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HEDGING AT SPEED IN SOVEREIGN BOND MARKETS

by Onofrio Panzarino* and Antonio Perrella*

Abstract

This paper examines the adoption of an emerging class of algorithmic trading strategies, known as Auto-Hedging (AH), among market makers in the secondary market for Italian government bonds. AH strategies enable market makers to rapidly offset exposures following quote executions, mitigating inventory risk and adverse selection. Using trade-level data from the MTS market, we document a sharp increase in AH usage since 2020, with widespread adoption across dealers and instruments. Our empirical analysis shows that variations in AH adoption are primarily driven by time-invariant, entity-specific characteristics, while market liquidity conditions exert a more modest yet statistically significant influence. Moreover, we find that AH can also be influenced by external factors beyond the immediate trading environment. Overall, the study highlights the growing role of algorithmic trading in market-making risk management and the challenges faced by dealers in increasingly fast-paced and competitive electronic markets.

JEL Classification: G11, G12, G14, G20.

Keywords: market making, algorithmic trading, government bonds.

Sintesi

Il lavoro esamina l'adozione di una classe emergente di strategie di trading algoritmico, note come Auto-Hedging (AH), da parte dei market maker attivi nel mercato secondario dei titoli di Stato italiani. Le strategie di AH consentono ai market maker di riequilibrare rapidamente le esposizioni derivanti dall'esecuzione delle proprie quotazioni, mitigando i rischi connessi con l'assunzione di posizioni in portafoglio e con la selezione avversa. Utilizzando dati a livello di singola transazione del mercato MTS, il lavoro documenta un forte incremento del ricorso a tali strategie a partire dal 2020, con una diffusione estesa tra operatori e strumenti. L'analisi empirica mostra che le differenze nell'utilizzo dell'AH sono riconducibili principalmente a caratteristiche specifiche e persistenti dei singoli intermediari, mentre le condizioni di liquidità del mercato esercitano un'influenza più contenuta, sebbene statisticamente significativa. I risultati indicano che il ricorso all'AH può essere influenzato anche da fattori esterni all'ambiente di negoziazione. Nel complesso, lo studio mette in luce il ruolo crescente del trading algoritmico nella gestione dei rischi associati all'attività di market-making e le sfide che gli operatori affrontano in mercati elettronici sempre più rapidi e competitivi.

* Banca d'Italia, Directorate General for Payments and Market Infrastructures.

CONTENTS

1. Introduction[1]

Over the past decades, the microstructure of financial markets has been profoundly reshaped by technological innovation and the widespread adoption of electronic trading. In particular, the rise of algorithmic and low-latency trading strategies has altered the way transactions are conducted, risks are managed, and prices are formed across a wide range of asset classes.

While a vast literature has examined the impact of algorithmic and high-frequency trading on market quality and price formation, most studies focus on equity and derivatives markets. By contrast, fixed-income markets, and government bond markets in particular, have received comparatively less attention, despite their systemic relevance and central role in monetary policy transmission and financial stability. This gap partly reflects structural features of fixed-income trading, including greater market fragmentation, lower standardization of instruments, and the historical reliance on over-the-counter (OTC) transactions, all of which have slowed the process of electronification.[2] In addition, the limited availability of granular data and the complexity of bond market microstructure have also constrained academic research in this area.

This study contributes to this literature by examining the adoption of Auto-Hedging (AH) strategies, an emerging class of algorithmic trading techniques employed by market makers in the secondary market for Italian government bonds. These strategies enable market makers to reduce inventory imbalances and adverse-selection risks by executing near-instantaneous offsetting trades following the execution of their quotes. Despite their increasing diffusion in electronic markets, little is known about the prevalence of these strategies, the conditions under which they are employed, and their interaction with market liquidity.

The empirical setting of our analysis is the Italian sovereign bond market, one of the largest in Europe and among the earliest adopters of an electronic trading infrastructure. In particular, we focus on the "Mercato Telematico dei Titoli di Stato" (MTS), the electronic interdealer platform launched in 1988, where market makers play a central role in liquidity provision. Recent reports from the Italian Treasury (e.g., MEF, 2023; 2024; 2025; 2026) document the growing diffusion of AH strategies on the MTS platform, suggesting that automated hedging is becoming an increasingly important component of market-making activity. Using supervisory trade-level data from the MTS market, this study investigates both the growing adoption of AH strategies and their interaction with prevailing liquidity conditions in the secondary market. The goal of this research is twofold. First, we take a closer look at these strategies by exploring their underlying rationale and the costs and benefits associated with their implementation. This will be supported by an empirical investigation of their usage, based on an identification method we have developed to detect AH activity. Second, we empirically investigate whether reliance on AH strategies is influenced by prevailing market

[1] Any views expressed in this paper are the authors' and do not necessarily represent those of the Bank of Italy. We are grateful to Giuseppe Grande, Luca Filidi, Gioia Guarini, Luca Arciero and the anonymous referee for valuable comments and suggestions. We express our sincere gratitude to Stefano Marcelli for his crucial role in optimizing the implementation of the algorithm for identifying AH transactions, which was vital to the success of this study. All the errors are our own.

[2] As noted by Bech *et al.* (2016), although electronic trading has expanded in some fixed-income segments, including government bonds, these markets remain less automated than equity markets and continue to rely more heavily on trading mechanisms outside central limit order books (CLOBs).

conditions. This is based on the expectation that greater market liquidity may foster their deployment by reducing their execution costs.

Our findings indicate that AH activity has increased substantially in recent years, confirming the growing role of automated risk-management strategies in sovereign bond markets. Moreover, we find that the deployment of AH strategies cannot be fully understood through market conditions alone, pointing instead to the relevance of persistent differences across market makers in the use of automated risk-management techniques. These findings contribute to the literature on algorithmic trading by offering one of the first empirical investigations of automated risk-management strategies employed by market makers in government bond markets.

The remainder of the paper is organized as follows. Section 2 recalls the broader literature on algorithmic and high-frequency trading, and on market making and liquidity provision. Section 3 introduces AH strategies, emphasizing their role in mitigating key market making risks, including inventory imbalances, adverse selection, and quote decay. Section 4 describes the dataset and the methodology used to identify AH transactions, and provides an overview of their adoption in the Italian sovereign bond market. Section 5 presents the empirical analysis, along with the main results and a set of robustness checks. Section 6 concludes.

2. Related literature

This study relates to several strands of academic literature that explore the evolving role of technological innovation in financial markets and the increasing use of automated trading strategies, a process often referred to as “electronification” of trading. Within this broad context, the present work contributes to two main research areas: first, the adoption and implementation of algorithmic trading by market participants; second, the literature on market making and liquidity provision, with a focus on the role of speed and automation in managing key risks, such as adverse selection and inventory risks.

A large body of research has examined how algorithmic and high-frequency trading, enabled by technological innovation, has reshaped the speed, structure, and functioning of financial markets. Technological advances have reduced transaction costs, increased trading volume, and accelerated execution, contributing to improved market efficiency and tighter bid-ask spreads (Kirilenko and Lo, 2013). At the same time, speed has become a strategic variable: faster traders can process and act upon information more quickly than their competitors, thereby gaining a systematic advantage and generating adverse selection costs for slower participants (Brogaard *et al.*, 2014; Baron *et al.*, 2019). This asymmetry fosters competition for speed, encouraging firms to invest heavily in faster trading technology. Since the benefits of these investments are largely driven by relative advantages over competitors, they can generate a technological arms race in which the resources devoted to increasing speed exceed the corresponding gains in market efficiency and social welfare (Biais, Foucault and Moinas, 2015).

More broadly, the literature emphasizes that the rise of HFT has not simply accelerated trading but has fundamentally transformed market microstructure. O’Hara (2015) shows that strategic interactions among market participants are increasingly shaped by the design of trading platforms and the rules of the limit order book, which play a central role in determining market outcomes. In parallel, Menkveld (2016) provides a comprehensive synthesis highlighting multiple channels through which low-latency trading affects market quality, including faster incorporation of information into prices, improved intermediation, and the ability to arbitrage across fragmented markets. However, these benefits coexist with potential costs, such as increased volatility, intensified competition for speed, and greater exposure to adverse selection. Taken together, this literature points to a nuanced view in which the impact of HFT on market quality depends on the interaction between technological capabilities, market design, and strategic behavior.

Against this backdrop, modern market making models have increasingly come to rely on fast and automated trading strategies to support liquidity provision. Market makers have historically been a key pillar of modern financial systems, supporting market liquidity by continuously posting bid and ask quotes that allow other participants to trade, thereby facilitating price discovery and the efficient functioning of markets. While they primarily profit from the bid-ask spread, they face significant risks, most notably adverse selection, arising from trading against better-informed counterparties, and inventory risk, linked to holding unwanted or risky positions. These risks are managed through a combination of funding and hedging strategies, including participation in repo markets (Di Luigi, Perrella and Ruggieri, 2024) and the use of derivatives and secondary markets (Panzarino, Potente and Puorro, 2016). Understanding market makers' behaviour and their response to changing market conditions is therefore key for assessing the resilience of market liquidity, especially during periods of stress (Cartea, Jaimungal and Penalva, 2015; O'Hara and Zhou, 2021).

Traditional market making models (Glosten and Milgrom, 1985; Kyle, 1985) emphasize that market makers interact with both informed and uninformed order flows, typically losing to the former while profiting from the latter. In modern electronic markets, these dynamics are amplified by speed and competition. Market makers must continuously revise quotes in response to incoming information while operating in an environment characterized by rapid price movements and intense strategic interaction.

The ability to update quote quickly is critical for managing risk and maintaining profitability. In high-speed environments, quotes can quickly become *stale*, remaining active in the order-book after new information has rendered them obsolete and before they can be revised or cancelled by the market maker. This exposes market makers to significant adverse selection risk, as fast or better-informed traders can exploit outdated quotes. Extensive research has examined the implications of stale quotes and speed asymmetries. Examples include Foucault, Röell, and Sandås (2003), Menkveld and Zoican (2016), and Budish, Cramton, and Shim (2015), who show that even marginal speed advantages allow traders to systematically profit from slower competitors. Baron *et al.* (2019) document the difficulties faced by market makers to maintain competitive quotes without being adversely selected, while Ge, Yang and Douklas (2024) show that the presence of low-latency traders discourages aggressive quoting by others and increases the exploitation of stale liquidity.

These findings are consistent with broader evidence that competition in high-frequency environments has shifted market-making activity away from purely passive liquidity provision towards more active trading strategies (Banerjee and Roy, 2024). At the same time, continuous quoting remains essential for market makers to capture the bid-ask spread and benefit from uninformed trading (Hagströmer and Nordén, 2013). It also allows them to leverage order flow information by monitoring trading patterns and book dynamics to infer short-term price movements (Baron *et al.*, 2019). While reducing quoting activity can reduce exposure to adverse selection, it might entail significant opportunity costs. In this setting, fast and automated strategies implemented by market makers, including, for example, AH, can provide additional risk management tools that complement proactive quoting, helping market makers strike a better balance between profitability and risk in fast-paced electronic markets. However, these strategies also involve trade-offs, which are examined in greater detail in the next section.

3. Auto-Hedging: an emerging class of automated hedging strategies

3.1 Definition

This study focuses on a specific class of algorithmic trading strategies, referred to as AH, which are increasingly implemented by market makers in the secondary market for Italian government securities. For the purposes of this paper, we define an AH transaction as a rapid, algorithmically driven trade executed by a market maker to mitigate or fully neutralise an inventory shock resulting from a preceding transaction that has consumed the market maker's quote.

As we further illustrate in this section, AH strategies enable market makers to rapidly manage inventory imbalances and adverse selection risks while providing liquidity and immediacy to market participants. In this respect, AH can be viewed as a specialised form of hedging. Although market makers may employ a broader set of hedging techniques, either by using different asset classes (e.g., futures or other sovereign bonds) or alternative trading venues, our analysis focuses on AH activity given its growing importance in the MTS market, as highlighted in recent Italian Treasury reports on secondary market liquidity conditions.[3]

The remainder of this section discusses the economic rationale underlying AH strategies and evaluates the costs and benefits associated with their implementation.

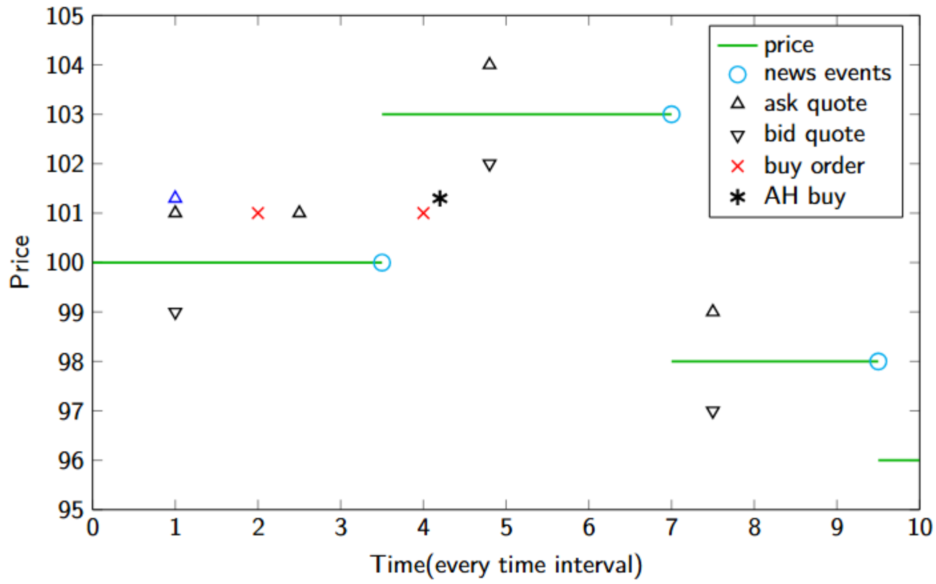
3.2 AH strategies: implementation and driving factors

By facilitating the rapid rebalancing of trading positions, AH strategies help mitigate the risks associated with holding imbalanced or unwanted inventories, particularly in fast-moving or volatile market environments, and limit losses stemming from trades against better informed or faster counterparties.

To illustrate this, we present a simplified example based on Ge, Yang and Doukas (2024), as shown in Figure 1. The chart depicts the evolution of the fundamental value of a security (green line) over a short time window, alongside market maker quotes – bid and ask (triangles) – and transactions (crosses). The true fundamental value is not directly observable but is inferred by market participants based on the information available to them.

[3] See, e.g., MEF (2025; 2026).

Figure 1: Illustrative example



Note: Example of transaction paths and price dynamics, based on Ge, Yang and Doukas (2024). Market-makers set quotes according to their information set. Transactions can occur at any time.

At time $t = 1$, a market maker posts a two-sided quote (black triangles), setting the ask price at $p = 101$ and the bid price at $p = 99$. A less competitive ask quote is also present in the order book at $p = 101.3$ (blue triangle).

At $t = 2$, an investor buys the bond at the best ask price of $p = 101$, while the true fundamental value of the security is $p = 100$. This transaction yields a profit of 1 unit for the market maker.

The market maker then reposts the same ask quote at $p = 101$. Shortly afterward, news arrives that raises the fundamental value of the bond to $p = 103$. A buyer then executes a trade at the now-stale ask price of $p = 101$, resulting in a gain for the buyer and a loss of 2 units for the market maker (who sells the bond at $p = 101$ when its true value is $p = 103$).

If the market maker enters an AH transaction by repurchasing the bond at another stale ask quote still available in the market – possibly at the same price or slightly higher, but below the updated fundamental value – they can reduce the incurred loss. For instance, in our example, the stale ask quote is still available in the book at $p = 101.3$. By repurchasing the bond at this price (the 'AH trade', marked by a black asterisk in the figure), the market maker still realizes a loss – buying back at $p = 101.30$ after having sold at $p = 101$ – but limits the loss to 0.30 units, instead of 2 units had they held the position.

This example illustrates how even small delays in updating quotes can expose market makers to adverse selection, and how AH strategies can mitigate this risk by enabling timely offsetting trades. Three key points are worth noting.

First, the fundamental value of an asset is not directly observable or immediately known. Whether a quote is genuinely stale – and whether the market maker faces adverse selection – depends not only on the speed of quote updates, but also on the market maker's ability to correctly infer changes in the asset's value. For example, if no change in the fundamental value has occurred, the second trade in the example may not be adverse, and no loss is realized by the market maker. Therefore, entering an AH transaction is not always advantageous: if prices later move in a favourable direction relative to the acquired inventory, the hedge might turn out to be unnecessary or even suboptimal. The effectiveness of AH implementation is therefore highly contingent on market-maker-specific factors, such as their ability to assess asset value and anticipate short-term price movements – shaped by their market expertise, technological infrastructure, quality of available information, risk appetite, and confidence in their assessments.

Second, the viability of an AH strategy hinges on its cost. In the example, the AH transaction still results in a loss, which must be weighed against the potentially larger but uncertain loss that could result from inaction. If the expected benefit of hedging does not exceed its cost – a decision involving subjective judgment, as previously discussed – a market maker may rationally choose not to hedge. Market liquidity plays an important role in this cost-benefit analysis. In liquid markets, narrow bid–ask spreads and high quantities quoted reduce hedging execution costs, making AH strategies more attractive. In contrast, during periods of low liquidity, wider spreads and thinner order books raise execution costs, potentially making AH less effective or even counterproductive. Consequently, liquidity conditions can affect the frequency with which AH strategies are employed over time.

Third, AH activity may also be influenced by factors beyond the immediate trading environment. Regulatory frameworks can impose quoting obligations or minimum liquidity provision requirements, potentially increasing the need for hedging. Additional incentives may arise from sovereign issuers, who often promote market-making activity to support efficient issuance in government bond markets. For example, primary dealers in Italian government bonds are subject to specific obligations, including participation in auctions and continuous liquidity provision in secondary markets, and their performance is regularly assessed by the Italian Treasury.[4] The introduction in 2025 of a dedicated monitoring criterion for AH activity within the broader evaluation framework,[5] with potential implications for rankings and remuneration (see MEF, 2026), provides a useful setting to examine how external incentives may affect the use of these strategies, an aspect further explored in our empirical analysis.

AH can therefore play a vital role in supporting effective risk management by market makers and helping to maintain liquidity in today's fast-paced trading environment. However, the use of these strategies depends on several factors, as market makers must carefully balance speed, information accuracy, and execution costs when deciding whether to hedge a position immediately or hold it temporarily. An important consideration is the prevailing market environment and liquidity conditions, which directly influence the cost of executing an AH trade. The remainder of this paper presents our empirical investigation into these factors and their impact on the adoption of AH strategies.

[4] For further details on the institutional framework for primary dealers in Italy, see also Panzarino (2023).

[5] For major details on the evaluation criteria, see Evaluation Criteria of Specialists in Government bonds (Primary Dealers) – Year 2025.

4. Data and identification of AH transactions

4.1 Trade activity data

The analysis is based on confidential transaction-level data from MTS Italy, a major interdealer venue for Italian sovereign bonds. The dataset covers all trades concluded on the trading platform, along with associated metadata, over the period from January 2010 to April 2026.

Each observation includes the following information: timestamp (with second precision); ISIN of the traded security; trade size; execution price; identification codes for the counterparts involved; side of the trade (equal to 1 when the transaction is a sell order in which the market maker, or quote provider, acts as the buyer, and 0 otherwise). The analysis is conducted on the full sample of traded Italian government bonds.

The dataset is further enriched with two additional layers of information at the trade level, which are described in the following paragraphs. First, for each transaction we incorporate market microstructure indicators to capture the ex-ante state of the order book, namely the bid–ask spread and market depth. Second, the high granularity of the dataset allows for a precise identification of AH activity. To this end, we develop an identification strategy that determines, for each transaction, whether it triggers an AH response by the market maker.

4.2 Market liquidity data

As discussed in the previous section, market liquidity conditions are likely to influence the costs of executing AH trades and, ultimately, the propensity of market makers to adopt such strategies. To account for these effects, we augment our dataset with standard liquidity measures, designed to proxy ex-ante liquidity conditions prevailing in the market prior to each transaction. Specifically, we rely on two widely used microstructural indicators[6] as proxies for transaction costs:

- bid-ask spread, measured as the absolute difference between the best quoted ask and bid yields (in basis points);
- market depth, measured as the average quantity available at the top level of the order book between the bid and ask sides (in EUR bn).

Both measures are constructed as market-wide indicators across all quoted Italian government bonds and are matched to each transaction using the nearest available timestamp prior to each trade. Since market liquidity snapshots are available at a 5-minute frequency, the maximum time gap between a liquidity observation and a subsequent transaction is bounded at 5 minutes. This approach allows us to capture intraday liquidity dynamics at the system level, prior to each trade. As such, these variables reflect the prevailing trading environment faced by market makers and can be interpreted as proxies for execution costs, influencing AH decisions.

[6] As highlighted in the existing literature, these metrics are primarily driven by factors such as increased risk perceived by market makers, who may widen bid-ask spreads to mitigate inventory (Garman, 1976; Stoll, 1978; Ho and Stoll, 1981) and adverse selection risks (Copeland and Galai, 1983; Kyle, 1985; Glosten and Milgrom, 1985), and by other factors including, for example, market competition (Ho and Stoll, 1983). Regarding the latter, given the presence of numerous specialized market makers competing on the MTS market under a primary dealer scheme established by the Italian Treasury, we expect these liquidity measures to predominantly reflect risk perceptions rather than competitive dynamics.

4.3 Identification of AH transactions

We identify an 'AH trade' as a rapid, algorithmically driven, transaction executed by a market maker with the aim of mitigating or fully neutralising an inventory shock generated by a preceding transaction that consumed its quote.

A trade j is flagged as 'auto-hedged' when the following conditions are simultaneously satisfied.

(1) *Timing proximity*: a second trade i occurs within a brief forward-looking window of 1 second from when trade j occurred.

(2) *Agent continuity*: the aggressor code of trade i matches the quote provider of trade j. This condition ensures that the subsequent trade i is triggered by the market maker that was originally hit by trade j.

(3) *Inventory directionality*: the direction of trade i coincides with that of trade j (i.e., both are buys or both are sells from the perspective of the initiating party). For instance, if trade j is a buy order, implying that the market maker sells, a subsequent purchase by the same market maker in trade i represents an offsetting transaction aimed at rebalancing inventory.

While conditions (2) and (3) are dictated by the definition of AH activity and do not involve discretionary choices, condition (1) necessarily entails some degree of judgment. In our baseline specification, we set the maximum execution window to one second to specifically capture fast and automated hedging strategies. Sensitivity tests, however, show that relaxing this condition, for example by extending the time window up to five seconds, does not materially affect the results, thereby supporting the robustness of the identification procedure.

In addition, and consistent with the definition of "robust" or "pure" AH proposed in MEF (2025; 2026), we impose the following condition:

(4) *Same instrument condition*: trade i involves the same bond as trade j

Under this additional restriction, the market maker is deemed to rebalance its inventory through transactions in the same instrument that generated the initial inventory shock. Accordingly, in the baseline specification adopted in the empirical analysis below (Section 5), an AH event is identified as an offsetting trade initiated by the market maker shortly after its quote has been executed and in the same security.

In practice, however, inventory management may also occur through transactions in different but closely correlated securities. To ensure that our findings are not driven by an ex-ante restriction on the set of eligible instruments for hedging,[7] we perform additional robustness checks in which condition (4) is fully relaxed. This extension allows for greater flexibility in identifying cross-instrument AH activity and, as shown in Section 5.3, does not materially affect the results.

[7] Also, it is generally observed that securities issued by the same issuer and characterized by similar liquidity profiles tend to exhibit highly correlated returns.

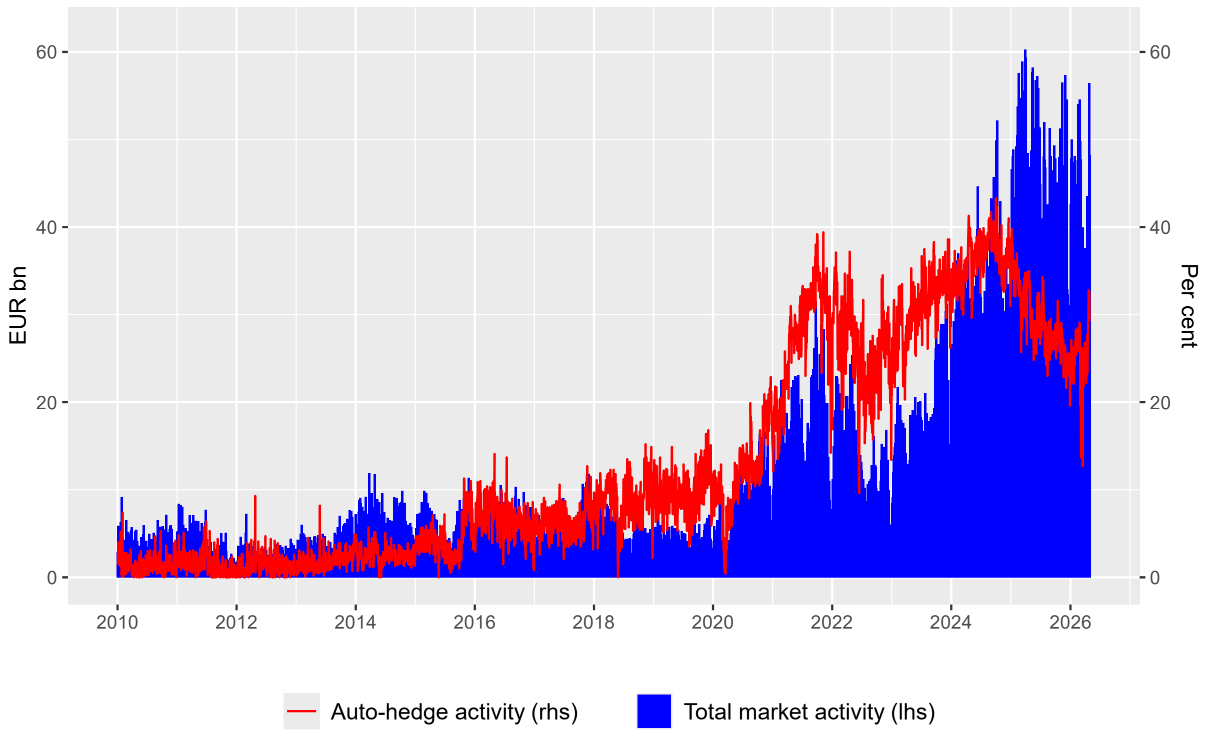
Overall, the identification approach outlined in this paragraph provides a consistent and behaviourally grounded estimate of AH activity based on observable temporal and transactional patterns, without requiring access to proprietary strategy information.

4.4 Evidence on the use and recent developments of AH activity in the MTS market

The results of the identification approach described in the previous paragraph are presented in Figure 2. The evidence suggests that AH activity is not entirely new, as our identification algorithm detects transactions attributable to such strategies even in the early years of the sample; however, AH usage has increased significantly in recent years. Three distinct phases can be identified.

In the period before 2016, AH activity remained largely residual, accounting for only a very small share of total market transactions. Between 2016 and 2019, AH strategies became more visible but still modest, typically representing around 5–10% of overall market activity. From the second half of 2020, AH activity expanded significantly, both in absolute terms and relative to total trading activity, reaching peaks of about 40% at the end of 2024, suggesting a structural increase in the adoption and reliance on these algorithmic strategies.

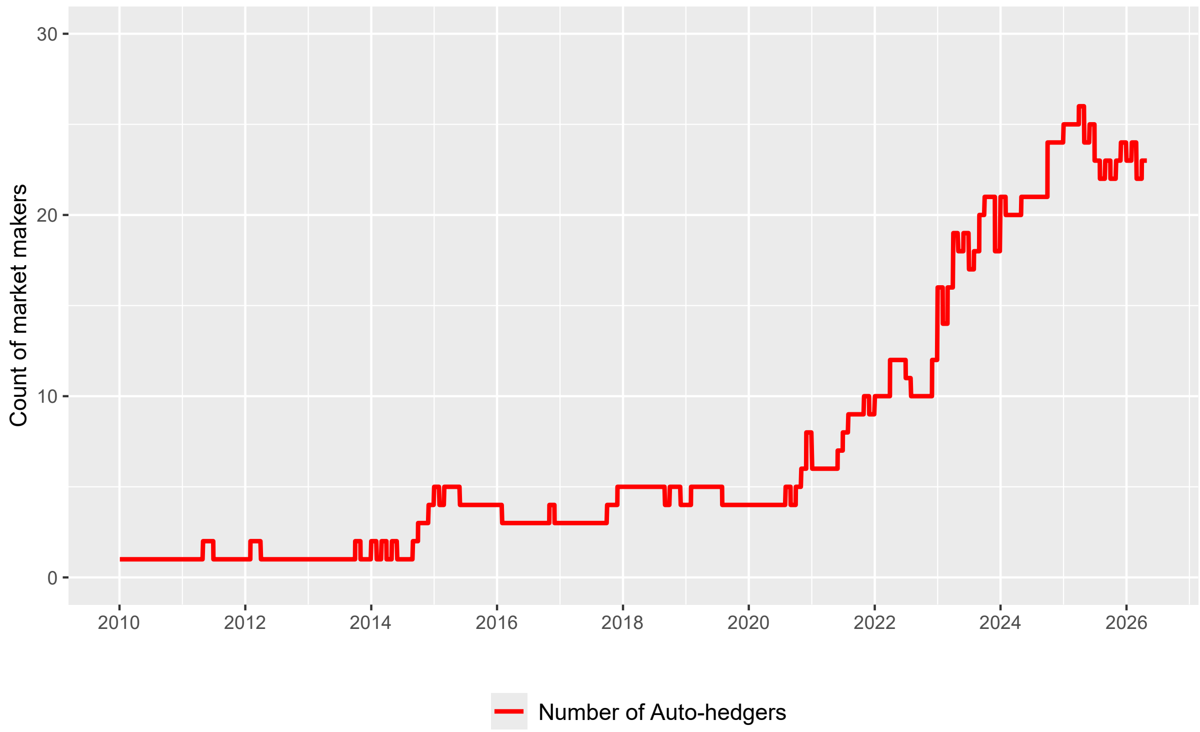
Figure 2: Market turnover and AH activity



Note: Daily market turnover on the MTS market (left-hand axis) expressed in euro billions and share of AH activity reported in percentage points (right-hand axis). Source: MTS data, authors' calculations.

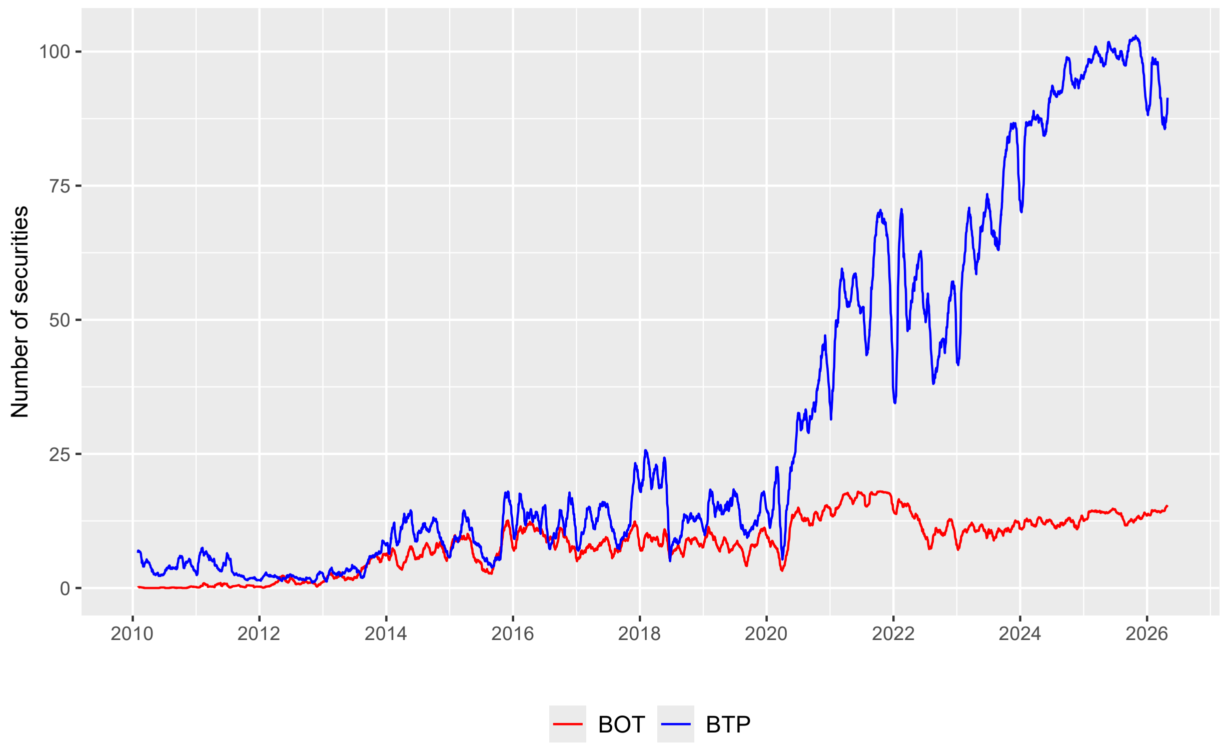
This expansion coincides with a notable increase in overall market turnover, as shown in Figure 2. While AH may have contributed to this growth, other external factors, such as increased government bond issuance post-COVID, Eurosystem asset purchase programs, and improved secondary market liquidity also likely played a role (Bank of Italy, 2021).

Figure 3: Number of market makers using AH strategies



Note: Number of market makers using AH strategies, according to the identification approach adopted. A participant is counted if it executes over EUR 50 mn (nominal value) in AH trades within a given month. Source: MTS data, authors' calculations.

Figure 4: Distinct bonds involved in AH strategies



Note: Number of distinct bonds involved in at least one AH transaction, by type: zero-coupon securities (red) and fixed-coupon securities (blue). 20-day moving average. Source: MTS data, authors' calculations.

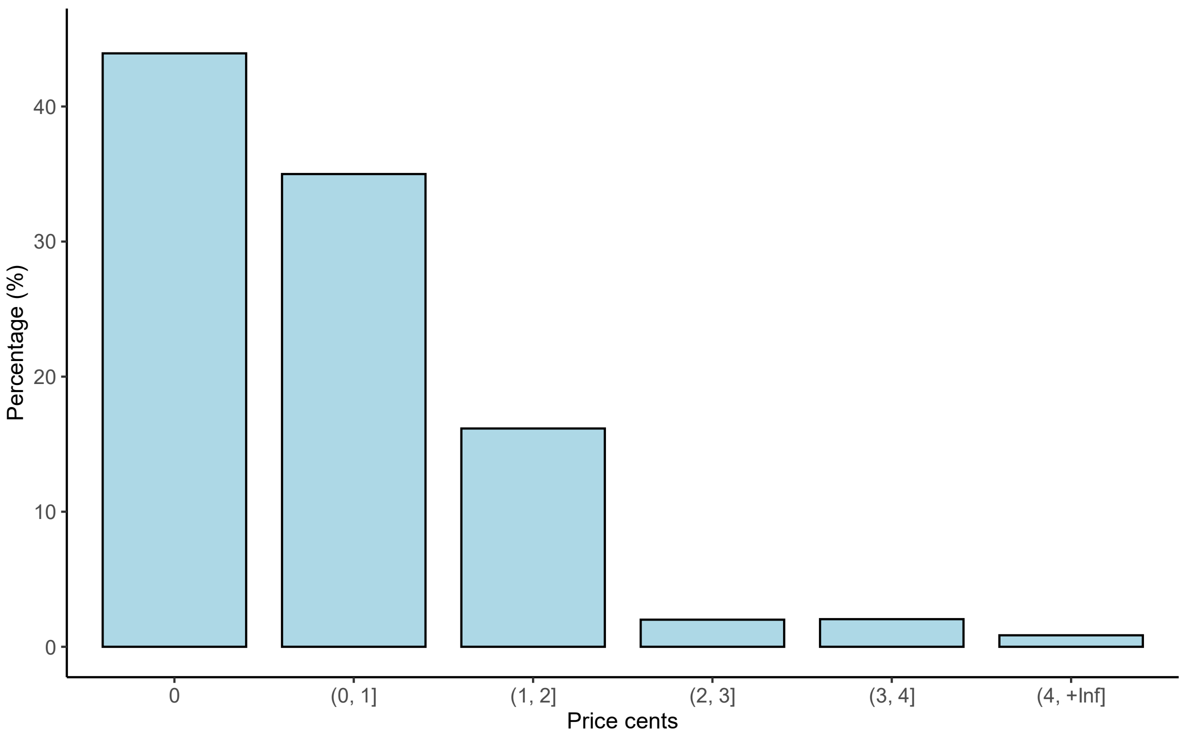
The increase in AH usage appears primarily driven by a growing number of market makers adopting these strategies. Figure 3 shows the steady rise in the number of market makers employing AH strategies, mirroring the three phases identified in overall AH activity. During the first phase (before 2016), only one or two market makers experimented with AH. In the second phase (2016–2019), participation remained limited, with around three to five active users. From 2020 onward, however, adoption accelerated sharply, and by mid-2025 more than 22 market makers were regularly using AH strategies, underscoring the growing diffusion of these trading approaches.

Moreover, AH has expanded across a wider range of securities, including various types and maturities. As shown in Figure 4, the daily number of distinct bonds involved in at least one AH transaction significantly increased and is now covering nearly the entire universe of instruments – both fixed-coupon bonds and bills.

Beyond individual dealer choices, broader factors, such as market liquidity, can also influence the adoption of AH strategies by shaping the costs associated with their execution. As noted in Section 3.2, AH decisions are unlikely to be purely mechanical; rather, they may reflect a continuous cost–benefit assessment, where market makers balance the advantages of immediate hedging against the potential costs of doing so.

Figure 5 illustrates the distribution of AH execution costs, measured as the price difference (in cents) between an AH trade and the preceding transaction it hedges. The data show that 43% of AH trades incur zero cost, and most of the remaining transactions involve very small costs, typically below 2 cents. As execution costs rise, the frequency of AH usage declines sharply.

Figure 5. Distribution of AH execution costs



Note: Transaction-level data from January 2023 to April 2026, covering all Italian government bonds. The last bin includes also residual cases of costs greater than 5 cents. Source: MTS data, authors' calculations.

These patterns suggest that hedging costs influence AH adoption. Our hypothesis is that under conditions of ample liquidity, when execution costs are relatively low, market makers are more inclined to promptly offload inventory risk through auto-hedging strategies. Conversely, during periods of deteriorating liquidity, when execution costs rise, market makers are expected to behave more selectively, temporarily retaining positions rather than engaging in immediate automatic hedging. Assessing the extent to which liquidity conditions affect the use of AH strategies constitutes the main objective of the empirical analysis presented in the following sections.

5. Empirical analysis: methodology and results

5.1 Empirical setting

The primary objective of this study is to estimate the probability that an AH strategy is executed conditional on prevailing market conditions, with a particular focus on market liquidity. To investigate the factors influencing the use of AH strategies, we estimate the following logit model:

$$\mathbb{P}(AH_{mbth} = 1 \mid \mathcal{F}_{th}) = \tag{1}$$

$$f(\, \beta_1 \cdot BidAsk_\tau + \beta_2 \cdot MktDepth_\tau + \beta_3 \cdot X_{mbth} + \mu_m + \mu_b + \mu_t \,)$$

where AH_{mbth} is a binary indicator equal to one if the trade executed against the quotes posted by market maker m, on bond b, on day t, and at time h, is subsequently auto-hedged according to the identification strategy described in Section 4.3, and zero otherwise. $\mathcal{F}_{th}$ denotes the information set available up to day t and time h.

The variables $BidAsk_\tau$ and $MktDepth_\tau$ proxy for prevailing market liquidity conditions. Specifically, they measure the market-wide bid-ask spread and market depth, respectively, observed at time τ, defined as the most recent observation within the time interval $[th$−5min, $th)$ prior to the execution of the trade. As discussed in Section 4.2, these liquidity indicators are available at a 5-minute frequency, allowing us to capture intraday variations in order-book conditions. Their inclusion enables us to assess whether the state of market liquidity influences the likelihood of a trade being auto-hedged, which constitutes the primary focus of the analysis.

The vector X_{mbth} contains trade-specific control variables, including trade size and trade direction. These controls account for the possibility that the propensity to engage in AH may differ depending on whether the trade involves a small or large quantity, and whether it is buyer- or seller-initiated. $f(x)$ denotes the logistic function. We include μ_m and μ_b to control for market maker fixed effects and bond fixed effects, respectively. These account for time-invariant dealer heterogeneity and bond-specific characteristics (such as cash flow structure). Day fixed effects (μ_t) are also included to control for common shocks and other market-wide factors that may affect trading activity on a given day. Standard errors are clustered at the market maker and bond levels to account for potential heteroskedasticity within these dimensions. Finally, we focus our empirical investigation on the period in which AH activity is more mature, namely from January 2023 to April 2026, when the share of market makers relying on AH exceeded 50% of primary dealers (Section 4.4). Summary statistics for the main variables included in the regression analysis are reported in Table 1.

Table 1: Summary statistics

Variable	Unit	N	Mean	SD	1%	25%	50%	75%	99%
AH trade	0-1 dummy	4,500,980	0.33	0.47	0.00	0.00	0.00	1.00	1.00
Bid-Ask spread	basis points	84,261	3.72	4.09	1.20	1.91	2.78	4.62	15.01
Market depth	EUR bn	84,261	19.13	5.66	7.84	15.52	18.19	21.95	34.63
Trade directionality	0-1 dummy	4,500,980	0.54	0.50	0.00	0.00	1.00	1.00	1.00
Trade size	EUR mn	4,500,980	5.56	4.59	2.00	2.50	5.00	7.00	20.00

Note: Transaction-level data from January 2023 to April 2026, covering all Italian government bonds. Liquidity indicators (bid-ask spread and depth) are market-wide averages computed every five minutes. Reported values include the number of observations, the mean, the standard deviation, and selected percentiles (1, 25, 50, 75 and 99). Source: MTS data, authors' calculations.

Table 2 presents the correlation matrix of the main variables and show generally low pairwise correlations. Notably, the bid-ask spread and market depth exhibit a negative correlation of -0.21, which is consistent with economic intuition. Both variables serve as proxies for market liquidity, with narrower spreads and greater depth typically associated with better liquidity conditions. The relatively modest magnitude of this correlation in our sample may reflect the high-frequency nature of the data. Since the metrics are observed at 5-minute intervals, the weak relationship may arise from asynchronous adjustments by market participants. For example, market makers may selectively update either quoted prices or quantities to manage risk, leading to partially uncoordinated movements between the two liquidity measures. These asynchronous and potentially strategy-dependent behaviours may dampen the observed correlation, while also mitigating concerns about multicollinearity. To further address this, we include the liquidity variables separately in robustness checks to test the stability of our estimates. Other variables, such as trade direction and trade size, display correlations close to zero, indicating limited linear relationships among these factors within our sample.

Table 2: Correlation matrix

	Bid-Ask spread	Market depth	Trade direction	Trade size
Bid-Ask spread	1.000	−0.206	0.010	−0.003
Market depth	−0.206	1.000	−0.007	0.061
Trade direction	0.010	−0.007	1.000	0.008
Trade size	−0.003	0.061	0.008	1.000

Note: Correlation matrix of main variables. Source: MTS data, authors' calculations.

5.2 Findings

Table 3 presents the regression results. In our baseline specification, we include time (daily), market maker, and bond fixed effects. The results show that both measures of market liquidity – bid-ask spread and market depth – are statistically significant and have the expected signs. Although their overall impact is modest relative to other factors (as further elaborated below), a higher bid-ask spread is associated with a lower probability of auto-hedging, indicating that wider spreads, which reflect higher execution costs, discourage AH activity. Likewise, limited market depth exerts a negative effect on the likelihood of auto-hedging, consistent with the theoretical premise that lower liquidity discourages reliance on AH.

The coefficient on trade direction is positive and significant. Specifically, when the initiating trade is a sell order (dummy = 1), i.e. the market maker buys the bond, the transaction is slightly more likely to be auto-hedged. This result might reflect at least two mechanisms. First, it can suggests market makers to be more inclined to unwind long inventory positions through AH than short positions in our sample period. More generally, dealers may exhibit different propensities to hold long versus short inventories of the underlying bond. Consistent with this interpretation, MEF (2026) documents imbalances in AH activity depending on trade direction, showing that during periods of sovereign spread widening, AH activity following sell-initiated trades (i.e. when market makers acquire long positions) tends to be more frequent or more intense than for trades of the opposite sign. Second, liquidity conditions in the order book may display asymmetries between the bid and ask sides, making it relatively easier to quickly unwind positions on one side and thus providing stronger incentives to resort to AH in that direction. While both mechanisms may be at play in our sample, disentangling their relative importance and examining how their interaction evolves over time is left for future research. Trade size is not significant in the baseline specification.

The overall explanatory power is relatively high ($R^2 = 0.29$), indicating that the included fixed effects and liquidity measures capture a substantial share of variation in auto-hedging probabilities. Models (1) and (2) explore the sensitivity of results to the exclusion of specific fixed effects. Removing bond fixed effects in Model (1) results in only a marginal decline in explanatory power ($R^2 = 0.28$), suggesting that bond-level heterogeneity contributes little to explaining the probability of auto-hedging once market maker and time effects are controlled for. In contrast, Model (2), which excludes market maker fixed effects, shows a dramatic reduction in explanatory power, with the R^2 dropping from 0.29 to 0.01. This sharp decline indicates that the explanatory power of the model is largely driven by market maker-level variation. In other words, persistent differences across market makers, such as technological capabilities, trading strategies, inventory management practices, or risk tolerance, account for most of the variation in auto-hedging behavior. When these market maker fixed effects are omitted, the model's ability to explain auto-hedging probabilities virtually disappears, even though the coefficients on liquidity variables remain statistically significant.

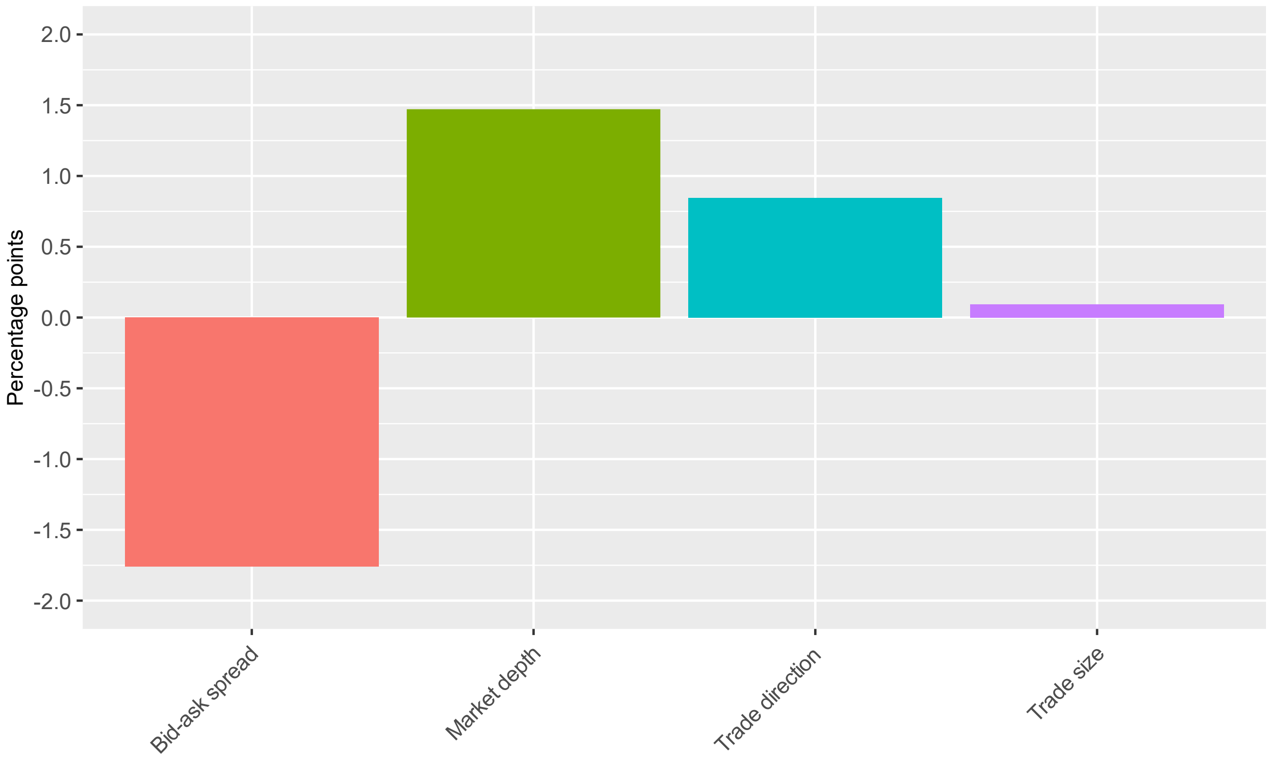
In Model (3), the specification replaces the continuous trade size variable with categorical indicators. The results show that only very large transactions (defined as trades exceeding EUR 20 mn) have a statistically significant effect. Relative to the omitted category of small(er) trades (EUR 2 mn), these transactions are substantially less likely to be auto-hedged. This may primarily reflect practical constraints faced by market makers when managing large positions, such as concerns about market impact risk. The lack of significance for smaller trade size categories suggests that within normal trade-size ranges, auto-hedging likelihood does not vary meaningfully. The overall explanatory power ($R^2 = 0.29$) remains comparable to the baseline model, indicating that treating trade size as a discrete rather than continuous measure does not materially affect the fit of the model but provides additional granularity in understanding the behavior of extreme trade sizes.

Table 3: Regression results

	Baseline	(1)	(2)	(3)	(4)
Bid-Ask spread	-0.028***	-0.029***	-0.023***	-0.028***	-0.029***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.003)
Market depth	0.017***	0.018***	0.014***	0.017***	0.016***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Trade direction	0.111***	0.118***	0.087***	0.109***	0.109***
	(0.021)	(0.021)	(0.017)	(0.021)	(0.022)
Trade size	0.001	0.003	0.005		-0.004
	(0.012)	(0.010)	(0.014)		(0.012)
Trade size (EUR (20, ∞) mn)				-0.734**	
				(0.256)	
Trade size (EUR (10, 20] mn)				0.180	
				(0.225)	
Trade size (EUR (5, 10] mn)				0.154	
				(0.146)	
Trade size (EUR (2, 5] mn)				0.096	
				(0.094)	
Primary Dealer x Year 2025-26					-2.215*
					(1.008)
N	4,478,370	4,478,370	4,497,881	4,478,370	4,478,370
R2	0.29	0.28	0.01	0.29	0.30
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Market maker fixed effects	Yes	Yes	No	Yes	Yes
Bond fixed effects	Yes	No	No	Yes	Yes

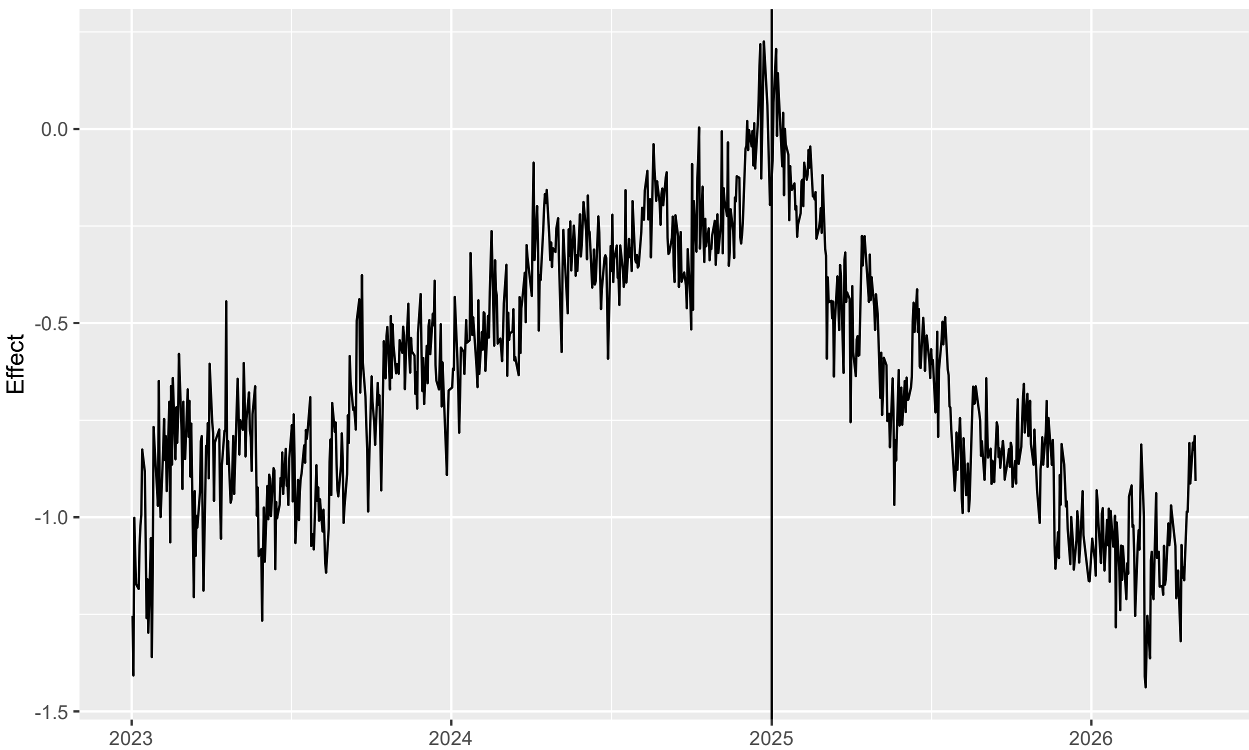
Note: Logit regression results from estimating Eq. (1). Robust standard errors are reported in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Figure 6: Marginal effects



Note: Average marginal effects on the probability of a trade being auto-hedged, based on a one-standard deviation increase of the selected variable. Source: MTS data, authors' calculations.

Figure 7: Time FE



Note: Time series of day FE estimated in Eq. (1). Source: MTS data, authors' calculations.

The marginal effects reported in Figure 6 offer additional insight into the economic significance of the estimated coefficients through the baseline model. Both market depth and bid-ask spread have economically meaningful impacts on the likelihood of a trade being auto-hedged. A one-unit increase in market depth (equivalent to EUR 1 bn in additional quoted volume on the platform) raises the predicted probability of auto-hedging by 0.26 percentage points, while a one-standard deviation increase (approximately EUR 5.7 bn) corresponds to an effect of about 1.47 percentage points, holding other variables constant. Conversely, a one-unit widening of the quoted bid-ask spread (1 basis point) decreases the predicted probability of AH by 0.43 percentage points, and a one-standard deviation increase (around 4 basis points) reduces it by about 1.76 percentage points. Trade directionality also exhibits a positive and statistically significant effect: when the initiating trade is a sale, the predicted probability of the trade being auto-hedged increases by 1.69 percentage points, controlling for other factors. Overall, these marginal effects indicate that market liquidity variables, namely bid-ask spreads and market depth, have economically modest yet statistically significant effects on the propensity for trades to be auto-hedged.

Finally, the inclusion of time fixed effects allows the analysis to capture time-specific patterns in AH activity while controlling for liquidity conditions, trade characteristics, and heterogeneity across market makers and bonds. Figure 7 plots the estimated day fixed effects from the baseline model and shows a decline in the propensity to auto-hedge since the beginning of 2025. This pattern coincides with the introduction by the Italian Treasury of the additional monitoring criterion for AH activity (MEF, 2026). To investigate more closely whether this change might have affected the use of AH by primary dealers,[8] we augment the baseline specification with an interaction term between a dummy identifying market makers that are also primary dealers (and are therefore subject to the Treasury's annual evaluation process) and a post-January 2025 dummy variable. The two variables are not included separately, as they are absorbed by the market maker and day fixed effects, respectively. The results, reported in Table 3, Model (4), show that since the beginning of 2025 primary dealers have reduced their reliance on AH more than other market makers active on the platform.

5.3 Robustness

We conduct several robustness checks to verify that our findings are not driven by modeling assumptions or particular sample features. As a first step, we confirm that the results are not sensitive to the functional form by re-estimating the model using a linear probability specification (Table A1, in the Annex). The OLS estimates closely resemble those from the logistic regression, both in sign and statistical significance, indicating that our conclusions do not hinge on the use of a specific methodology.

We also explore alternative treatments of the error structure. In addition to our baseline specification, which clusters standard errors simultaneously by market maker and bond, we consider heteroskedasticity-robust errors (White-type), one-way clustering, and two-way clustering along different dimensions. In all cases, statistical significance remains unaffected or even improves, suggesting that our results are not an artifact of specific clustering choices.

[8] MEF (2026) reports the introduction of the new criterion in the dealer evaluation framework, with potential implications for dealer rankings and remuneration.

To further assess the robustness of the model, we examine its performance across different subsamples of securities (Table A2, in the Annex). While the baseline specification includes all instruments, the model exhibits stronger explanatory power when the analysis is restricted to BTPs and BOTs separately. For BTPs, both market depth and trade direction remain statistically significant, whereas they lose significance in the BOT subsample. By contrast, the bid–ask spread remains highly significant across all specifications, including BOTs, where its coefficient approximately doubles in magnitude. The model also proves to be stable for the remaining group of securities.

We further investigate whether the inclusion of control variables and fixed effects drives our findings by introducing them stepwise into the specification (Models (1) and (2) in Table 3 and Models (1) – (4) in Table A3, in the Annex). Beginning with the baseline liquidity measures alone, we then add trade directionality and trade size, followed by the sequential inclusion of market maker, bond, and day fixed effects. Across this sequence of specifications, the coefficients on liquidity measures remain stable, confirming that the main relationships are not sensitive to the set of included controls. As an additional robustness check, we address a potential timing discrepancy between the transaction-level data and the market liquidity variables, the latter of which are observed at five-minute intervals. This temporal discrepancy implies that, for some trades, the ex-ante liquidity snapshot may not accurately reflect prevailing market conditions at the moment of trade execution. To account for this issue, we re-estimate the model considering only transactions occurring within a narrow window following the liquidity observation, namely, within 30 seconds, and, alternatively, within 10 seconds (Models (5) and (6) in Table A3, in the Annex). In all cases, the results remain stable in terms of statistical significance, and the coefficients associated with market liquidity conditions become even stronger, reinforcing the robustness of the baseline findings.

To account for potential period-specific effects, we re-estimate the model over different subperiods (2023, 2024, 2025 and 2026; see Table A3, in the Annex). The effects of bid-ask spread and market depth persist across these subsamples, suggesting that the influence of prevailing liquidity conditions on AH usage is stable over time.

Finally, as discussed in Section 4.3, we consider the possibility that hedging transactions are executed in different but closely related securities rather than in the same bond as the original trade. To account for this, we relax the same ISIN condition used to identify AH trades (i.e., condition (4) in Section 4.3). This extension allows for the identification of cross instrument AH activity and ensures that the results are not driven by an ex-ante restriction on the set of eligible hedging instruments. As reported in Table A4, the findings remain consistent with the baseline specification. This result is unsurprising given that same-ISIN auto-hedging remains the dominant strategy in our sample. Our estimates suggest that approximately 80–90% of identified AH transactions are executed in the same bond, with the share being highest for BOTs and lowest for BTPs. Nevertheless, MEF (2026) documents a decline in same-ISIN AH activity since 2025, suggesting that cross-instrument hedging may become increasingly important. Future research on the evolution of AH should therefore continue to rely on both same-instrument and broader cross-instrument identification strategies, which offer complementary perspectives and, when combined, provide a more comprehensive measure of overall AH activity.

Taken together, these robustness tests demonstrate that our main findings are stable across alternative estimation approaches, inference procedures, variable specifications, and time periods.

6. Conclusions

The Italian government bond market is one of the largest and most liquid in Europe. It underwent an early wave of electronification, driven by the development of the interdealer platform MTS. In this segment, market makers operate in a highly competitive environment and have increasingly adopted automated, low-latency trading strategies to manage traditional market-making risks, such as adverse selection and the accumulation of risky inventory positions.

This analysis focuses on AH strategies, a class of algorithmic trading techniques adopted by market makers that has gained significant attention due to its rapid and widespread adoption in recent years. We document a substantial increase in the use of AH strategies beginning in the second half of 2020, with around a third of trades being auto-hedged in recent years, and near-universal adoption across dealers, bond types and maturities.

Our empirical investigation shows that variation in the likelihood of AH implementation is largely driven by time-invariant, entity-level factors. While we do not directly observe the underlying determinants of this heterogeneity, our findings are consistent with the view that differences in market expertise, technological capabilities, information sets, risk preferences, and pricing ability play an important role. Market liquidity effects are economically modest yet statistically significant: a one standard deviation increase in the bid-ask spread or a one standard deviation decrease in market depth reduces the probability of AH usage by 1–2 percentage points. Finally, AH usage has declined since early 2025, coinciding with changes in the Italian Treasury's monitoring framework for primary dealers' performance related to AH, suggesting that factors beyond the immediate trading environment may also influence market makers' reliance on such strategies.

This paper opens several avenues for future research. First, it would be valuable to examine the interaction between AH and other hedging mechanisms across different instruments and trading venues, such as futures markets, and to assess whether the growing use of AH reflects a substitution effect across these channels. Second, future work could explore further the evolution of AH adoption over time and its responsiveness to changing risk factors. Third, while our analysis focuses on how liquidity conditions influence AH usage, an important extension would be to investigate the reverse relationship, namely whether the adoption of AH strategies itself affects market liquidity and overall market quality.

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Annex

Table A1: Linear regression with OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bid-Ask spread	-0.003**	-0.003***	-0.003**	-0.002**			
	(0.001)	(0.001)	(0.001)	(0.001)			
Market depth	0.002***	0.003***	0.003***		0.002***		
	(0.001)	(0.001)	(0.001)		(0.001)		
Trade direction	0.017***	0.018***	0.019***			0.017***	
	(0.004)	(0.005)	(0.005)			(0.004)	
Trade size	0.000	0.002	0.001				0.000
	(0.001)	(0.004)	(0.003)				(0.001)
N	4,497,881	4,497,881	4,497,881	4,497,881	4,497,881	4,500,980	4,500,980
R2	0.28	0.01	0.01	0.28	0.28	0.28	0.28
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market maker fixed effects	Yes	No	No	Yes	Yes	Yes	Yes
Bond fixed effects	Yes	Yes	No	Yes	Yes	Yes	Yes

Note: Linear regression results from estimating Eq. (1). Robust standard errors are reported in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Table A2: Regression results by bond type

	Baseline	BTP	BOT	Other
Bid-Ask spread	-0.028***	-0.023***	-0.057***	-0.031***
	(0.004)	(0.004)	(0.009)	(0.009)
Market depth	0.017***	0.020***	0.014	0.009+
	(0.003)	(0.003)	(0.010)	(0.005)
Trade direction	0.111***	0.121***	0.089	0.093**
	(0.022)	(0.022)	(0.060)	(0.029)
Trade size	0.001	0.008	-0.003	-0.003
	(0.012)	(0.013)	(0.021)	(0.014)
N	4,478,370	3,237,342	488,615	634,276
R2	0.29	0.31	0.39	0.30
Time fixed effects	Yes	Yes	Yes	Yes
Market maker fixed effects	Yes	Yes	Yes	Yes
Bond fixed effects	Yes	Yes	Yes	Yes

Note: Logit regression results from estimating Eq. (1). Robust standard errors are reported in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Table A3: Regression robustness checks

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	2023	2024	2025	2026
Bid-Ask spread	-0.028***	-0.020***				-0.045***	-0.054***	-0.034***	-0.028***	-0.026***	-0.040***
	(0.004)	(0.004)				(0.006)	(0.009)	(0.005)	(0.006)	(0.004)	(0.004)
Market depth	0.017***		0.012***			0.046***	0.056***	0.023***	0.023***	0.012***	0.020***
	(0.002)		(0.002)			(0.006)	(0.007)	(0.004)	(0.003)	(0.003)	(0.003)
Trade direction	0.111***			0.111***		0.138***	0.148***	0.130***	0.073*	0.131***	0.129**
	(0.021)			(0.022)		(0.027)	(0.034)	(0.030)	(0.028)	(0.032)	(0.042)
Trade size	0.001				0.001	0.003	0.004	-0.004	-0.018	-0.008	-0.016
	(0.012)				(0.012)	(0.017)	(0.018)	(0.012)	(0.021)	(0.014)	(0.011)
N	4,478,370	4,478,370	4,478,370	4,481,458	4,481,458	292,961	105,599	712,463	1,346,193	1,808,117	502,962
R2	0.29	0.29	0.29	0.29	0.29	0.31	0.31	0.37	0.33	0.32	0.42
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market maker fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Logit regression results from estimating Eq. (1). Robust standard errors are reported in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

Table A4: Regression results relaxing same-ISIN condition

	Baseline	(1)	(2)	(3)	(4)
Bid-Ask spread	-0.026***	-0.029***	-0.026***	-0.026***	-0.027***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Market depth	0.011***	0.011***	0.010***	0.011***	0.010***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Trade direction	0.106***	0.096***	0.075***	0.104***	0.105***
	(0.022)	(0.023)	(0.018)	(0.021)	(0.022)
Trade size	0.013	0.000	0.008		0.010
	(0.009)	(0.008)	(0.013)		(0.008)
Trade size (EUR (20, ∞) mn)				-0.512**	
				(0.182)	
Trade size (EUR (10, 20] mn)				0.406*	
				(0.173)	
Trade size (EUR (5, 10] mn)				0.359**	
				(0.116)	
Trade size (EUR (2, 5] mn)				0.160*	
				(0.079)	
Primary Dealer x Year 2025-26					-2.105*
					(0.946)
N	4,459,077	4,459,077	4,471,515	4,459,077	4,459,077
R2	0.26	0.24	0.01	0.26	0.27
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Market maker fixed effects	Yes	Yes	No	Yes	Yes
Bond fixed effects	Yes	No	No	Yes	Yes

Note: Logit regression results from estimating Eq. (1). Robust standard errors are reported in parentheses. *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

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