Into the Dark

A study of the 2014, 2019, and 2020 post-trade anonymity reforms at Nasdaq Nordic and their impact on metrics of market quality

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Abstract

We test the impact of three post-trade anonymity regimes implemented by Nasdaq Nordic in 2014, 2019, and 2020. Using a sample of Mid Cap and Large Cap stocks listed in Stockholm, Copenhagen, and Helsinki, we examine the effect of different anonymity setups on standard measures of market quality through a difference-in-differences approach. Contrary to recent literature, we are unable to establish a market-wide relationship between post-trade anonymity and improved liquidity. In aggregate, daily relative bid-ask spreads do not tighten following the introduction of anonymity, nor does daily turnover increase. Post-trade anonymity does, however, improve bid-ask spreads by about six percent for the very largest stocks, which are characterised by lower information asymmetry as well as higher international and high-frequency trading activity. Our discussion suggests that the information content of broker codes, and thus the effect of post-trade anonymity, has been diluted by technological advancements and recent market reforms at Nasdaq Nordic.

Keywords: Market microstructure, Post-trade anonymity, Broker codes, Liquidity, Nasdaq Nordic

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1 Introduction

Does anonymous trading lead to better functioning markets? While theory and empirical research have not reached a definite answer, stock exchanges around the world have gradually decreased the degree to which market participant identities are revealed before (pre-trade anonymity) and after trades (post-trade anonymity), often claiming that anonymous markets are more efficient in terms of price discovery and trading costs. In this paper, we evaluate the introduction of three post-trade anonymity regimes in 2014, 2019, and 2020 on the Nasdaq Nordic exchanges in Stockholm, Copenhagen, and Helsinki. Specifically, we assess the impact of post-trade anonymity on relative end-of-day bid-ask spreads and daily turnover. Our research suggests that the different forms of post-trade anonymity implemented by Nasdaq Nordic do not improve liquidity in aggregate, but that trading in the very largest stocks, which are characterised by low information asymmetry and many international and high-frequency traders, benefit from post-trade anonymity.

Following the introduction of the MiFID regulation in 2007, Nasdaq Nordic introduced its first post-trade anonymity regime in 2008. While this regime was reversed after a year, Nasdaq Nordic has since then increased the level of post-trade anonymity in a stepwise fashion by introducing three additional post-trade anonymity regimes in 2014, 2019, and 2020. Using an event study methodology and a difference-in-differences approach, we exploit the quasi-experimental settings created by these regimes. We expect the 2014 regime, in which order book trading in Large Cap stocks switched from transparent to voluntarily anonymous, to decrease bid-ask spreads and increase overall turnover in line with recent literature. Following the 2019 and 2020 regimes, on the other hand, we do not expect market quality to improve. These regimes entail a move from voluntary to mandatory post-trade anonymity for index constituents (2019) and Large Cap stocks (2020), for which we expect investors who demand anonymity to already have opted for anonymous trading since the 2014 regime.

The theoretical argument for introducing post-trade anonymity is that it limits the amount of information market participants can infer from recently executed orders. With broker codes on display, uninformed traders can infer the private information of informed traders by observing their trading behaviour. The informed trader is forced to take costly measures, such as using multiple brokers, bluffing, or splitting orders into smaller trades, to conceal her private information. Under anonymity, however, she does not have to protect her private information, which reduces the costs of execution and makes her more willing to participate in trading. Through this mechanism, post-trade anonymity leads to better price discovery and lower spreads. While broker codes convey private information, the setting in which anonymity is introduced has the potential to alter outcomes to the extent that liquidity instead decreases. Risk-neutral informed traders, for example, impose greater price impact of their trades and thus higher costs to market markers for supplying liquidity, leading to higher spreads in post-trade anonymous markets. Similarly, the empirical evidence is also mixed, with studies documenting different effects of anonymity depending on the time period, country, and type of anonymity studied. However, studies on data from the late 2000s suggest that liquidity improves under post-trade anonymity.

Our contribution to the literature is threefold: (i) we study data from the 2010s, which is important because previous empirical studies suggest that the impact of anonymity is time-varying, (ii) we evaluate market-wide reforms on three major Nordic stock exchanges, including the Stockholm and Copenhagen stock exchanges which have not previously been studied in detail, and (iii) we examine Nasdaq Nordic's three regime introductions and thus not only the effect of anonymity, but also the incremental effect of switching from voluntary to mandatory post-trade anonymity.

Contrary to recent literature, we are unable to establish a market-wide relationship between post-trade anonymity and improved daily relative bid-ask spreads and turnover. While expected for the 2019 and 2020 regimes, we hypothesised that the 2014 regime would have had a positive impact on liquidity. When we extend our analysis of the 2014 regime, we do however find that post-trade anonymity improves bid-ask spreads by about six percent in the very largest stocks, which are characterised by lower information asymmetry as well as higher international and high-frequency trading activity. Potential explanations include that the information content of broker codes has been diluted in recent years and that major market reforms, such as the introduction of central counterparty clearing, have changed the market dynamics to the extent that the introduction of post-trade anonymity has no observable benefits in terms of liquidity. As such, our paper supports the idea that the impact of post-trade anonymity is time-varying.

The rest of the paper is organised as follows. Section 2 describes the Nasdaq Nordic exchanges, the regulatory setting, and the Nasdaq Nordic post-trade anonymity regimes. Section 3 reviews the theoretical and empirical literature on anonymous trading. Section 4 presents hypotheses and research contribution. Section 5 describes the research setting, data collection, and the difference-in-differences methodology. Section 6 presents and discusses the empirical results. Section 7 considers identification concerns and Section 8 concludes.

2 Institutional Setting

2.1 The Nasdaq Nordic stock exchanges

Nasdaq Nordic is a group of Northern European security marketplaces under the global Nasdaq brand with a combined market capitalisation of USD 2.6 trillion (WFE, 2022). It is the 12th largest group of exchanges worldwide with regulated markets in Stockholm, Copenhagen, Helsinki, and Iceland, as well as exchanges in the Baltics and a multilateral trading facility for smaller companies, First North Growth Market. In total, 1,236 companies were listed on the Nasdaq Nordic marketplaces as of December 2021. About half reside on the regulated main markets (608) in Stockholm (357), Helsinki (128), and Copenhagen (123) (Nasdaq, 2022).[1]

Companies listed on Nasdaq Nordic are also grouped in terms of size. There were 175 Large Cap, 231 Mid Cap, and 202 Small Cap companies listed on Nasdaq Nordic as of December 2021. Companies belong to one of the three segments based on their market capitalisation, where those with a market cap above EUR 1 billion belong in Large Cap, those with a market cap below EUR 150 million belong in Small Cap, and those in between belong in Mid Cap (Nasdaq, 2021). Since 2010, Nasdaq Nordic reviews its segments annually, based on the average market cap in November, with revisions taking effect on the first trading day the following year. To prevent excessive movement between segments, a company's market cap must be 50 percent above or below a threshold to qualify for a new segment in January. Companies whose market cap does not meet this criterion, while crossing a threshold, are subject to a one-year transition period and an additional review before qualifying for a new segment. Furthermore, each main market has a main index with its most traded stocks, representing the investible universe in each country (Nasdaq, 2022). For instance, Sweden has the OMX Stockholm 30 (OMXS30), which measures the performance of the 30 most traded stocks in Stockholm. Similarly, there is the OMX Copenhagen 25 (OMXC25) and the OMX Helsinki 25 (OMXH25).[2] While the constituent inclusion process differs slightly between the indexes, the main idea is to capture the performance of the most traded securities in each market. The indexes are reviewed bi-annually: in January and July for the OMXS30, June and December for the OMXC25, and February and August for the OMXH25.

In October 2009, Nasdaq Nordic introduced full central counterparty clearing (CCP) for all Large Cap stocks, and for all Mid Cap stocks in Helsinki (Nasdaq, 2009). By February 2015, CCP clearing

[1] The number of main market companies is retrieved from the 'Nasdaq Nordic Main Market Instruments' report and excludes companies main-listed in Norway and Iceland, companies on the Pre List and Xterna List, Special Purpose Acquisition Companies (SPACs), as well as equity warrants, rights, convertibles, and other non-equity securities.
[2] In December 2017, the OMX Copenhagen 25 replaced the OMX Copenhagen 20.

had been extended to the Mid Cap segments in Stockholm and Copenhagen (Nasdaq, 2014). The shift from bilateral clearing to CCP was the 'biggest structural change since trading became electronic in the early 1990s'. While reducing counterparty risk and transaction costs, another objective of CCP was to encourage international liquidity. From August 2009 to December 2014, the share of international trading at Nasdaq Nordic increased from 25 to 60 percent (Brazier, 2015). Another important market reform occurred in February 2010, when Nasdaq Nordic introduced the electronic high-speed order-pairing platform INET (Nasdaq, 2010). This platform is still in use and allows for conventional limit and market orders, as well as other order types.[3]

2.2 Regulatory background

2.2.1 MiFID

Markets in Financial Instruments Directive (MiFID) is a 2007 legal act of the European Union aimed at increasing investor protection, competition, and transparency by regulating securities markets, intermediaries, and trading venues (European Comission, 2010). MiFID requires operators of order-matching systems, such as Nasdaq Nordic, to disclose certain pre- and post-trade information (e.g., the five best quotes and depth of offers in order books). Operators are further required to display traded quotes and volume in near real time. Indirectly, MiFID also impacted pre- and post-trade market disclosure by (i) abolishing the 'concentration rule', (ii) introducing alternative trading venues, (iii) allowing investment firms to execute orders against internal order flow, and (iv) requiring investment firms to seek the most favourable options when executing client orders (Meling, 2021). Under the concentration rule, all trading took place on regulated domestic stock exchanges. With its abolishment, the introduction of alternative venues, internal order-matching, and best execution, order flow fragmented across many trading venues (e.g., Chi-X, BATS, Turquoise). New venues compete with traditional exchanges on trading conditions such as high bids and low asks, but also by offering attractive trading terms relating to, for example, anonymity. One type of trading venue that has grown in popularity is dark pools. Run by banks, exchanges, or independent operators, dark pools allow for completely anonymous trading. Prior to 2007, all non-dual listed stocks on Nasdaq Nordic traded only on Nasdaq Nordic marketplaces. Following MiFID, trading fragmented and Nasdaq Nordic's market share of order book trading in Nasdaq Nordic-listed stocks dropped to about 70 percent.

[3] Throughout the paper, we consider only trades routed through the Nasdaq Nordic order book. Our discussion and implications are not applicable for manual trades, which are subject to other anonymity policies (the Nasdaq Nordic Market Model contains information on manual trades). We also exclude Norwegian stocks that are admitted to trading at Nasdaq Stockholm, as these trade under the Oslo Stock Exchange post-trade anonymity regulation.

2.2.2 MiFID 2 and MiFIR

In 2014, an updated version of MiFID was approved which included fewer exemptions and a broader scope of financial companies, products, and activities (Finberg, 2020). The new directive, known as MiFID 2, was accompanied by the Markets in Financial Instruments and Amending Regulation (MiFIR), which primarily consists of reporting requirements aimed at enhancing pre- and post-trade information. MiFIR requires basic details of trades to be reported and made available to the public in near real time, and more in-depth transaction information, such as buyer and seller details, to be sent to regulators one trading day after the transaction is completed. MiFID 2 also harmonised tick sizes, the minimum pricing increment, across all European trading venues, preventing very small pricing increments from being used as a competitive tool between venues (ESMA, 2018). The directive also limits trading in dark pools, potentially leading to volumes returning to traditional exchanges. MiFID 2 and MiFIR have been in effect since January 2018.

2.3 Anonymous trading at Nasdaq Nordic

In the early days of electronic trading, stock exchanges were characterised by a high degree of transparency, tracing back to when trading occurred at physical trading floors. Before 2006, the limit order book at Nasdaq Nordic included not only details on volume and price quotes, but also what broker was associated with unexecuted orders. However, on March 13, 2006, Nasdaq Nordic switched to pre-trade anonymity, removing all market participant identification codes (MPIDs) from unexecuted orders in the limit order book (Meling, 2021).[4] For a visualisation of the difference between post-trade transparency and anonymity, we refer to Table 1. While many major stock exchanges also switched to post-trade anonymity in the early 2000s, the Nasdaq Nordic market model has a long history built on transparency.[5] However, equity markets have changed tremendously over the last two decades, not least in terms of execution speed and high-frequency algorithmic trading. By early 2010, Nasdaq Nordic had launched several initiatives specifically aimed at increasing the attractiveness for high-frequency trading (HFT), hoping it would boost volume by 25 percent within a year (Baird, 2010). The main initiatives were the shift to the INET platform, harmonisation of tick sizes, introduction of CCP clearing, and the introduction of a capped fee structure by January 1, 2010. This was estimated to have brought down trading costs by 84 percent by the end of 2010, and by 90 percent compared to three years earlier (Baird, 2010).

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[4] We use ‘MPIDs’, ‘broker codes’, and ‘broker IDs’ interchangeably throughout this paper. They all refer to identification codes of a party engaged in a trade, a ‘broker’, representing an investor.

[5] For example, the London Stock Exchange, the Frankfurt Stock Exchange, and Nasdaq switched to post-trade anonymity between 2001 and 2003.

Proponents of anonymity argue that the increased use of algorithmic trading on transparent markets is problematic, as it can exploit trading patterns based on broker IDs. At Nasdaq Nordic, this fear led to a steep increase in 'sponsored access' trading, where investors routed their orders through other members to conceal their identity and private information (Bursell, 2015). In February 2014, for instance, Merrill Lynch International (broker code MLI) was the largest broker on Nasdaq Nordic, with about 12 percent market share in terms of total exchange turnover. The majority turned out to be sponsored access trading with Merrill Lynch's market share dropping below 5 percent already by May 2014, when the introduction of voluntary post-trade anonymity for Large Cap stocks limited the need for such trading (Nasdaq, 2014). The considerable share of sponsored trading at Nasdaq Nordic was in fact the main argument for introducing post-trade anonymity in 2014: '[sponsored trading] is problematic as it works against transparency. We cannot see, and others cannot see, who trades behind [the sponsoring broker] and our market surveillance body cannot have a direct relationship with them' (Bursell, 2014). Thus, Nasdaq Nordic argued that the decrease in counterparty visibility would increase the transparency from the perspective of the exchange, as investors trading through sponsored access would instead become paying Nasdaq Nordic members of their own. Other benefits, according to Nasdaq Nordic, is that anonymity lowers trading costs, reduces price impact, and increases the overall competitiveness of their marketplaces. Opponents to anonymous trading, on the other hand, argue that smaller traders and uninformed investors are worse off, as they participate in fewer trades and cannot replicate strategies of informed traders (Dennis & Sandås, 2020).

This illustrates the conflicting interests of stakeholders in a diverse marketplace such as Nasdaq Nordic. It is generally difficult to determine a common definition of 'market quality' amongst participants as the interests of HFT firms have little overlap with those of 'low-frequency' investors, such as long-term fund managers and retail investors. Furthermore, trading venues must adhere to the demands of regulators and market surveillance bodies. What the vast majority of stakeholders have in common though, is a view that an efficient market is characterised by well-functioning market surveillance and high liquidity where market orders can be executed swiftly without dramatic price impacts. Hence, citing improved market surveillance and liquidity through decreased bid-ask spreads and increased trading volumes, Nasdaq Nordic has increased the level of post-trade anonymity in a stepwise fashion by introducing four anonymity regimes since June 2, 2008 (Mölne, 2022). While the first regime was reversed after a year, the regimes introduced since 2014 have increased the degree of post-trade anonymity compared to the preceding one. These regimes are outlined in Sections 2.3.1 to 2.3.4 below (see Table 2 for an overview).

2.3.1 The 2008 post-trade anonymity regime

On June 2, 2008, Nasdaq Nordic introduced a post-trade anonymity (PoTA) regime for all equity instruments in Helsinki and Iceland as well as for the 5 most traded stocks in Stockholm (Nasdaq, 2008). For these stocks, MPIDs were no longer visible in the real time data feed, other than to the counterparties in the specific trade.[6] The remaining stocks in Stockholm as well as all instruments in Copenhagen remained transparent. Nasdaq Nordic's rationale was that many major stock exchanges already applied PoTA and that the internationalisation of financial markets in the Nordics had led to an increasing number of international members, who preferred to trade anonymously. Nasdaq Nordic also stated that concealing broker IDs is favourable for electronic trading and will increase market liquidity. Less than a year later, on April 14, 2009, Nasdaq Nordic reversed the decision and reverted to post-trade transparency for all but the 5 most traded stocks in Helsinki and stocks listed in Iceland (Nasdaq, 2009). No motivation was given for the reversal, other than that it was based on member consultation.

2.3.2 The 2014 voluntary post-trade anonymity regime

On March 24, 2014, Nasdaq Nordic reintroduced post-trade anonymity in Stockholm, Copenhagen, and Helsinki (Nasdaq, 2014). The new, voluntary post-trade anonymity (vPoTA) model was applicable for the largest and most traded stocks in Helsinki and all CCP-cleared stocks in Stockholm and Copenhagen. This included all current Large Cap stocks, as well as the main index constituents of OMXS30, OMXC20, and OMXH25. Additionally, trading in *former* Large Cap and index stocks also became voluntarily post-trade anonymous. The voluntary feature of this regime gave members the option, on a monthly basis and for each separate exchange, to hide their MPIDs when trading current and former Large Cap and main index stocks.

2.3.3 The 2019 post-trade anonymity regime

On April 8, 2019, Nasdaq Nordic introduced an updated regime, making all order book trading in the main indexes (OMXS30, OMXC25, OMXH25) post-trade anonymous by default (PoTA), while keeping it voluntary to trade with post-trade anonymity (vPoTA) in non-index Large Cap stocks (Nasdaq, 2019). All other stocks were subject to post-trade transparency unless they had previously been part of the Large Cap segment or main indexes, according to the 2014 regime.

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[6] The 2008 regime represents a move from multilateral (MPIDs visible to all members) to bilateral transparency (MPIDs visible only to trade counterparties). Complete anonymity was enabled by the introduction of CCP in 2009.

2.3.4 The 2020 post-trade anonymity regime

Lastly, on April 1, 2020, Nasdaq Nordic expanded mandatory post-trade anonymity to also include non-index Large Cap stocks (PoTA), removing the voluntary opt-in possibility altogether (Nasdaq, 2020). Furthermore, Nasdaq Nordic decided to no longer include former Large Cap constituents in the regime, making PoTA only applicable to stocks currently belonging to the main indexes or Large Cap segments. Consequently, if a stock no longer belongs to the indexes or Large Cap segments, its shares cease to trade under post-trade anonymity and reverts to full transparency.

Table 1: Illustration of recently executed trades under transparency and anonymity

The table illustrates the data feed from recently executed trades. Post-trade anonymity entails removing broker identification codes (MPIDs) from recently executed orders. Panel A illustrates a list of executed trades under post-trade transparency, and Panel B the same trades reported under post-trade anonymity.

Panel A: Post-trade transparent visualisation of recently executed trades				
MPID (buy)	MPID (sell)	Ticker	Volume	Price (SEK)
AVA	XTXE	ERIC B	8	64.53
JPAG	MSE	ERIC B	506	64.54
MLI	MSE	ERIC B	238	64.55
Panel B: Post-trade anonymous visualisation of recently executed trades				
MPID (buy)	MPID (sell)	Ticker	Volume	Price (SEK)
-	-	ERIC B	8	64.53
-	-	ERIC B	506	64.54
-	-	ERIC B	238	64.55

Table 2: Overview of the Nasdaq Nordic post-trade anonymity regimes

The table outlines the Nasdaq Nordic post-trade anonymity regimes. We study the 2014, 2019, and 2020 regimes (bolded). On October 11, 2022, Nasdaq Nordic announced its intention to extend PoTA to Mid Cap and Small Cap stocks, as well as stocks listed on First North Growth Market on December 1, 2022.

Introduced	Replaced	OMXS30, OMXC20/25, OMXH25	Large Cap (excl. index)	Mid Cap, Small Cap, First North
-	June 2, 2008	Transparent	Transparent	Transparent
June 2, 2008	April 14, 2009	Partial PoTA	Partial PoTA	Partial PoTA
April 14, 2009	March 24, 2014	Transparent	Transparent	Transparent
March 24, 2014	**April 9, 2019**	**vPoTA**	**vPoTA**	**Transparent**
April 9, 2019	**April 1, 2020**	**PoTA**	**vPoTA**	**Transparent**
April 1, 2020	**December 1, 2022**	**PoTA**	**PoTA**	**Transparent**
December 1, 2022	-	PoTA	PoTA	PoTA

3 Literature Review

The literature is divided into two fields: pre- and post-trade anonymity. The pre-trade anonymity literature study the extent to which traders can observe identities in unexecuted orders and its impact on market quality. While we focus on post-trade anonymity, the pre-trade literature complements the understanding of the relevant market dynamics. Thus, this section starts with an outline of the pre-trade anonymity field, before discussing post-trade anonymity in greater detail.

3.1 Pre-trade anonymity

Simaan, Weaver, and Whitcomb (2003) study the impact of pre-trade anonymity on the quotation behaviour at Nasdaq and find that market makers quote lower spreads under anonymity. Similarly, Comerton-Forde, Frino, and Mollica (2005) document improved market quality through reduced spreads under pre-trade anonymity on the Paris Bourse, the Tokyo Stock Exchange, and the Korean Stock Exchange. Foucault, Moinas, and Thiessen (2007) study the Paris Bourse in 2001 and predict that lower bid-ask spreads stem from informed traders posting better prices under anonymity because the risk of piggybacking behaviour from uninformed traders is lower. They argue that anonymity is less favourable for stocks with high information asymmetry (as it compounds adverse selection costs and illiquidity) but promotes liquidity in stocks with lower asymmetry. Comerton-Forde and Tang (2009) document lower spreads and greater order flow on the Australian Stock Exchange in 2005 after the introduction of pre-trade anonymity and delayed post-trade reporting. The pre-trade anonymity field is not unanimous though, with several papers finding that pre-trade anonymity instead worsens liquidity and increases adverse selection costs (e.g., Röell (1990), Admati and Pfleiderer (1991), Foster and George (1992), Pagano and Röell (1996), and Baruch (2005)).

Rindi (2008) connects these contradictory findings through a theoretical model: when information acquisition is exogenous, anonymity increases information asymmetry and harms liquidity. When information acquisition is endogenous, however, anonymity increases the incentive for uninformed traders to acquire private information, turning them into informed market participants and thus effective liquidity providers. Both pre- and post-trade literature emphasise that less transparent markets become more attractive for informed traders. However, there is an important distinction underpinning the increased willingness to trade: pre-trade anonymity reduces the costs associated with informed traders' limit order trades, while post-trade anonymity reduces the informed traders' need for costly actions to conceal their private information (Meling, 2021).

3.2 The information content of broker codes

Post-trade anonymity is achieved by hiding the broker IDs of the parties involved in executed trades, making it difficult for other market participants to infer the parties' private information from observing their trading behaviour. Ellis, Michaely, and O'Hara (2002) study the Nasdaq dealer market and find that stocks tend to be dominated by a single broker, broker markets tend to be concentrated, and bid-ask spreads increase as the market share of the dominant broker increases. Schultz (2003) reports similar findings, arguing that broker concentration and broker IDs constitute predictive signals for other market participants. Informed traders are therefore likely to use multiple brokers and split orders into many trades to minimise the information content of their orders and avoid front-running by uninformed traders, despite the extra costs (Dennis & Sandås, 2020). Van Kervel and Menkveld (2019) confirm, showing that a group of institutional investors on average split orders into 156 trades to avoid detection by less informed traders.

Linnainmaa and Saar (2012) investigate the information content of broker IDs on the Helsinki Stock Exchange. They find that while institutional investors try to conceal their identities by executing trades through several brokers, broker codes still convey sufficient information for other participants to infer the type of investor behind the trades. As these trades are executed, other investors start trading alongside the institutional investor, increasing her execution costs. They conclude that the information content of broker codes in transparent markets is sufficient to impact prices, despite institutional order-splitting strategies. Frino, Johnstone, and Zheng (2010) further find that consecutive buyer- or seller-initiated trades by the same broker have a high market impact in transparent markets and predict that anonymous markets are more efficient.

Lepone, Segara, and Wong (2012) study whether broker anonymity impairs the ability of market participants to detect informed trading in the run-up to takeover announcements, thus focusing on the information content of broker codes in a setting with significant information asymmetry. They find that informed traders are less detected, and thus better off under anonymity than under transparency. Similar to Frino, Johnstone, and Zheng (2010), they find that the market attributes greater information content to successive unidirectional trades by a single broker.

To conclude from the relatively coherent literature on the information content of broker codes, there must be market frictions (e.g., transaction costs or agency problems) preventing investors from using multiple brokers, rendering broker codes to convey sufficient information to increase the trading costs for informed traders with private information (Dennis & Sandås, 2020).

3.3 Theoretical trader dynamics under post-trade anonymity

In transparent markets, informed traders face increased costs due to the information their trades signal to others. Uninformed traders act on the information and engage in trading-ahead and piggybacking behaviour, increasing the execution costs for informed traders (Harris, 1996). Thus, a large literature (e.g., Röell (1990), Admati and Pfleiderer (1991), Forster and George (1992), Fisherman and Longstaff (1992), and Rindi (2008)) predict that informed traders prefer anonymous trading venues (Comerton-Forde, Putniņš, & Tang, 2011).

Buffa (2013) and Yang and Zhu (2017) theoretically model how informed market participants trade based on their private information against an uninformed market maker. Their models are based on two-period models following Kyle (1985). Market makers face an adverse selection problem in supplying informed and uninformed traders with liquidity in that she, on average, loses on informed traders' orders as prices rise after informed buys and falls after informed sells, while she breaks even on uninformed traders' orders as they do not impact prices. To cover these adverse selection costs, the market maker charges trading costs in the form of bid-ask spreads. Buffa (2013) varies whether trader identities are revealed after the trade and Yang and Zhu (2017) add an uninformed trader and vary whether this trader can observe the informed trader's first-period trades and adjust her actions in the second period. The trade-off for the informed trader is whether to fully exploit her private information in the first period and reveal it to uninformed traders before the second period. Anonymity changes how much she wants to trade and thus the market's overall volume as well as the costs charged by the market maker to supply liquidity.

Yang and Zhu (2017) find that anonymity leads to increased informed trading, forcing the market maker to quote higher bid-ask spreads, which leads to reduced liquidity. Risk-neutral informed traders impose even greater costs on the market maker because more orders are exploiting private information and fewer are so called 'bluffing' orders. However, Buffa (2013) introduces a risk-averse informed trader, who wants to trade more aggressively on her private information under anonymity in the first period as she dislikes uncertainty about future prices and prefer to exploit her information immediately. Consequently, the price impact and information content of her later orders are lower, which is good for liquidity. Hence, the theoretical models predict that anonymity can be either positive or negative for market quality depending on the underlying trader assumptions. This points to the need for empirical evidence on post-trade anonymity and its impact on market quality. Next, we turn to empirical findings in papers similar to ours.

3.4 The empirical literature on post-trade anonymity

In 2003, the Australian Stock Exchange published a market consultation paper arguing that disclosing broker IDs encouraged predatory trading and increased trading costs (ASX, 2003). This can also deter efficient price discovery as informed traders move to alternative trading venues with less visibility. This reasoning is in line with Barclay, Hendershott, and McCormick (2003), who study the competition between two markets with varying degree of counterparty visibility. They find that less visible markets attract informed traders, leading to better price discovery. Hachmeister and Schiereck (2010) and Friederich and Payne (2014) analyse the introduction of CCP clearing and the accompanying shift from bilateral transparency to complete anonymity, on the Frankfurt and London Stock Exchanges, respectively. Hachmeister and Schiereck (2010) find that complete anonymity leads to a 25 percent reduction in transaction costs and that informed traders are incentivised to provide additional liquidity under anonymity. Similarly, Friedreich and Payne (2014) find that complete anonymity improves liquidity while lowering transaction costs.

Dennis and Sandås (2020) study the impact of the 2008 post-trade anonymity regime at Nasdaq Nordic, by matching anonymous stocks to stocks outside the scope of the regime and using a difference-in-differences (DiD) model. They document improved market quality and 50 basis points lower spreads on average. As they discuss, the study coincides with the Global Financial Crisis, which could distort their results. Dennis and Sandås (2020) differs from previous empirical studies as they (i) include two sequential events (switch to anonymity followed by a reversal) and because they (ii) investigate a move from multilateral transparency (everyone can observe broker IDs of recent trades) to bilateral transparency (IDs only observable to trade counterparties) as Nasdaq Nordic had not yet introduced CCP.

Meling (2021) study the impact of post-trade anonymity at the Oslo Stock Exchange, where the 25 highest turnover stocks traded anonymously between 2008 and 2010. He uses a regression discontinuity (RD) model, comparing the least traded anonymous stocks to the most traded transparent stocks outside the index. He finds that anonymity leads to 40 percent lower bid-ask spreads and 50 percent higher volume. To further explain his findings, Meling (2021) references the theoretical predictions of Buffa (2013) and Yang and Zhu (2017) outlined earlier. Specifically, he tests and confirms three hypotheses. First, informed (institutional) trading increases under anonymity as informed traders no longer have to take costly action to hide their information when executing trades. Given that this was never a concern for uninformed (retail) traders, they do not change their trading under anonymity. Second, informed (institutional) traders execute their orders in a way that induces positive autocorrelation in the direction of the trades. Third, risk-averse (institutional) investors demanding liquidity impose smaller adverse selection costs on market makers under anonymity, who in turn can charge lower spreads to cover their costs.

All studies, however, do not point toward post-trade anonymity necessarily improving standard measures of market quality. For example, Gemmill (1996) and Board and Sutcliffe (2000) investigate a setting where the publication of block trades were delayed on the London Stock Exchange, thus decreasing the level of post-trade visibility. They find no evidence of improved liquidity. Furthermore, Thiessen (2003) studies varying degrees of post-trade anonymity in Germany and finds that the impact of anonymity depends on characteristics of the stocks being traded: traders prefer transparency for less liquid stocks and anonymity for blue chip stocks.

There are also studies suggesting that post-trade anonymity hurts liquidity. Waisburd (2003) documents 25 percent higher bid-ask spreads on the Paris Bourse following the introduction of post-trade anonymity. Poskitt et al. (2011) study post-trade anonymity at the New Zealand Stock Exchange and find that spreads and adverse selection costs increased in the largest group of stocks following the introduction. However, they also find that dual-listed stocks become more attractive following the switch to anonymity. They conclude that although institutional investors and the stock exchange itself might benefit from anonymity, liquidity demanders face higher transaction costs as a result. Finally, Pham, Swan, and Westerholm (2015) find that post-trade anonymity leads reduces trading volume by more than 50 percent in South Korea.

Meling (2021) tries to reconcile the empirical disparities by pointing out that the time at which the anonymity regimes were introduced differ. The two papers that document strictly negative effects, Waisburd (2003) and Pham, Swan, and Westerholm (2015), both study reforms in the mid-1990s, using before-and-after designs. Hachmeister and Schiereck (2010), Friederich and Payne (2014), Dennis and Sandås (2020), and Meling (2021) all study events in the 2000s. The impact of anonymity could have reversed from negative to positive over this time. Meling (2021) also points out the possibility that the before-and-after designs are confounded by market-wide trends that are better accounted for in the DiD and RD designs of later studies. While recent literature indicate that market quality tends to improve under post-trade anonymity, the empirical literature is mixed and benefits from further research. Moreover, as the impact of anonymity could be time-varying, estimating the effect in a more recent setting is relevant and valuable to the literature.

4 Hypotheses and Contribution

Building on previous literature, we test the impact of the three post-trade anonymity regimes in 2014, 2019, and 2020 on the Nasdaq Nordic stock exchanges in Stockholm, Helsinki, and Copenhagen in terms of daily relative bid-ask spreads and turnover. The bid-ask spread is a common measure of stock-level liquidity, but to some extent it also captures the volatility of a stock as spreads tend to increase during rapid price movements. In combination with turnover (the total amount traded in a stock), bid-ask spreads produce a strong indicator of a stock's liquidity on the observation-level and the overall market liquidity when aggregated. We formally introduce the outcome variables in Section 5.3.1. Below, we outline our hypotheses.

4.1 Hypothesis 1: the 2014 vPoTA regime

First, we test the impact of the switch from transparency to voluntary post-trade anonymity for Large Cap stocks following the introduction of the 2014 vPoTA regime. By satisfying informed trader demand for anonymity, and thus reducing front-running and piggybacking costs, we expect market quality to improve through lower spreads and higher turnover as informed traders are more willing to trade under anonymity. Hence, we expect to reject the following null hypotheses:

H_0^{1A}: bid-ask spreads do not decrease due to the introduction of vPoTA

H_0^{1B}: turnover in euro does not increase due to the introduction of vPoTA

4.2 Hypothesis 2: the 2019 and 2020 PoTA regimes

Second, we test the impact of the incremental increase in anonymity during the switch from voluntary to mandatory post-trade anonymity for index and Large Cap stocks in 2019 and 2020, respectively. As informed traders demanding anonymity already had the possibility to trade anonymously in these stocks since the 2014 regime, we expect that the introductions of the 2019 and 2020 PoTA regimes do not improve market quality and liquidity through lower bid-ask spreads and higher turnover. Hence, we do not expect to reject the following null hypotheses:

H_0^{2A}: bid-ask spreads do not decrease due to the introduction of PoTA

H_0^{2B}: turnover in euro does not increase due to the introduction of PoTA

4.3 Research contribution

Equity markets continually fine-tune their designs to improve market quality. One way to do this is adjusting the degree of counterparty visibility. Over the last 20 years, major stock exchanges have moved towards less visibility. However, neither theoretical models nor empirical research have unanimously concluded whether anonymity is good or bad for liquidity. We contribute to the growing market microstructure literature relating to post-trade anonymity in two main ways.

First, we test the impact of post-trade anonymity in a more recent setting than comparable studies. Meling (2021) and Dennis and Sandås (2020) document positive effects using data from the late 2000s. However, earlier studies using data from the mid-1990s, for instance Pham, Swan, and Westerholm (2015), document a negative relationship. In the last decade, equity markets have transformed and adapted to increasingly computerised and fragmented trading and the potential benefits or costs of anonymity could have changed over time. As Meling (2021) points out, the effects of anonymity could very well be time-varying. Studying three reforms at more recent points in time (2014, 2019, and 2020), we provide nuance to the existing literature.

Second, we examine the incremental impact of different levels of post-trade anonymity through Nasdaq Nordic's three separate regimes. Specifically, this setting allows us to compare the impact of switching from transparency to voluntary post-trade anonymity, and from voluntary to mandatory post-trade anonymity. As stock exchanges compete for increasingly fragmented trading volume, the question arises of what type of anonymity constitutes the best trade-off between MiFID's aim for increased transparency and simultaneously satisfying investor demand for anonymity? The novelty of our research setting allows us to investigate this question in detail. Coincidentally, Dennis and Sandås (2020) conclude their paper by reflecting on the 2014 Nasdaq Nordic anonymity reform: '...in 2014 the exchange began allowing members to hide their identity if they so choose. Future research is needed to evaluate whether this or other versions of post-trade reporting lead to better liquidity.' Our paper does precisely this when comparing the incremental impact of the 2014, 2019, and 2020 anonymity regimes respectively, and thus contributes to the field not only by studying the effects of anonymity on market quality, but also the effect at different levels of anonymity.

Recently, Nasdaq Nordic announced that it will extend the 2020 PoTA regime to also include Mid Cap and Small Cap stocks, as well as stocks listed on First North Growth Market as of December 1, 2022. With this final regime, Nasdaq Nordic will have fulfilled its stepwise post-trade anonymity implementation, which started more than ten years ago. Similar to when previous anonymity regimes were introduced, the announcement caused some stir. For instance, the largest financial newspaper in Sweden, Dagens Industri, published an article, arguing that the 2022 anonymity regime is implemented, not to improve market quality, but because it is profitable for Nasdaq Nordic (Axelsson, 2022). While this regime is too recent to consider as part of this paper, it highlights the relevance of the topic in today's equity markets.

5 Methodology and Data

5.1 The quasi-experimental setting

On March 24, 2014, Nasdaq Nordic introduced the possibility for its members to conceal their MPIDs when trading Large Cap and main index stocks, per exchange and on a monthly basis. On April 8, 2019, trading in all main index constituents became post-trade anonymous by default (PoTA), while the remaining Large Cap stocks continued with vPoTA. Lastly, on April 1, 2020, trading in all remaining Large Cap stocks switched to PoTA. The three regimes constitute quasi-experimental settings with distinct events and treatment groups, why we can apply a difference-in-differences (DiD) approach to study the impact of anonymity. The DiD model is a simple but robust econometric specification used for isolating a treatment effect in settings with pre and post periods as it can sort out time-varying as well as group-specific effects (Bertrand, Duflo, & Mullainathan, 2004). DiD is also the most frequently used approach in similar studies.

While there are alternative quasi-experimental approaches that could potentially be used in our setting, they stipulate requirements that our setting does not meet. As discussed, Meling (2021) uses an RD design, which relies on less strict and to a greater degree testable assumptions than the DiD model. The RD requires an assignment rule at an arbitrary point along a continuous variable, for example that the 25 most traded stocks trade anonymously as in Meling (2021). In our setting, treatment (post-trade anonymity) is mainly assigned based on market cap segment and, as outlined in Section 2.1, this is not based on a continuous variable but on a set of criteria, rendering the RD design ill-fitted for our research setting.

5.1.1 Event window formation

The DiD approach is based on an event-study methodology. Hence, to capture the treatment effect from the post-trade anonymity introductions, we form event windows around each introduction date with a balanced number of trading days on each side. We let each pre-event period start on the first trading day of the year as this date coincides with Nasdaq Nordic's annual market cap segment reviews. We form post-event periods with the corresponding number of trading days. We purposely exclude one week on each side of the event to eliminate potential confounding effects around the introductions. We illustrate the event windows in Figure 1 (a-c).[7]

[7] The main results remain quantitatively and qualitatively similar when including the two-week period around the events as well as when using shorter pre- and post-event periods of 30 trading days around the event.

Figure 1a: Event window for the 2014 vPoTA introduction

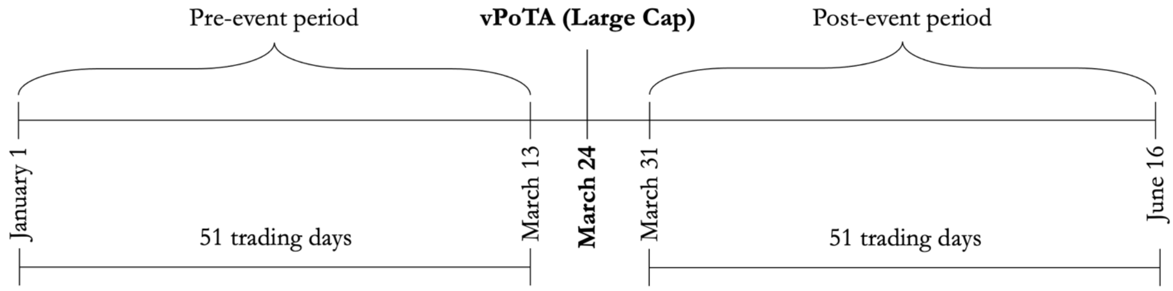


Figure 1b: Event window for the 2019 PoTA introduction

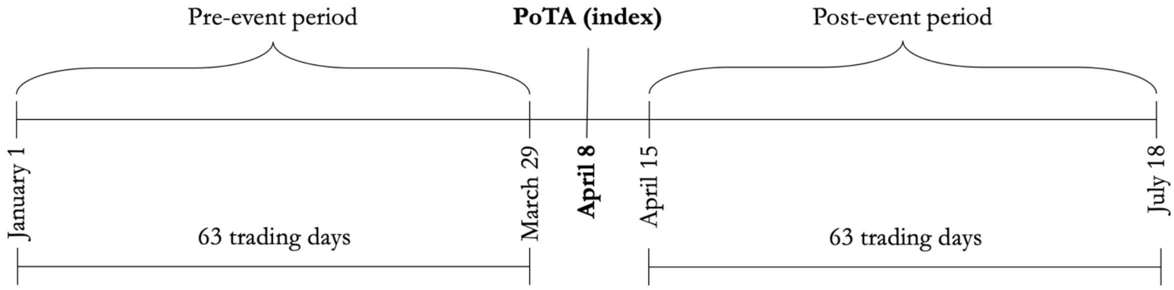
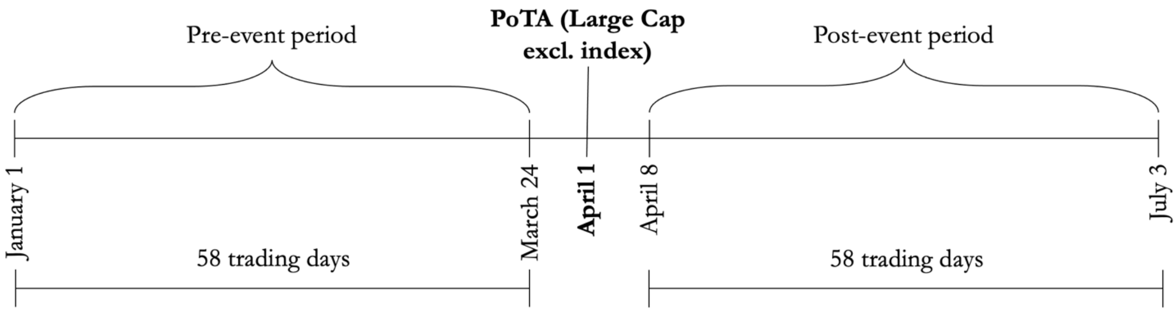


Figure 1c: Event window for the 2020 PoTA introduction



5.2 Data and sample

We gather daily trading data from FinBas, provided by the Swedish House of Finance (SHoF), for all instruments traded on the Nasdaq Nordic exchanges over our event windows. The Nasdaq Nordic monthly 'Equity Trading by Company and Instrument' reports provide non-trading related instrument-level data, which we collect for all instruments over our sampling period. Daily market cap data for all instruments is retrieved from Nasdaq Nordic's Economic & Statistical Research department. Because the market cap data is on share-class level, we compute the daily company market cap in two steps. For dual-listed stocks (one ISIN trading on two or more exchanges) we only consider the market cap for the stock traded on the main exchange as it includes the market cap of stocks listed on other exchanges as well. For companies with multiple share classes (multiple ISINs trading on one or more exchanges) we sum the market cap of each share class to obtain the company market cap. During the 2014 and 2019 regimes, Nasdaq Nordic published monthly reports for stocks trading with vPoTA. From these, we make note of all stocks, both current and former Large Cap, that received vPoTA treatment. We follow a similar procedure to form our main index stock samples for 2019 and 2020. Nasdaq Nordic reviews these indexes bi-annually, and we collect index constituent information from press releases for the December (OMXC25), January (OMXS30), and February (OMXH25) index reviews. We control for changes made at the mid-year reviews in June (OMXC25) and July (OMXS30) as they overlap with our event windows. We remove stocks that move in and out of the indexes during the events.[8] Nasdaq Nordic updates its Large Cap segments annually on the first trading day in January; thus, we collect market cap constituencies in January each year. Lastly, we collect daily exchange rates from the European Central Bank for translating SEK and DKK to EUR for comparability across the full sample.

As we are only concerned with stocks in the Large Cap and Mid Cap segments on the Stockholm (SSE), Helsinki (HSE), and Copenhagen (CSE) main exchanges, we drop instruments that are not part of these or listed on other Nasdaq Nordic exchanges.[9] We remove dual-listed stocks not primary-listed on SSE, HSE and CSE (e.g., AstraZeneca plc) as well as companies with preference shares as they have different characteristics and dynamics than ordinary stock and distorts market cap computations. Given that Nasdaq Nordic only provides daily market cap figures for listed share classes, we remove stocks that have unlisted share classes or treasury shares that distorts the calculated market cap in excess of ten percent in either direction when we cross-check our data with total market cap figures from S&P Capital IQ. We drop stocks that have intermittent ISINs during list changes and mergers or otherwise show signs of abnormal behaviour. We also drop observations with missing data on our outcome variables, bid-ask spread and turnover. For consistency, we drop (i) former Large Cap and main index stocks that trade under vPoTA during the 2014 and 2019 regimes, (ii) the five most traded stocks on HSE that remained under PoTA after the 2009 reversal, and (iii) the main index constituent stocks in our 2020 sample, as these already trade under PoTA since 2019. Stocks dropped for violating the assumption of consistency are listed in Appendix 1 (a-c). Lastly, to ensure sufficient trading activity, we exclude stocks with less than 50 trading days on either side of the event for each regime (Appendix 2 lists these stocks).

[8] In June 2019, The Drilling Company of 1972 A/S replaced Sydbank A/S in the OMXC25. In February 2020, Kojamo Oyj joined the OMXH25 (not replacing another stock). In June 2020, Bavarian Nordic A/S replaced Topdanmark A/S in the OMXC25. These stocks are dropped as they move in and out of the indexes over our event windows.
[9] These include Norwegian main-listed stocks, Pre List stocks, Xterna List stocks, and Special Purpose Acquisition Companies (SPACs), as well as equity warrants, rights, convertibles, and other non-equity securities.

5.2.1 Treatment and control group formation

For the 2014 event, we let Large Cap stocks be our treatment group (subject to vPoTA) and a Mid Cap stocks be our control group (subject to post-trade transparency). For the 2019 event, we let main index stocks be our treatment group and the remaining Large Cap stocks trading with vPoTA be the control group. We use Large Cap stocks as the control group to keep the two groups as similar as possible. For the 2020 event, we let Large Cap stocks excluding main index constituents be the treatment group and Mid Cap stocks be the control group. In studying the 2014 regime and the 2019 and 2020 regimes, we investigate the impact on market quality after switching to vPoTA and from vPoTA to PoTA, respectively. This generates the sample sizes presented in Table 3.

Table 3: Sample sizes

Event	Groups	Total	SSE	HSE	CSE
2014	Treatment (Large Cap)	118	70	26	22
2014	Control (Mid Cap)	111	60	32	19
2019	Treatment (index)	62	25	16	21
2019	Control (Large Cap excl. index)	118	84	17	17
2020	Treatment (Large Cap excl. index)	111	83	12	16
2020	Control (Mid Cap)	164	104	40	20

In their papers, Friederich and Payne (2014) and Dennis and Sandås (2020) form treatment and control groups by matching on propensity scores (PSM) to adjust for confounding by balancing the groups on observable pre-event period covariates. This adjustment is generally considered attractive in a DiD setting as it, theoretically, can reduce distortion between the groups (Rosenbaum & Rubin, 1983). However, Assel et al. (2019) highlight two problems with claims that multivariable adjustment would remove confounding or mimic a randomised trial.

First, Assel et al. (2019) argue that the value of variables in the sample often are approximate and may not reflect the actual group-level differences. Second, a multivariate adjustment only can adjust for so many variables, why the risk remains of leaving important differences in observable characteristics. Even slight misspecification of a PSM can result in substantial bias of estimated treatment effects (Kang & Schafer, 2007). Imai and Ratkovic (2014) call this the 'paradoxical nature of the propensity score', where it is designed to reduce the dimension of covariates, while its estimation requires modelling of dimensional covariates. A third reason, put forward in Daw and Hatfield (2018), is that matching can prove spurious due to the phenomenon of regression to the mean, where extreme values tend to revert to the group mean on subsequent measurements. The risk is then that matching can introduce bias whereas, in absence of matching, the populations are different in the pre-event period and remain that way in the post-intervention period.

Hence, Assel et al. (2019) challenge the common assumption that matching provides better adjustments for confounding than traditional covariate-adjusted analyses, and state that propensity score matching gives 'extremely similar' results to multivariate regression. There are strengths and weaknesses to both approaches but matching on covariates is less important in our research setting. Moreover, any benefits of a matched sample are too small to outweigh the costs of reducing the sample size, as this would lead to lower power in our statistical tests.

5.3 Difference-in-differences model specification

5.3.1 Outcome variables

To assess the treatment effect of post-trade anonymity, we consider two standard measures of market quality: relative end-of-day bid-ask spread and daily turnover in euro. The bid-ask spread is the primary measure of stock-level liquidity and in combination with turnover it produces a strong indicator of market quality when aggregated. While turnover is a noisy metric, it is still an important measure of a stock's liquidity (Hagströmer, 2021). We define our outcome variables as:

$$Spread\ (log)_{i,t} = \ln\big((Bid_{i,t} - Ask_{i,t})/((Bid_{i,t} + Ask_{i,t})/2)\big)$$
$$Turnover\ (log)_{i,t} = \ln\ (Daily\ Euro\ Turnover_{i,t})$$

where:

$Bid_{i,t}$ = the highest bid price for stock i by the end of trading day t

$Ask_{i,t}$ = the lowest ask price for stock i by the end of trading day t

$Daily\ Euro\ Turnover_{i,t}$ = the total amount traded in stock i on trading day t

These are 'low-frequency' daily measures, as opposed to high-frequency intra-day data. Although low-frequency market data is well-suited for our research setting (it is simple to use and common when studying market quality over longer time periods (e.g., as in Meling (2021)), we would ideally include higher-frequency measures to better reflect trading behaviours as to increase the validity and generalisability of our results. While such data is possible to retrieve from SHoF, it cannot be done for any larger samples over extended periods of time. An option would be to significantly reduce our event windows and consider fewer stocks. However, as anonymity might impact trading in specific stocks differently (recall, for example, Thiessen (2003)), using a much smaller sample would likely produce unreliable results. Given the institutional setting and that market participants might not adjust immediately following the introduction, we believe that longer event windows with larger sample sizes are required to capture the treatment effect.

5.3.2 Model assumptions

The DiD approach relies on three main assumptions. First, the group compositions must be stable, that is treatment and control groups in the pre- and post-event periods do not change. We let the event windows start on the first day of the year, after the market cap segment reviews, to ensure that no stocks move between groups during the events. As the main indexes are reviewed bi-annually at different times, we remove stocks that enter or leave them during our event windows. We also remove stocks with less than 50 trading days in either period around the events to ensure stocks listed and delisted mid-event are excluded. Second, there can be no spillover of the treatment effect between treatment and control groups, future treatment should not impact previous outcomes, and treatment must not vary with a stock's liquidity. We remove former Large Cap and main index stocks trading under vPoTA during the 2014 and 2019 vPoTA regimes, as well as the five Finnish stocks that remained anonymous after the 2009 reversal.[10] As the regimes were implemented market-wide on a single date, any change in the outcome variables prior to the implementation would not have come from anonymity. As the treatment was applied uniformly and did not vary during the events, we know that the level of treatment given was not determined by the market quality metrics of said stock.

The third and most important assumption is that of parallel trends, meaning that the outcome for treated group would have evolved in parallel with the mean outcome for the untreated group absent of treatment (Roth et al., 2022). Unlike cross-sectional approaches, the DiD model does not require covariate-balanced treatment and control groups. A covariate that differs by treatment group and is associated with the outcome does not necessarily constitute a confounder in a DiD, but covariates that differ by group and are associated with *trends* in the outcome are (Zeldow & Hatfield, 2021). This means that we must assume that the post-event outcome for the control group is a good proxy for the post-event outcome for the treatment group if no treatment had been assigned. While earlier assumptions are verifiable, parallel trends is essentially untestable as it involves counterfactual outcomes. Nonetheless, we must credibly assume that the difference in outcome between the two groups would remain constant absent of treatment (Roth et al., 2022). Roth et al. (2022) highlight that an appealing feature of the DiD design is that it allows for a natural *plausibility* check of this assumption by controlling if the outcomes for the groups move in parallel prior to treatment. To this end, we generate event plots to control for any variance in trends between the treatment and control groups for each event. We refer to Figure 2 (a-c) in Section 6.1,

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[10] The Finnish stocks that remained under PoTA were Nokia Oyj (ticker NOK1V, NOKIA), Fortum Oyj (FUM1V, FORTUM), UPM-Kymmene Oyj (UPM1V, UPM), Sampo Oyj (SAMAS, SAMPO), and Stora Enso Oyj (STERV).

6.2.1, and 6.2.2 for the 2014, 2019, and 2020 events, respectively. We observe that the outcomes are different but that the difference remains relatively constant over time, indicative of parallel trends. While this observation is statistically untested there are risks with being overly reliant on tests of parallel trends in the pre-event period. Roth et al. (2022) compile recent research on the validity of assuming parallel trends. First, parallel pre-trends do not guarantee parallel post-trends. Second, due to low power, tests of parallel pre-trends may fail to reject the null of parallel trends despite there actually being non-parallel trends. Third, conditioning analyses on 'passing' pre-trends tests induces selection bias: despite there being violation of the parallel pre-trends in a population, a sample drawn from the population might show parallel pre-trends (Roth, 2022).

5.3.3 Covariates

Harris (1994) presents a regression framework for explaining variation in bid-ask spreads. He suggests using (i) a measure of trading activity, (ii) a measure of return volatility, (iii) a measure of dealer competitiveness, and (iv) a measure that captures the degree of information asymmetry at the stock level.[11] Harris (1994) further suggests regressing on price to capture the discreteness of stock prices. Meling (2021) and Dennis and Sandås (2020) largely follow this approach. Meling (2021) controls for share price (log), returns, market cap (log), price/book, and company-level operating metrics. He also controls for tick sizes as his sample stretches over an extended time period. Dennis and Sandås (2020) conduct PSM matching using market cap (log), share price (log), return volatility, broker concentration, and the average bid-ask spread over a month before their pre-event period. They argue that company size, volatility, and share price should capture any variation in spreads not coming from the post-trade anonymity treatment.

We add three covariates to our model. These are $Market\ Cap\ (log)_{i,t}$, the natural log of a stock's daily company market capitalisation in million euro, $Stock\ Price\ (log)_{i,t}$, the natural log of a stock's daily closing price in euro, and, $Price\ Variability_{i,t}$, the relative daily price variation measured as daily high over daily low minus one expressed in percent. Subscript i identifies the stock and t the date. All covariates but $Price\ Variability_{i,t}$ are log-transformed to improve linearity with our outcome variables. We expect $Spread\ (log)_{i,t}$ to increase with $Price\ Variability_{i,t}$ as traders are risk averse, decrease with $Market\ Cap\ (log)_{i,t}$ due lower information asymmetry in larger stocks, and decrease with $Stock\ Price\ (log)_{i,t}$, which has empirically been shown to be a statistically significant determinant, even after controlling for other covariates (Harris, 1994). One reason is that the share

[11] Harris (1994) suggests that company size is a viable proxy for the degree of public information available about a stock, thus representing an observable variable that captures unobservable information asymmetries.

price in part determines the tick size, which sets the lower bound for bid-ask spreads. As $Spread\ (log)_{i,t}$ and $Turnover\ (log)_{i,t}$ are inversely correlated, the covariates are expected to change signs when the outcome variable of interest is instead $Turnover\ (log)_{i,t}$.

Table 4: Correlations

	$Spread\ (log)_{i,t}$	$Turnover\ (log)_{i,t}$	$Market\ Cap\ (log)_{i,t}$	$Stock\ Price\ (log)_{i,t}$
$Turnover\ (log)_{i,t}$	-0.704			
$Market\ Cap\ (log)_{i,t}$	-0.613	0.640		
$Stock\ Price\ (log)_{i,t}$	-0.275	0.081	0.347	
$Price\ Variability_{i,t}$	0.192	0.009	-0.211	-0.138

Table 4 contains correlation figures between our covariates and outcome variables in the 2014 pre-event period. Other than the small positive relationship between $Turnover\ (log)_{i,t}$ and $Price\ Variability_{i,t}$, the covariates have the expected signs and relatively limited correlation with each other. This suggests that multicollinearity problems are unlikely, even when all variables are included in the complete regression model. The corresponding tables for the 2019 and 2020 pre-event periods produce similar results, with the same signs and similar sizes.

5.3.4 Final model specification

We construct two regression models. Model (1) constitutes the baseline DiD regression, leaving covariates out. We let $Post_t$ indicate the time period ($Post_t = 0$ for the pre-event period and 1 for the post-event period) and $Treated_i$ indicates the group constituency ($Treated_i = 0$ for a stock in the control group and 1 for a stock in the treatment group) for stock i at date t. The interaction variable $Post_t \cdot Treated_i$ captures the treatment effect. Model (2) includes the previously defined covariates to control for characteristics that have been shown to explain liquidity measures of stocks. We run the regressions on both of our outcome variables, $Spread\ (log)_{i,t}$ and $Turnover\ (log)_{i,t}$. Model (1) and (2) are presented below:

Model (1): $$Y_{i,t} = \beta_0 + \beta_1 Post_t + \beta_2 Treated_i + \beta_3 (Post_t \cdot Treated_i) + \varepsilon_i$$

Model (2): $$Y_{i,t} = \beta_0 + \beta_1 Post_t + \beta_2 Treated_i + \beta_3 (Post_t \cdot Treated_i) + \beta_4 Market\ Cap\ (log)_{i,t} + \beta_5 Stock\ Price\ (log)_{i,t} + \beta_6 Price\ Variability_{i,t} + \varepsilon_i$$

5.4 Descriptive statistics

Table 5 (a-c) present descriptive statistics for the three pre-event period samples. Across the board, control group stocks have higher bid-ask spreads and lower daily turnover, with the median spread (turnover) being 6, 3, and 2 (16, 10, and 7) times larger (smaller) in 2014, 2019, and 2020, respectively. Market capitalisation and stock price show the same relationship. The daily price variability is narrower in the treatment groups, indicative of less volatile trading due to the higher overall liquidity. Given the assignment rules for anonymous trading, these differences are general across all three events: the treatment groups consist of larger, more liquid, and less volatile stocks, with lower spreads and higher turnover. However, permanent differences do not constitute an assumption violation in the DiD estimation.

Table 5a: Descriptive statistics (2014)

The treatment and control groups consist of 118 Large Cap and 111 Mid Cap stocks, respectively. Spread is the relative end-of-day spread expressed in basis points. Turnover is the daily turnover in thousand euro. Market Cap is the daily company market cap in million euro. Stock Price is the daily closing price in euro. Price Variability is measured as daily high over daily low minus one expressed in percent.

Treatment (Large Cap)	**5 pct.**	**25 pct.**	**50 pct.**	**75 pct.**	**95 pct.**	**N**
Spread (bps)	3.32	5.85	9.56	21.34	89.68	6,605
Turnover (EURk)	75	2,462	8,329	32,362	151,416	6,605
Market Cap (EURm)	1,136	2,129	3,702	8,597	30,269	6,605
Stock Price (EUR)	3.61	5.98	9.65	15.68	61.27	6,605
Price Variability (%)	0.80	1.26	1.75	2.46	4.35	6,605
Control (Mid Cap)	**5 pct.**	**25 pct.**	**50 pct.**	**75 pct.**	**95 pct.**	**N**
Spread (bps)	16.56	32.26	51.93	84.73	211.38	6,202
Turnover (EURk)	16	152	528	1,532	8,836	6,202
Market Cap (EURm)	150	281	388	708	1,026	6,202
Stock Price (EUR)	0.49	2.13	4.36	9.45	28.22	6,202
Price Variability (%)	0.76	1.51	2.31	3.44	6.17	6,202

Table 5b: Descriptive statistics (2019)

The treatment and control groups consist of 62 main index and 118 non-main index Large Cap stocks.

Treatment (index)	**5 pct.**	**25 pct.**	**50 pct.**	**75 pct.**	**95 pct.**	**N**
Spread (bps)	2.84	5.29	7.89	10.94	19.79	4,204
Turnover (EURk)	2,633	10,749	21,482	41,570	178,883	4,204
Market Cap (EURm)	2,156	4,602	7,338	17,549	29,010	4,204
Stock Price (EUR)	3.42	8.79	16.86	35.84	157.09	4,204
Price Variability (%)	0.88	1.34	1.82	2.56	4.33	4,204
Control (Large Cap excl. index)	**5 pct.**	**25 pct.**	**50 pct.**	**75 pct.**	**95 pct.**	**N**
Spread (bps)	6.47	12.99	20.26	37.45	117.88	7,963
Turnover (EURk)	15.44	364.41	2,155	6,213	18,924	7,963
Market Cap (EURm)	820	1,444	2,318	4,660	19,307	7,963
Stock Price (EUR)	2.28	6.80	10.20	17.39	51.24	7,963
Price Variability (%)	0.84	1.42	1.98	2.76	4.72	7,963

Table 5c: Descriptive statistics (2020)

The treatment and control groups consist of 111 Large Cap and 164 Mid Cap stocks, respectively. Index stocks have been removed from the treatment group as they already trade under PoTA since 2019.

Treatment (Large Cap excl. index)	**5 pct.**	**25 pct.**	**50 pct.**	**75 pct.**	**95 pct.**	**N**
Spread (bps)	6.30	11.99	19.76	42.25	135.46	6,984
Turnover (EURk)	18	583	3,185	9,087	26,858	6,984
Market Cap (EURm)	811	1,593	2,719	5,371	19,818	6,984
Stock Price (EUR)	2.71	7.44	11.29	20.32	58.09	6,984
Price Variability (%)	0.95	1.75	2.91	5.46	11.19	6,984
Control (Mid Cap)	**5 pct.**	**25 pct.**	**50 pct.**	**75 pct.**	**95 pct.**	**N**
Spread (bps)	13.36	25.77	44.99	78.84	183.49	10,325
Turnover (EURk)	31	171	478	1,305	5,315	10,325
Market Cap (EURm)	117	226	344	575	952	10,325
Stock Price (EUR)	0.80	4.19	7.82	13.51	29.55	10,325
Price Variability (%)	1.14	2.25	3.75	6.54	13.08	10,325

6 Results

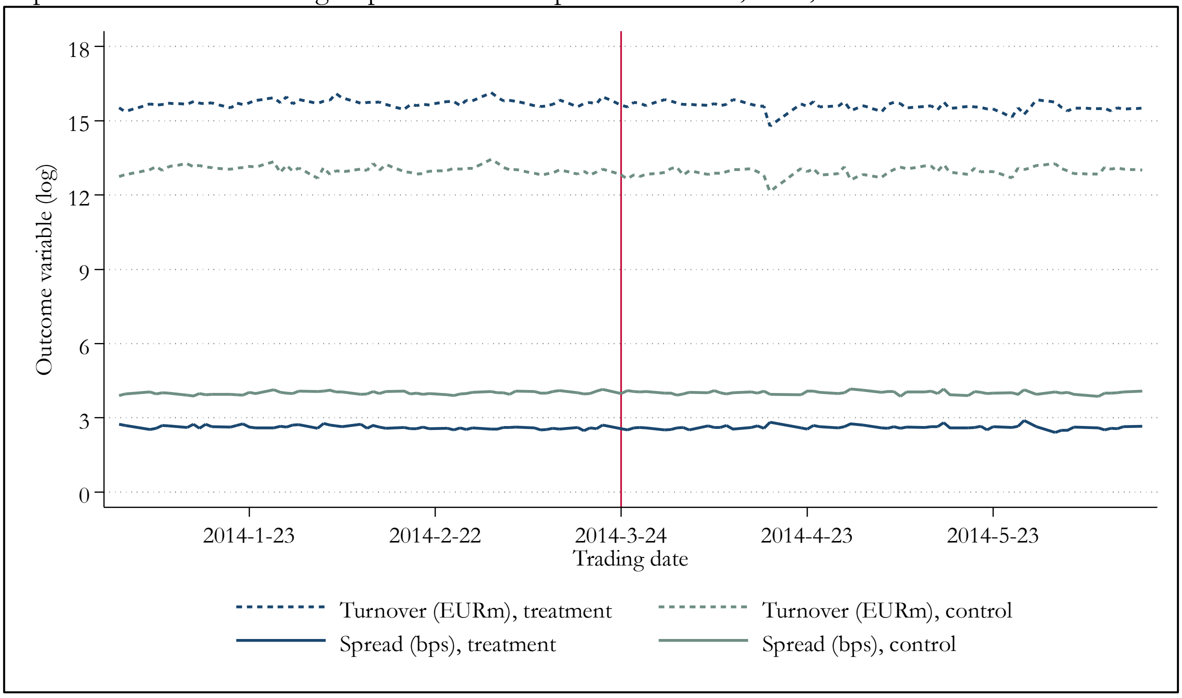
Section 6 presents the main results, starting with the 2014 vPoTA regime in Section 6.1, followed by the switch from vPoTA to PoTA in 2019 and 2020 in Section 6.2. In Section 6.3, we connect our findings to previous literature and introduce additional tests to nuance our results.

6.1 Hypothesis 1: the 2014 vPoTA regime

The null of our first hypothesis, which we expect to reject, is that the introduction of vPoTA in 2014 did not improve liquidity measures. To graphically illustrate the development (and parallel trends) of our outcome variables $Spread\ (log)_{i,t}$ and $Turnover\ (log)_{i,t}$, we construct event-study plots over the pre- and post-event periods, separated by a line indicating the day of the regime implementation. While there are differences between the groups in Figure 2a, we observe no notable downward (upward) shift in $Spread\ (log)_{i,t}$ and ($Turnover\ (log)_{i,t}$) for the treated stocks.

Figure 2a: Pre- and post-event trends in outcome variables (2014)

The figure presents daily relative bid-ask spreads in basis points (log) and turnover in million euro (log) around the switch from post-trade transparency to voluntary post-trade anonymity on March 24, 2014. The event window stretches from January 1 to June 16, 2014. The treatment group consists of 118 Large Cap stocks and the control group of 111 Mid Cap stocks on SSE, HSE, and CSE.



To formalise the comparison over time and between groups, we run our previously defined DiD regression models in Table 6a. The dummy variables $Post_t$ and $Treated_i$ isolate potential time-varying and group-specific confounding effects, while the interaction variable $Post_t \cdot Treated_i$ captures the potential treatment effect. While the interaction coefficient has the expected negative sign for $Spread\ (log)_{i,t}$, neither model (1) nor (2) capture any treatment effect meeting the conventional standards for statistical significance for either outcome variable. Thus, we cannot reject the null that vPoTA does not improve $Spread\ (log)_{i,t}$ and $Turnover\ (log)_{i,t}$. Furthermore, we do not find significant time-variation but a large and significant group-specific difference in $Spread\ (log)_{i,t}$, in line with what we observed in Figure 2a. This reflects the lower average spread charged for trading in Large Cap versus Mid Cap stocks. For $Turnover\ (log)_{i,t}$, we find a small significant time-variation (at the 10 percent level) in model (2), but the statistical significance of the group-specific differences is lost and is instead captured by $Market\ Cap\ (log)_{i,t}$ (which to a large extent overlaps with the $Treated_i$ variable).

Table 6a: Effect of vPoTA on daily relative bid-ask spreads and turnover (2014)

The table presents the effects on daily relative bid-ask spreads in basis points (log) and turnover in million euro (log) of the switch from post-trade transparency to voluntary post-trade anonymity on March 24, 2014. The results are OLS regression coefficients based on random effects difference-in-differences estimations, with a pre-event period of 51 trading days (January 1 to March 14, 2014), and a post-event period of 51 trading days (March 31 to June 16, 2014). The treatment group consists of 118 Large Cap stocks and the control group of 111 Mid Cap stocks on SSE, HSE, and CSE. The table presents significance by 10% (*), 5% (**) and 1% (***). Robust standard errors clustered at the stock level are presented in parentheses.

Outcome variable	$Spread\ (log)_{i,t}$		$Turnover\ (log)_{i,t}$	
Model	(1)	(2)	(1)	(2)
$Post_t$	0.017 (0.022)	0.023 (0.021)	-0.074 (0.048)	-0.068* (0.041)
$Treated_i$	-1.378*** (0.085)	-0.759*** (0.141)	2.692*** (0.264)	0.426 (0.383)
$\boldsymbol{Post_t \cdot Treated_i}$	**-0.025** **(0.028)**	**-0.018** **(0.027)**	**-0.084** **(0.062)**	**-0.081** **(0.055)**
$Market\ Cap\ (log)_{i,t}$		-0.235*** (0.048)		1.106*** (0.148)
$Stock\ Price\ (log)_{i,t}$		-0.037 (0.035)		-0.295** (0.118)
$Price\ Variability_{i,t}$		0.027** (0.013)		0.189*** (0.034)
$Constant$	4.003*** (0.050)	8.648*** (0.944)	13.039*** (0.173)	-9.002*** (2.881)
N	23,120	23,120	23,120	23,120

6.2 Hypothesis 2: the 2019 and 2020 PoTA regimes

In April 2019, index stocks switched from vPoTA to PoTA, while non-index Large Cap stocks remained under vPoTA. One year later, trading in non-index Large Cap stocks became post-trade anonymous by default. The null of our second hypothesis, which we do not expect to reject, is that these introductions did not improve liquidity. We follow the outline in 6.1 throughout 6.2.1 and 6.2.2, first illustrating the development (and parallel trends) of our outcome variables

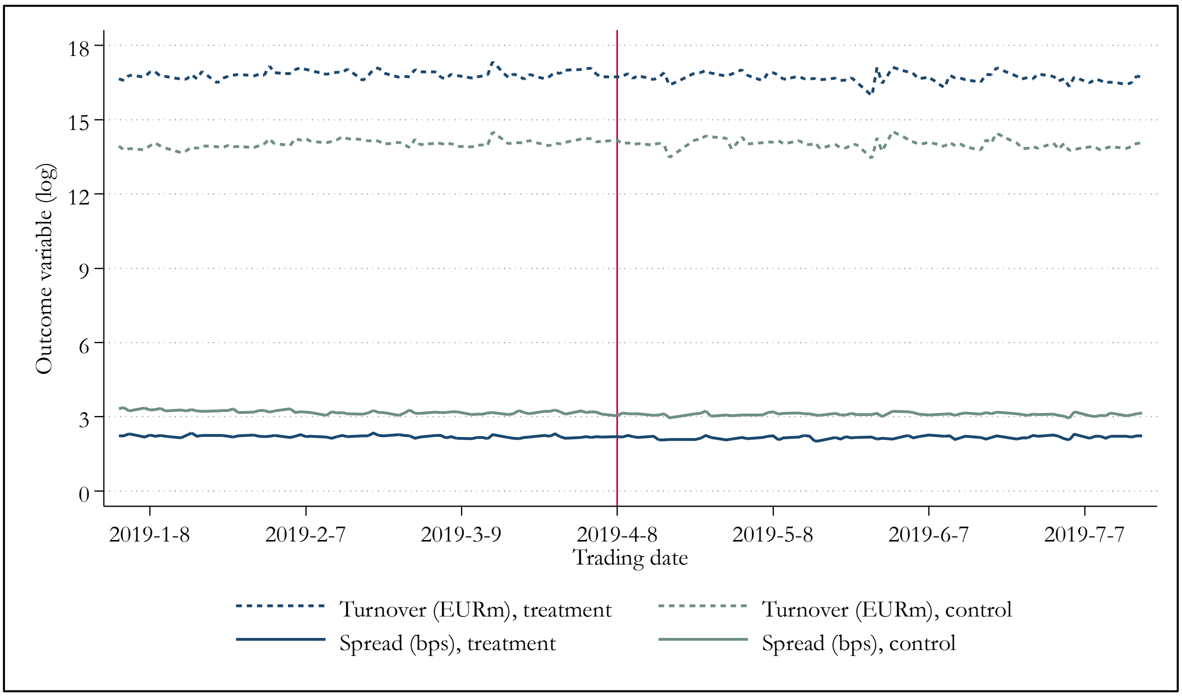
$Spread\ (log)_{i,t}$ and $Turnover\ (log)_{i,t}$ in event-study plots and then formalising the analysis through DiD regressions.

6.2.1 The switch from vPoTA to PoTA in main index stocks (2019)

With index stocks as the treatment group and non-index Large Cap stocks as control group, Figure 2b shows the higher turnover and lower bid-ask spreads in index stocks than in non-index stocks throughout the event. In line with our hypothesis, there appears to be no increase in $Turnover\ (log)_{i,t}$ or decrease in $Spread\ (log)_{i,t}$ after the event on April 8, 2019.

Figure 2b: Pre- and post-event trends in outcome variables (2019)

The figure presents daily relative bid-ask spreads in basis points (log) and turnover in million euro (log) around the switch from voluntary to mandatory post-trade anonymity on April 8, 2019. The event window stretches from January 1 to July 18, 2019. The treatment group consists of 62 stocks in the main indexes and the control group of 118 Large Cap stocks on SSE, HSE, and CSE that are not part of the main indexes.



In the regressions presented in Table 6b, we find a small but statistically significant (10 percent level) increase in $Spread\ (log)_{i,t}$ of about five percent following the switch from vPoTA to PoTA. Our results thus show that relative bid-ask spreads *increased* following the switch that Nasdaq Nordic argued would improve liquidity. Concurrently, at the 10 percent level, we reject our null hypothesis that the switch from vPoTA to PoTA would not have a significant impact on $Spread\ (log)_{i,t}$. This contradicts our expectations in two ways. We did not expect a significant impact, but if there was one, we expected PoTA to enhance liquidity through lower relative bid-ask spreads, and not the other way around. Neither model show any statistically significant effect on $Turnover\ (log)_{i,t}$, and our data does not suggest that switching from vPoTA to PoTA improved liquidity through increased trading volumes.

Considering our $Post_t$ and $Treated_i$ variables, we observe a significant time-varying decrease in $Spread\ (log)_{i,t}$ (1 percent level) in our treatment group and a significant group-specific difference across both outcome variables (1 percent level). Unlike in section 6.1, the group-specific difference remains significant for $Turnover\ (log)_{i,t}$ when we control for market capitalisation in model (2), which is explained by the differentiating factor between the treatment and control group no longer being market cap but turnover (recall that the OMX main indexes consist of the most traded stocks in each market, not by the highest market cap stocks).

Table 6b: Effect of PoTA on daily relative bid-ask spreads and turnover (2019)

The table presents the effects on daily relative bid-ask spreads in basis points (log) and turnover in million euro (log) of the switch from voluntary to mandatory post-trade anonymity for main index stocks on April 8, 2019. The results are OLS regression coefficients based on random effects difference-in-differences estimations with a pre-event period of 63 trading days (January 1 to March 29) and a post-event period of 63 trading days (April 15 to July 18). The treatment group consists of 62 stocks in the main indexes and the control group of 118 Large Cap stocks on SSE, HSE, and CSE that are not part of the main indexes. The table presents variable significance by 10% (*), 5% (**) and 1% (***). Robust standard errors clustered at the stock level are presented in parentheses.

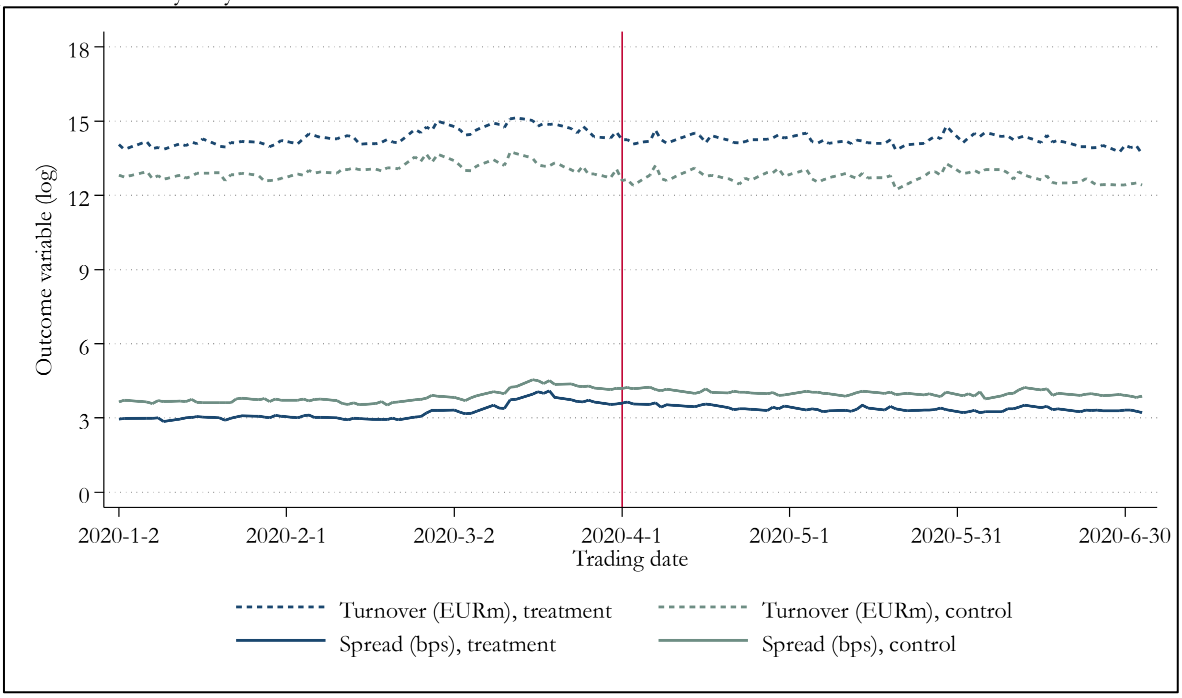
Outcome variable	$Spread\ (log)_{i,t}$		$Turnover\ (log)_{i,t}$	
Model	(1)	(2)	(1)	(2)
$Post_t$	-0.100*** (0.023)	-0.098*** (0.022)	-0.018 (0.049)	-0.028 (0.045)
$Treated_i$	-0.990*** (0.083)	-0.851*** (0.104)	2.809*** (0.248)	2.462*** (0.313)
$\boldsymbol{Post_t \cdot Treated_i}$	**0.052*** **(0.030)**	**0.053*** **(0.029)**	**-0.111** **(0.074)**	**-0.103** **(0.071)**
$Market\ Cap\ (log)_{i,t}$		-0.152*** (0.048)		0.410*** (0.149)
$Stock\ Price\ (log)_{i,t}$		0.056 (0.042)		-0.101 (0.126)
$Price\ Variability_{i,t}$		0.060*** (0.018)		0.187*** (0.054)
$Constant$	3.202*** (0.064)	6.226*** (1.056)	14.018*** (0.197)	4.905 (3.192)
N	22,352	22,352	22,352	22,352

6.2.2 The switch from vPoTA to PoTA in Large Cap stocks (2020)

From the 2019 regime, the incremental impact of switching from vPoTA to PoTA remains ambiguous with no significant impact on $Turnover\ (log)_{i,t}$ and a significant impact on $Spread\ (log)_{i,t}$, but toward worsened liquidity. We now turn to the second vPoTA-PoTA event that occurred on April 1, 2020, where all Large Cap stocks not part of the main indexes switched from vPoTA to PoTA. Before diving into the details, however, we must keep in mind that the event overlaps with a time of significant market turmoil caused by the Covid-19 pandemic. Over the course of 18 trading days (February 20 to March 16), for example, the SSE fell by more than 30 percent (corresponding to about 60 percent of the total decline during the Global Financial Crisis of 2007-2008 in just five percent of the time). As is seen in Figure 2c, the market turmoil in March and April drove relative bid-ask spreads and turnover higher, reflecting investor uncertainty in both Large Cap and Mid Cap stocks. Moreover, and more critically, the 'permanent difference' between the treatment and control groups decreased in the volatile market preceding the event on April 1, 2020, indicating potential violations of the assumptions of parallel trends.

Figure 2c: Pre- and post-event trends in outcome variables (2020)

The figure presents daily relative bid-ask spreads in basis points (log) and turnover in million euro (log) around the switch from voluntary to mandatory post-trade anonymity for non-index Large Cap stocks on April 1, 2020. The event window stretches from January 1 to July 3, 2020. The treatment group consists of 111 Large Cap stocks and the control group of 164 Mid Cap stocks on SSE, HSE, and CSE. Main index constituent stocks have been removed from the treatment group as they already trade under mandatory post-trade anonymity since 2019.



The results in Table 6c show no statistically significant treatment effect on $Spread\ (log)_{i,t}$, but a significant increase in $Turnover\ (log)_{i,t}$ (5 and 1 percent level in model (1) and (2), respectively). When re-running regressions on shorter pre- and post-event periods (30 trading days) to test the robustness of the 2020 results, we lose the statistically significant effect for $Turnover\ (log)_{i,t}$, and $Spread\ (log)_{i,t}$ instead shows a small significant decrease at the five percent level. Hence, the results are sensitive to the choice of event window, which is unsurprising given the degree of market volatility at the time. Across both model specifications and outcome variables of interest, there is a time-varying effect significant at the one percent level. Specifically, $Spread\ (log)_{i,t}$ increased while $Turnover\ (log)_{i,t}$ decreased in the post-event period. This is endemic of a market with deteriorating liquidity, and while the pandemic hit during the pre-event period, the treatment occurred on April 1 which leaves more trading days impacted by the pandemic in the post-event period.

Table 6c: Effect of PoTA on daily relative bid-ask spreads and turnover (2020)

The table presents the effects on daily relative bid-ask spreads in basis points (log) and turnover in million euro (log) of the switch from voluntary to mandatory post-trade anonymity on April 1, 2020. The results are OLS regression coefficients based on random effects difference-in-differences estimations, with a pre-event period of 58 trading days (January 1 to March 24) and a post-event period of 58 trading days (April 8 to July 3). The treatment group consists of 111 Large Cap stocks and the control group of 164 Mid Cap stocks on SSE, HSE, and CSE. The table presents variable significance by 10% (*), 5% (**) and 1% (***). Robust standard errors clustered at the stock level are presented in parentheses. Main index constituent stocks have been removed from the treatment group as they already trade under mandatory post-trade anonymity since 2019.

Outcome variable	$Spread\ (log)_{i,t}$		$Turnover\ (log)_{i,t}$	
Model	(1)	(2)	(1)	(2)
$Post_t$	0.172*** (0.022)	0.171*** (0.021)	-0.308*** (0.042)	-0.211*** (0.039)
$Treated_i$	-0.631*** (0.078)	-0.130 (0.125)	1.341*** (0.234)	-0.156 (0.388)
$\boldsymbol{Post_t \cdot Treated_i}$	**-0.007** **(0.034)**	**-0.012** **(0.032)**	**0.132**** **(0.059)**	**0.140***** **(0.053)**
$Market\ Cap\ (log)_{i,t}$		-0.235*** (0.048)		0.791*** (0.159)
$Stock\ Price\ (log)_{i,t}$		0.078** (0.032)		-0.129 (0.115)
$Price\ Variability_{i,t}$		0.039*** (0.005)		0.159*** (0.015)
$Constant$	3.826*** (0.037)	8.113*** (0.930)	13.041*** (0.113)	-3.046 (3.089)
N	31,675	31,675	31,675	31,675

6.3 Discussion

Contrary to recent literature, we find no positive relationship between the introduction of post-trade anonymity in 2014 and improved market quality on Nasdaq Nordic. Nor do the 2019 and 2020 PoTA regimes seem to improve liquidity relative to vPoTA. The sole statistically significant improvement to liquidity is the small increase in turnover in 2020, which is sensitive to the length of our event windows. There is a risk that this result is driven by the Covid-19 market turmoil, as the trend in outcome variables for our treatment and control groups appears to violate the parallel trends assumption. Therefore, we cannot reject the null in either our first hypothesis, which is surprising, nor our second hypothesis, which we expected. In the following discussion, we provide additional nuance to primarily the 2014 regime while much of the reasoning likely extends to the 2019 and 2020 regimes as well.

A key difference between our setting and those in Dennis and Sandås (2020) and Meling (2021), who find strong positive relationships between anonymity and liquidity, is that we study anonymity reforms in the 2010s while they study data from the 2000s. Over this period, the Nasdaq Nordic exchanges have undergone several considerable changes. The most noteworthy is perhaps the introduction of CCP clearing for Large Cap stocks in early 2009. According to Nasdaq Nordic, this represented 'the biggest structural change since trading became electronic in the early 1990s'. CCP clearing did not only reduce counterparty risk and trading costs, but also led to higher international attention.[12] In fact, the share of foreign trading at Nasdaq Nordic increased from 25 to 60 percent between 2009 and 2014. Moreover, in January 2010, Nasdaq Nordic capped its trading fees and in February the INET trading platform was introduced, with capacity to handle a million messages per second at an average processing speed of 250 microseconds (Hagströmer & Nordén, 2013). Together, these changes cut transaction costs by as much as 84% by the end of 2010 compared to early 2009. The changes were also aimed at stimulating HFT activity, which was a new phenomenon on Nasdaq Nordic at the time (Baird, 2010). The steep increase in international volume, sharp reduction in transaction costs, and computer-enabled HFT trading represent fundamental changes to how the Nasdaq Nordic marketplaces operated only a few years earlier. Consequently, it is plausible that the positive effect of anonymity on market quality observed in the late 2000s has seen diluted by technological advancements and market reforms. This argument supports the idea that the effect of anonymity is time-varying put forward by Meling (2021).

To better understand this dynamic, we revisit the theoretical arguments for introducing post-trade anonymity in the first place; namely, that broker codes convey private information to other market participants. Under transparency, informed investors must take measures to conceal their private information. The costs of these measures (e.g., broker fees and transaction costs) prevent informed investors to take sufficient action as to render broker codes useless for other market participants (Dennis & Sandås, 2020). If, however, transaction costs drop by 84% in less than two years, it is conceivable that informed investors will be able to conceal their information at lower costs and to a greater degree protect their private information. Such changes to investor behaviour would dilute

[12] CCP clearing is also a prerequisite for complete post-trade anonymity. In the absence of CCP, counterparties must have bilateral transparency to facilitate clearing and settlement of trades. Thus, CCP clearing changes the nature of 'anonymity' where it remained bilaterally transparent in the pre-CCP settings studied by previous papers.

the information content of broker codes, and subsequently the expected benefits of introducing post-trade anonymity. The surge in sponsored access trading, dark pools, and trading on alternative venues between the introduction of MiFID in 2007 and Nasdaq Nordic's introduction of vPoTA in 2014 work to further diminish the potential benefit of switching from transparency to post-trade anonymity. Given the previously mentioned unavailability of high-frequency data, we are unable to formally test the information content of broker codes within the scope of this paper.

Nevertheless, as we have reason to believe that broker codes carry less information in the 2010s, we can consider situations in which previous empirical literature have observed varying impact of post-trade anonymity introductions (and subsequently varying levels of information content conveyed through broker codes). Thiessen (2003) find that anonymity is preferred for highly liquid blue-chip stocks, but that traders prefer transparency in less liquid stocks. In a later paper, Foucault, Moinas, and Thiessen (2007) argue that anonymity is less favourable for stocks with high information asymmetry but promotes liquidity in stocks with lower information asymmetry. To dissect our results from Section 6.1, we thus consider the impact of post-trade anonymity across stocks with different degrees of information asymmetry. Harris (1994) argues that company size is a viable proxy for the amount of public information available about a listed stock. Hence, we use a company's market cap as a proxy for the degree of information asymmetry. We split the 2014 treatment group into tertiles (low, mid, and high) based on the average pre-event period market capitalisation. We list these stocks and their tertile constituency in Appendix 3.

In Table 7, we re-run our full specification DiD model for each market cap tertile, keeping Mid Cap stocks as our control group. Dividing our dataset into tertiles based on the level of information asymmetry (proxied by market cap) provides additional insights of the anonymity impact on market quality. In line with Thiessen (2003), we find that post-trade anonymity reduces $Spread\ (log)_{i,t}$ by about six percent (five percent level) in the high tertile of Large Cap stocks while it does not improve for the low and mid tertiles. We find a significant reduction (five percent level) in $Turnover\ (log)_{i,t}$ for the largest stocks, but with a small coefficient of -0.159, in a noisy measure of liquidity with an average of about 16 for the high tertile. While previous studies have been able to establish market-wide relationships between post-trade anonymity and improved market quality, the fact that we find improved bid-ask spreads only for the sub-group of stocks with the lowest information asymmetry suggests that broker codes carry less information than they used to. The results are consistent throughout our two model specifications.

Table 7: Effect of vPoTA per Large Cap company size tertile (2014)

The table presents the effects on daily relative bid-ask spreads in basis points (log) and turnover in million euro (log) of the switch from post-trade transparency to voluntary post-trade anonymity on March 24, 2014. The results are OLS regression coefficients based on random effects DiD estimations, with a pre-event period of 51 trading days (January 1 to March 14) and a post-event period of 51 trading days (March 31 to June 16). The low, mid, and high tertile treatment groups consists of 39, 39, and 38 Large Cap stocks split into tertiles based on average daily market cap over the pre-event period. The control group consists of 111 Mid Cap stocks. All stocks are listed at SSE, HSE, and CSE. The table presents variable significance by 10% (*), 5% (**) and 1% (***). Robust standard errors clustered at the stock level are presented in parentheses.

Outcome variable	$Spread\ (log)_{i,t}$			$Turnover\ (log)_{i,t}$		
Company size	Low	Mid	High	Low	Mid	High
$Post_t$	0.026 (0.021)	0.025 (0.021)	0.026 (0.021)	-0.075* (0.041)	-0.074* (0.041)	-0.073* (0.041)
$Treated_i$	-0.562*** (0.150)	-0.366* (0.219)	-0.094 (0.390)	-0.238 (0.415)	-0.619 (0.598)	-1.594 (0.999)
$\boldsymbol{Post_t \cdot Treated_i}$	**0.022** **(0.033)**	**0.004** **(0.044)**	**-0.065**** **(0.029)**	**-0.010** **(0.073)**	**-0.108** **(0.080)**	**-0.159**** **(0.076)**
$Market\ Cap\ (log)_{i,t}$	-0.432*** (0.077)	-0.460*** (0.074)	-0.409*** (0.085)	1.705*** (0.227)	1.805*** (0.217)	1.544*** (0.248)
$Stock\ Price\ (log)_{i,t}$	-0.084*** (0.031)	-0.032 (0.036)	-0.055* (0.030)	-0.371*** (0.115)	-0.464*** (0.103)	-0.270** (0.125)
$Price\ Variability_{i,t}$	0.016 (0.014)	0.016 (0.013)	0.023 (0.016)	0.189*** (0.036)	0.204*** (0.039)	0.204*** (0.037)
$Constant$	12.651*** (1.510)	13.147*** (1.439)	12.140*** (1.677)	-20.767*** (4.378)	-22.669*** (4.185)	-17.771*** (4.807)
N	15,160	15,113	15,047	15,160	15,113	15,047

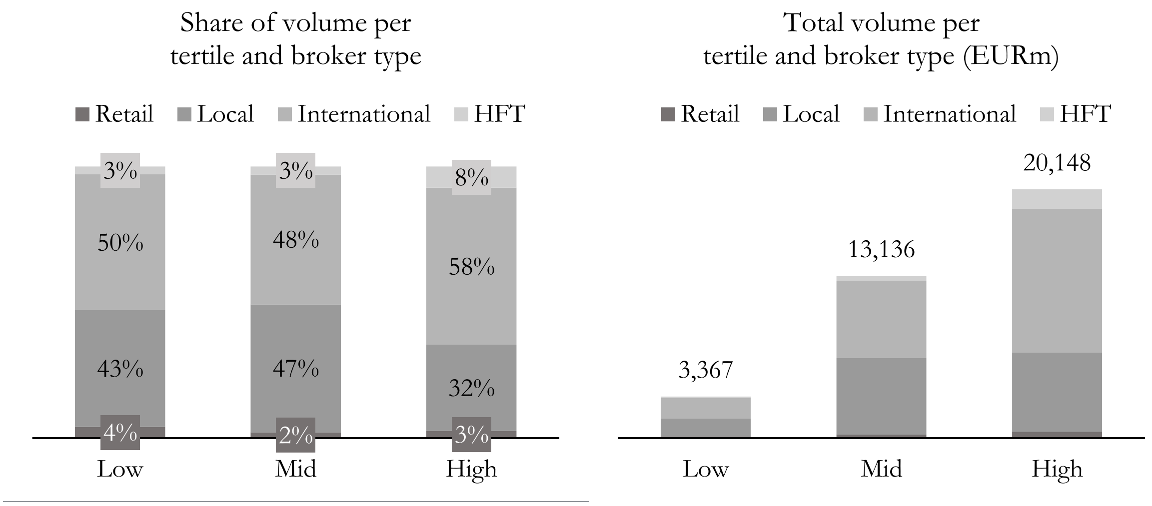
To further dissect this varying impact of anonymity, we turn to the empirical findings of Linnainmaa and Saar (2012). They argue that the type of trader who prefer anonymity the most is also the most informed, exercising the highest price impact when trading. Therefore, we compare the broker composition of the three tertiles following the introduction of post-trade anonymity in 2014 to further explain the dynamics in our setting. Using the 'Nasdaq Nordic Member Market Shares per Instrument' report in April 2014 (the first full month of trading after the introduction), we find 85 active brokers at the Nasdaq Nordic exchanges. We collect information from broker websites on the type of clients they primarily cater to and categorise them into local institutions (34 brokers), international institutions (25), HFT firms (19), and retail investors (7).[13] We then map their total trading turnover in April 2014 onto the stocks in our treatment group, divided into the beforementioned tertiles. Figure 3 presents market shares in the high, mid, and low tertiles,

[13] The broker categories are consistent with previous literature (e.g., van Kervel and Menkveld (2019) and Meling (2021)). For a comprehensive list of brokers and their categorisation, we refer to Appendix 4.

respectively. The high tertile, consisting of the largest Large Cap stocks, differs from the other tertiles in terms of broker composition. In the high tertile, HFT traders and international brokers have considerably larger market shares compared to the other groups (170 and 18 percent higher), while local firms and retail investors have lower market shares (29 and 18 percent lower).

Figure 3: Broker composition per Large Cap size tertile

The figure presents the broker composition across the Nasdaq Nordic Large Cap segments. The segments are divided into tertiles based on the average daily market cap during the pre-event period. The trade volume data is collected from Nasdaq Nordic's trading report for April 2014. The low, mid, and high tertiles corresponds to 39, 39, and 38 Large Cap stocks, respectively.



Linnainmaa and Saar (2012) study Finnish data from 2000 and 2001. They find that local institutions exercise the highest price impact, have the most private information, and subsequently gain the most from anonymity. Applying this line of reasoning to our setting, where liquidity only improves from anonymity in the basket of stocks with the greatest presence of international and HFT firms, renders a different conclusion: HFT firms and international institutions have reasons to prefer anonymity more than other brokers. Thus, a potential explanation as to why our results differ from those of previous papers lies in the steep increase of international and HFT trading over the last decade. Importantly, this is precisely in line with the rationale for introducing anonymity in the first place. In 2008, Nasdaq Nordic argued that the internationalisation of the Nordic financial markets had led to a large and growing share of international members who preferred to trade anonymously. While we cannot say where this preference comes from (be it greater levels of private information, advanced trading algorithms that benefit from being undetected, a greater coherence between international exchanges, etc.), this finding points to the relevance of re-visiting the field of price impact and the adjacent information content of broker codes, for instance by extending the work of Linnainmaa and Saar (2012) in a more recent setting.

While HFT firms tend to concentrate their activity on the most traded stocks, the concentration of HFT trading in the highest tertile stocks is especially interesting as such firms spend significant resources on developing their strategies and do not want other market participants to be able to track and understand them. Unfortunately, Nasdaq Nordic never reported the share of anonymous versus transparent trading during vPoTA, nor did they publish broker-level data prior to the introduction of vPoTA. These data limitations make us unable to investigate how the composition of traders changed as Nasdaq Nordic switched from post-trade transparency to voluntary anonymity, or how much of the trading really became anonymous under the voluntary 2014 regime. Therefore, we cannot statistically confirm that HFT activity increased following the introduction of post-trade anonymity nor that these firms opted for anonymity in 2014. It is plausible, however, that the difference in trader compositions in different tertiles underpins the varying impact of anonymity on trading metrics as discussed and presented in Table 7. For example, just days before the introduction of the 2014 regime, Nasdaq Nordic announced two new members: HFT firms SSW Trading (broker code IAT) and Hudson River Trading Europe (HRT). In recent months, HRT consistently ranked among the five brokers with the highest turnover and, in 2021, HRT was the second most active broker at Nasdaq Nordic.

7 Identification Concerns

7.1 Sample limitations

In terms of sample construction, selection bias and data quality are our main identification concerns. Selection bias stems from the treatment assignment being non-random throughout the regimes. Stocks in our treatment and control groups are notably different, as shown in the descriptive data tables and event-study plots, because anonymity was assigned based on Large Cap or main index constituency. As outlined above, the market cap in one year does not perfectly predict transfers between segments as (i) the segments are reviewed annually and (ii) a stock must cross the segment thresholds by more or less than 50 percent to transfer the following year or qualify via a second-year review. While index membership is based on trading volume, the segment is reviewed bi-annually and subject to Nasdaq Nordic discretion as to, for example, not include stocks that are to be delisted in indexes, despite them qualifying in terms of trading volume. This is not necessarily an issue in the DiD setting as discussed in Section 5.3.2, given that the outcome variables move in parallel absent of treatment. We also introduce bias when trimming our sample based on data quality issues relating primarily to unlisted share classes, non-Nordic primary listings, and missing outcome variable data. Therefore, it is important to keep in mind that our samples do not fully reflect the investable universe of stocks at the Nasdaq Nordic exchanges.

7.2 Index inclusion effects

Another potential source of confounding is simultaneous changes to trading behaviour coinciding with the treatment application. As we compare Large Cap stocks against Mid Cap stocks and stocks in the main indexes against Large Cap stocks that are not part of those indexes, a natural worry arises from the considerable differences in trading patterns and broker dynamics between the groups (presented continuously throughout the paper). If we would analyse the impact of anonymity when moving from the Mid Cap to Large Cap segments or entering the indexes, this would likely be a profound source of confounding. For example, there are index mutual funds and ETFs facilitating exposure toward baskets of stocks such as the OMX main indexes, which would structurally change the trading behaviour in a stock that enters an index, rendering it difficult to capture the true treatment effect of anonymity. As we purposely consider introductions of new regimes and form our event windows as to exclude any such market cap segment migration and further control and adjust for movements in and out of the indexes, this is a negligible source of confounding in our paper.

7.3 Simultaneous market events and reforms

Given the nature of our event-study methodology, it is important to control for any simultaneous market events coinciding with the anonymity regime introductions, especially other events that might impact market quality at Nasdaq Nordic. While our analysis stretches over several years, we do not perform any comparisons between, for example, the 2014 and 2020 regimes directly. Thus, market-wide trends that happen over long periods of time do not constitute a problem in our research setting. Furthermore, the variable $Post_t$ captures trends between the pre- and post-event periods. What remains a potential source of confounding is shocks to the market around the events on March 24, 2014, April 8, 2019, and April 1, 2020. As discussed, the Covid-19 pandemic generated historically large and rapid declines across equity markets. Shortly after, however, markets recovered as governments responded with big stimulus packages. Naturally, this makes the 2020 results uncertain, and we thus remain cautious in drawing conclusions based on the shift from vPoTA to PoTA in 2020. To control for other shocks, we analyse the stock market climate around the events and research headlines in the financial press.[14] During our 2014 event window, equity markets were primarily concerned about two things: the emerging market currency crisis in late January and Russia's annexation of Crimea in February and March. In 2019, markets were instead spooked by the China-U.S. trade war and a weakening European economy throughout the

[14] Specifically, we focus on news reporting around trading days (weeks) where the OMXS30, the OMXC25, or the OMXH25 moved up or down more than two percent (five percent).

event window. While these events led to stock market declines, often followed by rebounds, it is unlikely that these events impact our treatment and control groups enough that it skews our results.

Lastly, we check the Nasdaq Nordic website for any simultaneous market reforms which could have an impact on market quality. While there were no other equity market reforms at Nasdaq Nordic during our event windows, a new tick size regime under MiFID 2 was introduced on systemic internalisers in June 2020. Systemic internalisers, a type of investment firm, act as counterparties to investors, and not trading venues, but trading through systematic internalisers naturally relates to trading on regulated markets such as Nasdaq Nordic. The new tick size regime may therefore impact trading on Nasdaq Nordic indirectly, but as the overlap between the introduction and the end of our 2020 post-event period is limited (June 26 versus July 3), we believe any potential impact from this to be trivial in our research setting.

8 Conclusion

We find no evidence of market-wide liquidity improvements following the switch from transparency to voluntary post-trade anonymity in 2014. Moreover, we find no incremental benefit in switching from voluntary to mandatory post-trade anonymity in 2019. While we document a small but statistically significant increase in turnover following the 2020 regime, the effect is highly sensitive to the length of our event window and there is a risk that the result is driven by the Covid-19 market turmoil. As we extend our analysis of the 2014 regime, we do, however, find that post-trade anonymity improves bid-ask spreads by about six percent in the largest stocks, which are characterised by lower information asymmetry and higher international and high-frequency trading activity. Our discussion suggests that the information content of broker codes has been diluted by technological advancements and lower trading costs. Major market reforms, such as the introduction of central counterparty clearing, have potentially changed the market dynamics to the extent that the incremental benefit of post-trade anonymous trading for liquidity is close to none.

In December 2022, Nasdaq Nordic reached the end of a decade-long journey towards anonymity when Mid Cap, Small Cap, and First North Growth Market stocks started to trade with post-trade anonymity. In an interview commenting the 2022 post-trade anonymity regime, Nasdaq Nordic claimed that ‘we will be able to create a more efficient market with better liquidity, lower spreads, and higher trading volumes, which we have seen following the [post-trade anonymity] introductions in the Large Cap segment’ (Swee, 2022). To the best of our knowledge, Nasdaq Nordic has not disclosed figures supporting improved market quality. We recognise that an exchange has many reasons underpinning a shift toward anonymous trading, for example improved market surveillance, financial benefits from a growing number of paying members, international alignment with other exchanges, and increased competitiveness versus other trading venues. However, our study suggests that in recent years, anonymity reforms have not lead to improvements in liquidity to the extent that Nasdaq Nordic had hoped, and that empirical research have documented in the past. While Nasdaq Nordic and other stock exchanges around the world seem to have made up their minds, the debate regarding post-trade anonymity is not yet settled. Further research is needed to evaluate whether anonymous trading does in fact lead to better functioning markets and what underlying mechanisms are important in explaining these results.

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10 Appendixes

Appendix 1a: Previous Large Cap and index stocks that trade under vPoTA

The table presents previous Large Cap stocks that keep vPoTA from March 24, 2014, to April 1, 2020. We drop these from the control samples for consistency, so that stocks in control samples do not receive treatment.

Year	Exchange	Ticker	Segment	Year	Exchange	Ticker	Segment
2014	CSE	DNORD	Mid Cap	2020	CSE	BAVA	Mid Cap
2014	CSE	NKT	Mid Cap	2020	CSE	DNORD	Mid Cap
2014	CSE	RBREW	Mid Cap	2020	CSE	NKT	Mid Cap
2014	HSE	CTY1S	Mid Cap	2020	HSE	OTE1V	Mid Cap
2014	HSE	SDA1V	Mid Cap	2020	SSE	AOI	Mid Cap
2014	SSE	BALD B	Mid Cap	2020	SSE	COLL	Mid Cap
2014	SSE	INDT	Mid Cap	2020	SSE	FING B	Mid Cap
2014	SSE	LIAB	Mid Cap	2020	SSE	LEO	Mid Cap
2014	SSE	LOOM B	Mid Cap	2020	SSE	LIAB	Mid Cap
2014	SSE	NOBI	Mid Cap	2020	SSE	QLINEA	Mid Cap
2014	SSE	SMF	Mid Cap	2020	SSE	SMF	Mid Cap
2019	CSE	BAVA	Mid Cap				
2019	CSE	DNORD	Mid Cap				
2019	CSE	NKT	Mid Cap				
2019	HSE	OTE1V	Mid Cap				
2019	SSE	AOI	Mid Cap				
2019	SSE	COLL	Mid Cap				
2019	SSE	FING B	Mid Cap				
2019	SSE	HEM B	Mid Cap				
2019	SSE	LEO	Mid Cap				
2019	SSE	LIAB	Mid Cap				
2019	SSE	MYCR	Mid Cap				
2019	SSE	QLINEA	Mid Cap				
2019	SSE	SMF	Mid Cap				

Appendix 1b: Finnish stocks that remain under PoTA since 2008

The table presents the five Finnish stocks that receive PoTA in the 2008 and keep it through our events. We drop these for consistency so that stocks in treatment samples have not already received treatment.

Exchange	Name	Ticker	Segment
HSE	NOKIA OYJ	NOK1V	Large Cap
HSE	NOKIA OYJ	NOKIA	Large Cap
HSE	SAMPO OYJ	SAMAS	Large Cap
HSE	SAMPO OYJ	SAMPO	Large Cap
HSE	STORA ENSO OYJ	STERV	Large Cap
HSE	UPM-KYMMENE OYJ	UPM1V	Large Cap
HSE	UPM-KYMMENE OYJ	UPM	Large Cap
HSE	FORTUM OYJ	FUM1V	Large Cap
HSE	FORTUM OYJ	FORTUM	Large Cap

Appendix 1c: Main index stocks (2020)

The table presents main index stocks dropped in the 2020 event as they already trade under PoTA since 2019, to ensure that that stocks in treatment sample have not already received treatment.

Exchange	Ticker	Exchange	Ticker
CSE	MAERSK A	SSE	ELUX B
CSE	MAERSK B	SSE	SKF B
CSE	CARL B	SSE	VOLV B
CSE	CHR	SSE	ALFA
CSE	COLO B	SSE	ASSA B
CSE	DANSKE	SSE	ATCO B
CSE	DEMANT	SSE	ATCO A
CSE	DSV	SSE	BOL
CSE	FLS	SSE	ESSITY B
CSE	GMAB	SSE	GETI B
CSE	GN	SSE	HEXA B
CSE	LUN	SSE	INVE B
CSE	ISS	SSE	KINV B
CSE	JYSK	SSE	NDA SE
CSE	ORSTED	SSE	SAND
CSE	PNDORA	SSE	SECU B
CSE	ROCK B	SSE	SEB A
CSE	RBREW	SSE	SKA B
CSE	SIM	SSE	SSAB A
CSE	TOP	SSE	SCA B
CSE	TRYG	SSE	SHB A
CSE	VWS	SSE	SWED A
		SSE	SWMA
HSE	ELISA	SSE	TEL2 B
HSE	HUH1V	SSE	ERIC B
HSE	KEMIRA	SSE	TELIA
HSE	KESKOB		
HSE	KOJAMO		
HSE	KCR		
HSE	METSB		
HSE	METSO		
HSE	NESTE		
HSE	TYRES		
HSE	NDA FI		
HSE	ORNAV		
HSE	OUT1V		
HSE	TELIA1		
HSE	TIETO		
HSE	VALMT		
HSE	WRT1V		

Appendix 2: Stocks dropped due to illiquidity or listing and delisting during the event

The table presents stocks with less than 50 days of trading in either the pre- or post-event periods, dropped due to illiquidity or listing/delisting during the event

Year	Exchange	Ticker	Segment
2014	CSE	CARL A	Large Cap
2014	CSE	JDAN	Mid Cap
2014	HSE	AKTRV	Mid Cap
2014	HSE	FLG1S	Mid Cap
2014	SSE	ELUX A	Large Cap
2014	SSE	HOLM A	Large Cap
2014	SSE	MTG A	Large Cap
2014	SSE	SCV A	Large Cap
2014	SSE	SCV B	Large Cap
2014	SSE	HEBA B	Mid Cap
2014	SSE	IFS A	Mid Cap
2014	SSE	SWEC A	Mid Cap
2019	CSE	LASP	Mid Cap
2019	HSE	POY1V	Mid Cap
2019	SSE	AHSL	Large Cap
2019	SSE	HUFV C	Large Cap
2019	SSE	ACAN B	Mid Cap
2019	SSE	CHER B	Mid Cap
2019	SSE	MRG	Mid Cap
2019	SSE	VICP A	Mid Cap
2019	SSE	VICP B	Mid Cap
2020	CSE	LASP	Mid Cap
2020	CSE	VELO	Mid Cap
2020	HSE	DNA	Large Cap
2020	HSE	METSO	Large Cap
2020	HSE	CRA1V	Mid Cap
2020	HSE	HOIVA	Mid Cap
2020	SSE	HEM B	Large Cap
2020	SSE	HEMF	Large Cap
2020	SSE	HUFV C	Large Cap
2020	SSE	CAT A	Mid Cap
2020	SSE	MSON A	Mid Cap
2020	SSE	SVOL A	Mid Cap
2020	SSE	SWOL B	Mid Cap

Appendix 3: Treatment group tertiles (2014)

The table presents the 2014 treatment group (Large Cap stocks) divided into tertiles based on their average daily company market cap in the pre-event period.

Ticker	Tertile	Ticker	Tertile	Ticker	Tertile
AAK	Small	BOL	Mid	ALFA	Large
AMEAS	Small	CHR	Mid	ASSA B	Large
AXFO	Small	DSV	Mid	ATCO A	Large
AXIS	Small	EKTA B	Mid	ATCO B	Large
BILL	Small	ELI1V	Mid	CARL B	Large
CAST	Small	ELUX B	Mid	COLO B	Large
FABG	Small	GETI B	Mid	DANSKE	Large
FIS1V	Small	GN	Mid	ERIC A	Large
FLS	Small	HUSQ A	Mid	ERIC B	Large
GEN	Small	HUSQ B	Mid	HEXA B	Large
HOLM B	Small	ICA	Mid	INVE A	Large
HPOL B	Small	INDU A	Mid	INVE B	Large
HUFV A	Small	INDU C	Mid	KINV A	Large
HUH1V	Small	JYSK	Mid	KINV B	Large
IJ	Small	KBHL	Mid	MAERSK A	Large
JM	Small	KESAV	Mid	MAERSK B	Large
KCR1V	Small	KESBV	Mid	MIC SDB	Large
KRA1V	Small	LATO B	Mid	NDA DKK	Large
LJGR B	Small	LUN	Mid	NDA SEK	Large
MTG B	Small	LUPE	Mid	NDA1V	Large
NCC A	Small	MEDA A	Mid	SAND	Large
NCC B	Small	MELK	Mid	SCA A	Large
ORI SDB	Small	MEO1V	Mid	SCA B	Large
OUT1V	Small	NES1V	Mid	SEB A	Large
RATO A	Small	NRE1V	Mid	SEB C	Large
RATO B	Small	ORNAV	Mid	SHB A	Large
SAA1V	Small	ORNBV	Mid	SHB B	Large
SAAB B	Small	OTE1V	Mid	SKA B	Large
SOBI	Small	PNDORA	Mid	SKF A	Large
SSAB A	Small	POH1S	Mid	SKF B	Large
SSAB B	Small	ROCK A	Mid	STE A	Large
STCAS	Small	ROCK B	Mid	STE R	Large
STCBV	Small	SECU B	Mid	STEAV	Large
SYDB	Small	SWMA	Mid	SWED A	Large
TIEN	Small	TDC	Mid	TLSN	Large
TOP	Small	TEL2 A	Mid	VOLV A	Large
VALMT	Small	TEL2 B	Mid	VOLV B	Large
WALL B	Small	VWS	Mid	WRT1V	Large
YTY1V	Small	WDH	Mid		

Appendix 4: Broker classification (2014)

The table presents the active members on Nasdaq Nordic in April 2014 and their broker classification. Classifications have been made based on previous literature and research.

Name	MPID	Type	Name	MPID	Type
Aktieinvest FK AB	AIV	Retail	ABN AMRO Clearing Bank N.V.	FORL	International
Avanza Bank AB	AVA	Retail	ABN AMRO Clearing Bank N.V.	FORU	International
Erik Penser Bankaktiebolag	EPB	Retail	Banque Internationale à Luxembourg SA	BIL	International
Netfonds Bank AS	NTF	Retail	Barclays Capital Securities Limited Plc	BRC	International
Saxo Bank A/S	SAX	Retail	Citigroup Global Markets Limited	SAB	International
SAXO Privatbank A/S	DIF	Retail	Commerzbank AG	CBK	International
SkandiaBanken AB	SBN	Retail	Credit Suisse Securities (Europe) Ltd	CSB	International
ABG Sundal Collier Norge ASA	ABC	Local	Deutsche Bank AG	DBL	International
Ålandsbanken Abp	AAL	Local	FIM Bank Ltd	FIM	International
Alm. Brand Bank A/S	ALM	Local	Goldman Sachs International	GSI	International
Arbejdernes Landsbank A/S	ALB	Local	HSBC Bank plc	HBC	International
Arctic Securities ASA	ARC	Local	Instinet Europe Limited	INT	International
Carnegie Investment Bank AB	CAD	Local	J.P. Morgan Securities plc	JPM	International
Carnegie Investment Bank AB	CAR	Local	Jefferies International Limited	JEF	International
Carnegie Investment Bank AB	CBA	Local	Joh. Berenberg, Gossler & Co. KG	BBB	International
Danske Bank A/S	DDB	Local	Kepler Capital Markets	KCM	International
DNB Bank ASA	DNM	Local	Merrill Lynch International	MLI	International
Evli Bank Abp	EVL	Local	Morgan Stanley & Co. International plc	MSI	International
Jyske Bank A/S	JYB	Local	RBC Europe Limited	RBCE	International
Lån & Spar Bank A/S	LAS	Local	Société Générale S.A.	SGL	International
Länsförsäkringar Bank AB	LFB	Local	Société Générale S.A.	SGP	International
LocalTapiola Bank Plc	TAP	Local	UBS Limited	UBS	International
Maj Invest Markets	LDM	Local	UBS Limited	UBSR	International
Mangold Fondkommission AB	MGF	Local	Algo Engineering Europe Ltd.	AEE	HFT
Nordea Bank AB (publ)	NDS	Local	All Options International B.V.	AOI	HFT
Nordea Bank Finland Plc	NRD	Local	BNP Paribas Arbitrage	BPA	HFT
Nordnet Bank AB	NON	Local	BNP Paribas Arbitrage SNC	BPP	HFT
Nykredit Bank	NYB	Local	Flow Traders B.V.	FLW	HFT
Pareto Securities	PAS	Local	Hardcastle Trading AG	HCT	HFT
Pohjola Pankki Oyj	POH	Local	IMC Trading B.V.	IMA	HFT
Remium Nordic AB	REM	Local	KCG Europe Limited	GEL	HFT
SEB Wealth Management	SEE	Local	KCG Europe Limited	KEM	HFT
Skandinaviska Enskilda Banken AB	ENS	Local	MMX Trading B.V	MMX	HFT
Spar Nord Bankaktieselskab	SNB	Local	Neonet Securities AB	NEO	HFT
Sparekassen Kronjylland	KRO	Local	Nyenburgh Holding B.V.	NYE	HFT
Svenska Handelsbanken AB	SHB	Local	Optiver VOF	OPV	HFT
Swedbank AB	SWB	Local	Spire Europe Limited	SRE	HFT
Sydbank A/S	SYD	Local	SSW Trading GmbH	IAT	HFT
UB Securities Ltd	UB	Local	Susquehanna International Securities Ltd	SIS	HFT
Valo Research and Trading	LAV	Local	Timber Hill Europe AG	TMB	HFT
Winterflood Securities Ltd	WSL	Local	Webb Traders B.V	WEB	HFT
ABN AMRO Clearing Bank N.V.	FOR	International	Wolverine Trading UK Ltd	WLV	HFT
ABN AMRO Clearing Bank N.V.	FORC	International			