

Market Making without Adverse Selection: Evidence from Retail Savings Plans

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Abstract

We study how market makers price predictable, uninformed order flow, which allows the isolation of inventory costs from adverse selection. Retail savings plans (SPs) provide a unique laboratory for this analysis, as their pre-determined nature eliminates adverse selection risk. Using proprietary data from LS Exchange, a major European retail venue with a single market maker, we develop a novel methodology to identify SP trades and benchmark their execution prices against the reference market Xetra. While overall execution quality is high, we find that the market maker extracts small, systematic rents. For ETFs, the dominant SP asset class, execution is paradoxically worse than for similar in size non-SP trades, with the market maker charging a size-independent premium of approximately one basis point. Contrary to theory, this premium cannot be meaningfully explained by inventory risk. Our results show that even in the absence of adverse selection, market makers price predictable order flow distinctly worse than discretionary trades, challenging classic models of spread components and further motivating regulatory discussions regarding payment for order flow.

Keywords: Automated Investments, Predictable Order Flow, ETFs, Retail Trading, Execution Quality

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1. Introduction

Demographic change and the associated decline in state pension entitlements have increased the importance of alternative pillars of retirement provision such as occupational pensions and personal savings schemes (Büßemeyer et al., 2021). Among these, private savings plans (SPs) that automatically and periodically invest in exchange-traded funds (ETFs), equities, or mutual funds have emerged as a cost-effective and scalable vehicle for long-term wealth accumulation. The market has expanded rapidly in recent years, with Germany representing the core market for SPs in Europe. In Germany alone, the number of ETF SPs increased from 2.5 million in 2020 to 9.5 million in 2024, an annual growth rate of nearly 40 %. Other central European markets are growing even faster, albeit coming from a lower level with currently 1.3 million ETF SPs.¹ This strong growth underscores the increasing relevance of SPs for retail investors’ portfolio building and financial security.

Compared to the well-studied 401(k) retirement plans in the United States (e.g., Agnew et al., 2003; Benartzi and Thaler, 2007; Choi et al., 2002; Madrian and Shea, 2001), academic research on European SPs remains limited. Existing studies focus primarily on participation decisions, product choices, or the interaction between SPs and robo-advisors (Bräuer, 2021; Harms, 2021), whereas the execution quality of SP orders has received virtually no attention. This gap is important because execution quality directly affects the realized returns of retail investors and, ultimately, the performance of long-term savings. SP trades also exhibit distinctive market microstructure characteristics: they are highly predictable in timing and direction, occur in large bundled volumes (as brokers aggregate the individual SP orders of their customers) and represent entirely uninformed order flow, as the underlying investment decisions were made in advance by retail investors. According to market microstructure theory (Glosten and Milgrom, 1985; Kyle, 1985), such trades should entail no adverse selection risk for market makers and therefore be executed at prices close to the fundamental value. Systematic deviations from this benchmark would raise questions about the fairness and efficiency of SP trade practices.

Beyond this practical relevance, SP trades offer a unique opportunity from an academic perspective to study how market makers price liquidity when facing fully uninformed, predictable, and non-strategic order flow. While theoretical models predict that such trades should receive favorable execution terms, actual outcomes depend on the competitive structure of retail trading venues, especially under payment for order flow (PFOF) arrangements. Under these arrangements, brokers route client orders to specific market makers in exchange for rebates, potentially creating conflicts of interest if execution quality suffers as a result. Evidence from the U.S. market is mixed: Battalio and Loughran (2008), Adams et al. (2021), and Ernst and Spatt (2022) show that PFOF can lead to inferior execution quality, whereas Jain et al. (2024) find instances of price improvement due to cost competition. In the Euro-

¹See the report “The ETF Savings Plan Market in Continental Europe 2024” by extraETF Research, available at: https://cdn.extraetf.com/downloads/research/2024/study/European_Saving_Plan_Study_EN_XETF-19112024.pdf.

pean context, [Hoffmann and Jank \(2024\)](#) document exceptionally high returns for retail market makers operating on affiliated trading venues, which they attribute to the lower adverse selection and inventory risk associated with retail order flow. European regulators similarly highlight concerns about the fairness of such execution arrangements², prompting the European Union to ban PFOF from July 2026 onward ([European Parliament and Council, 2024](#)). Nevertheless, [Meyer et al. \(2025\)](#) show that fewer than 1% of all orders routed from a large German zero-commission broker to a specialized retail trading venue were executed at prices worse than those available on the reference market, suggesting that poor execution is not pervasive.

Our paper also contributes to the growing literature on retail trading in general. The increasing participation of retail investors, amplified by the COVID-19 trading boom and the spread of zero-commission brokerage models, has renewed academic and regulatory interest in the microstructure of retail trading. Recent studies examine the execution quality of retail orders under PFOF arrangements (e.g., [Adams et al., 2021](#); [Schwarz et al., 2023](#); [Dyhrberg et al., 2025](#)) and highlight substantial variation in trading costs and price improvements. Theoretical contributions further explain how internalization of retail flow can generate rents and reduce inventory risk for market makers ([Parlour and Rajan, 2003](#); [Barardehi et al., 2021](#); [Baldauf et al., 2024](#)). We extend this literature by focusing on a novel and economically important form of retail trading, i.e., automated SPs, which represent predictable, uninformed, and large retail flow whose execution quality has not been studied to date.

This paper contributes to these discussions by providing the first comprehensive empirical analysis of SP trade execution quality on a major European retail trading venue. Specifically, we study bundled SP orders routed from Germany’s largest zero-commission broker, Trade Republic, to LS Exchange, which is a specialized trading venue dedicated to retail order flow. On LS Exchange, a single market maker (Lang & Schwarz TradeCenter AG) executes all incoming orders. Leveraging detailed public trade data, we identify SP trades based on their distinctive timing and volume patterns and compare their execution prices to multiple benchmarks, including contemporaneous best ask quotes from the German reference market Xetra and the volume-weighted average prices (VWAPs) of non-SP trades on LS Exchange. This approach allows us to isolate whether observed price differences can be explained by legitimate inventory cost considerations or whether they indicate systematic markups on uninformed retail flow.

Our results show that SP trades, despite their large size, are typically executed at prices corresponding to the best ask on the reference market Xetra, implying generally high execution quality from the perspective of individual savers. However, price differences exhibit considerable cross-sectional variation, particularly for ETFs, where most SP activity is concentrated. These deviations cannot be explained by inventory costs or other trade size effects for ETF SPs and only partially explain

²See, e.g., [German Federal Financial Supervisory Authority \(BaFin\) \(2022\)](#), [Dutch Authority for the Financial Markets \(AFM\) \(2022\)](#), and [Spanish National Securities Market Commission \(CNMV\) \(2022\)](#).

them for stock SPs. Moreover, we find that SP trades are executed systematically worse than similarly large non-SP trades, though the average difference with around one basis point (bps) is economically small. Importantly, SP trades do not receive systematic price improvements, even though they impose no adverse selection risk on the market maker. Taken together, our findings suggest that while SP investors receive fair execution on average, the market maker appears to extract additional rents from the predictable, uninformed SP order flow.

This study makes three main contributions. First, it fills a significant gap in the literature by identifying SP trades in public data and providing the first empirical assessment of SP trade execution quality in European markets. Second, it contributes to the broader literature on retail trading and market microstructure by offering evidence on how market makers price predictable, uninformed order flow. Third, it informs the ongoing policy debate on PFOF and best execution obligations by providing data-driven insights into how such arrangements affect retail investors' effective execution outcomes.

The remainder of this paper is structured as follows. Section 2 introduces the institutional background and data. Section 3 describes the identification of SP trades in public post-trade data. Section 4 presents our main analysis of execution quality and determinants of price differences. Section 5 concludes.

2. Institutional Background and Data

2.1. Institutional Background

The past decade has witnessed a substantial surge in retail trading across Europe, driven by technological innovation, regulatory changes, and the emergence of neobrokers offering low-cost market access. Mobile-first platforms like Trade Republic in Germany have significantly lowered entry barriers, contributing to rapid growth in retail market participation by providing convenient access to a broad range of equities and ETFs.

The business model of many European neobrokers relies on PFOF arrangements and partnerships with specialized market makers. Consequently, the retail trading landscape in Germany is notably fragmented, with order execution often concentrated at a few retail-oriented venues rather than on primary exchanges.

A central venue in this ecosystem is the Lang & Schwarz Exchange (LS Exchange), which operates as the exclusive trading venue for Trade Republic, Germany's largest neobroker.³ LS Exchange is a quote-driven market organized around a single market maker, Lang & Schwarz TradeCenter AG, which is responsible for providing continuous bid and ask quotes. All incoming retail orders from partner brokers are executed directly against these quotes, with no interaction between individual orders. This

³By September 2025, Trade Republic reported serving over 10 million customers with more than €150 billion in assets under management. The press release is available at https://assets.traderepublic.com/assets/files/250915_TradeRepublic_PressRelease_Private_Markets_INT_EN.pdf.

structure contrasts with the order-driven model of primary exchanges like Xetra, operated by Deutsche Börse AG, which features a central limit order book where orders from all participant types interact anonymously.

To ensure quote quality, the rules of LS Exchange stipulate that its market maker’s quotes must closely track prices on a designated reference market, which for the securities in our study is Xetra. Nonetheless, the execution mechanism creates a segmented market: LS Exchange functions exclusively as a retail execution venue, while Xetra remains open to institutional, professional, and retail participants.

A key product within this neobroker ecosystem is the automated SP, which allows investors to regularly invest fixed amounts into selected securities. Trade Republic first introduced ETF SPs in 2019 and subsequently expanded its product universe with equity SPs available since September 2020. The platform expanded its ETF offering in February 2021 to include issuers such as Xtrackers, Amundi, and Lyxor⁴, and further broadened its product range in October 2022 by adding Vanguard, Invesco, and other established ETF providers⁵. For these SPs, Trade Republic bundles customer orders for execution on four predetermined dates (SP days) each month: the 2nd, 9th, 16th, and 23rd.⁶ This structured and significant flow of automated retail investment makes it a relevant setting for studying execution quality.

2.2. Data

Our empirical analysis relies on a comprehensive dataset constructed from two primary sources. The core of our data consists of proprietary transaction-level records from LS Exchange, which we use to identify SP trades. Additionally, we include limit order book data from the reference market Xetra to evaluate execution quality.

Our sample period runs from October 2020 to June 2025. The start date is motivated by the introduction of equity SPs in September 2020, which complemented the existing ETF offerings on major platforms like Trade Republic. To ensure our analysis focuses on liquid securities popular among retail investors, we restrict our sample to the most actively traded securities on LS Exchange during this period. Specifically, the sample comprises the 20 most-traded ETFs and the top 10 German and top 11 U.S. equities, respectively.⁷ To maintain a homogenous sample representative of typical passive investment strategies, we exclude leveraged ETFs and any securities not continuously available due to mergers or other corporate actions. For some securities, the time series begins later within our sample period, reflecting recent IPOs or their

⁴See https://assets.traderepublic.com/assets/files/Trade_Republic_Pressemitteilung_New_savings_products_DE.pdf (in German).

⁵See https://assets.ctfassets.net/vkizfq3pbtzc/40XSa3ExKShkI2b0SYBqDF/2adc26b5d221f8f8be08d765c69b574cc/221028_TradeRepublic_PressRelease_WorldSavingsDay.pdf.

⁶See <https://support.traderepublic.com/en-ie/849-When-are-savings-plans-executed>.

⁷One ETF (ISIN: LU1781541179) was excluded from the sample because it merged with another fund from the same provider that is not among the most actively traded ETFs on LS Exchange. To maintain a sample of 20 ETFs, we replaced it with the next most actively traded ETF on LS Exchange.

delayed inclusion in SP offerings. A complete list of the securities in our sample is provided in Table A.1 in Appendix A.

The LS Exchange data provides granular details for each trade, including the ISIN, a timestamp with granularity up to the second, execution price, traded volume, and trade direction. This granularity is essential for the precise identification of trade patterns characteristic of SPs. Since SP volumes on the 9th and 23rd are relatively low⁸, which makes precise identification difficult, we focus on the 2nd and 16th of each month only.

To assess execution quality, we compare the identified SP trades on LS Exchange with reliable market benchmarks. For this purpose, we use high-frequency data from Xetra, the primary German securities exchange, which serves as the official reference market⁹ for all securities in our sample. This benchmark data, sourced from the A7 platform of Deutsche Börse AG, includes both trade-level and order book-level information. It allows us to construct robust benchmark prices, which will be described in more detail in Section 4, to rigorously evaluate the execution quality of the SP trades.

Table 1: Daily trading statistics for Xetra and LS Exchange

This table reports descriptive statistics for buy-side trading activity on Xetra and LS Exchange for our sample of 41 instruments from October 2020 to June 2025. Statistics are presented separately for SP days (the 2nd and 16th trading day of each month) and non-SP days (the trading day immediately following each SP day).

	(a) ETFs		(b) Equities	
	Xetra	LS	Xetra	LS
Daily trades (SP day)	291	505	3,624	1,021
Daily trades (non-SP day)	216	453	2,865	956
Avg. trade size (SP day)	22,117	8,244	9,352	2,915
Avg. trade size (non-SP day)	21,600	2,255	9,260	2,526
Avg. daily trade volume (SP day)	5,135,193	3,671,869	34,620,798	3,310,574
Avg. daily trade volume (non-SP day)	3,671,797	837,910	26,746,904	2,678,073

Table 1 reports daily trading statistics for Xetra and LS Exchange. Consistent with its role as a retail-exclusive venue, trading on LS Exchange involves smaller average trade sizes than on Xetra across both asset classes. For equities, the disparity in total volume is substantial; average daily volume on Xetra is approximately €34 million on SP days and €26 million on non-SP days, roughly ten times the volume on LS Exchange. The pattern for ETFs is more nuanced. On SP days, ETF volume on LS Exchange reaches €3.6 million, which is not far away from Xetra’s €5.1 million. On

⁸This likely reflects that most investors receive their income at the end or in the middle of the month, while standard SPs are executed on a monthly basis; see, for example, https://cdn.extraetf.com/downloads/research/2024/study/European_Saving_Plan_Study_EN_XETF-19112024.pdf.

⁹See https://www.ls-tc.de/media/site/bibliothek/LS_B1_Exchange.pdf (in German).

non-SP days, however, LS Exchange’s ETF volume falls to less than a quarter of that on Xetra. Notably, aggregate volumes decline significantly on non-SP days, falling by approximately 40% for ETFs and between 23% and 30% for equities, highlighting the quantitative impact of SP trades. Table A.2 in Appendix A further details this by differentiating between German and U.S. equities and shows that German equity trading activity is much higher on Xetra than on LS Exchange whereas U.S. equity trading activity is comparable between both exchanges.

3. Identification of SP Trades

3.1. Methodology

We identify SP trades in transaction-level data from LS Exchange by exploiting their distinctive timing and execution characteristics. SP trades originate from automated investment plan orders set up by retail investors which are typically bundled into one or a few large transactions at recurring dates and times by the broker. In practice, brokers such as Trade Republic do not route each individual investor’s SP order directly to a trading venue. Instead, they aggregate the trading interest of all participating customers and execute the combined order as a single (or a small number of) large transaction(s).¹⁰

SP executions are characterized by (i) relatively large aggregated volumes, (ii) execution times during the opening hours of the reference market Xetra, and (iii) occurrence on known SP days.¹¹ When these regular SP days coincide with weekends or public holidays, executions are shifted to the next trading day which then becomes the SP day.¹² These institutionalized execution patterns allow SP trades to be clearly distinguished from ordinary retail or institutional trades.

We first identify unusually large trades by calculating standardized trade sizes (z-scores) relative to the daily distribution of trade volumes for each security. Trades with a z-score greater than three are flagged as potential SP trades. For each security, we then assess these candidate trades based on their volume, execution time, and the number of constituent transactions into which they are split, which we call *child* trades being part of the aggregate *parent* trade.¹³ Typically, SP trades occur not only on specific SP days, but also cluster at nearly identical times of the day or follow a highly regular intraday pattern, as illustrated in Table B.1, where executions concentrate around 16:35 local time.

¹⁰Retail investors specify a fixed monetary amount to be invested at regular intervals, typically monthly. The broker then creates and executes aggregated SP orders by pooling the trading interest of all customers.

¹¹See <https://support.traderepublic.com/en-ie/849-When-are-savings-plans-executed>.

¹²See Trade Republic’s customer contract agreement (in German) at https://assets.traderepublic.com/documents/DE/CONTRACT_CUSTOMER_AGREEMENT_20240613165612.pdf.

¹³For a given security and SP day, brokers such as Trade Republic appear to avoid sending a single extremely large SP order when the corresponding SP volume is very high (e.g., in the millions of euros). Instead, they split the parent order up into multiple child orders.

To ensure completeness, we employ a backward-induction approach that serves two purposes: (i) to capture smaller but related trades that belong to the same SP batch, and (ii) to identify corresponding SP trades in the same security on earlier SP days.¹⁴ These additional trades, typically with slightly lower z-scores, are included when they occur in close temporal proximity to identified SP trades and exhibit consistent clustering across SP days. We further verify that the identified trades display stable patterns in timing and execution structure across consecutive SP days, ensuring that recurring patterns reflect systematic SP execution rather than isolated large trades.

It is important to note that we distinguish between securities as well as between the first and second SP day of each month to account for systematic differences in asset classes and trading volumes across these days. While most equity SPs are executed as a single large transaction (except for the most actively traded ones in later years), ETF SPs are typically executed through multiple trades due to their larger aggregate volume. Similarly, total SP volume, and thus the number of trades, is generally higher on the first SP day (typically the 2nd day of each month) compared with the second (typically the 16th day of each month).

All classifications were independently reviewed by three researchers, and only those trades for which consensus was achieved were retained in the final sample. Illustrative examples of identified SP trades and their characteristic execution patterns are presented in [Table B.1](#) for an equity instrument and in [Table B.2](#) for an ETF with multiple child trades executed on the same SP day. Furthermore, the identification procedure is outlined in a structured, step-by-step format in [Appendix C](#).

3.2. Characteristics of Identified SP Trades

Following the application of our identification methodology, we conduct a descriptive analysis of the identified SP trades. [Table 2](#) presents summary statistics for the single child SP trades, the aggregate parent SP trades and contrasts them with all other non-SP trades on LS Exchange during our sample period.

As hypothesized, the analysis reveals that identified parent SP trades are substantial in scale, distinguishing them sharply from typical retail trades. The median child ETF SP trade amounts to €621,000 (€1.1 million for parent trades), while the median equity SP trade is €116,000 (€129,000 for parent trades). These values stand in stark contrast to the median sizes of non-SP trades, which are only €421 for ETFs and €732 for equities. This vast difference in magnitude highlights the nature of SP trades as large transactions within an aggregate parent trade and validates our identification approach.

A significant asymmetry exists between the use of SPs for ETFs versus individual equities. Over our sample period, the total volume of identified ETF SP trades is nearly €6.3 billion, accounting for more than one-fifth of all ETF trading volume on

¹⁴Some SP trades may not be directly captured by the applied z-score when SP volumes are low and fall slightly below this threshold. This is the case on some days for some equity SPs, for which non-SP trading volume is comparatively high, or when SPs are still in their early stages in general (particularly in 2020)).

Table 2: Descriptive statistics of SP trades

This table shows descriptive statistics on the trading volume (in €) of the identified SP trades on LS Exchange between October 2020 and June 2025. Non-SP trades are transaction not identified SP trades during the whole observation period.

(a) ETF			
	Child SP Trade	Parent SP Trade	Non-SP Trade
N	7,340	2,090	10,117,936
Mean	858,036	3,013,390	2,020
Std	722,089	6,890,786	10,175
Min	1,629	1,629	5
1%	39,522	37,656	15
25%	183,394	450,466	123
Median	621,515	1,116,583	421
75%	1,498,951	2,551,280	1,147
99%	2,001,152	37,611,418	26,952
Max	4,970,497	80,014,897	3,812,550
Sum	6,297,984,073	6,297,984,073	20,441,805,663
(b) Equity			
	Child SP Trade	Parent SP Trade	Non-SP Trade
N	3,249	2,326	24,613,477
Mean	204,273	285,332	3,022
Std	192,719	406,474	10,008
Min	1,032	1,032	1
1%	3,527	3,610	26
25%	53,247	50,087	248
Median	116,164	129,980	732
75%	346,661	339,190	2,226
99%	688,054	1,976,276	39,957
Max	1,395,360	3,038,279	6,046,250
Sum	663,681,448	663,681,448	74,369,892,886

LS Exchange. In contrast, equity SP trades total only €663 million, representing less than 1% of the total equity trading volume on the venue, even though both product types were available to investors in that period. This finding is consistent with the notion that retail investors predominantly use automated SPs as a vehicle for broad, passive market exposure through ETFs rather than for accumulating positions in single equities.

Furthermore, we observe differences in the execution mechanics, likely driven by the disparate trade sizes. Due to their massive volume, ETF parent trades are frequently split into multiple smaller child trades for execution. This is evidenced by the high ratio of individual trades to parent trades and the observation that the average child trade constitutes only about one-third of the total parent trade volume. This practice is far less pronounced for equity SP trades, which are smaller and less likely to require such splitting.

Collectively, these descriptive results confirm the distinct nature of SP trades: they are large-scale transactions that stand out from the regular flow of retail trades, and their economic significance is far more pronounced within ETF trading than for equities.

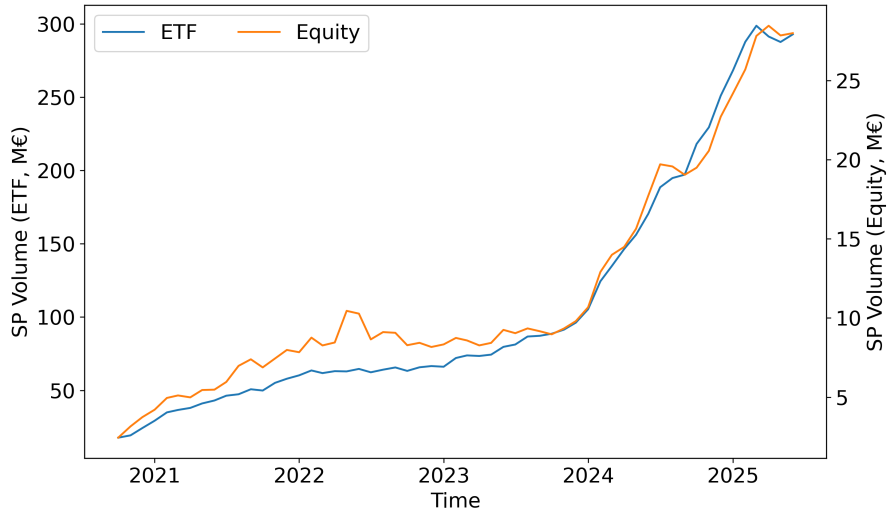


Figure 1: Development of SP trade volume for ETFs and equities over time

To further validate our identification, we analyze the evolution of SP trade volume over time. Figure 1 illustrates the aggregate identified monthly SP volume from October 2020 to June 2025. A clear upward trend is visible: the total monthly SP volume shows consistent growth throughout the observation period. This growth is observed for both ETF and equity SPs, albeit at different magnitudes, which is plausible and aligns with the broader European trend of retail investors increasingly adopting systematic SPs for long-term wealth accumulation.

A more granular analysis, presented in Appendix B, offers deeper insights. Figures B.1 and B.2 depict the monthly SP trade volume for each of the 20 ETFs in our sample, disaggregated by the two primary SP days (the 2nd and 16th of each month).

The figures also plot the growth of Trade Republic’s customer base. Here, two key patterns emerge. First, for any given ETF, the SP volume follows a highly similar trajectory on both SP days. Second, the aggregate SP volume for these assets exhibits a strong positive correlation with the growth in the neobroker’s customer count. These findings increase confidence in our identification approach. As an ETF gains popularity among investors, demand should increase consistently across all available SP days, and a larger customer base should mechanically lead to higher aggregate investment volumes.

Figures B.3 and B.4 show the corresponding time series for German and U.S. equities, respectively. While the results show a similar overall growth trend, the volume in individual equity SPs is significantly more volatile and appears to be influenced by security-specific news and heightened investor attention. This is particularly evident in the plots for securities like Nvidia and Rheinmetall, which show sharp spikes in SP volume that likely correspond to periods of high market interest, i.e. the growing hype around AI and increased defense spending across European countries.

In summary, the temporal dynamics of the identified SP trades align well with the institutional features of these investment products and broader market trends. Their consistent growth, correlation with the broker’s user base, and distinct behavior across asset classes confirm that our identification method effectively captures the intended transactions.

4. Execution Quality of SP Trades

4.1. Price Comparison with Benchmark

Execution quality of SP trades on LS Exchange is assessed relative to the German reference market, Xetra, which also serves as the reference market for LS Exchange’s market maker. Since all SP trades are buyer-initiated trades, we benchmark execution quality against the Xetra best ask price prevailing at the time of the SP trade.

Public LS Exchange trade data are timestamped only to the second, whereas the Xetra order book updates at nanosecond granularity. To account for this temporal mismatch, we compute the minimum and maximum Xetra best ask observed within the same second in which the SP trade was executed. This yields a robust reference range.

We then compare the SP execution price to the Xetra best ask range. The relative price difference $\Delta_{i,t}^{Xetra}$ for an SP trade in security i at time t is defined as:

$$\Delta_{i,t}^{Xetra} = \begin{cases} 0, & \text{if } P_{i,t}^{Xetra,min} \leq P_{i,t}^{SP} \leq P_{i,t}^{Xetra,max} \\ \frac{P_{i,t}^{SP} - P_{i,t}^{Xetra,max}}{P_{i,t}^{Xetra,max}}, & \text{if } P_{i,t}^{SP} > P_{i,t}^{Xetra,max} \\ \frac{P_{i,t}^{SP} - P_{i,t}^{Xetra,min}}{P_{i,t}^{Xetra,min}}, & \text{if } P_{i,t}^{SP} < P_{i,t}^{Xetra,min} \end{cases} \quad (1)$$

Positive (negative) values of $\Delta_{i,t}^{Xetra}$ indicate execution at a worse (better) price relative to Xetra, meaning SP investors paid more (less) than the contemporaneous best ask on the reference market.¹⁵

As an alternative benchmark, we compute the VWAP of non-SP trades executed on LS Exchange during the five minutes preceding the SP trade. However, this measure is less reliable for two reasons: (i) not every SP trade has preceding trades within the five-minute window, especially early in the sample, and (ii) the LS Exchange’s market maker may adjust quotes in anticipation of SP trades, given their predictable timing. The corresponding relative price difference is defined as follows:

$$\Delta_{i,t}^{LS\ VWAP} = \frac{P_{i,t}^{SP} - P_{i,t}^{LS\ VWAP}}{P_{i,t}^{LS\ VWAP}} \quad (2)$$

To construct a counterfactual for comparison, we identify, for each security, the largest buy trade executed on the day following the SP day, restricted to Xetra’s main trading hours to ensure consistency with the timing of SP trades. Using the following trading day also prevents the inadvertent inclusion of SP-related trades, thereby also excluding those placed through other brokers connected to LS Exchange.¹⁶ The resulting trades serve as a representative measure of regular market activity in the absence of SP trades. Although these non-SP trades are selected to be broadly comparable in nature to SP trades, they are still typically smaller in size (see [Figure 2](#)), particularly for ETFs, reflecting that SP trades constitute some of the largest and most systematic order flow on LS Exchange.

4.2. Descriptive Statistics on Execution Quality

Table 3 presents descriptive statistics for the execution price differences of SP trades, measured in bps, relative to two benchmarks: (a) the contemporaneous Xetra best ask price, and (b) the LS VWAP over the five minutes prior to the trade. The statistics are reported for three distinct asset classes: ETFs, U.S. equities, and German equities. When benchmarked against the Xetra best ask price, the execution quality distributions are characterized by low dispersion and central tendencies clustered around zero. For both ETFs and German equities, the median price difference is exactly 0 bps, with the 25th percentile also being 0. This indicates that a substantial portion of these trades are executed within the prevailing best ask price benchmark on Xetra. The slightly positive means of 0.56 bps for ETFs and 0.63 bps for German equities, when compared to the zero median, suggest a right-skewed distribution. This skew is driven by a tail of trades with positive costs (i.e., worse executions compared to the Xetra benchmark), as evidenced by the 99th percentile values of 8.07 bps and 5.27 bps, respectively. Overall, SP trades are executed rather fairly against

¹⁵We do not take into account order execution fees and other possible explicit transaction costs as SPs are also offered for zero explicit transaction costs on the reference market Xetra ([Deutsche Börse AG, 2022](#)).

¹⁶Besides the main order flow provider Trade Republic, there are also other brokers connected to LS Exchange, e.g., as a fallback option. However, none of these brokers execute SP orders on the SP days of Trade Republic or the day after.

the market maker with very little positive deviations to the best ask on Xetra. The average small additional costs for SP trades are negligible especially when considering the large inventory risks the market makers faces. U.S. equities, however, exhibit a distinct pattern. The median is also 0 bps, but the mean is negative (-1.12 bps), suggesting a left-skewed distribution where instances of price improvement (negative costs) are more impactful than those with positive costs. This is supported by the 25th percentile at -2.44 bps, which means at least a quarter of all U.S. equity trades were executed at a price better than the Xetra ask. In aggregate, when evaluated against a contemporaneous quote, the pricing for SP trades appears highly competitive, with the market maker frequently providing trades at or inside the spread. The small positive average costs for ETFs and German equities may reflect compensation for the liquidity provision and internalization services.

Table 3: Descriptive statistics on SP execution price comparison

This table reports descriptive statistics for price differences in bps of the execution price of identified SP trades compared with two pricing benchmarks: (a) the best ask price on Xetra, and (b) the VWAP on LS Exchange during 5 minutes prior to the trade.

	(a) Xetra Best Ask			(b) LS VWAP t-5m		
	ETFs	U.S. Equit.	DE Equit.	ETFs	U.S. Equit.	DE Equit.
N	7,135.00	2,077.00	1,143.00	6,521.00	1,987.00	973.00
Mean	0.56	-1.12	0.63	0.67	2.12	1.43
Std	2.13	5.45	1.21	7.14	18.52	10.27
Min	-21.38	-61.88	-1.78	-59.47	-98.23	-47.12
1%	-3.71	-22.05	0.00	-20.12	-49.00	-28.59
25%	0.00	-2.44	0.00	-1.94	-6.01	-3.42
Median	0.00	0.00	0.00	0.10	1.56	1.07
75%	0.96	0.00	1.06	3.17	10.53	6.74
99%	8.07	12.13	5.27	23.68	54.87	30.88
Max	33.63	40.19	6.78	108.07	94.80	65.22

The distributions change markedly when execution prices are compared to the 5-minute pre-trade VWAP on LS. This benchmark reveals substantially higher dispersion and consistently positive mean execution costs across all asset classes (ETFs, U.S. equities, and German equities). Across the three categories, the mean and median price differences are positive, indicating that, on average, SP trades are executed at a price higher than the recent VWAP. The means are 0.67, 2.12, and 1.43 bps, respectively. The distributions are heavily right-skewed, with the mean being notably larger than the median in all cases. This suggests a significant tail of trades occurring at prices substantially higher than the 5-minute VWAP. Overall, when comparing SP execution prices with the prevailing VWAP on LS Exchange, a worse execution is shown. This indicates that the market maker is executing SP trades differently than other trades which is likely a result of inventory risk when executing such large volumes as with SP trades.

To investigate the execution quality of SP trades, we compare the corresponding price differences across SP and non-SP trades and plot them against trade volume to examine whether inventory-related costs contribute to observed price discrepancies¹⁷. Based on systematic differences visible in these relationships, we subsequently conduct separate analyses for ETFs, German equities, and U.S. equities. Figure 2 shows the plots for the three asset classes in each row. In the left column, all price differences for the largest trades after each SP day (referred to as non-SP trades) are shown, while the right column displays the SP trades. Green colored dots represent trades for which the execution resulted in a price improvement, red ones on the other hand are trades with a worse price and black dots perfectly match the benchmark price. For better visualization, the trade volume on the x-axis is capped at €2 Million. The same plot without a capped trade volume is provided by Figure D.5 in Appendix D.

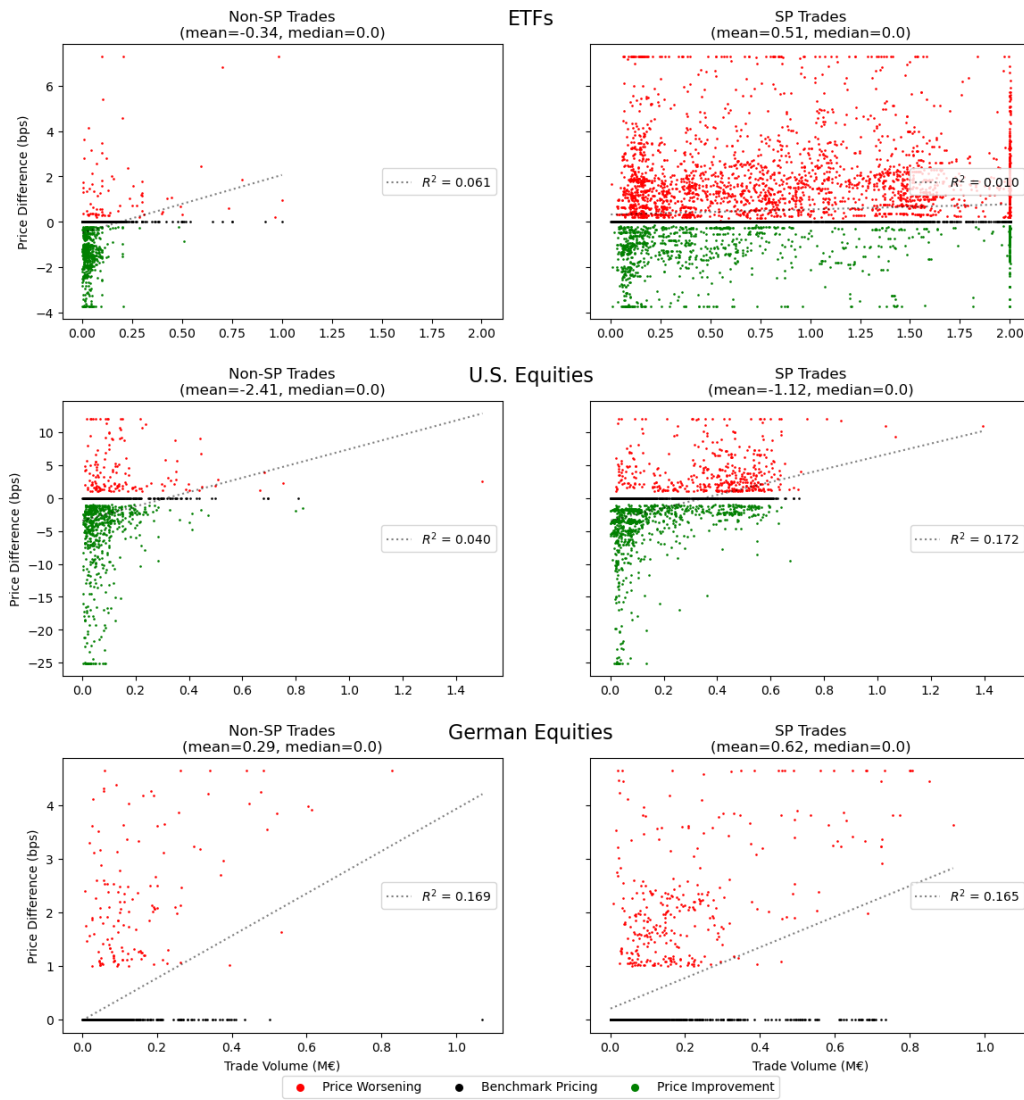
For ETF trades, there is a clear divergence in execution quality. On average, SP trades are executed at prices worse than the best ask price on the reference market, whereas non-SP trades receive a price improvement. However, a direct comparison is complicated by a substantial disparity in trade volumes. The distribution of SP trade volumes is relatively uniform, often reaching sizes well over €1 million. In contrast, non-SP trades are clustered at sizes below €250,000. This size difference suggests that the inferior execution of SP trades could be a function of their sheer magnitude rather than a characteristic of SPs themselves. Intriguingly, when analyzing SP trades' execution behavior, we find no relationship between trade size and execution costs. This finding is remarkable, as it implies that the market maker at LS can execute a multi-million-euro trade with the same relative execution quality as one of a few thousand euros. This contradicts standard models of inventory risk, where larger trades typically incur higher costs. The most plausible explanation is the recurrent and predictable nature of SP trades, which allows the market maker to anticipate and manage inventory preemptively.

For U.S. equity trades, the results differ notably from the ETF sample. Both buyer-initiated SP and large non-SP trades tend to be executed at prices better than the best ask on Xetra, with the price improvement being more pronounced for non-SP trades. While trade volumes in the SP and non-SP samples are more comparable than for ETFs, SP trades remain systematically larger. In contrast to the ETF findings, the U.S. equity sample shows some evidence consistent with inventory risk, indicated by a general trend where larger trades incur higher execution costs. However, this trend is not uniform, as several very large trades still receive significant price improvement. The tendency for the market maker to offer price improvement on large (non-)SP trades in U.S. equities is likely attributable to the liquidity profile of the reference market. U.S. equities are less liquid on Xetra than on their primary U.S. exchanges, resulting in wider spreads and potentially stale benchmarks. The market maker on LS Exchange likely manages his inventory by hedging on these more liquid U.S. venues.

¹⁷Table A.3 in Appendix A provides descriptive statistics on price differences of the counterfactual non-SP trades.

Figure 2: Comparison of execution quality of SP and large non-SP trades relative to their trade volumes

This figure shows the execution quality measured as price differences between execution price of SP trades and the best ask price on Xetra in the right column and large-in-scale non-SP trades in the left column. Each column shows the results differentiated for our three asset classes, namely ETFs, U.S. equities and German equities. Large non-SP trades are observed on the day after an SP day as the largest transaction on that day. The price differences on the y-axis are given in bps and red colored observations mean worse execution, green colored observations mean price improvements and black points are executed exactly at the benchmark price. The x-axis shows the trade volume in millions of euros. A regression line is given as a gray dotted line. The price differences are winsorized at the 1% and 99% level and the trade volumes are capped to a maximum of €2 Million (and thus the means slightly deviate from those reported in Table 3).



In doing so, he can execute trades at prices superior to Xetra’s and pass a portion of this improvement on to the customer.

The results for German equities align most closely with theoretical expectations. A market maker’s spread is theoretically composed of compensation for fixed costs, adverse selection risk, and inventory risk (Ho and Stoll, 1981; Glosten and Milgrom, 1985). In our setting, adverse selection risk is negligible due to the exclusively uninformed retail order flow, and fixed costs can be assumed to be constant. This leaves inventory risk as the primary determinant of variations in execution costs. An opportunistic market maker, obligated only to match the best Xetra price for standard-sized trades, would be expected to reflect inventory risk for large trades in his prices, resulting in executions at or worse than the benchmark. This is precisely what we observe. For German equities, not a single observation of price improvement was recorded. Both large SP and non-SP trades were, on average, executed at prices worse than the best ask on Xetra. This effect is more pronounced for the larger SP trades, which is consistent with the market maker charging a premium for bearing greater inventory risk.

In summary, the descriptive results suggest that SP trades are mostly executed at prices close to the prevailing reference market benchmark, with only marginal price worsening. However, the patterns of price improvement and worsening are not consistent with standard theories of market making. The general absence of a relationship between trade size and execution cost, particularly for the very large ETF trades, contradicts the expected impact of inventory risk. Furthermore, the frequent price improvements for ETF and U.S. equity trades lack a clear economic rationale if the market maker were benchmarked solely against his obligation to Xetra. This suggests the market maker actively manages inventory across more liquid, alternative venues or the OTC market and passes a portion of the resulting gains to clients. However, one key puzzle remains: despite the predictability of SP trades, which should theoretically lower handling costs, SP trades, especially in ETFs, are on average executed at worse prices than their large non-SP counterparts.

4.3. Regression-Based Comparison of SP and Non-SP Trades

In order to further analyze the execution quality of SP trades, especially price improvements and worsenings, we conduct a series of panel regression analyses using non-SP trades as counterfactual. The central idea is to benchmark the realized execution outcomes of SP trades against similarly large non-SP trades in the same securities that serve as a counterfactual. This comparison allows us to isolate whether SP trades receive systematically different execution quality after controlling for observable market and security characteristics. Equation 3 presents the model specification, which is applied consistently across the two benchmark comparisons. To account for potential heterogeneity, we estimate the model separately for the three distinct groups of securities (ETFs, U.S. equities, and German equities). The empirical design thus identifies structural differences in execution outcomes conditional on both trade-specific and market-specific conditions.

$$\begin{aligned}
\Delta_{i,t} = & \alpha + \beta_1 \cdot \text{Trade Size}_{i,t} + \beta_2 \cdot SP_{i,t} + \beta_3 \cdot \text{Trade Size}_{i,t} \cdot SP_{i,t} \\
& + \beta_4 \cdot \text{Relative Spread}_{i,t} + \beta_5 \cdot \text{Volatility}_{i,t} + \beta_6 \cdot \text{Level 1 Depth}_{i,t} \\
& + \beta_7 \cdot OBI_{i,t} + \beta_8 \cdot \text{Market Cap}_{i,t} + \beta_9 \cdot \text{Inverse Price}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t}
\end{aligned} \tag{3}$$

where μ_i and λ_t denote security and time (year-month) fixed effects, respectively, and $\varepsilon_{i,t}$ is the idiosyncratic error term. The dependent variable $\Delta_{i,t}$ captures the execution price difference measure for security i at time t .

The principal variables of interest are $\text{Trade Size}_{i,t}$, the euro-denominated size of the executed trade (in millions of euros), the SP dummy variable $SP_{i,t}$ taking value 1 for SP trades and 0 otherwise, and their interaction term $\text{Trade Size}_{i,t} \cdot SP_{i,t}$. The coefficient on the SP dummy, β_2 , indicates whether SP trades differ from comparable non-SP trades in their average execution quality, while β_3 captures whether any difference scales with trade size. Any price differences stemming from market maker's inventory costs are reflected by β_1 .

To control for variation in liquidity and trading conditions, we include several standard control variables (e.g., O'Hara and Ye, 2011; Gresse, 2017): (i) the average $\text{Relative Spread}_{i,t}$ on the reference market Xetra measured in the 30 minutes preceding the trade; (ii) $\text{Volatility}_{i,t}$, defined as the standard deviation of logarithmic midpoint returns based on one-minute intervals within the 30 minutes preceding the trade on Xetra; (iii) $\text{Level 1 Depth}_{i,t}$, the euro volume quoted at the first order book level; (iv) $OBI_{i,t}$, defined as the order book imbalance computed by dividing the euro volume on the first bid level by the entire volume at both best bid and best ask; (v) $\text{Market Cap}_{i,t}$, representing the market capitalization of the security on the trade day; and (vi) $\text{Inverse Price}_{i,t}$, the inverse of the daily closing price, following conventional microstructure scaling.

The specification is estimated using security fixed effects to account for time-invariant differences in trading venue or product characteristics and time fixed effects to account for common shocks or market-wide conditions that vary over time but affect all securities equally. Standard errors are computed to be heteroskedasticity-robust and double-clustered by security and by time to mitigate cross-sectional and temporal dependence in residuals. In an additional analysis, we rely on daily measures for spread, volatility, and trading volume on Xetra to control for the market environment. The results of this analysis are qualitatively similar and reported in Table D.3 in Appendix D.

The results of this analysis are reported in Table 4. First, with the exception of U.S. equities, SP trades tend to be executed at slightly inferior prices relative to the counterfactual sample of large non-SP trades. The estimated differences are economically small yet statistically meaningful, ranging between 0.97 and 1.50 bps for ETFs and between 0.18 and 1.65 bps for German equities. This pattern holds consistently across both price benchmark specifications, suggesting that SP trades face minor but measurable execution disadvantages.

Second, the coefficient on trade size is generally positive and statistically significant, indicating that larger trades experience worse execution, consistent with

inventory-management and market-maker inventory-cost theory (Ho and Stoll, 1981). Quantitatively, the average deterioration equals approximately 4.4 bps per additional million euros for ETFs, 9.2 bps for U.S. equities, and 5.6 bps for German equities when measured relative to the Xetra best ask benchmark. When using the LS VWAP benchmark, the effect remains significant only for ETFs.

Third, the interaction term between trade size and the SP dummy suggests that this adverse size effect is mitigated or even eliminated for SP trades. Specifically, the coefficient of the interaction term is estimated at about -4.0 bps for ETFs and -1.5 bps for German equities, while it is not significant for U.S. equities. These findings imply that inventory considerations play a smaller role for SP trades and, in the case of ETFs, almost no role at all. The results for ETFs are qualitatively similar under the LS VWAP benchmark.

Finally, the control variables generally behave as expected, although their significance varies across specifications. Higher short-term volatility tends to be associated with inferior execution prices, whereas securities with larger market capitalization rather experience slight improvements in execution prices, consistent with lower trading frictions. Moreover, higher order book imbalance on the bid side is associated with inferior execution prices for SP trades, which are always buyer-initiated.

Table 4: Regression results on execution quality of SP and non-SP trades

This table shows the regression results on the execution quality of SP and large-in-scale non-SP trades for three asset classes: ETFs, U.S. equities and German equities. The dependent variable is the difference of execution price and the benchmark price in bps. Two benchmarks are used in this regression: the best ask price on Xetra at the same time and the VWAP on LS Exchange measured over 5 minutes prior to the trade. Trade size is the volume of the (non-)SP trade in millions of euros. SP is a dummy variable which takes one if the trade is an SP trade. Volatility is given as the log midpoint return volatility 30 minutes prior to the trade. Relative spread and log trading volume are measured as the average over the 30 minutes preceding the trade. Level one depth is given as the total quoted euro volume at the best bid and ask. Order book imbalance is calculated as the volume on the best bid divided by the total quoted volume on the first order book level. Market capitalization is measured in millions of euros. Inverse price is calculated as one divided by the closing auction price of the respective trading day. To mitigate issues regarding multicollinearity, we exclude the relative spread for the German equities regression model. Asterisks denote that the coefficient is different from zero at the 90% (*), 95% (**), and 99% (***) confidence levels, respectively.

	ETFs (Best Ask)	U.S. Equities (Best Ask)	DE Equities (Best Ask)	ETFs (LS VWAP)	U.S. Equities (LS VWAP)	DE Equities (LS VWAP)
Intercept	0.49	-0.44	-0.27	1.68	-4.99	-3.47
Trade Size (M€)	4.43***	9.17***	5.58***	6.87***	2.81	1.36
SP	0.97***	0.51	0.18***	1.50***	1.37	1.65**
Trade Size x SP	-3.94***	-1.97	-1.46***	-6.29***	-0.83	2.62
Volatility	0.05***	0.01	0.01***	0.00	0.37***	0.08
Relative Spread	0.03***	-0.13***		0.13***	0.03	
Level 1 Depth	0.00***	-0.07***	-0.02***	0.00	-0.06	-0.03
OBI	0.56***	2.46***	0.39	0.01	8.84**	3.95
Market Cap	-9.29***	-1.03***	-2.61**	10.02	-0.69	15.30
Inverse Price	-828.11	2674.31*	-2247.70	-7073.89	2918.33	-23 058.49
R-squared	0.15	0.21	0.32	0.05	0.05	0.07
R-squared Adj.	0.14	0.19	0.30	0.04	0.02	0.03
Entity FE	yes	yes	yes	yes	yes	yes
Year-Month FE	yes	yes	yes	yes	yes	yes

4.4. Determinants of SP Execution Price Differences

In order to examine the determinants of price differences between SP trades executed on LS Exchange and the respective benchmark prices, we estimate the following panel regression model (Equation 4). The specification is conceptually similar to the model introduced in Equation 3, except that this model only includes SP trades (and not the counterfactual non-SP trades) and the set of explanatory variables is adjusted to capture execution dynamics within the SP setting.

$$\begin{aligned} \Delta_{i,t} = & \alpha + \beta_1 \cdot \text{Trade Size}_{i,t} + \beta_2 \cdot \text{SP Day } 1_t \\ & + \beta_3 \cdot \text{Number Child Trades}_{i,t} + \beta_4 \cdot \text{Relative Spread}_{i,t} \\ & + \beta_5 \cdot \text{Volatility}_{i,t} + \beta_6 \cdot \text{Level 1 Depth}_{i,t} + \beta_7 \cdot \text{OBI}_{i,t} \\ & + \beta_8 \cdot \text{Market Cap}_{i,t} + \beta_9 \cdot \text{Inverse Price}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \quad (4)$$

Specifically, we replace the SP dummy and its interaction term with variables reflecting the structure of SP execution: *SP Day 1_t*, a dummy equal to 1 on the first SP day in a month, and *Number Child Trades_{i,t}*, the number of child trades associated with each single SP trade resulting from the same parent trade. These variables allow us to identify whether recurring SP days or the fragmentation of SP trades into multiple child trades systematically influence execution prices. We also keep *Trade Size_{i,t}*, the euro-denominated size of the executed SP trade to control for potential inventory-related price dynamics.

All other control variables remain consistent with the previous specification. These include trade- and security-specific characteristics such as relative spread, short-term volatility, order book depth and imbalance on Xetra during the 30-minute pre-execution window, daily market capitalization, and the inverse of the closing price. Security (μ_i) and time (λ_t) account for time-invariant heterogeneity across securities and common temporal shocks affecting all securities, and standard errors are computed to be heteroskedasticity-robust and double-clustered by security and time. As before, the model is estimated separately for ETFs, U.S. equities, and German equities to address potential structural and liquidity differences across markets. In addition, we also run a full model that includes SP trades from all three groups to analyze whether the execution of ETF SP trades systematically differs. In this model, we also include an *ETF* dummy and the interaction term *ETF · Trade Size*.

Table 5: Regression results on drivers of pricing differences for SP trades

This table shows the regression results on the execution quality of SP trades for three asset classes: ETFs, U.S. equities, German equities, as well as a full model. The dependent variable is the difference of execution price and the benchmark price in bps. Two benchmarks are used in this regression: the best ask price on Xetra at the same time and the VWAP on LS Exchange measured over 5 minutes prior to the trade. Trade size is the volume of the SP trade in millions of euros. SP day 1 is a dummy variable which takes one if the trade is an SP trade on the first monthly SP day, i.e. the 2nd. The number of child trades measures how many SP trades are executed in the same asset on the same day. Volatility is given as the log midpoint return volatility 30 minutes prior to the trade. Relative spread and log trading volume are measured as the average over the 30 minutes preceding the trade. Level one depth is given as the total quoted euro volume at the best bid and ask. Order book imbalance is calculated as the volume on the best bid divided by the total quoted volume on the first order book level. Market capitalization is measured in millions of euros. Inverse price is calculated as one divided by the closing auction price of the respective trading day. A ETF dummy is included in the full model which takes one if the asset is an ETF. To mitigate issues regarding multicollinearity, we exclude the relative spread and number of child trades for the German equities regression model. Asterisks denote that the coefficient is different from zero at the 90% (*), 95% (**), and 99% (***) confidence levels, respectively.

	ETFs (Best Ask)	U.S. Equities (Best Ask)	DE Equities (Best Ask)	All (Best Ask)	ETFs (LS VWAP)	U.S. Equities (LS VWAP)	DE Equities (LS VWAP)	All (LS VWAP)
Intercept	1.76***	1.47	0.16	0.77	5.60**	-5.81	-11.47**	-3.84*
Trade Size (M€)	0.50***	9.39***	4.92***	7.60***	0.70***	1.22	4.56	4.95***
SP Day 1	0.37***	0.18	0.01	0.31***	-0.37*	1.24	-0.03	0.02
No. Child Trades	-0.02***	0.14***		-0.01***	0.01	0.04		0.00
Volatility	0.01	-0.03*	0.03***	0.00	-0.03	0.11	0.07	0.09**
Relative Spread	0.06***	-0.14***		-0.09***	0.20***	-0.05		0.03
Level 1 Depth	0.00***	-0.05***	-0.03***	0.00***	0.00	-0.02	0.00	0.00
OBI	0.86***	3.46***	0.79*	1.17***	-0.29	6.42	6.63	0.75
Market Cap	5.13	-1.62***	-5.11***	-1.00***	8.23	-1.61	21.42	-0.20
Inverse Price	-777.21	6452.48***	-4950.43	3915.08***	-2372.98	-2345.08	25 027.87	-2776.67
ETF				1.30***				2.15*
ETF x Trade Size				-7.15***				-4.42***
R-squared	0.16	0.31	0.43	0.24	0.06	0.06	0.11	0.03
R-squared Adj.	0.15	0.29	0.39	0.24	0.05	0.03	0.04	0.02
Entity FE	yes	yes	yes	yes	yes	yes	yes	yes
Year-Month FE	yes	yes	yes	yes	yes	yes	yes	yes

The results of this analysis are reported in [Table 5](#). Overall, the findings indicate that trade size, and thus inventory risk, only to some extent plays a role in explaining price differences between SP trades and the benchmark prices. Larger SP trades tend to be executed at slightly inferior prices, consistent with compensation for inventory risk. This effect, however, is primarily driven by U.S. and German equities. Execution prices worsen by about 9 bps per additional million euros in SP trade size for U.S. equities and by around 5 bps for German equities, while for ETFs the effect is economically negligible (about 0.5 bps). These results corroborate our earlier findings that inventory-based explanations are of limited relevance for ETF SP trades. Despite their comparatively large trade size, SP trades in ETFs display price differences that are largely unrelated to inventory considerations.

We observe some evidence of less favorable trades on the first SP day, but only for ETFs and under the Xetra benchmark. This pattern could be driven by larger aggregate parent trades on the first SP day, which typically exhibit higher trading volume compared to subsequent days. Moreover, the coefficient on the number of child trades on a SP day in a specific security is statistically significant and negative for ETFs, suggesting that splitting aggregate SP trades into a higher number of child trades modestly improves execution quality. While statistically discernible, the magnitude of this effect is economically small. For U.S. equities, the relationship is positive, indicating that splitting up SP trades does not improve execution outcomes, and for German equities, the limited number of observations with multiple child trades, combined with resulting multicollinearity issues, precludes meaningful inference and is thus omitted.

When combining SP trades from all securities in the full model, we find that ETF SP trades are executed at slightly inferior prices (by about 1 bps) compared to equity SPs. As we control for standard costs for liquidity provision and trading conditions, this difference between equity and ETF SPs remains questionable. Consistent with our earlier results, the interaction term $ETF_i \cdot Trade\ Size_{i,t}$ nearly offsets the direct size effect, indicating that inventory risks again do not materially influence ETF SP trades despite their large size.

The control variables enter with signs broadly consistent with prior analyses: higher short-term volatility is associated with larger price deteriorations for ETFs but not for equities, and greater market capitalization corresponds to slightly better execution prices for equity SPs. Higher order book depth is beneficial for the execution outcome of ETF SPs, while we find the opposite for equity SPs. Highly robust across all security types, a higher order imbalance indicating market pressure on the bid side is related to worse execution outcomes of SP trades, which are always buyer-initiated trades.

Under the alternative LS VWAP benchmark, coefficient directions and magnitudes remain qualitatively similar though statistical significance weakens, underscoring the robustness but also the limited economic magnitude of the effects.

Several limitations should be acknowledged. Our identification of SP trades relies on pattern recognition based on volume and timing, which may not capture all SP trades with perfect accuracy. The analysis also focuses on a single broker–venue pair within one regulatory environment, which limits generalizability. Future research

could extend this framework to other retail trading venues, brokers, or asset classes, and examine how execution quality and market maker pricing evolve once PFOF arrangements are phased out and competition in retail execution intensifies.

Taken together, the results of our analysis suggest that standard microstructure theories cannot fully account for the observed price differences in SP trades. SP trades do not expose market makers to adverse selection risks and, at least in case of SP trades in ETFs, do not appear to expose market makers to meaningful inventory costs. Hence, the deviations from benchmark prices likely stem from differences in market-maker procurement strategies, potentially allowing market makers to capture structural rents rather than merely compensating for risk.

5. Conclusion

This paper provides the first systematic analysis of the execution quality of automated SP trades in a major European retail trading venue. Using detailed trade data from LS Exchange, a specialized retail trading platform where a single market maker executes all order flow, we identify SP trades based on characteristic volume and timing patterns and benchmark their execution prices against contemporaneous quotes of the reference market Xetra and alternative LS Exchange-based measures.

Our results show that SP trades, despite their predictable and often large size, are typically executed at prices close to the Xetra best ask, indicating generally high execution quality from the perspective of individual investors. Nevertheless, we document small but systematic price differences relative to benchmark prices, on average around one bps, indicating that the market maker extracts modest rents from this uninformed and predictable retail flow. Moreover, SP trades are executed at slightly less favorable prices than similarly large non-SP trades, indicating that market makers price predictable SP order flow differently from comparable discretionary retail trades, despite the completely uninformed nature of SP order flow. These price discrepancies are most pronounced for ETFs, where SP activity is concentrated, and cannot be attributed to inventory costs, which play virtually no role in this segment and only partially explain price differences for SPs in individual stocks.

Regression analyses reveal that execution quality systematically varies with trade size, market capitalization, and timing. Larger SP trades tend to be priced less favorably, particularly for equity SPs, consistent with temporary inventory or risk-management effects. In contrast, for ETF SPs, the expected deterioration with trade size is largely absent, indicating that inventory risk does not meaningfully drive execution prices in this segment.

From a retail investor's perspective, the observed execution differences are economically small in isolation but accumulate across the large aggregate volume of SP trades executed monthly. From a market structure perspective, the evidence demonstrates that even in an environment without adverse selection, market makers charge markups and capture rents from predictable retail trading, raising questions about the competitiveness and transparency of retail execution models. This highlights the importance of transparency and competition in retail order execution, particularly in light of the forthcoming EU ban on PFOF from 2026 onward.

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Appendix A. Included Securities and Descriptive Statistics

Table A.1: Overview of covered ETFs and equities

This table lists all ETFs and individual equities included in our analysis of SP trade execution quality. It shows the first and last month for which an SP trade is observable in the dataset. Since Trade Republic introduced equity SPs in September 2020, the sample begins in October 2020 for both equities and ETFs to ensure that all analyzed securities have established SPs. Observation periods start later for non-iShares ETFs because Trade Republic began offering Xtrackers and Amundi ETFs from March 2021 onward and added Vanguard and SPDR ETFs in October 2022 (we again start one month later to ensure that SPs have been established). Similarly, the *iShares Physical Gold ETC* appears from March 2021 onward. For most equities, SP observations start in October 2020, with exceptions for firms that gained investor interest after specific events (e.g., *Rheinmetall AG* following the Russian invasion of Ukraine) or after their IPO in case of *Coinbase Global Inc.*

ISIN	Type	Name	Start Date	End Date
DE0005933931	ETF	iShares Core DAX UCITS ETF (DE) EUR (Acc)	2020-10	2025-06
DE000A0F5UF5	ETF	iShares Nasdaq 100 UCITS ETF (DE)	2020-10	2025-06
IE00B0M62Q58	ETF	iShares MSCI World UCITS ETF (Dist)	2020-10	2025-06
IE00B1XNHC34	ETF	iShares Global Clean Energy Transition UCITS ETF USD (Dist)	2020-10	2025-06
IE00B3WJKG14	ETF	iShares S&P 500 Information Technology Sector UCITS ETF USD (Acc)	2020-10	2025-06
IE00B4L5Y983	ETF	iShares Core MSCI World UCITS ETF USD (Acc)	2020-10	2025-06
IE00B53SZB19	ETF	iShares Nasdaq 100 UCITS ETF (Acc)	2020-10	2025-06
IE00B5BMR087	ETF	iShares Core S&P 500 UCITS ETF USD (Acc)	2020-10	2025-06
IE00B6R52259	ETF	iShares MSCI ACWI UCITS ETF USD (Acc)	2020-10	2025-06
IE00BKM4GZ66	ETF	iShares Core MSCI Emerging Markets IMI UCITS ETF (Acc)	2020-10	2025-06
IE00BYX2JD69	ETF	iShares MSCI World SRI UCITS ETF EUR (Acc)	2020-10	2025-06
IE00B4ND3602	ETF	iShares Physical Gold ETC	2021-05	2025-06
LU0908500753	ETF	Amundi Core Stoxx Europe 600 UCITS ETF (Acc)	2021-04	2025-06
LU1681048804	ETF	Amundi S&P 500 Swap UCITS ETF EUR (Acc)	2021-04	2025-06
IE00BFY0GT14	ETF	SPDR MSCI World UCITS ETF	2022-11	2025-06
IE00B3RBWM25	ETF	Vanguard FTSE All-World UCITS ETF USD (Dist)	2022-11	2025-06
IE00BK5BQT80	ETF	Vanguard FTSE All-World UCITS ETF USD (Acc)	2022-11	2025-06
IE00BGV5VN51	ETF	Xtrackers Artificial Intelligence & Big Data UCITS ETF 1C	2021-04	2025-06
IE00BJ0KDDQ92	ETF	Xtrackers MSCI World UCITS ETF 1C	2021-04	2025-06
LU0274211480	ETF	Xtrackers DAX UCITS ETF 1C	2021-04	2025-06
DE0005140008	German Equity	Deutsche Bank AG	2020-10	2025-06
DE0005557508	German Equity	Deutsche Telekom AG	2020-10	2025-06
DE0007030009	German Equity	Rheinmetall AG	2021-04	2025-06
DE0007100000	German Equity	Mercedes Benz Group AG	2020-10	2025-06
DE0007164600	German Equity	SAP SE	2020-10	2025-06
DE0007664039	German Equity	Volkswagen AG Vz	2020-10	2025-06
DE0008404005	German Equity	Allianz SE	2020-10	2025-06
DE000BASF111	German Equity	BASF SE	2020-10	2025-06
DE000BAY0017	German Equity	Bayer AG	2020-10	2025-06
DE000ENER6Y0	German Equity	Siemens Energy AG	2021-07	2025-06
US02079K3059	U.S. Equity	Alphabet Inc. Class A	2020-10	2025-06
US0231351067	U.S. Equity	Amazon.com Inc.	2020-10	2025-06
US0378331005	U.S. Equity	Apple Inc.	2020-10	2025-06
US09075V1026	U.S. Equity	BioNTech SE (ADR)	2021-07	2025-06
US19260Q1076	U.S. Equity	Coinbase Global Inc.	2021-05	2025-06
US5949181045	U.S. Equity	Microsoft Corp.	2020-10	2025-06
US67066G1040	U.S. Equity	NVIDIA Corp.	2020-10	2025-06
US69608A1088	U.S. Equity	Palantir Technologies Inc.	2021-01	2025-06
US70450Y1038	U.S. Equity	PayPal Holdings Inc.	2020-10	2025-06
US72919P2020	U.S. Equity	Plug Power Inc.	2020-10	2025-06
US88160R1014	U.S. Equity	Tesla Inc.	2020-10	2025-06

Table A.2: Daily trading statistics for Xetra and LS Exchange

This table reports descriptive statistics for buy-side trading activity on Xetra and LS Exchange from October 2020 to June 2025. Statistics are presented separately for SP days (the 2nd and 16th trading day of each month) and non-SP days (the trading day immediately following each SP day).

Panel (a): ETFs		
	Xetra	LS
Daily trades (SP day)	291	505
Daily trades (non-SP day)	216	453
Avg. trade size (SP day)	22,117	8,244
Avg. trade size (non-SP day)	21,600	2,255
Avg. daily trade volume (SP day)	5,135,193	3,671,869
Avg. daily trade volume (non-SP day)	3,671,797	837,910
Panel (b): German Equities		
	Xetra	LS
Daily trades (SP day)	6,954	599
Daily trades (non-SP day)	5,491	519
Avg. trade size (SP day)	9,512	2,835
Avg. trade size (non-SP day)	9,439	2,525
Avg. daily trade volume (SP day)	65,393,673	2,183,135
Avg. daily trade volume (non-SP day)	50,555,615	1,583,571
Panel (c): U.S. Equities		
	Xetra	LS
Daily trades (SP day)	597	1,403
Daily trades (non-SP day)	478	1,354
Avg. trade size (SP day)	9,207	2,988
Avg. trade size (non-SP day)	9,097	2,527
Avg. daily trade volume (SP day)	6,645,457	4,335,519
Avg. daily trade volume (non-SP day)	5,102,621	3,673,075

Table A.3: Descriptive statistics on non-SP execution price comparison

This table reports descriptive statistics for price differences in bps of the execution price of counterfactual non-SP trades which are comparable large in size compared with two pricing benchmarks: (a) the best ask price on Xetra, and (b) the VWAP on LS Exchange during 5 minutes prior to the trade.

	(a) Xetra Best Ask			(b) L&S VWAP t-5m		
	ETFs	US Stocks	DE Stocks	ETFs	US Stocks	DE Stocks
N	2,050.00	1,214.00	1,110.00	1,317.00	1,096.00	895.00
Mean	-0.35	-2.53	0.14	-0.37	1.28	-0.74
Std	1.24	7.91	4.43	6.98	28.15	12.41
Min	-12.01	-93.46	-142.50	-61.90	-128.00	-88.75
1%	-3.81	-27.98	-1.47	-21.89	-75.10	-35.89
25%	-0.36	-3.52	0.00	-2.82	-7.64	-6.51
Median	0.00	0.00	0.00	-0.07	0.00	-0.07
75%	0.00	0.00	0.00	1.99	9.67	4.81
99%	1.79	11.32	4.21	19.47	86.02	35.57
Max	24.70	75.47	14.50	63.84	346.88	75.36

Appendix B. Additional Information on Identified SP Trades

Table B.1: Example for Identification of SP Trades

Panel A shows all identified SP trades for *Microsoft Corp.* from October 2020 to December 2021. For brevity and readability, the table ends in December 2021 although the SP continues until the end of the observation period in June 2025. Panel B reports all buyer-initiated trades executed on LS Exchange for *Microsoft Corp.* on October 16, 2021, which is the second SP day in that month, between 16:30 and 16:45 local time. The identified SP trade with a size of 1,031 shares is highlighted in bold. In later periods, and particularly for ETFs, multiple SP trades can occur on a single SP day, as shown in the example in [Table B.2](#).

Panel A: Identified SP Trades for Microsoft Corp. from 2020-10 to 2021-12						Panel B: Buyer-Initiated Trades on 2021-12-16 from 16:30 to 16:45		
Date & Time	Volume	Price	Euro	Volume	SP Day	Time	Volume	Price
2020-10-02 16:35:14	723	179.50		129,779	1	16:45:34	2	293.45
2020-10-16 16:37:03	713	189.20		134,900	2	16:43:48	2	293.50
2020-11-02 16:35:34	995	174.98		174,105	1	16:43:25	58	293.50
2020-11-16 16:35:21	848	183.32		155,455	2	16:43:02	1	293.60
2020-12-02 16:35:36	1,186	176.98		209,898	1	16:42:25	52	293.60
2020-12-16 16:35:21	922	178.00		164,116	2	16:42:17	30	293.85
2021-01-04 16:35:38	1,149	179.70		206,475	1	16:41:25	53	293.65
2021-01-18 16:35:13	1,012	176.12		178,233	2	16:41:03	3	293.70
2021-02-02 16:35:24	1,220	199.88		243,854	1	16:40:25	56	293.80
2021-02-16 16:35:31	1,011	201.65		203,868	2	16:39:25	62	293.70
2021-03-02 16:35:30	1,297	194.46		252,215	1	16:39:07	50	293.65
2021-03-16 16:35:20	923	201.65		186,123	2	16:38:25	58	293.75
2021-04-06 16:35:27	1,154	209.10		241,301	1	16:38:17	3	293.70
2021-04-16 16:35:15	1,055	216.45		228,355	2	16:37:57	1	293.45
2021-05-03 16:37:58	1,528	210.55		321,720	1	16:37:39	1	293.35
2021-05-17 16:35:26	1,217	201.55		245,286	2	16:37:25	53	293.30
2021-06-02 16:35:48	1,565	204.05		319,338	1	16:36:25	52	293.20
2021-06-16 16:35:23	1,113	214.30		238,516	2	16:35:52	1,031	293.45
2021-07-02 16:36:51	1,494	232.60		347,504	1	16:35:28	5	293.45
2021-07-16 16:35:58	1,181	238.95		282,200	2	16:35:23	1	293.45
2021-08-02 16:35:40	1,639	240.10		393,524	1	16:33:46	10	293.25
2021-08-16 16:36:26	1,272	247.20		314,438	2	16:33:01	2	293.55
2021-09-02 16:35:53	1,819	255.20		464,209	1	16:32:16	13	293.45
2021-09-16 16:36:00	1,342	257.10		345,028	2	16:31:52	30	293.75
2021-10-04 16:35:42	1,862	242.30		451,163	1	16:31:42	2	293.90
2021-10-18 16:36:54	1,227	261.60		320,983	2	16:31:22	6	294.25
2021-11-02 16:36:14	1,388	287.30		398,772	1	16:31:14	2	294.20
2021-11-16 16:36:01	1,068	297.10		317,303	2	16:31:07	5	294.25
2021-12-02 16:37:14	1,521	290.70		442,155	1	16:30:33	1	294.30
2021-12-16 16:35:52	1,031	293.45		302,547	2	16:30:17	11	294.15

Table B.2: Example for identification of SP trades

Panel A shows all identified SP trades for the *Amundi S&P 500 Swap UCITS ETF EUR (Acc)* from January 2025 to June 2025. For brevity and readability, the table only begins in January 2025. Panel B reports all buyer-initiated trades executed on LS Exchange in the same ETF on June 2, 2025, which is the first SP day of that month, between 16:09 and 16:59 local time. The identified SP trades on that day are highlighted in bold.

Panel A: Identified SP Trades for the Amundi S&P 500 Swap UCITS ETF EUR (Acc) from 2025-01 to 2025-06					Panel B: Buyer-Initiated Trades on 2025-06-02 from 16:09 to 16:59		
Date & Time	Volume	Price	Euro Volume	SP Day	Time	Volume	Price
2025-01-02 17:08:56	8,463	112.785	954,499	1	16:59:34	1	101.955
2025-01-02 17:12:12	9,946	112.900	1,122,903	1	16:59:34	4	101.920
2025-01-02 17:12:20	9,877	112.905	1,115,163	1	16:59:24	1	101.910
2025-01-02 17:13:37	9,827	112.805	1,108,535	1	16:58:46	1	101.890
2025-01-16 16:23:56	4,188	113.550	475,547	2	16:58:46	9	101.890
2025-01-16 16:25:17	9,632	113.535	1,093,569	2	16:55:44	1	101.840
2025-01-16 16:25:38	9,843	113.475	1,116,934	2	16:55:44	9	101.840
2025-02-03 16:35:17	2,340	114.160	267,134	1	16:55:13	1	101.825
2025-02-03 16:40:47	9,672	114.225	1,104,784	1	16:54:50	1	101.830
2025-02-03 16:45:34	9,623	114.330	1,100,198	1	16:54:48	9	101.855
2025-02-03 16:47:23	9,587	114.390	1,096,657	1	16:50:44	3	101.830
2025-02-03 17:17:41	9,354	114.410	1,070,191	1	16:50:22	3	101.825
2025-02-17 16:24:54	4,704	114.915	540,560	2	16:50:17	2	101.825
2025-02-17 16:26:42	9,419	114.895	1,082,196	2	16:49:26	2	101.795
2025-02-17 16:26:43	9,516	114.905	1,093,436	2	16:46:56	1	101.790
2025-03-03 16:34:13	2,671	111.590	298,057	1	16:45:30	1	101.755
2025-03-03 16:43:23	9,760	111.775	1,090,924	1	16:45:30	3	101.760
2025-03-03 16:43:23	9,534	111.775	1,065,663	1	16:44:52	1	101.730
2025-03-03 16:43:23	9,717	111.775	1,086,118	1	16:44:18	2	101.725
2025-03-03 16:44:57	9,653	111.890	1,080,074	1	16:43:40	9,756	101.710
2025-03-17 16:31:40	4,425	101.850	450,686	2	16:43:37	9,392	101.720
2025-03-17 16:32:07	10,101	101.825	1,028,534	2	16:43:13	2	101.700
2025-03-17 16:32:43	9,912	101.790	1,008,942	2	16:43:11	9,763	101.730
2025-04-02 16:41:31	9,925	102.505	1,017,362	1	16:43:10	9,561	101.730
2025-04-02 16:42:26	9,975	102.500	1,022,438	1	16:42:52	1	101.735
2025-04-02 16:43:44	9,849	102.400	1,008,538	1	16:42:52	2	101.735
2025-04-02 16:43:48	1,774	102.415	181,684	1	16:42:07	1	101.735
2025-04-02 16:48:17	9,893	102.310	1,012,153	1	16:42:07	3	101.735
2025-04-16 16:23:55	4,768	92.578	441,412	2	16:41:41	3	101.780
2025-04-16 16:24:46	10,404	92.658	964,014	2	16:39:40	3	101.705
2025-04-16 16:24:46	10,468	92.660	969,965	2	16:34:37	1,651	101.720
2025-05-02 16:24:40	1,213	98.484	119,461	1	16:32:51	1	101.690
2025-05-02 16:25:40	9,873	98.466	972,155	1	16:32:50	3	101.700
2025-05-02 16:25:40	9,946	98.466	979,343	1	16:29:36	3	101.725
2025-05-02 16:25:40	10,001	98.466	984,758	1	16:27:03	2	101.730
2025-05-02 16:25:40	10,070	98.466	991,553	1	16:23:35	2	101.665
2025-05-16 16:23:59	4,526	104.555	473,216	2	16:22:33	1	101.605
2025-05-16 16:24:18	8,894	104.575	930,090	2	16:22:29	4	101.605
2025-05-16 16:24:37	9,023	104.565	943,490	2	16:22:23	1	101.600
2025-06-02 16:34:37	1,651	101.720	167,940	1	16:17:11	1	101.500
2025-06-02 16:43:10	9,561	101.730	972,641	1	16:16:08	3	101.435
2025-06-02 16:43:11	9,763	101.730	993,190	1	16:14:21	1	101.490
2025-06-02 16:43:37	9,392	101.720	955,354	1	16:14:21	4	101.500
2025-06-02 16:43:40	9,756	101.710	992,283	1	16:11:45	1	101.390
2025-06-16 16:24:48	4,426	102.920	455,524	2	16:11:43	2	101.370
2025-06-16 16:26:57	9,159	102.920	942,644	2	16:10:07	10	101.435
2025-06-16 16:26:57	8,957	102.920	921,854	2	16:09:58	1	101.460

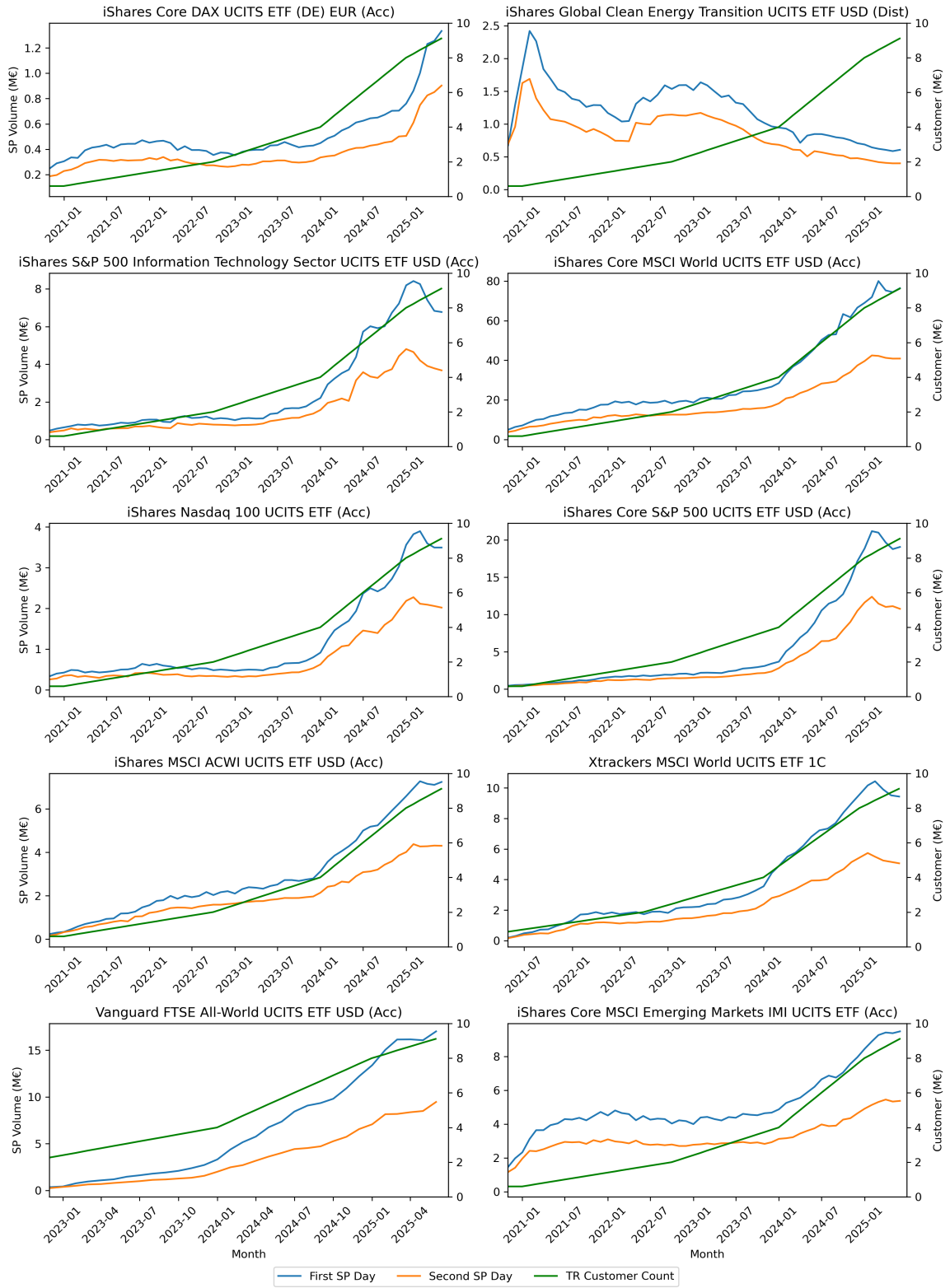


Figure B.1: SP trade volume for ETFs over time (part 1)

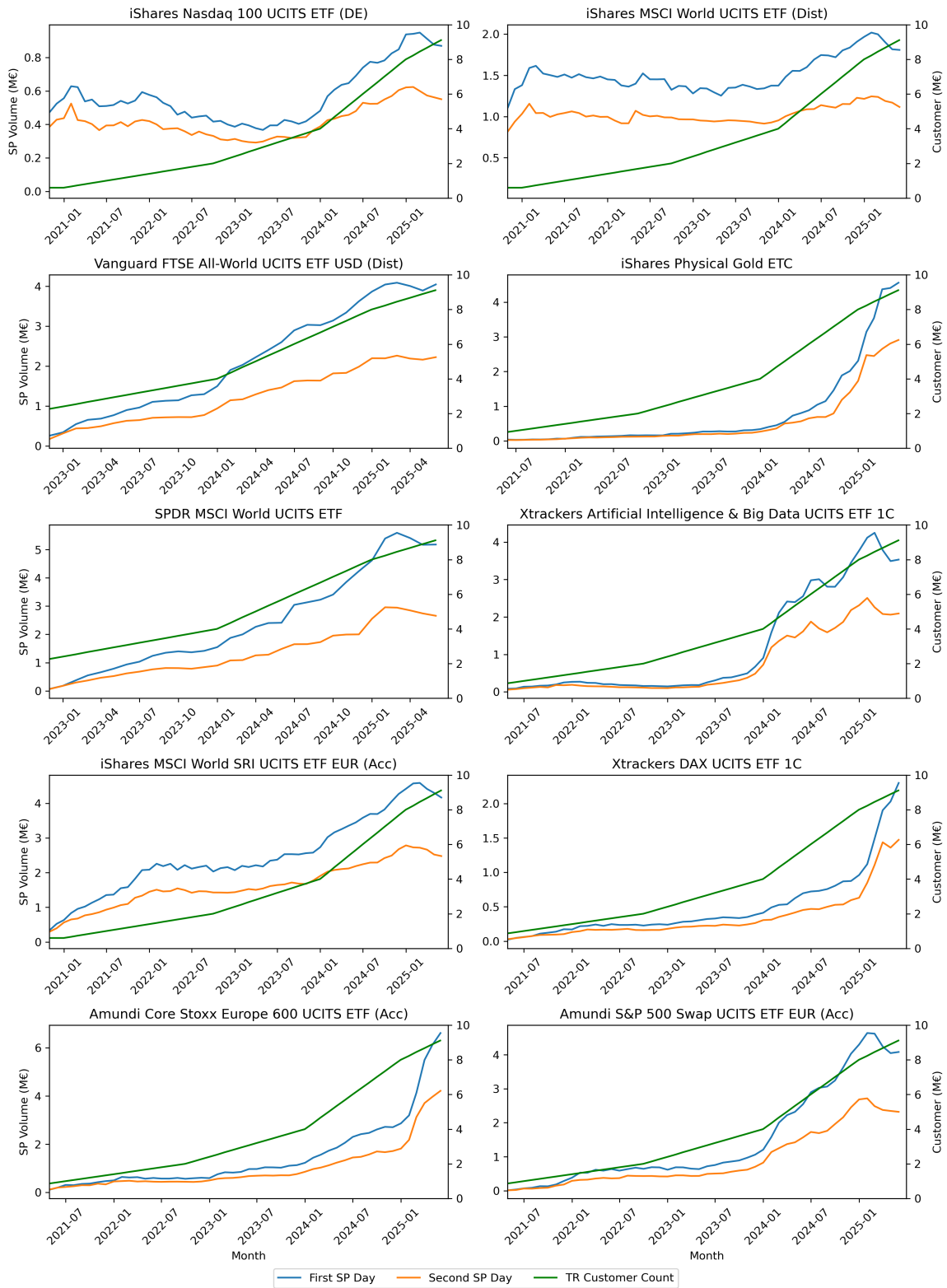


Figure B.2: SP trade volume for ETFs over time (part 2)

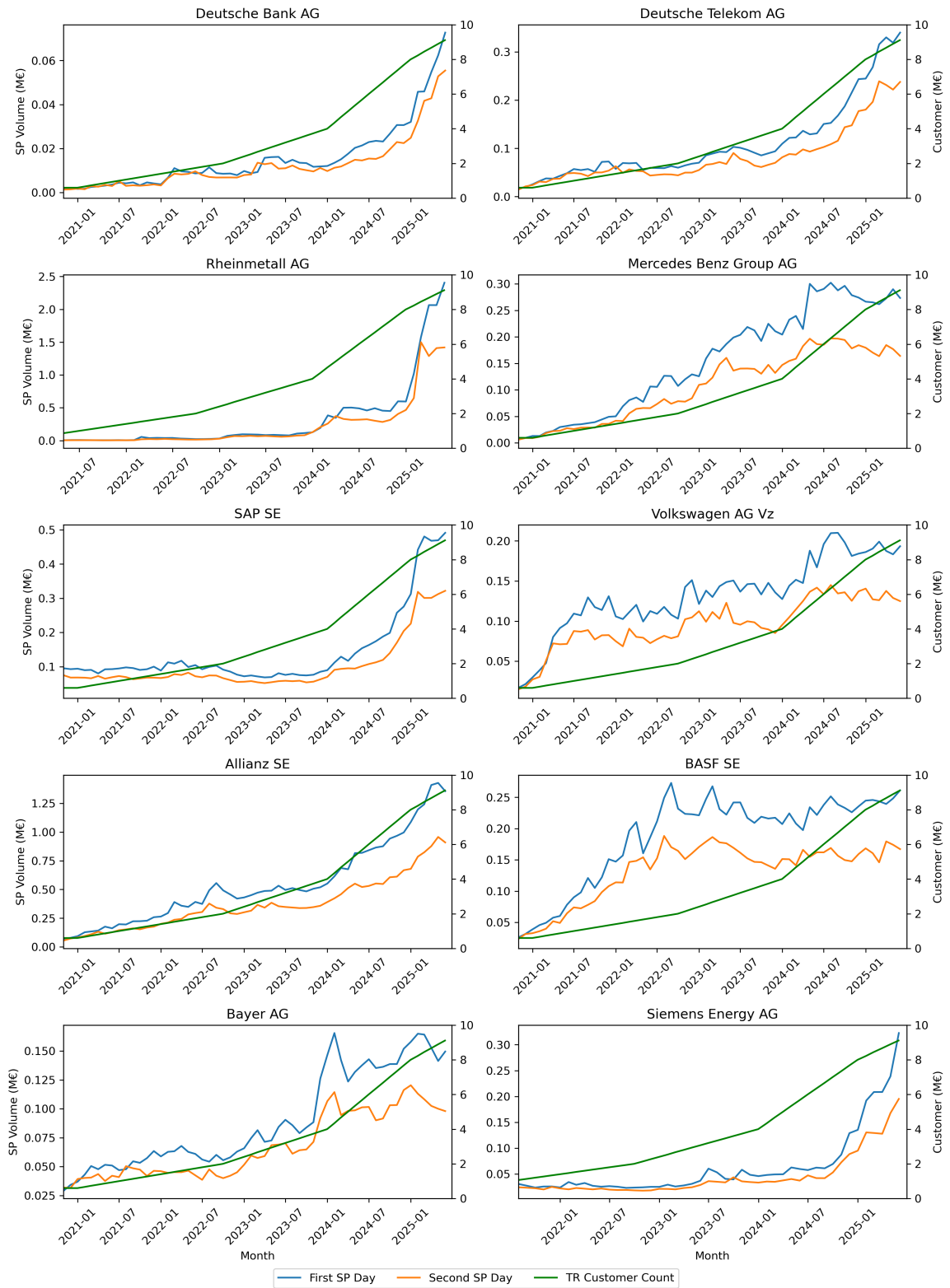


Figure B.3: SP trade volume for German Stocks over time

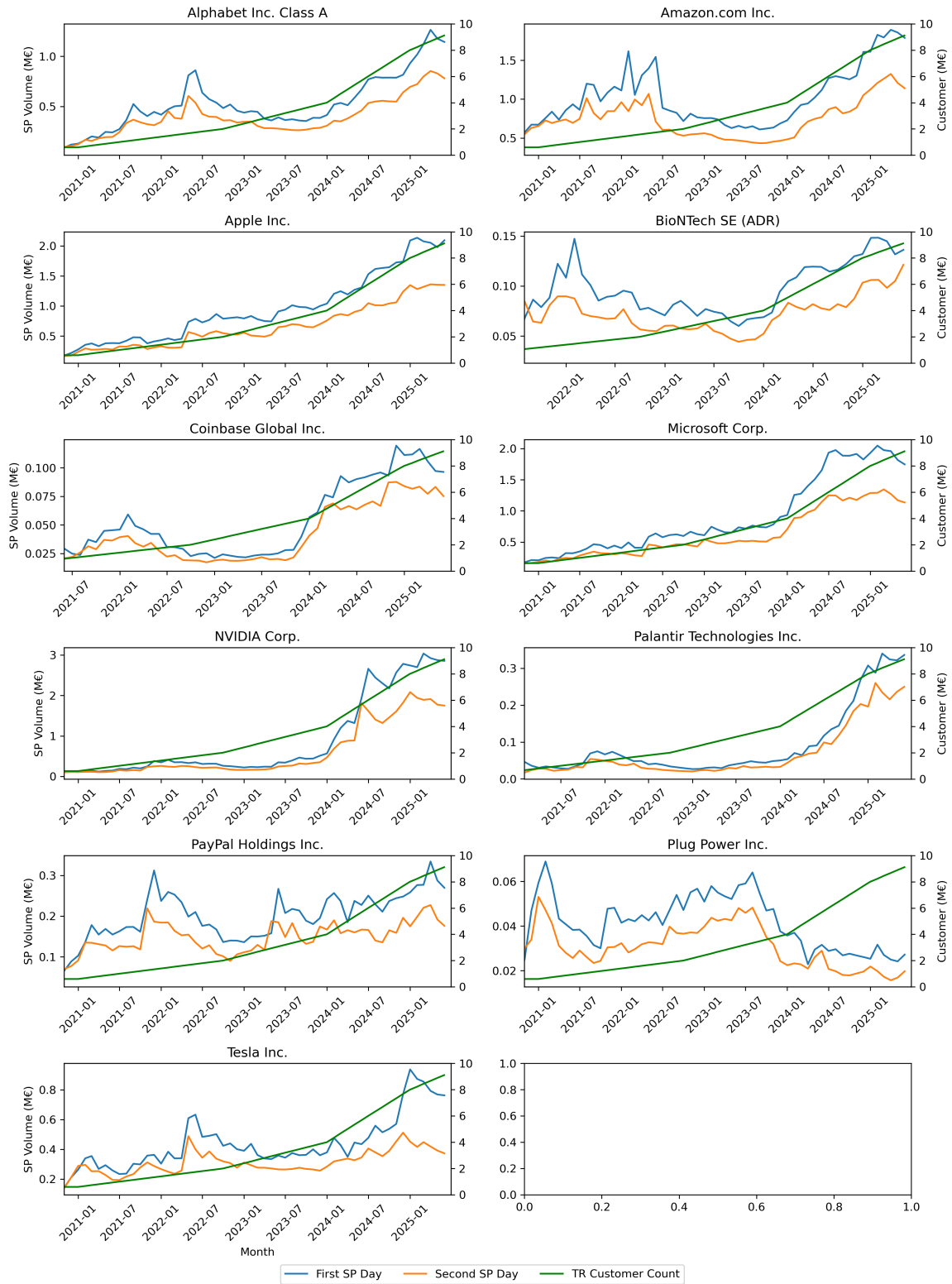


Figure B.4: SP trade volume for U.S. Equities over time

Appendix C. Identification Algorithm for SP Trades

This appendix provides a detailed, step-by-step description of the procedure used to identify SP trades in transaction-level data from LS Exchange. The algorithm builds on the recurring execution patterns of automated investment plans and is designed to distinguish bundled SP trades from regular market activity.

Step 1. Data Preparation

1. Collect transaction-level data for all securities traded on LS Exchange, including trade volume, price, timestamp, and buy/sell indicator.
2. Restrict the sample to trading days that correspond to potential SP days, namely the 2nd and 16th of each month.
3. If an SP day falls on a weekend or public holiday, shift to the next trading day which then becomes the SP day.
4. Separate data by security and SP day for all subsequent steps.

Step 2. Outlier Detection

1. For each security and SP day, calculate the z-score of each trade's volume relative to the mean and standard deviation of volumes on that day:

$$z_{i,t} = \frac{V_{i,t} - \mu_t}{\sigma_t},$$

where $V_{i,t}$ denotes the trade volume of transaction i on day t , μ_t is the mean trade volume of all buyer-initiated transactions on that day, and σ_t is the corresponding standard deviation.

2. Flag all trades with z-score > 3 as volume outliers and retain them as initial SP trade candidates.

Step 3. Identification of Candidate SP Trades

1. For each security, evaluate the set of flagged trades based on:
 - (a) Trade volume (must be large relative to other trades),
 - (b) Execution time (recurring timestamps across SP days within Xetra hours), and
 - (c) Number of constituent trades (similar to previous and subsequent SP days).
2. Restrict attention to buyer-initiated trades only.
3. Identify clusters of large trades that occur at similar times of day across SP days.
4. Mark these clusters as candidate SP trades.

Step 4. Forward-Backward-Induction and Cross-SP-Day Comparisons

1. Apply a forward-backward-induction procedure to refine and expand the identified set of SP trades by identifying smaller but still large trades with lower z-scores that occur close in time to a detected SP trade or on SP days where no SP trade was identified in the previous step by ensuring that:
 - (a) These trades are still large relative to other trades and occur at similar times of day.
 - (b) Both individual and cumulative volumes should be comparable in size to those on previous and subsequent SP days.
 - (c) The cumulative volume of all SP child trades on a given day should exhibit a parallel development between the first and second SP day of each month.
 - (d) The number of child trades per SP day exhibits a stepwise increase over time and parallel trends between the first and second SP day of each month.
 - (e) Ensuring temporal and structural consistency across days.
2. Add all trades that meet these temporal and pattern-based criteria to the SP dataset.

Step 5. Consistency Verification

1. For each identified SP, verify time- and volume-consistent patterns across all SP days for a given security:
 - (a) A stable, typically increasing development in cumulative trading volume per SP day, without abrupt jumps.
 - (b) A stable or stepwise increase in the number of executions per SP day.
 - (c) Parallel or recurring timing patterns between the first and second SP day of each month (e.g., parallel trends in trading volume and the number of child trades per SP day).
2. Exclude trades that do not exhibit these systematic patterns or that occur only once without cross-day recurrence.

Step 6. Researcher Validation

1. The full identification process is independently replicated by three researchers.
2. Only trades for which all researchers reach consensus are retained in the final dataset.
3. The final list of identified SP trades is used for the analysis of SP execution quality.

Appendix D. Additional Results and Robustness Tests

Figure D.5: Comparison of execution quality of SP and large non-SP trades relative to the trade volume

This figure shows the execution quality measured as price differences between execution price of SP trades and the best ask price on Xetra in the right column and large-in-scale non-SP trades in the left column. Each column shows the results differentiated for asset classes, namely ETFs, U.S. Equities and German Equities. Large non-SP trades are observed on the day after an SP execution day as the largest transaction on that day. The price differences on the y-axis are given in bps and red colored observations indicate worse execution, green colored observations indicate price improvements and black points constitute observations executed exactly at the benchmark price. The x-axis shows the trade volume in millions of euros. A regression line is shown as a gray dotted line. The price differences are winsorized at the 1% and 99% level, respectively.

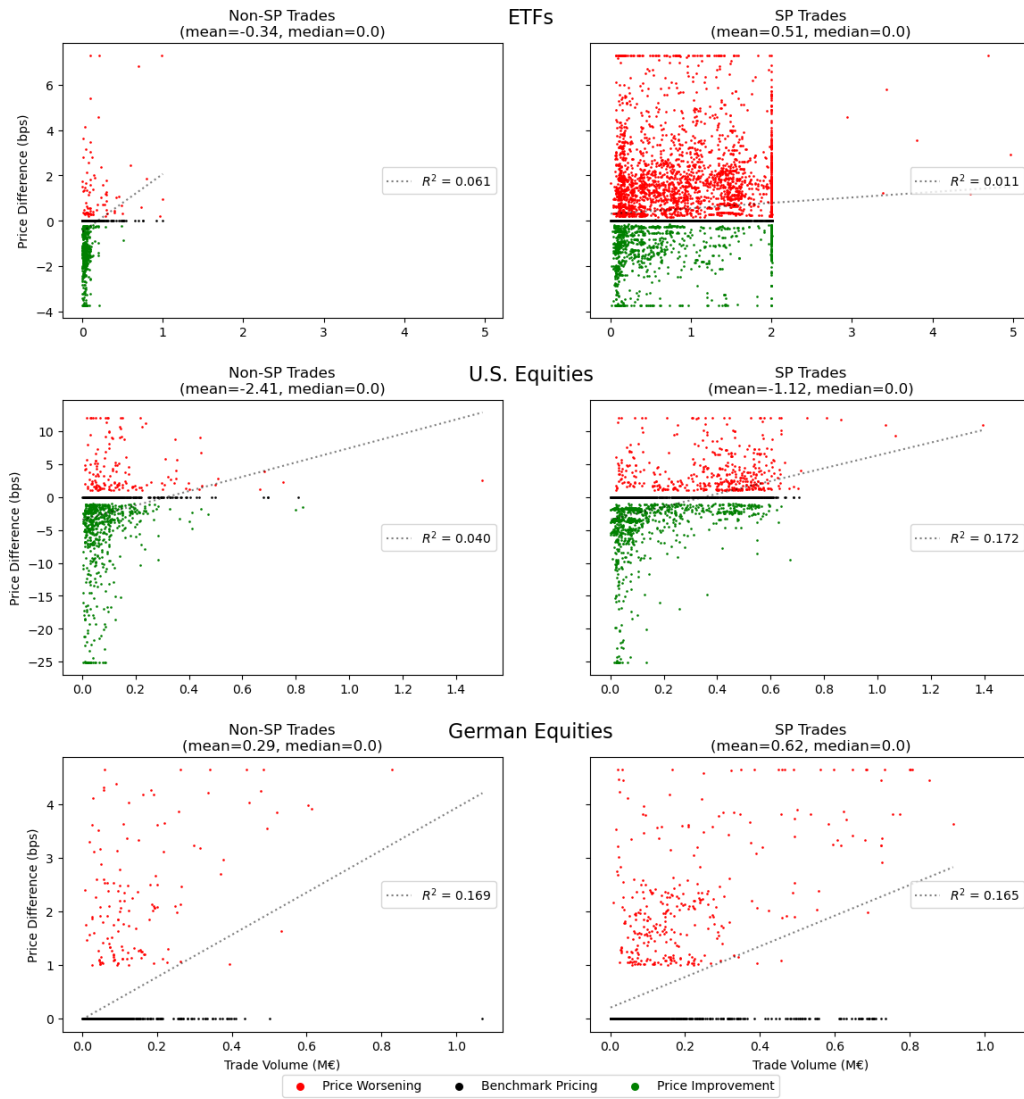


Table D.3: Regression results on execution quality of SP and non-SP trades

This table shows the regression results on the execution quality of SP and large-in-scale non-SP trades for three asset classes: ETFs, U.S. equities and German equities. The dependent variable is the difference of execution price and the benchmark price in bps. Two benchmarks are used in this regression: the best ask price on Xetra at the same time and the VWAP on LS Exchange measured over 5 minutes prior to the trade. Trade size is the volume of the (non-)SP trade in millions of euros. SP is a dummy variable which takes one if the trade is an SP trade. Volatility is given as a daily annualized measure of the log midpoint returns. Relative spread is measured as the daily time-weighted average and log trading volume is measured based on the summed daily trading volume. The order book imbalance is given as the daily time-weighted average level one imbalance. Level one depth is given as the total quoted euro volume at the best bid and ask. Order book imbalance is calculated as the volume on the best bid divided by the total quoted volume on the first order book level. Market capitalization is measured in millions of euros. Inverse price is calculated as one divided by the closing auction price of the respective trading day. To mitigate issues regarding multicollinearity, we exclude the relative spread for the German equities regression model as well as the order book imbalance in both equity-based regression models. Asterisks denote that the coefficient is different from zero at the 90% (*), 95% (**), and 99% (***) confidence levels, respectively.

	ETFs (Best Ask)	U.S. Equities (Best Ask)	DE Equities (Best Ask)	ETFs (LS VWAP)	U.S. Equities (LS VWAP)	DE Equities (LS VWAP)
Intercept	-0.46	0.19	-1.22	0.52	-6.58	1.53
Trade Size (M€)	4.09***	9.75***	5.16***	6.89***	-1.07	3.36
SP	1.05***	0.43	0.37**	1.60***	0.75	1.75**
Trade Size x SP	-3.62***	-2.25	-1.52	-6.33***	4.31	1.30
Volatility	2.46***	0.99	1.65	1.57	24.09***	4.68
Relative Spread	0.01	-0.15***		0.14***	-0.08	
Level 1 Depth	0.00	0.00***	0.00***	0.00	0.00	0.00
Log Trading Volume	-0.10***	-0.23	0.11	-0.13	-0.87	-1.88**
OBI	0.68***			0.18		
Market Cap	-8.44***	-0.82**	-4.04	12.04	-1.59	10.46
Inverse Price	-4999.88*	2463.77	2345.27	-13 537.62	10 489.14	-13 953.36
R-squared	0.14	0.19	0.07	0.05	0.05	0.07
R-squared Adj.	0.14	0.17	0.04	0.04	0.02	0.03
Entity FE	yes	yes	yes	yes	yes	yes
Year-Month FE	yes	yes	yes	yes	yes	yes

Table D.4: Regression results on drivers of pricing differences for SP trades

This table shows the regression results on the execution quality of SP trades for three asset classes: ETFs, U.S. equities, German equities, as well as a full model. The dependent variable is the difference of execution price and the benchmark price in bps. Two benchmarks are used in this regression: the best ask price on Xetra at the same time and the VWAP on LS Exchange measured over 5 minutes prior to the trade. Trade size is the volume of the SP trade in millions of euros. SP day 1 is a dummy variable which takes one if the trade is an SP trade on the first monthly SP day, i.e. the 2nd. The number of child trades measures how many SP trades are executed in the same asset on the same day. Volatility is given as a daily annualized measure of the log midpoint returns. Relative spread is measured as the daily time-weighted average and log trading volume is measured based on the summed daily trading volume. The order book imbalance is given as the daily time-weighted average level one imbalance. Level one depth is given as the total quoted euro volume at the best bid and ask. Order book imbalance is calculated as the volume on the best bid divided by the total quoted volume on the first order book level. Market capitalization is measured in millions of euros. Inverse price is calculated as one divided by the closing auction price of the respective trading day. A ETF dummy is included in the full model which takes one if the asset is an ETF. To mitigate issues regarding multicollinearity, we exclude the relative spread and number of child trades for the German equities regression model as well as the order book imbalance for all equity based models. Asterisks denote that the coefficient is different from zero at the 90% (*), 95% (**), and 99% (***) confidence levels, respectively.

	ETFs (Best Ask)	U.S. Equities (Best Ask)	DE Equities (Best Ask)	All (Best Ask)	ETFs (LS VWAP)	U.S. Equities (LS VWAP)	DE Equities (LS VWAP)	All (LS VWAP)
Intercept	0.09	2.68*	−0.06	0.95*	3.67	−1.82	−3.56	−2.16
Trade Size (M€)	0.48***	8.75***	4.51***	7.68***	0.67***	1.43	6.27*	5.02***
SP Day 1	0.43***	0.28	0.03	0.33***	−0.30	1.09	0.02	0.02
No. Child Trades	−0.02***	0.09**		−0.01***	0.01	0.02		0.00
Volatility	2.27***	−1.39	1.70***	−0.64	0.46	8.86**	−1.44	5.07***
Relative Spread	0.03***	−0.10***		−0.07***	0.26***	−0.05		0.02
Level 1 Depth	0.00	0.00***	0.00***	0.00**	0.00	0.00	0.00	0.00
Log Trading Volume	−0.26***	−0.04	0.13	−0.03	−0.31	−0.44	−1.63	−0.23
OBI	0.89***			0.91***	−0.06			−0.53
Market Cap	5.72	−1.32***	−4.98***	−1.00***	8.54	−2.24	18.29	−0.14
Inverse Price	−7374.97**	4108.46**	−5375.05*	3106.98***	−17 954.78	11.25	38 325.32	404.93
ETF				0.88***				1.60
ETF x Trade Size				−7.25***				−4.53***
R-squared	0.16	0.27	0.43	0.22	0.06	0.07	0.11	0.04
R-squared Adj.	0.15	0.24	0.39	0.22	0.05	0.03	0.04	0.03
Entity FE	yes	yes	yes	yes	yes	yes	yes	yes
Year-Month FE	yes	yes	yes	yes	yes	yes	yes	yes