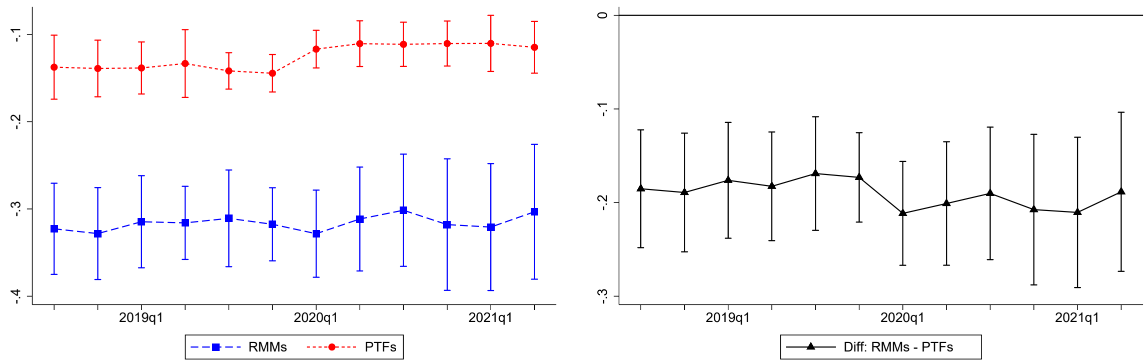
Figure 8: Inventory risk over time



Panel A: Inventory mean reversion speed (κ)



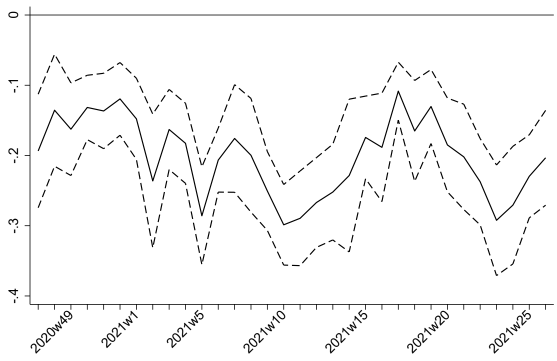
Panel B: Passive component (κ^P)



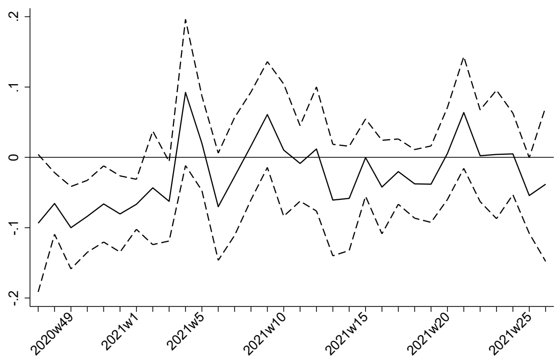
Panel C: Active component (κ^A)

This figure depicts the quarterly evolution of inventory mean reversion speed (κ, Panel A), its passive component (κ^P, Panel B) and its active component (κ^A, Panel C). In each Panel, the left graph presents the averages for RMMs (long-dashed line, squared markers) and PTFs (short-dashed line, round markers), while the right graph shows their difference (solid line, triangular markers). The capped bars indicate 90% confidence bands.

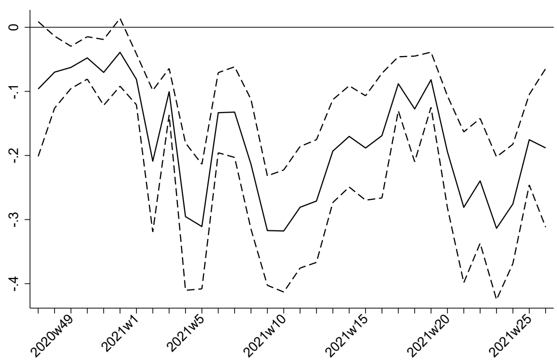
Figure 9: Inventory risk - Gamestop



Panel A: Inventory mean reversion speed (κ)



Panel B: Passive component (κ^P)



Panel C: Active component (κ^A)

This figure depicts the weekly evolution of inventory mean reversion speed (κ, Panel A), its passive component (κ^P, Panel B) and its active component (κ^A, Panel C) for RMM trading in Gamestop (GME) from November 2020 to June 2021. The dashed lines indicate 90% confidence bands.

Table 1: RMM Activity

	N	Mean	St. Dev.	Median
Panel A: Overall activity				
Trading volume	3,780	121.63	105.88	80.10
Trading volume RTH	3,780	95.34	70.44	67.64
Trading volume OTH	3,779	15.94	15.94	9.98
#stocks	3,780	270.65	45.00	269.00
#stocks RTH	3,780	258.33	48.39	254.00
#stocks OTH	3,779	185.62	68.32	175.00
Inventory ratio	3,780	0.59	0.61	0.44
Inventory ratio RTH	3,780	0.91	0.78	0.75
Inventory ratio OTH	3,779	4.24	4.19	3.34
Capital usage	3,780	3.98	13.72	2.31
Panel B: Venue breakdown				
Pct. Own Venues	3,780	54.27	27.30	56.61
Pct. PLOMs	3,780	26.50	15.09	28.18
Pct. XOFF	3,780	14.78	18.51	N/A
Pct. Other	3,780	4.45	2.97	4.20

This table contains summary statistics on RMMs' trading activity at the RMM-day level. Variables ending with RTH/OTH refer to variables computed during regular trading hours/outside trading hours, while the remaining variables refer to daily aggregates. *Trading volume* is the total EUR amount traded (in million EUR) across all securities. *#stocks* denotes the corresponding number of stocks with non-zero trading volume. *Inventory ratio* refers to the absolute value of the end-of-period inventory position (in EUR) divided by per-period total trading volume, expressed in percentage points. *Capital usage* is the daily maximum absolute inventory position in million EUR. *Pct. Own Venues* is the share of trading volume that is executed in affiliated trading venues. *Pct. Exchanges*, *Pct. XOFF* and *Pct. Other* refer to the share of trading volume executed either in PLOMs, off-exchange (labelled as "XOFF"), and all remaining trading venues, respectively. "N/A" indicates that the statistic cannot be disclosed under Bundesbank's confidentiality rules.

Table 2: RMM profitability

	N	Mean	St. Dev.	Median
Panel A: Profitability				
Revenue	3,780	36.71	48.60	17.42
Revenue RTH	3,780	18.84	27.33	9.82
Revenue OTH	3,779	17.87	23.90	N/A
Revenue by Volume	3,780	2.55	2.01	2.47
Revenue by Volume RTH	3,780	1.62	1.89	1.55
Revenue by Volume OTH	3,779	9.99	7.13	9.19
Daily return	3,780	20.11	26.73	10.16
Daily return RTH	3,780	9.81	15.00	4.58
Daily return OTH	3,779	10.30	13.85	5.17
Panel B: Risk vs. return				
Mean revenue	5	36.71	40.80	
Mean revenue RTH	5	18.84	21.89	
Mean revenue OTH	5	17.87	19.05	
St. Dev. revenue	5	27.10	19.28	
St. Dev. revenue RTH	5	16.75	10.19	
St. Dev. revenue OTH	5	13.95	10.38	
Sharpe Ratio	5	17.85	6.71	
Sharpe Ratio RTH	5	14.37	7.28	
Sharpe Ratio OTH	5	17.16	5.63	

Panel A of this table contains summary statistics of RMM profitability measures at the RMM-day level. Variables ending with RTH/OTH refer to variables computed during regular trading hours/outside trading hours, while the remaining variables refer to daily aggregates. *Revenue*, *Revenue OTH* and *Revenue RTH* are daily gross trading revenues as defined in equation (2), and expressed in thousands of EUR. *Revenue by Volume* scales revenues by trading volume, as is expressed in basis points (cents per 100 EUR traded). *Daily return* is computed as revenues divided by estimated capital, which is defined as an RMM's maximum portfolio level position over the entire sample period, following Baron et al. (2019). Panel B reports measures for assessing the RMMs' risk-return tradeoff, computed at the

RMM level (N=5). *Mean revenue* and *St. Dev. Revenue* denote the time-series mean and standard deviation of RMMs' *Revenue* as computed in Panel A, expressed in million EUR. The Sharpe is given by an RMM's mean revenue divided by its standard deviation, and annualized by multiplication with $\sqrt{252}$. "N/A" indicates that the statistic cannot be disclosed under Bundesbank's confidentiality rules.

Table 3: RMM activity and profitability at the RMM-stock-day level

	N	Mean	St. Dev.	P25	P50	P75
Panel A: Overall activity						
Trading volume	1,023,063	449.40	1,569.91	7.85	39.76	219.11
Trading volume RTH	976,486	369.05	934.10	7.50	37.56	203.71
Trading volume OTH	701,476	85.87	215.21	2.83	11.41	50.75
Inventory ratio	1,023,063	29.80	37.06	1.66	10.00	49.42
Inventory ratio RTH	976,486	31.98	37.97	2.09	11.72	57.79
Inventory ratio OTH	701,476	52.17	40.26	11.30	45.49	100.00
Capital usage	1,023,063	50.31	94.24	4.29	14.18	46.74
Panel B: Profitability						
Revenue	1,022,217	135.74	693.94	-24.00	8.30	129.52
Revenue RTH	976,486	72.93	600.35	-36.10	2.85	95.65
Revenue OTH	698,976	96.63	344.95	-2.00	11.78	83.60
Revenue by Volume	1,022,217	25.51	1,044.47	-5.79	2.14	23.78
Revenue by Volume RTH	976,486	20.83	1,106.47	-8.23	0.91	20.38
Revenue by Volume OTH	698,976	40.94	559.33	-2.27	11.80	52.44

This table contains summary statistics on RMMs' trading activity and profitability at the RMM-stock-day level. All variables are defined as in Table 1 and Table 2. *Trading volume* and *Capital usage* are expressed in thousands of EUR. *Revenue* is expressed in EUR.

Table 4: PTF Activity

	N	Mean	St. Dev.	Median
Panel A: Overall activity				
Trading volume	13,996	156.25	274.87	17.97
#stocks	13,996	100.90	73.86	82.00
Inventory ratio	13,996	9.56	17.88	2.34
Capital usage	13,996	8.40	21.78	1.44
Panel B: Venue breakdown				
Pct. PLOMs	13,996	85.09	26.36	97.95
Pct. XOFF	13,996	6.34	14.82	0.00
Pct. Other	13,996	8.56	21.21	0.00

This table contains summary statistics at the PTF-day level. *Trading volume* is the total EUR amount traded (in million EUR) across all securities. *#stocks* denotes the corresponding number of stocks with non-zero trading volume. *Inventory ratio* refers to the absolute value of the end-of-period inventory position (in EUR) divided by per-period total trading volume, expressed in percentage points. *Capital usage* is the daily maximum absolute inventory position in million EUR. *Pct. PLOMs* is the share of trading volume that is executed in PLOMs, while *Pct. XOFF* and *Pct. Other* refer to the share of trading volume labelled as "XOFF" or all other remaining trading venues, respectively.

Table 5: PTF profitability

	N	Mean	St. Dev.	Median
Panel A: Profitability				
Revenue	13,996	17.79	50.92	3.69
Revenue by Volume	13,996	3.82	22.38	1.39
Daily return	13,996	6.03	13.09	1.33
Panel B: Risk vs. return				
Mean revenue	21	17.19	31.49	
St. Dev. revenue	21	30.63	26.74	
Sharpe Ratio	21	7.42	7.72	

Panel A of this table contains summary statistics of PTF profitability measures at the PTF-day level. remaining variables refer to daily aggregates. *Revenue* denotes daily gross trading revenues as defined in equation (2), and expressed in thousands of EUR. *Revenue by Volume* scales revenues by trading volume, as is expressed in basis points (cents per 100 EUR traded). *Daily return* is computed as revenues divided by estimated capital, which is defined as a PTF's maximum portfolio level position over the entire sample period, following Baron et al. (2019). Panel B reports measures for assessing the PTFs' risk-return tradeoff, computed at the PTF level (N=21). *Mean revenue* and *St. Dev.Revenue* denote the time-series mean and standard deviation of PTFs' *Revenue* as computed in Panel A, expressed in million EUR. The *Sharpe Ratio* is given by a PTF's mean revenue divided by its standard deviation, and annualized by multiplication with $\sqrt{252}$.

Table 6: PTF activity and profitability at the PTF-stock-day level

	N	Mean	St. Dev.	P25	P50	P75
Panel A: Overall activity						
Trading volume	1,412,249	1,548.47	4,549.13	13.89	85.68	705.82
Inventory ratio	1,412,249	32.01	38.52	0.99	11.27	59.99
Capital usage	1,412,249	179.73	462.73	6.86	28.76	123.56
Panel B: Profitability						
Revenue	1,412,249	176.32	2,379.54	-67.50	8.80	197.75
Revenue by Volume	1,412,249	8.19	103.09	-8.28	1.94	19.75

This table contains summary statistics on RMMs' trading activity and profitability at the RMM-stock-day level. All variables are defined as in Table 4 and Table 5. *Trading volume* and *Capital usage* are expressed in thousands of EUR. *Revenue* is expressed in EUR.

Table 7: Effective spreads and decomposition

	(1)	(2)	(3)	(4)
Panel A: Effective spread				
RMM	4.58***	4.36***	4.40***	4.44***
	(11.60)	(14.28)	(13.97)	(13.85)
PTF	5.87***	5.99***	5.97***	5.94***
	(7.37)	(7.86)	(7.91)	(8.32)
$RMM - PTF$	-1.30	-1.63*	-1.57*	-1.50*
	(-1.59)	(-1.94)	(-1.88)	(-1.89)
Panel B: Price impact				
RMM	0.25*	0.13	0.15	0.19
	(2.03)	(0.74)	(0.85)	(1.10)
PTF	4.70***	4.76***	4.75***	4.73***
	(10.54)	(11.34)	(11.49)	(12.19)
$RMM - PTF$	-4.45***	-4.63***	-4.60***	-4.54***
	(-9.71)	(-9.63)	(-9.72)	(-10.20)
Panel C: Realized spread				
RMM	4.30***	4.20***	4.22***	4.23***
	(10.05)	(11.17)	(11.09)	(11.04)
PTF	1.15***	1.20***	1.19***	1.19***
	(2.74)	(2.94)	(2.93)	(3.03)
$RMM - PTF$	3.15***	3.00***	3.03***	3.04***
	(5.48)	(5.25)	(5.28)	(5.41)
Fixed effects	day	stock	stock & day	stock-day
Clustering	MM & stock	MM & stock	MM & stock	MM & stock

This table presents coefficient estimates from the regression equation

$$y_{i,t,m} = \alpha RMM_m + \beta PTF_m + \epsilon_{i,t,m},$$

where $y_{i,t,m}$ denotes a measure of market quality for stock i on day t and market maker m, and RMM_m (PTF_m) is a dummy variable equal to one whenever m is a RMM (PTF). The row $RMM - PTF$

presents the results from a hypothesis test of $\alpha - \beta = 0$. In Panel A, the dependent variable is the effective spread, whereas it is the 10-second price impact in Panel B, and the realized spread in Panel C. These variables are defined in equations (6)-(8) in the main text. All variables are computed as equal-weighted averages across all relevant trades on the same day and stock by the same market maker. For RMMs, we consider all passive executions on own trading venues, and for PTFs we base calculations on all passive execution across all venues. The different columns correspond to different fixed effects specifications with increasing stringency: from day and stock fixed effects in columns (1) and (2), to stock and day fixed effects in column (3) and stock-day fixed effects in column (4). T-statistics based on standard errors double-clustered at the market maker and stock level are given in parentheses. One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively.

Table 8: Inventory risk

	(1)	(2)	(3)	(4)
Panel A: Mean reversion coefficient (κ)				
RMM	-0.48***	-0.47***	-0.47***	-0.48***
	(-21.59)	(-22.04)	(-21.89)	(-20.51)
PTF	-0.21***	-0.21***	-0.21***	-0.21***
	(-28.68)	(-29.59)	(-29.75)	(-26.47)
$RMM - PTF$	-0.26***	-0.26***	-0.26***	-0.26***
	(-11.04)	(-11.53)	(-11.16)	(-10.22)
Panel B: passive component (κ^P)				
RMM	-0.16***	-0.16***	-0.16***	-0.16***
	(-9.86)	(-9.60)	(-9.54)	(-9.83)
PTF	-0.09***	-0.09***	-0.09***	-0.09***
	(-6.04)	(-6.21)	(-6.04)	(-6.29)
$RMM - PTF$	-0.07***	-0.07***	-0.07***	-0.07***
	(-3.15)	(-3.21)	(-3.06)	(-3.18)
Panel C: active component (κ^A)				
RMM	-0.31***	-0.31***	-0.31***	-0.32***
	(-9.51)	(-9.70)	(-9.60)	(-9.28)
PTF	-0.12***	-0.12***	-0.12***	-0.12***
	(-7.74)	(-8.05)	(-7.82)	(-7.99)
$RMM - PTF$	-0.19***	-0.19***	-0.19***	-0.19***
	(-5.15)	(-5.39)	(-5.19)	(-5.11)
Fixed effects	day	stock	stock & day	stock-day
Clustering	MM & stock	MM & stock	MM & stock	MM & stock

This table presents coefficient estimates from the regression equation

$$y_{i,t,m} = \alpha RMM_m + \beta PTF_m + \epsilon_{i,t,m},$$

where $y_{i,t,m}$ denotes a measure of inventory mean reversion for stock i on day t and market maker m, and RMM_m (PTF_m) is a dummy variable equal to one whenever m is a RMM (PTF). The row

$RMM - PTF$ presents the results from a hypothesis test of $\alpha - \beta = 0$. In Panel A, the dependent variable is the mean-reversion coefficient κ, whereas it is the passive component κ^P in Panel B, and the active component κ^A in Panel C. The variables are the resulting estimates from regressions (9)-(11) in the main text. All variables are estimated from daily regressions at the 15-minute frequency. For RMMs, κ^P is based on all passive executions on own trading venues, while it is based on all passive execution across all trading venues for PTFs. The different columns correspond to different fixed effects specifications with increasing stringency: from day and stock fixed effects in columns (1) and (2), to stock and day fixed effects in column (3) and stock-day fixed effects in column (4). T-statistics based on standard errors double-clustered at the market maker and stock level are given in parentheses. One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively.

Online Appendix

to

“What is the value of retail order flow?”

For online publication only.

Table OA.1: RMMs trading revenues of based on annual reports

Year	Baader Bank	Euwax	ICF Bank	Lang & Schwarz	Tradegate
2018	40.976	13.552	N/A	21.683	63.898
2019	46.149	14.155	N/A	18.720	63.359
2020	168.215	41.161	9.721	80.912	260.577
2021	185.030	65.873	18.870	115.056	244.222

This table collects the reported trading revenues ("Handelsergebniss") from the annual reports of five German RMMs. Numbers are in million EUR. No data is available for ICF Bank for the years 2018 and 2019. The reports are available on the following websites.

Baader Bank: `https://www.baaderbank.de/Investor-Relations/News-and-financial-reports/Financial-report`

Euwax: `https://www.euwax-ag.de/de/investor-relations` (German only)

ICF Bank: `https://icfbank.de/fileadmin/icf-bank/News_HV_Aktienvermittlung/Geschaeftsbericht_ICF_BANK_AG_2020-2021_ENGLISCH.pdf`

Lang & Schwarz: `https://www.ls-d.de/investor-relations/finanzberichte/geschaeftsberichte/530-geschaeftsbericht-2023`

Tradegate: `https://www.tradegate.ag/en/financial-reports.html`

Table OA.2: Aggregate Trading activity in German and US stocks.

	2019	2020	2021	Average
Deutsche Boerse AG	1.34	1.81	1.69	1.61
Total US	38.36	70.05	77.93	62.11
Cboe Global Markets	13.15	18.94	21.01	17.70
Nasdaq	15.91	24.92	27.83	22.89
NYSE	9.31	26.18	29.10	21.53
EUR/USD rate	1.119	1.142	1.183	1.148

This table collects information on the aggregate trading activity in German and US stocks. The data is obtained from the World Federation of Exchanges's (WFE's) Annual Statistics Guides (see e.g. https://www.world-exchanges.org/our-work/articles/2021-annual-statistics-guide. The datapoints refer to "Value of share trading. Electronic order book" and are expressed in trillions of local currencies. The EUR/USD exchange rate is from the ECB's statistical data warehouse (Series EXR.D.USD.EUR.SP00) at http://data.ecb.europa.eu/, where annual values are computed as equal-weighted averages across all observations.

Table OA.3: Sharpe ratios - robustness

	N	$p = 0.001$	$p = 0.005$	$p = 0.01$	$p = 0.015$	$p = 0.02$
Panel A: RMMs						
Mean revenue	5	39.68	37.93	36.71	35.81	35.10
Mean revenue RTH	5	22.08	20.26	18.84	17.88	16.97
Mean revenue OTH	5	20.85	19.10	17.87	16.98	16.26
St. Dev. revenue	5	34.23	29.46	27.10	25.68	24.68
St. Dev. revenue RTH	5	27.97	20.40	16.75	14.60	13.00
St. Dev. revenue OTH	5	22.52	16.76	13.95	12.25	11.05
Sharpe ratio	5	15.46	17.03	17.85	18.36	18.71
Sharpe ratio RTH	5	9.45	12.41	14.37	15.90	17.14
Sharpe ratio OTH	5	12.44	15.29	17.16	18.57	19.74
Panel B: PTFs						
Mean revenue	21	18.18	17.54	17.19	16.62	16.08
St. Dev. revenue	21	60.29	39.80	30.63	25.39	21.90
Sharpe ratio	21	5.28	6.41	7.42	8.25	9.01
Panel C: Willingness-to-pay						
ϕ		29.36	24.95	21.50	19.01	16.97

This Table produces the measures of RMM and PTF profitability from Table 2 and Table 5 for different levels of winsorization $p \in \{0.001, 0.005, 0.01, 0.015, 0.02\}$. The table also contains the resulting estimates for ϕ following the discussion in Section 6.

Table OA.4: Value-weighted effective spreads and decomposition - RMMs vs. PTFs

	(1)	(2)	(3)	(4)
Panel A: Effective spread				
RMM	5.37***	5.13***	5.18***	5.24***
	(10.95)	(12.92)	(12.63)	(12.54)
PTF	6.43***	6.55***	6.53***	6.50***
	(7.73)	(8.29)	(8.36)	(8.86)
$RMM - PTF$	-1.06	-1.42	-1.35	-1.26
	(-1.20)	(-1.57)	(-1.50)	(-1.48)
Panel B: Price impact				
RMM	0.32*	0.18	0.21	0.25
	(1.95)	(0.87)	(0.98)	(1.20)
PTF	5.41***	5.22***	5.21***	5.18***
	(11.24)	(12.36)	(12.55)	(13.44)
$RMM - PTF$	-4.82***	-5.03***	-5.00***	-4.93***
	(-10.04)	(-10.03)	(-10.12)	(-10.66)
Panel C: Realized spread				
RMM	5.02***	4.92***	4.94***	4.95***
	(9.36)	(10.10)	(10.01)	(99.99)
PTF	1.24***	1.29***	1.28***	1.27***
	(2.84)	(3.04)	(3.02)	(3.14)
$RMM - PTF$	3.77***	3.62***	3.65***	3.68***
	(5.67)	(5.48)	(5.50)	(5.64)
Fixed effects	day	stock	stock & day	stock-day
Clustering	MM & stock	MM & stock	MM & stock	MM & stock

This table presents coefficient estimates from the regression equation

$$y_{i,t,m} = \alpha RMM_m + \beta PTF_m + \epsilon_{i,t,m},$$

where $y_{i,t,m}$ denotes a measure of market quality for stock i on day t and market maker m, and RMM_m (PTF_m) is a dummy variable equal to one whenever m is a RMM (PTF). The row $RMM - PTF$ presents the results from a hypothesis test of $\alpha - \beta = 0$. In Panel A, the dependent variable is the effective spread, whereas it is the 10-second price impact in Panel B, and the realized spread in Panel C. The variable definitions are given in equations in the main text. All variables are computed as value-weighted averages (based on EUR amounts) across all relevant trades on the same day and stock by the same market maker. For RMMs, we consider all passive executions on own trading venues, and for PTFs we base calculations on all passive execution across all venues. The different columns correspond to different fixed effects specifications with increasing stringency: from day and stock fixed effects in columns (1) and (2), to stock and day fixed effects in column (3) and stock-day fixed effects in column (4). T-statistics based on standard errors double-clustered at the market maker and stock level are given in parentheses. One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively.

Table OA.5: Effective spreads and decomposition - sample split

	(1) DAX	(2) MDAX
Panel A: Effective spread		
RMM	2.73***	5.75***
	(13.33)	(14.20)
PTF	3.92***	7.46***
	(8.52)	(8.09)
$RMM - PTF$	-1.19**	-1.71*
	(-2.37)	(-1.70)
Panel B: Price impact		
RMM	0.19*	0.31*
	(1.82)	(1.70)
PTF	3.08***	6.01***
	(11.98)	(11.96)
$RMM - PTF$	-2.88***	-5.70***
	(-10.05)	(-10.47)
Panel C: Realized spread		
RMM	2.47***	5.44***
	(10.17)	(12.43)
PTF	0.81***	1.44***
	(2.98)	(2.87)
$RMM - PTF$	1.66***	4.00***
	(4.49)	(5.96)
Fixed effects	stock-day	stock-day
Clustering	MM & stock	MM & stock

This table presents coefficient estimates from the regression equation

$$y_{i,t,m} = \alpha RMM_m + \beta PTF_m + \epsilon_{i,t,m},$$

where $y_{i,t,m}$ denotes a measure of market quality for stock i on day t and market maker m, and RMM_m

(PTF_m) is a dummy variable equal to one whenever m is a RMM (PTF). The row $RMM - PTF$ presents the results from a hypothesis test of $\alpha - \beta = 0$. In Panel A, the dependent variable is the effective spread, whereas it is the 10-second price impact in Panel B, and the realized spread in Panel C. The variable definitions are given in equations in the main text. All variables are computed as equal-weighted averages across all relevant trades on the same day and stock by the same market maker. For RMMs, we consider all passive executions on own trading venues, and for PTFs we base calculations on all passive execution across all venues. The first column corresponds to components of the DAX index, while the second column corresponds to components of the MDAX index. We use stock-day fixed effects, and t-statistics are based on standard errors double-clustered at the market maker and stock level. One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively.

Table OA.6: Inventory risk - sample split

	(1) DAX	(2) MDAX
Panel A: Mean reversion coefficient (κ)		
RMM	-0.49***	-0.46***
	(-19.06)	(-19.15)
PTF	-0.20***	-0.23***
	(-20.22)	(-20.58)
$RMM - PTF$	-0.28***	-0.23***
	(-10.12)	(-8.37)
Panel B: passive component (κ^P)		
RMM	-0.15***	-0.17***
	(-8.54)	(-8.15)
PTF	-0.08***	-0.11***
	(-7.57)	(-4.83)
$RMM - PTF$	-0.07***	-0.06**
	(-3.51)	(-2.01)
Panel C: active component (κ^A)		
RMM	-0.33***	-0.29***
	(-8.15)	(-11.58)
PTF	-0.12***	-0.12***
	(-7.91)	(-7.91)
$RMM - PTF$	-0.21***	-0.17***
	(-4.75)	(-5.68)
Fixed effects	stock-day	stock-day
Clustering	MM & stock	MM & stock

This table presents coefficient estimates from the regression equation

$$y_{i,t,m} = \alpha RMM_m + \beta PTF_m + \epsilon_{i,t,m},$$

where $y_{i,t,m}$ denotes a measure of inventory mean reversion for stock i on day t and market maker

m, and RMM_m (PTF_m) is a dummy variable equal to one whenever m is a RMM (PTF). The row $RMM - PTF$ presents the results from a hypothesis test of $\alpha - \beta = 0$. In Panel A, the dependent variable is the mean-reversion coefficient κ, whereas it is the passive component κ^P in Panel B, and the active component κ^A in Panel C. The variables are the resulting estimates from regressions (9)-(11) in the main text. All variables are estimated from daily regressions at the 15-minute frequency. For RMMs, κ^P is based on all passive executions on own trading venues, while it is based on all passive execution across all trading venues for PTFs. The first column corresponds to components of the DAX index, while the second column corresponds to components of the MDAX index. We use stock-day fixed effects, and t-statistics are based on standard errors double-clustered at the market maker and stock level. One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively.