# Evaluation of the UK Emissions Trading Scheme: Phase 1 report – Annex 4

## Secondary market data analysis

A report to the UK ETS Authority prepared by the Institute for Sustainable Resources, University College London.

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# Contents

# 1. Introduction

This report lays out the results of the UK Emissions Trading Scheme (ETS) secondary market quality analysis. The main goal of this analysis is to assess price discovery and liquidity in the UK ETS secondary market, and to trace how these characteristics have evolved over time. Specifically, the analysis presented in this report comprises three parts.

The first part focuses on assessing the price discovery process in the UK ETS secondary market. This assessment is based on various approaches, including return predictability models, unbiasedness regressions and decomposing volatility into its components. This part of the analysis allows measurement of the extent to which the UK ETS secondary market reveals a price for UK allowances that is inclusive of all relevant information available at the time of trading.

The second part of the analysis is devoted to assessing the UK ETS secondary market quality in terms of liquidity. Specifically, we analyse the dynamics of spread and low frequency liquidity measures. The aim of this analysis is to assess how the market is performing its function of providing liquidity.

Price discovery and liquidity proxies are further examined in the third part of the analysis. Specifically, we analyse the differences in market quality proxies between trading days in weeks when UKA auctions are held and weeks when no auctions are held. We also examine the relationship between market quality proxies related to the liquidity and price discovery. Finally, to improve the interpretability of our price discovery and liquidity analysis, we compute and compare some UK ETS market quality proxies with those from the EU ETS secondary market, using data for a period common to both markets.

The key findings of the UK ETS secondary market quality analysis can be summarised as follows.

- There has been a substantial increase in trading activity in the market during the period 19 May 2021 to 15 September 2023, indicating a significant build-up in the market.
- Trading activity tend to be relatively higher (about 30%) in auction weeks than in non-auction weeks.
- Price volatility has also increased over the periods considered in the analysis, but about 80% of this observed volatility is information driven. (Total volatility can be decomposed into the information-driven volatility and noise-driven volatility. The information that drives volatility may include market and policy related information, such as press releases, announcements of policy changes, any news that may influence the behaviour and strategies of market participants, among others.)
- There is, nevertheless, indicative evidence that trading activity can predict short-run returns, implying that the process of price discovery may exhibit information inefficiency.

- However, it is worth noting that this predictability diminishes as liquidity increases, meaning that information efficiency in the market tends to improve when the market is relatively more liquid.
- Liquidity in the market has also improved over time.
- The results of the comparative analysis of the UK ETS and EU ETS secondary markets suggest that both markets exhibit similar average price volatility in returns from 1 December 2021 to 15 September 2023. However, there was a substantial difference in price volatility in the period from 28 July 2023 to 15 September 2023, although this volatility was largely driven by the incorporation of new information in both markets during this latter period. In addition, both markets exhibit a similar way in which the efficiency of the price discovery process unfolds through a typical trading day.
- We also find several dissimilarities between the two markets. Firstly, the extent to which trading activity explains variations in returns is also relatively higher in the UK ETS secondary market, suggesting that observed prices in this market are relatively less efficient compared to the EU ETS market. Secondly, the price discovery process during a typical trading day is more efficient in the EU ETS secondary market than in the UK ETS market. This relatively lower level of informational efficiency is expected in less mature markets such as the UK ETS secondary market. Finally, we find that while the average liquidity level is relatively slightly higher in the UK ETS market, over the period of analysis (28 July 2023 to 15 September 2023), it exhibits less stability in contrast to the EU ETS market. This finding is, however, not conclusive as it is based on data for a limited period.

The main limitations of the presented analysis relate to data availability (since bid and ask prices data used in the analysis is only available for a recent period of 83 trading days) and to the relatively low level of trading activity at the beginning of the UK ETS secondary market. Another limitation is that the comparative analysis of liquidity in the UK ETS secondary market vis-à-vis the EU ETS secondary market is based on the data for the period 28 July 2023 to 15 September 2023. This limited period could potentially influence the findings because the EU ETS secondary market experienced lower auction volumes in August 2023, primarily due to the European holidays, followed by higher auction volumes in September 2023.

The rest of the report is structured as follows.

- Section 2 provides a brief description of the UK ETS secondary market background.
- Section 3 presents the data set and describes our approach to market quality assessment.
- Section 4 presents and discusses the results of the analysis of market quality proxies, aligning with the “three parts” described in Section 1 above. This includes the results of the calculation of market quality proxies related to the price discovery process and liquidity in the UK ETS secondary market. In addition, the section presents and discusses the results of the further analysis examining the differences in market quality proxies between auction and non-auction weeks, the relationship between price

discovery and liquidity, as well as the comparative analysis of price discovery and liquidity in the UK ETS secondary market vis-à-vis the EU ETS secondary market.

- Section 5 summarises the results of the UK ETS secondary market quality assessment.

# 2. Background of the UK ETS Secondary Market

## 2.1 The UK ETS

The UK ETS was launched in January 2021 to replace the UK's participation in the European Union ETS. The UK ETS is designed in such a way that it sets a cap on the total amount of CO2-equivalent gas emissions and creates a carbon market to incentivise the decarbonisation of certain sectors of the economy and to meet the UK and devolved governments' climate change targets. The first phase of the scheme is planned to run from 2021 to 2030.

The UK ETS covers energy-intensive sectors such as aviation, power generation, offshore oil and gas, metals, chemicals, paper and pulp, ceramics, glass, refineries, food and drink. The term 'main scheme' is used in this report to indicate participants obliged to comply with the UK ETS by surrendering UKA via the UK ETS Registry. Some participants are also service providers (for example hospitals) but they qualify as 'Hospital or Small Emitter' installations and are not involved in trading allowances. UK ETS participants in the main scheme can be grouped into 'installation operators' and 'aircraft operators'. Installation operators include all installations with thermal input exceeding 20MW. Aircraft operators are those operating UK domestic flights, flights between the UK and Gibraltar, flights from Great Britain to Switzerland as well as flights departing from the UK to EEA states. According to the UK ETS Authority data for 2022[1], the number of participating installations operators was 715, and the number of participating aircraft operators was 463. Recently the UK ETS Authority announced plans to expand the scheme to the domestic maritime sector.

All UK ETS participants in the main scheme must report their total emissions annually and surrender an appropriate number of Allowances (UKAs). Scheme participants in certain sectors are eligible for 'free allowances', to reduce the impact of the scheme on their competitiveness. Allowances can also be obtained either through regular UK ETS auctions or through purchasing them on the UK ETS secondary market.

## 2.2 The UK ETS secondary market

This paper focuses on the secondary market in UK ETS futures that operates via the Intercontinental Exchange (ICE), because this provides a consistent and transparent market for analysis. Market participants can also trade 'off exchange' (sometimes referred to as 'Over the Counter') but these trades are bespoke arrangements between the buyer and seller for which transaction data is not readily available.

[1] https://www.gov.uk/government/publications/functioning-of-the-uk-carbon-market

Trading in UKA futures contracts on the secondary market officially commenced on 19 May 2021 and is hosted by ICE[2]. The UKA futures contract is a deliverable contract where each clearing member is obliged to take delivery of UKA to or from the UK Emissions Trading Registry on specified dates in the future. The size of each traded contract or ‘lot’ is 1000 UKA with each UKA being an entitlement to emit one tonne of carbon dioxide equivalent gas. The minimum trading size on ICE is 1 lot (1 contract) with a minimum tick size of £0.01 per UKA or £10.00 per contract. The normal trading day runs from 07:00 to 17:00 (London time) with a pre-open period of 06:45-07:00.

The ICE portal currently offers UKA futures contract with expiry dates set for March and December of the present year, as well as for the subsequent two years. The portal also offers up to three monthly UKA futures contracts, or as otherwise determined and announced by ICE.

In addition, UKA daily futures contracts are also traded on the ICE portal. The UKA daily futures contract operates as a deliverable agreement in which every clearing member holding an open position at the end of the trading is mandated to either make or receive deliveries of UKA through the UK Emissions Trading Registry, following the guidelines stipulated within the ICE Futures Europe Regulations.[3]

At the time of conducting this analysis, there were nine UKA futures contracts with different expiration dates being traded on the secondary market, in addition to the UKA daily futures contract. This includes three UKA futures contracts expiring in March (2024, 2025 and 2026), three UKA futures contracts expiring in December (2023, 2024 and 2025), and three UKA futures contracts expiring in October 2023, November 2023, and January 2024. For a detailed description of the traded UKA futures contracts and those chosen for the analysis, please refer to Section 3.1 and Appendix A2.1.

[2] https://www.ice.com/products/80216150/UKA-Futures
[3] Further details can be found here: https://www.ice.com/products/80216149/UKA-Daily-Futures

# 3. Methodology

## 3.1 Data and sample selection

The UK ETS secondary market data is provided through the ICE Connect portal and consists of two parts.

- The first type of data is real-time tick-by-tick UKA futures contract trade data which includes information about bid and ask prices, as well as information about executed trades (price and volume of each trade). This data is only available for the last 30 trading days.
- The second type of data comprises trading summaries for 1-minute trading intervals and includes data on transaction opening and closing prices, trading volume (namely number of UKAs traded) over the interval, and the highest and lowest prices. This data is available from the start of the trading in the UK ETS secondary market on 19 May 2021.

In this analysis, we make use of both types of data described above, and form two samples. The first sample includes data on 1-minute trading intervals (opening and closing prices, the lowest and the highest prices, traded volume). To construct this sample, we followed the existing literature and considered only futures contracts expiring in December since the inception of the secondary market (December 2021, December 2022, and December 2023 contracts). This is because the level of trading activity for other expiries is relatively low, while most of the market quality measures to be considered in this report can be correctly calculated only in case of the reasonably high level of trading activity. The average traded volumes for the futures contracts with different expiry dates are presented in Appendix A2.1.

To combine the data on futures contracts expiring in December 2021, 2022, and 2023, we rolled-over these contracts in a following way:

- Data on the contract to be delivered in December 2021 is used for the period 19 May 2021 to 30 November 2021.
- Data on the contract to be delivered in December 2022 is used for the period 1 December 2021 to 30 November 2022.
- Data on the contract to be delivered in December 2023 is used for the period 1 December 2022 to 15 September 2023.

The futures contracts expiring in December 2021 and December 2022 were truncated a full month before the expiry because of the high level of volatility and noisiness of trading which are usually observed in the closing stage of the contract's life. The similar roll-over procedure was previously used, for example, by Medina et al. (2014). The roll-over procedure allows for significant expansion of the period with relatively high level of trading activity. For example, for the futures contract expiring in December 2023 a reasonably high level of trading activity can be observed only starting from December 2022. Before this month, the average daily traded volume did not exceed 100 lots (see Appendix A2.1). Thus, the inclusion of data on contracts expiring in December 2021 and December 2022 considerably increased the number of 1-minute trading intervals with non-zero trading activity.

The second sample used for the analysis is based on the real-time tick-by-tick UKA trade data containing information about bid and ask prices, as well as information about executed trades (price and volume). This type of data is only available on the ICE Connect portal for the last 30 trading days. We downloaded this data three times: on July 20, July 31, and September 18, and then combined the results of these downloads to extend the period for which this type of data is available. The final sample used for the analysis spans from 22 May 2023 to 15 September 2023.

Therefore, the following samples form the basis for assessing the UK ETS secondary market quality.

- Sample 1. Data on opening/closing prices, the highest/lowest prices, traded volume for each 1-minute trading interval during the period 19 May 2021 to 15 September 2023 (602 trading days).
- Sample 2. Real-time tick-by-tick data on bid and ask prices, prices of executed trades, volumes of executed trades for the period 22 May 2023 to 15 September 2023 (83 trading days).

The descriptive analysis of the sample used in the analysis is presented in Appendix A2.1.

The UK ETS secondary market quality analysis based on these samples has two important limitations. First, a descriptive analysis of these samples shows that the level of trading activity was relatively low after the start of the secondary market in 2021. This makes it difficult to estimate some of the market quality proxies. Second, Sample 2 includes only 83 trading days. Thus, the market proxies based on this sample do not cover the initial stages of the UK ETS secondary market.

## 3.2 Market quality characteristics

A well-functioning financial market is characterised by its ability to offer a reliable and trusted price discovery mechanism and ensure liquidity in both regular market conditions and times of heightened uncertainty (O'Hara, 2003). Price discovery is a process of incorporation of available information (both private and public) into prices. The main goal of this process is to achieve informational efficiency when all relevant information is reflected in the prices (Ibikunle, 2023).  Liquidity in this case means the ability of the market to undertake transactions without triggering substantial or enduring changes in prices (Ibikunle, 2023).

The existing literature suggests that these two dimensions of market quality can be closely related. For example, Chordia et al. (2008) describe the following mechanism by which liquidity can be linked to the price discovery process. If market makers have limited risk-bearing capacity, they will find it difficult to execute all incoming orders if the number of buy and sell orders becomes significantly imbalanced. This situation leads to a deviation of the price from its fundamental level. As a result, it is possible to predict returns based on information about order imbalances in the previous periods. 'Informed market' participants can identify such deviations and place arbitrage trades to profit from the price deviation from them. 'Informed traders' refers to those who trade to exploit private information (value traders, technical traders, dealers, arbitrageurs). Another type of trader in the market is the uninformed trader (or 'liquidity trader'), whose trading is not primarily driven by the need to profit from the movement in price (for example, electricity producer trading in emission permits to offset its carbon footprint in accordance with the law).

These arbitrage trades will push the price back to the fundamental level. However, informed traders are more likely to place arbitrage orders in conditions of high liquidity. Therefore, when the market is relatively liquid, the price deviation from the fundamental level is eliminated more quickly, indicating better quality in the price discovery process.

The focus of this report is thus on the price discovery and liquidity in the UK ETS secondary market using a set of market quality proxies selected based on Ibikunle (2023), as well as the relationship between market quality proxies related to these two dimensions of market quality (see Section 4.3.2). Section 3.2.1 and Section 3.2.2 (below) discuss the nature of these proxies, their limitations and how they relate to each other. For a more in-depth description of these liquidity proxies, please refer to Appendix 1.

## 3.2.1 Price discovery

In this report, we explore three dimensions of the price discovery process in the UK ETS secondary market.

- First, we analyse price discovery in terms of the UKA price volatility. We then decompose the price volatility into two parts – the fractions explained by the market incorporating new information and by trading noise (price volatility, volatility decomposition into the efficiency price and pricing error – Section 4.1.1 and Section 4.1.2).
- Second, we assess the price discovery process in terms of price efficiency. This is measured by the extent to which the price can be predicted based on trading information from previous periods (coefficients of determination from returns predictability regressions – Section 4.1.3).
- Finally, we look at how the process of price discovery unfolds over the course of a typical trading day (signal-to-signal plus noise ratio – Section 4.1.4).

These three dimensions therefore allow us to assess both the process of price discovery and the outcome of that process, meaning the extent to which the market can establish an efficient and reliable price for the UKA. Overall, four different proxies for market quality were used to examine the price discovery process in the UK ETS secondary market, as defined below.

### 3.2.1.1 Price volatility

We measure price volatility as the standard deviation of the daily 1-minute returns, as shown in Appendix A1.1. This proxy aims to capture the excess volatility which is unlikely to be driven by incorporation of new information. The concept here is that information crucial for determining the price of an instrument is not typically released at very short intervals during a trading day. Therefore, substantial price fluctuations could be considered as an indication of reduced informational efficiency. A limitation of this proxy, however, is that it does not differentiate between the contributions of information and noise in driving price volatility.

### 3.2.1.2 Price volatility decomposition

To overcome the limitation mentioned above, we made use of the volatility decomposition approach proposed by Hasbrouck (1993). The aim of this approach is to decompose the price change into a 'random walk' component (efficient price) and a residual component (pricing error). (A 'random walk' is a process in which future behaviour is independent of history. In our case, it refers to the situation where the price evolves randomly, so that past movement or trend of the price cannot be used to predict its future movement.) Thus, the decomposition approach of Hasbrouck (1993) allows for a quantitative estimation of the roles of two main drivers of price changes - the incorporation of new information by the market and the pricing errors. The market quality proxy calculated based on the volatility decomposition is a share of information-driven volatility ($Q$, as per equation 7 in Appendix A1.2) which ranges between 0 and 1. A value of $Q$ close to 1 corresponds to a high level of market quality with respect to the price discovery process, so an increase in $Q$ signifies improved market quality, indicating that price volatility is largely a result of information rather than noise (meaning that it is not driven by information).

A potential limitation of this proxy is that it is based on the premise that neither the pricing error variance nor the deviation between the efficient price and the actual transaction price directly reveals anything about the private or social costs of foregone transactions (Hasbrouck, 1993). However, this limitation applies to most measures based on trade data, and can be overcome, for example, by excluding from the analysis certain trades that are likely to be based on superior information. The results of volatility decomposition are presented in Section 4.1.2. Detailed methodology of the volatility decomposition is presented in Appendix A1.2.

### 3.2.1.3 Price efficiency

An efficient price is expected to follow a 'random walk' process (Fama, 1970), which implies that current price cannot be predicted using other market variables, such as trading activity. Therefore, to assess price efficiency, we test the hypothesis that price (returns) can be predicted based on trading information from previous periods using the return predictability model (Chordia et al., 2008; Ibikunle et al., 2016). In this model, the order imbalance ratio in the previous period is used as a predictor of current returns (as shown in equation 8, Appendix A1.3). The order imbalance is defined as a ratio of the difference between buyer-initiated trades volume (in £) and seller-initiated trades volume (in £) to the total traded volume (in £) (as shown in equation 9, Appendix A1.3).

We then use the coefficient of determination from the return predictability regression as a quantitative measure of short run price efficiency. This reflects the share of returns variation that can be explained by the variation of order imbalance in the previous period. A higher value of the coefficient determination indicates that more of the variation in short run returns can be explained by trading activity, suggesting that the price is less efficient. Methodological details of the return predictability analysis can be found in Appendix A1.3. The results of the return predictability analysis are presented in Section 4.1.3.

#### 3.2.1.4 Signal to signal plus noise ratio estimated from unbiasedness regressions

The three proxies described above provide a snapshot of the overall price discovery quality a point in time, for example a trading day. However, the quality of the price discovery process may vary between the different time periods of a typical trading day.

One way to look at the evolution of the price of an instrument is that it is a combination of an efficient price change and a price change due to noise. This approach is based on estimating the extent to which price change is due to the incorporation of information (Ibinkule, 2023).

To assess how price discovery evolves over the course of a typical trading day, we follow Ibikunle (2013), and estimate signal-plus-noise ratios for each 1-hour trading interval (see methodological details in Appendix A1.4). This is defined as the ratio of signal (meaning information that leads to an enduring price change) to signal-plus-noise (meaning a price change that reverses quickly). More specifically, we employ an unbiasedness regression model (as shown in equation 10, Appendix A1.4) to estimate the signal-plus-noise ratios for each time interval (1 hour) during the trading day. Relatively high values of signal-to-signal plus noise ratio in this case mean that the level of noise during the trading interval is low and that price changes are mostly driven by the incorporation of new information.

The ideal pattern for the signal-to-signal plus noise ratio is to start the day at a high level (for example, higher than 0.8) and to stay that high until the end of the trading day. A high start is expected because the market endeavours to assimilate information from the overnight period (since the last trade the day before), as the new trading day commences. However, a decrease in this ratio is anticipated as the trading day draws to a close. Ultimately, this ratio is closely tied to trading activity, where heightened trading activity corresponds to a higher ratio. This reflects the opportunity for informed traders to execute their informed orders (signal) against the flow of uninformed trading orders (noise). As these informed trades are successfully executed, their information becomes incorporated into the price, consequently maintaining the signal-to-signal-plus-noise ratio.

An important limitation of this measure is that it is very aggregated (especially when calculated over long time periods) and does not consider variations between trading days (which can be significant). The results of these estimations are presented in Section 4.1.4.

### 3.2.2 Liquidity

Following existing literature on the financial markets' microstructure (Ibikunle, 2023), we consider two types of liquidity measures.

- The most widely used indicators of market liquidity in the market microstructure literature typically rely on proxies derived from bid-ask spreads (Ibikunle, 2023). These measures intuitively capture the probability that an economic agent will be able to execute a regular-sized order quickly, at a fair price, and with little or no price impact (meaning that they capture at least three of the five dimensions of liquidity, namely the tightness, depth, and immediacy dimensions of liquidity). Tightness corresponds to the difference between the fundamental price and the transaction price, depth is the ability of the market to absorb quantities without their having a large effect on price, while immediacy is the speed of order execution (Ibikunle, 2023). The other dimensions of liquidity are breadth and resilience. The resilience reflects the time it takes for prices to move back to equilibrium after a large trade, while the breadth corresponds to the number of market participants who do not wield significant power. These two dimensions are also captured by the bid-ask spread measures, but to a lesser extent than tightness, depth, and immediacy dimensions. The spread is thus defined as a non-zero cost born by traders that includes inventory holding cost, order processing cost, and adverse selection cost (Ibikunle, 2023). Ibikunle (2023) recommended four proxies based on the bid-ask spreads, namely the relative quoted spread, relative traded spread, effective spread, and realised spread (please see below for details on these proxies). The results of spread measures calculation are presented in Section 4.2.1 and in Appendix A2.4.

- Low frequency liquidity measure (Amihud (2002) price impact ratio) that accounts for the possible trades that can be a source of significant price shocks (Section 4.2.2). This measure is usually considered to fully capture resilience dimension of the liquidity (meaning the time it takes for prices to move back to equilibrium after a large trade) (Ibikunle, 2023).

Thus, the set of liquidity measures considered in this report captures all the five dimensions of liquidity mentioned above. We provide a brief overview of the liquidity proxies considered in the analysis below, along with a discussion of their limitations. For a more in-depth description of these liquidity proxies, please refer to Appendix 1.

### 3.2.2.1 Relative quoted spread

The relative quoted spread is defined as the difference between the best bid and the best ask prices observed over a short trading interval, divided by the midpoint price (the average of these two prices). Thus, this measure of liquidity can be interpreted as the round-trip cost of a regular transaction, measured as a percentage of the prevailing midpoint. The relative quoted spread is a widely used measure of round-trip cost of the transactions because of its simplicity in both calculation and interpretation.

However, it has a few limitations. As noted by Huang & Stoll (1996), “bid and ask quotes are not necessarily the prices at which trades take place, since it is possible to trade inside the quotes, especially if the spread is wide… “. In addition, in markets with relatively low trading activity, there may be no trades during the time interval for which the spread is calculated. In this case, the relative quoted spread is not a measure of the true cost of the round-trip transaction, as there are no transactions at this cost. Ibikunle (2023) also notes that the relative quoted spread could overstate or understate the execution cost for liquidity demanding traders when orders execute within or beyond prevailing bid and ask quotes/prices.

A detailed description of the relative quoted spread calculation procedure can be found in Appendix A1.5.

#### 3.2.2.2. Relative traded spread

Another spread measure which is very similar to the quoted spread is a traded spread. Relative traded spread is calculated in a similar way as the relative quoted spread. The main difference is that the bid and ask prices are replaced by the prices of the buyer-initiated trades and seller-initiated trades (as shown in equation 12, Appendix A1.6). Thus, while having characteristics of relative quoted spread, relative traded spread is based on transaction prices only.

The limitation of this measure in the context of our study is that it requires data on the direction of trade (whether each trade is buyer-initiated or seller-initiated). Data sourced from ICE Connect portal does not include trade direction indicator. This limitation can, however, be overcome by classifying trades as buyer-initiated or seller-initiated using specific procedures such as tick testing (Lee & Ready, 1993). Although these procedures have rather high level of classification accuracy, some classification errors are still possible. These classification errors can thus reduce the accuracy of relative traded spread estimates.

The methodological details related to the traded spread/relative traded spread calculation are presented in Appendix A1.6.

#### 3.2.2.3 Effective spread

Unlike the relative quoted spread and the relative traded spread that rely on one type of data, the effective spread is based on both data on bid and ask prices as well as data on transaction prices. The effective spread is defined as double the difference between the transaction price and the quote midpoint at the time of transaction (see details in Appendix A1.7).

Effective spread (in £) has the same interpretation as the relative quoted spread and relative traded spread. Specifically, higher spread values correspond to the higher cost of the round-trip transaction for market participants. The main limitation of the effective spread is that it overstates the liquidity provider profits and the trade's true execution cost when trades have positive price impact.

#### 3.2.2.4 Realised spread.

The realised spread represents the part of the effective spread related to the spread realised by the liquidity provider. Thus, it accounts for the limitation of the effective spread mentioned above. This spread measure considers the possible price impact of the trade, as it reflects the revenue earned by the dealer after the trade. The realised spread is defined by the formula 14 (Appendix A1.8). The limitation of this spread measure is that it does not account for the adverse selection cost component of the spread. The adverse selection component reflects the cost to the liquidity traders for taking the risk of trading with informed traders (meaning information risk) (Ibikunle, 2023). Liquidity traders trade for reasons not linked to profit making (for example, electricity producer trading in emission permits to offset its carbon footprint in accordance with the law). Informed traders are those who trade to exploit private information (value traders, technical traders, dealers, arbitrageurs).

The main part of this report is focussed on only two out of the four spread measures discussed above, the effective spread and the traded spread (see Section 4.2.1). These two measures were selected based on the similarities observed between the relative quoted spread and relative traded spread, as well as between the effective spread and realised spread. The relative traded spread is, however, preferred to the relative quoted spread because it is based on transaction prices and more accurately measures liquidity in cases of relatively low trading activity. On the other hand, the effective spread is preferred to the realised spread due to its comprehensive nature, encompassing both the realised spread and the associated adverse selection costs, resulting in a more thorough measurement of liquidity.

Nevertheless, we report the results of the relative quoted spread and realised spread as a robustness check in Appendix A2.4.

#### 3.2.2.6 Amihud (2002) price impact ratio

All the spread measures described above do not account for block (large) trades, which can be a source of significant price shocks (Ibikunle, 2023). To account for the possibility of block trades, we use an additional low-frequency measure of liquidity, which is Amihud (2002) price impact ratio. It is calculated as an average ratio of the daily absolute return to the trading volume on that day (see details in Appendix A1.9). This measure is volume-based; thus, it reflects the price impact of the transactions.

The Amihud (2002) price impact ratio is usually considered a poor substitute for the high-frequency measures such as spreads. However, as noted by Ibikunle (2023), "it intuitively captures the resilience dimension of liquidity since in less liquid markets any given level of trading volume will induce a large price impact corresponding to its illiquidity state". Thus, despite the limitations of the Amihud (2002) price impact ratio, it may be useful to consider this measure combined with spread to capture more dimensions of liquidity. Section 4.2.2 presents the results of the Amihud (2002) price impact ratio analysis.

# 4. Results of the UK ETS secondary market quality assessment

## 4.1 Evidence on price discovery process in the UK ETS secondary market

### 4.1.1 Price volatility

Table 1 (below) presents summary statistics of the daily volatility of 1-minute returns, while the dynamics over the periods considered in the analysis is shown in Figure 1 and Figure 2 (below). Figure 1 and Panel A of Table 1 correspond to the period 19 May 2021 to 15 September 2023 (Sample 1). We also present the results of price volatility analysis for the period covered by 22 May 2023 to 15 September 2023 (Sample 2). This is to facilitate the comparison of price volatility with other market quality proxies that can only be calculated using data for the period covered by Sample 2. Panel B of Table 1 (below) presents the descriptive statistics of price volatility using Sample 2 while Figure 2 (below) presents the dynamics of price volatility over this period.

**Table 1. Summary statistics for the 1-minute returns and the daily volatility of the 1-minute returns.**

| Variable/ Market quality proxy | Minimum | Median | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|
| Panel A. 19 May 2021 – 15 September 2023 (Sample 1) | | | | | |
| 1-minute returns (%) | -2.1295 | 0.0000 | -0.0015 | 3.0927 | 0.1056 |
| Daily volatility of the 1-minute returns | 0.0000 | 0.0711 | 0.0783 | 0.3308 | 0.0522 |
| Panel B. 22 May 2023 – 15 September 2023 (Sample 2) | | | | | |
| 1-minute returns (%) | -1.9512 | 0.0000 | -0.0038 | 1.5670 | 0.1217 |

| Variable/ Market quality proxy | Minimum | Median | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|
| Daily volatility of the 1-minute returns | 0.0302 | 0.0970 | 0.1028 | 0.2894 | 0.0483 |

**Notes***:* The 1-minute returns are calculated as the difference between the opening price and the closing price of each 1-minute trading interval, divided by the opening price of the interval and multiplied by 100%. The daily volatility is computed as the standard deviation of the 1-minute return over a single trading day. Descriptive statistics presented in Panel A are calculated using data for the period *19* May  2021 *to 15* September, 2023 (Sample 1) while Panel B corresponds to the period *22* May 2023 *to 15* September 2023 (Sample 2).

The mean daily standard deviation of 1-minute returns over the period 19 May 2021 to15 September 2023 is 0.0783%. However, on some trading days the daily standard deviation exceeds 0.15% or even 0.2% with a maximum value of about 0.3%, which can be considered as an indicator of excessive volatility caused by high trading noise.  During the period 19 May 2021 to 15 September 2023, the standard deviation of returns slightly increased with high levels of variability, as shown in Figure 1. The largest surge in returns standard deviation is observed in February 2022. This spike may be linked to the start of the Russian invasion of Ukraine on 24 February 2022 which created a considerable market uncertainty.

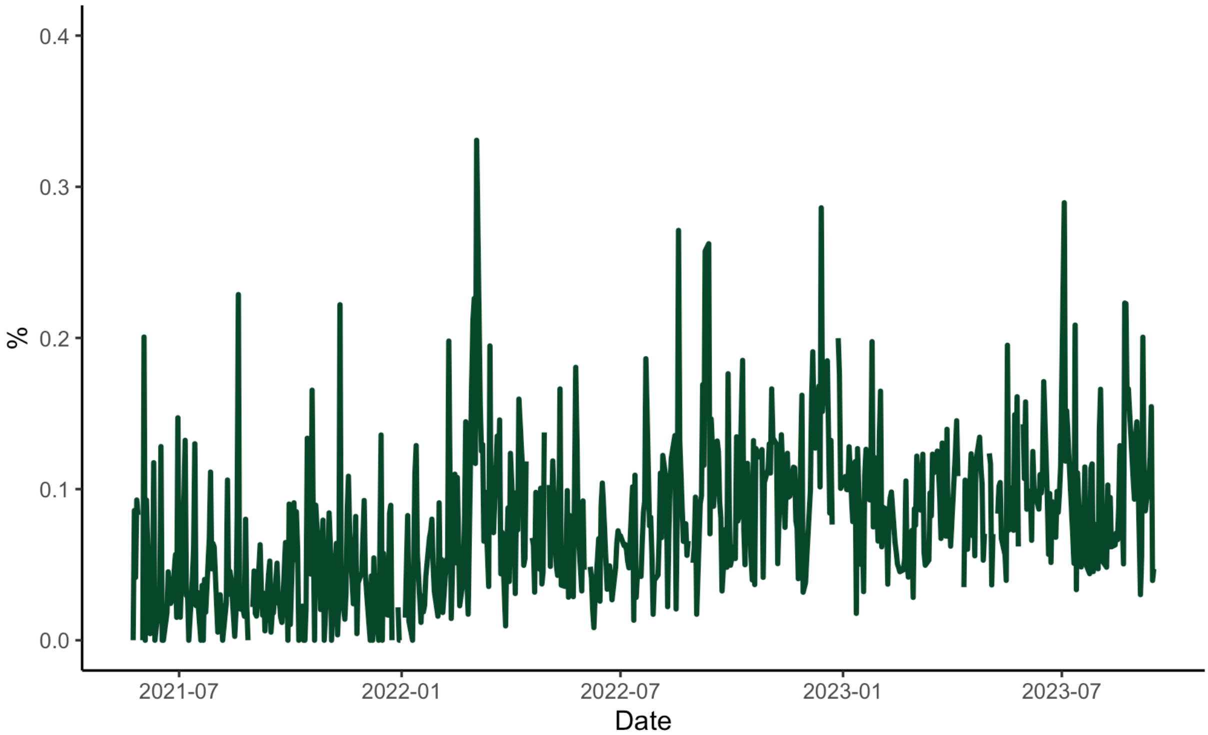


**Figure 1. The dynamics of daily volatility of 1-minute returns (Sample 1).**

**Notes**: The daily volatility is computed as the standard deviation of the 1-minute return over a single trading day. The 1-minute returns are calculated as the difference between the opening price and the closing price of each 1-minute trading interval, divided by the opening price of the interval and multiplied by 100%. This is based on data for futures contracts to be delivered in December 2021, December 2022, and December 2023 rolled into a single time series as described in Section 3.1  for the period 19 May 2021 to 15 September 2023.

Focussing on the smaller sample (Sample 2), we can observe a similar pattern in price volatility, fluctuating between 0.03% and 0.28%, with a mean value of 0.10% (see Figure 2). The highest volatility over this period was on July 3, 2023 (see Figure 2) which could be attributed to the UK ETS Authority's announcement of plans for future changes to the scheme.

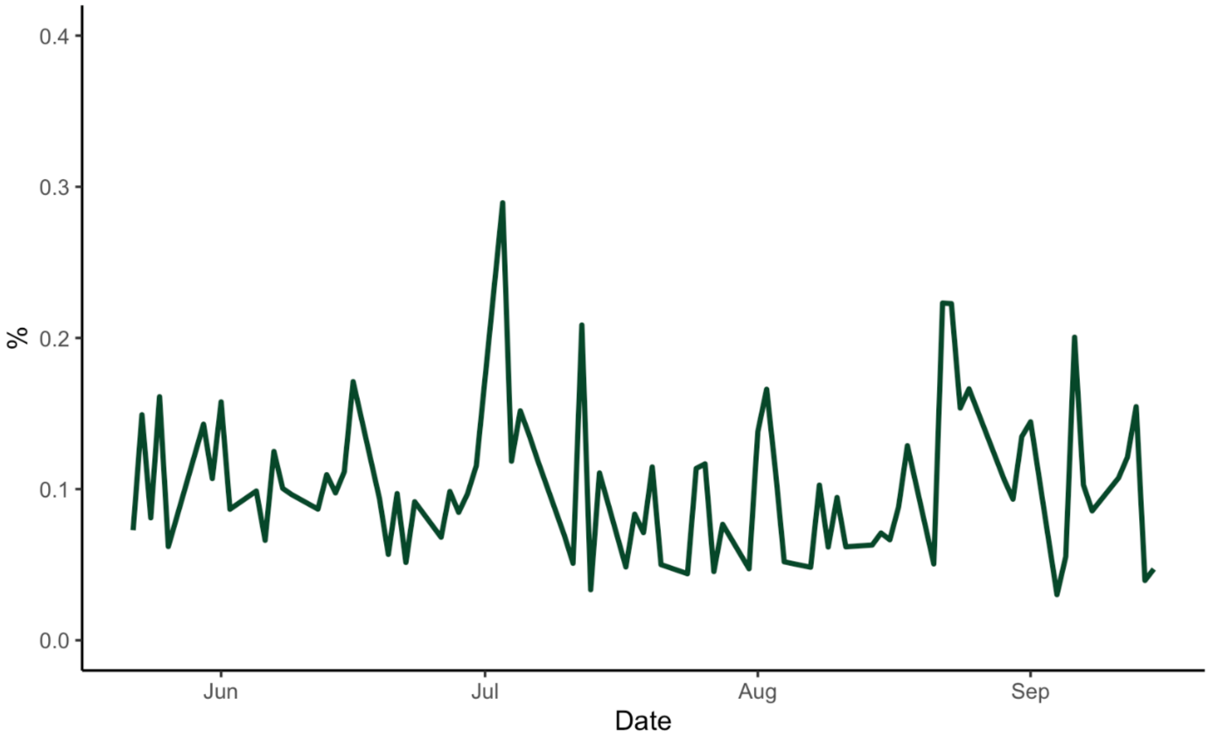


**Figure 2. The dynamics of daily volatility of 1-minute returns (Sample 2).**

**Notes**: The daily volatility is computed as the standard deviation of the 1-minute return over a single trading day. The 1-minute returns are calculated as the difference between the opening price and the closing price of each 1-minute trading interval, divided by the opening price of the interval and multiplied by 100%. This is based on data for futures contracts to delivered in December 2023 over the period 22 May 2023 to 15 September 2023.

It is worthy to mention that this increased average volatility should not be interpreted as indicating deteriorating market quality. As mentioned earlier, this volatility could be related to the incorporation of new information or noise. While the noise-related volatility is detrimental to financial markets, information volatility is desirable since it reflects the new information that is being incorporated into prices (Medina et al., 2014). We conduct this volatility decomposition in Section 4.1.2.

We also compare the price volatility in the UK ETS secondary market to that of the EU ETS, using data covering a period common to both markets in Section 4.3.3.2.1.

### 4.1.2 Price volatility decomposition

In this section, we further investigate the price discovery process in the UK ETS secondary market and estimate the extent to which price changes are driven by the incorporation of new information and the extent to which price dynamic is determined by pricing errors. We use the approach proposed by Hasbrouck (1993), which allows price changes to be disentangled into a ‘random walk’ component (efficient price) and a residual stationary component (pricing error).

Based on this decomposition, we then estimate the share of information-driven volatility ($Q$, as defined by equation 7 in Appendix A1.2).

Given the relatively high level of trading activity observed during the period covered by the data, we decompose volatility for each trading day in the sample. This allows us to track how price efficiency evolves over time. The descriptive statistics for the overall return volatility, its noisy component, and the share of information-driven volatility $Q$ , over the period 22 May 2023 to 15 September 2023, are presented in Table 2.

**Table 2. Summary statistics for the results of volatility decomposition for each trading day during the period 22 May 2023 to 15 September 2023 (Sample 2).**

| Variable/ Market quality proxy | Minimum | Median | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|
| $2\sigma_s^2 \times 100$ | 0.0005 | 0.0243 | 0.0459 | 0.4277 | 0.0718 |
| $\sigma_r^2 \times 100$ | 0.0094 | 0.0917 | 0.1625 | 1.6024 | 0.2432 |
| $Q$ | 0.4042 | 0.7331 | 0.7205 | 0.9480 | 0.1216 |

**Notes**: The table displays the descriptive statistics for the overall return's volatility, noisy component of returns volatility and for the market quality measure $Q$.The noisy component of return volatility is estimated based on the procedure proposed by Hasbrouck (1993) and summarised in Appendix A1.2. The estimates are obtained for each trading day during the period 22 May 2023 to 15 September 2023. $2 \times \sigma_s^2$ is a double variance of the pricing error calculated according to the procedure described in Appendix A1.2. $\sigma_r^2$ is a volatility (variance) of continuously compounded returns computed directly from the data. $Q$ is a market quality indicator (share of information-driven volatility) defined as $Q = 1 - \frac{2\sigma_s^2}{\sigma_r^2}$. Relatively high values of $Q$ correspond to the high level of market quality in terms of price discovery process. To make the volatility estimates comparable across trading days, we multiply each volatility estimate by the number of trades on the corresponding trading day as was done in Medina et al. (2014).

The measure of the quality of the market in terms of information driven volatility, $Q$, ranges from 0.4042 to 0.9480 with a mean value of 0.7205. This suggests that, on average, about 72% of the price volatility depicted in Figure 2 is information driven.

Figure 3 (below) displays the dynamics of market quality measure $Q$.[4] We observe that the share of information-driven volatility increases over time. The average of $Q$ daily estimates for the period 22 May 2023 to 5 June 2023 (the first 10 trading days in the sample) is 0.68, compared to 0.78 during 4 September 2023 to 15 September 2023 (the last 10 trading days in the sample). The lowest share of information-driven volatility (0.40) is observed on 10 August 2023. This is the trading day following the auction on 9 August 2023. Thus, the relatively high level of noise-related volatility on August 10 may be related to the additional market activity associated with the auction on the previous day.  The highest level of information-driven

[4] Appendix A2.2 contains more detailed results of volatility decomposition (pricing error variance and share of information driven volatility estimated for each trading day).

volatility (0.95) is observed on 14 September 2023, although this day was characterised by relatively low price volatility, as shown by the Figure 2.

It is also worth highlighting that the spike in volatility observed in July 2023 (as depicted in Figure 2) is largely (more than 80%) driven by information, which aligns with our assertion that this could be connected to the announcement of reforms to the UK ETS in early July 2023.

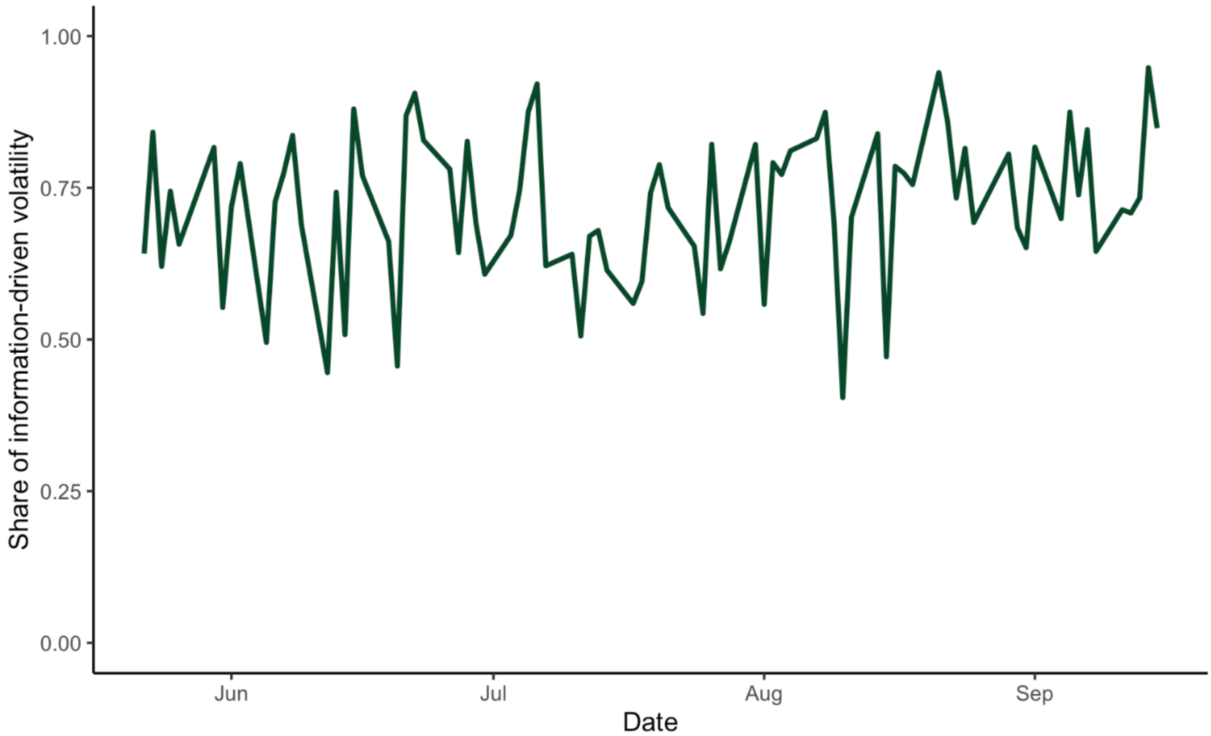


**Figure 3. The dynamics of the share of price volatility driven by information ( $Q$) estimated based on Hasbrouck's (1993) approach (Sample 2).**

**Notes**: The figure shows the dynamics of the market quality measure $Q$ estimated based on the Hasbrouck's (1993) approach for the period 22 May 2023 to 15 September 2023. $Q$ is defined as $Q = 1 - \frac{2\sigma_s^2}{\sigma_r^2}$, where $\sigma_s^2$ is a pricing error variance, $\sigma_r^2$ is a variance of the observed returns. Relatively high values of $Q$ correspond to the high level of market quality in terms of price discovery process. Estimates of the pricing error variance ($\sigma_s^2$) were multiplied by the number of trades during the corresponding trading day to make them comparable (Medina et al., 2014).

To obtain a more robust estimate of information-driven volatility, we perform a volatility decomposition based on the full sample (27,884 observations over the period 22 May 2023 - 15 September 2023). The results of volatility decomposition for the whole period are presented in Table 3.

The share of information-driven volatility estimated based on the full sample is slightly higher than the average of daily estimates. However, as the maximum theoretically possible value of $Q$ is 1, there was room for improvement in the quality considered period. Our estimates of returns variance, pricing error, and information-driven volatility ($Q$) are comparable to the same measures obtained by Medina et al. (2014) for the EU ETS secondary market based on the data for the period 2006-2010.

In Section 4.3.3.2.2, we conduct an additional analysis to compare the share of information-driven volatility shares in UK ETS secondary markets to that of the EU ETS using data covering a period common to both markets.

**Table 3. Decomposition of returns volatility based on Hasbrouck's (1993) approach (22 May 2023 to 15 September 2023, Sample 2).**

| Period | Sample size | $2 \times \sigma_s^2$ (x100) | $\sigma_r^2$ (x100) | $Q$ |
|---|---|---|---|---|
| 22 May 2023 – 15 September 2023 | 27,884 | 0.0240 | 0.1283 | 0.8129 |

**Notes**: The table displays the results of noisy component of return volatility estimation based on Hasbrouck's (1993) approach. $2 \times \sigma_s^2$ is a double variance of the pricing error calculated based on the VAR model according to the procedure described in Appendix A1.2. $\sigma_r^2$ is a volatility (variance) of continuously compounded returns computed directly from the data. $Q$ is a market quality indicator (share of information-driven volatility) defined as $Q = 1 - \frac{2\sigma_s^2}{\sigma_r^2}$. Relatively high values of $Q$ corresponds to the high level of market quality with respect to price discovery process.

## 4.1.3 Price efficiency

Price is efficient when it evolves randomly, meaning that it cannot be predicted based on different market-related variables, for example trading activity (Ibikunle, 2023). The idea of the market quality proxy discussed in this section is related to the analysis of the extent to which short-horizon returns can be predicted based on the data on order imbalance. The order imbalance ratio used in this approach reflects the discrepancy between the flows of buy and sell transactions.

The data from the ICE Connect portal used for this analysis does not contain indicators reflecting whether the trade is buyer- or seller-initiated. Thus, the first step of the return's predictability analysis is to classify all trades into these two categories. For classifying the trades, we use a tick test which was widely used in similar contexts in previous studies. For example, Ibikunle et al. (2013) used this test to classify the trades on the European Climate Exchange. As demonstrated by Lee & Ready (1993), the tick test procedure provides a reasonably high level of classification accuracy. According to the tick test, the trades at a price higher than the prevailing trade midpoint are classified as buyer initiated. The trades at a price lower than the prevailing trade midpoint are classified as seller-initiated (Lee & Ready, 1993).

The results of the tick test implementation suggest that around 47% of all trades during the period 22 May 2023 to 15 September 2023 are classified as buyer-initiated and around 53% as seller-initiated.

After classifying the trades, we proceed to the calculation of the order imbalance measure as defined by equation 9 (Appendix A1.3). Following Ibikunle et al. (2016), we calculate the order imbalance for each 15-minute trading interval. Respectively, the returns are also calculated for

15-minute trading intervals. Table 4 (below) presents the descriptive statistics for calculated 15-minute returns and 15-minute order imbalance ratio.

**Table 4. Descriptive statistics for the 15-minute returns and order imbalance (Sample 2).**

| Variable/ Market quality proxy | Minimum | Median | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|
| 15-minute returns (%) | -0.0439 | 0.0000 | 0.0000 | 0.0295 | 0.0039 |
| 15-minute order imbalance (£) | -1.0000 | 0.1151 | 0.0727 | 1.0000 | 0.7577 |

**Notes**: The table shows the descriptive statistics of 15- minutes returns and order imbalance (£) over the period 22 May 2023 to 15 September 2023. 15-minute returns are calculated as the difference between the opening price and the closing price of each 15-minute trading interval, divided by the opening price of the interval and multiplied by 100%. The order imbalance is defined as a ratio of the difference between buyer-initiated trades volume (in £) and seller-initiated trades volume (in £) to the total traded volume (in £) over the 15-minute trading interval.

Finally, to obtain a measure of return predictability we estimate the regression model (see equation 8 in Appendix A1.3) using ordinary least squares. We estimate the price efficiency for the whole period under consideration and separately for each trading day. It is important to highlight that the timeframe under examination in this analysis is distinct from that in Ibikunle et al. (2016). This disparity in timeframes could potentially account for the variations observed in the results.

Table 5 (below) shows the results of the model estimation for the whole period 22 May 2023 to 15 September 2023.  The results suggest that the order imbalance ratio in the previous period is a statistically significant predictor of current returns, for the entire sample used in the analysis. Thus, we observe some evidence of the influence of lagged order imbalances in the determination of market returns for the whole period under consideration, although the magnitude of the coefficient is relatively small (0.0003) compared to those estimated for the EU ETS secondary market. For instance, Ibikunle et al., (2016) estimated a statistically significant coefficient ranging from 0.0004 to 0.0006 for Phase two of the EU ETS (years one, two and four).

We also estimate a coefficient of determination, R2, of 0.4%, which implies that trading activity explains only 0.4% of the variation in returns over the period considered in the analysis. However, the magnitude of the coefficient of determination is relatively high compared to those estimated for the for the EU ETS secondary market.   Ibikunle et al., (2016) estimated a coefficient of determination ranging from 0.009% to 0.02% for Phase two of the EU ETS (years one, two and four). This suggests that the price discovery process in the UK ETS market is comparatively less informationally inefficient than in the EU-ETS market.

It is important to highlight that the timeframe under examination in this analysis is distinct from that in Ibikunle et al. (2016). This disparity in timeframes could potentially account for the variations observed in the results.

**Table 5. The results of the predictive regressions of 15-minute returns on lagged order imbalance for the whole period under consideration (22 May 2023 to 15 September 2023, Sample 2).**

| Variable | Estimate (x100) | P-value |
|---|---|---|
| Intercept | 0.0037 | 0.6414 |
| $\mathrm{OrderImbalance}_{t-1}$ | 0.0316 | 0.0027 *** |
| R2: 0.004<br>F-statistic: 4.5231 (p-value: 0.0340) | | |

Notes: The table shows the results of the 15-minute predictive regressions. The dependant variable is the 15–minute returns. The order imbalance is defined as a ratio of the difference between buyer-initiated trade volume (in £) and seller-initiated trade volume (in £) to the total traded volume (in £) over the 15-minute trading interval. The regression model is estimated using OLS based on the data for the period 22 May 2023 to 15 September 2023. "***" indicates the statistical significance of the parameter at a 0.01 level of significance.

Table 6 (below) presents the summary statistics of the estimated coefficient of determination (R2) from 15-minute return predictability models for each trading day. The estimated coefficients of determination ranges between 0 and 22.7%, with an average of 4%.

**Table 6. The descriptive statistics for the coefficient of determination (R2) from 15-minute return predictability models for each trading day (Sample 2).**

| Market quality proxy | Minimum | Median | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|
| $R^2$ from return predictability model | 0.0000 | 0.0159 | 0.0424 | 0.2270 | 0.0535 |

**Notes**: The table shows the descriptive statistics of the coefficients of determination (R2) that were estimated using the 15 minutes return predictability model for each trading day from 22 May 2023 to 15 September 2023. Coefficient of determination (R2) is defined as a share of variance of the 15-minute returns that can be explained by the variance of the 15-minute order imbalance ratio for each trading day.

Figure 4 (below) presents the dynamics of the coefficient of determination estimated based on the return predictability models for each trading day. The daily trend in return predictability by the lagged order imbalance is not stable over the period considered in the study. This suggests that there is a wide variation in the pricing efficiency across trading days. There are trading days where the pricing is more efficient compared to others. Specifically, the highest levels of returns predictability are observed on 29 June 2023 (0.1936), 10 July 2023 (0.2196), 10 August 2023 (0.2271). The UKA price most closely follows random walk (the least coefficient of determination) on 17 July 2023 (0.000002), 25 July 2023 (0.0001), and 2 August 2023 (0.00002).

On average, price efficiency does not differ significantly between auction days (average coefficient of determination is 0.0431) and non-auction days (average coefficient of determination is 0.0423). However, 29 June 2023 and 10 August 2023 (trading days with an unusually high degree of return predictability) are the next trading days after the auctions. In other words, order imbalances observed in the secondary market on auction days are likely to be predictive of the next trading day's return. However, given the limited sample size, we cannot test whether this is a consistent pattern or just a coincidence.

Also, the return predictability has generally declined over the period considered in this analysis. This decline in return predictability is expected to enhance pricing efficiency (Chordia et al., 2008).

In Section 4.3.3.2.3, we conduct an additional analysis to compare the degree of return predictability in UK ETS secondary markets to that of the EU ETS using data covering a period common to both markets.

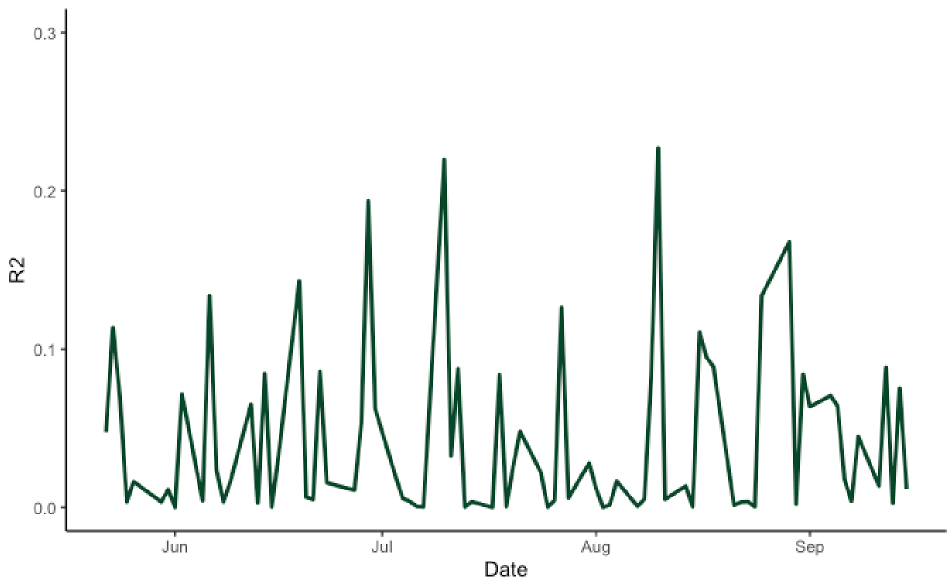


**Figure 4. The dynamics of the coefficient of determination from 15-minute return predictability models for each trading day (Sample 2).**

**Notes**: The figure displays the trend in the coefficients of determination that were estimated using the 15-minute return predictability model for each trading day from 22 May 2023 to 15 September 2023. The coefficient of determination (R2) is defined as a share of the variance of the 15-minute returns that can be explained by the variance of the 15-minute order imbalance ratio for each trading day.

### 4.1.4 Signal-to-signal plus noise ratio estimated from unbiasedness regressions.

Following Ibikunle et al. (2013), unbiasedness regression (see details in Appendix A1.4) separately for each time interval during the trading day (1-hour trading intervals). The data used for the estimation of model covers the period from 19 May 2021 to 15 September 2023. We also performed a unit-root test for each time series variable used in each regression to ensure that we do not face a problem of non-stationarity (Biais et al., 1999). (A non-stationary time series is a time series that changes its statistical properties (mean, variance and so on) over time). Examples of non-stationary time series are time series with a trend or with seasonality. The results of these tests suggest that all the time series used in the analysis are stationary (see details in Appendix A2.3). To account for possible heteroscedasticity and autocorrelation problems, we employ Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) covariance matrix of regression residuals.

The results of unbiasedness regressions estimations for 1-hour periods of the trading day are presented in Table 7. Figure 5 displays the estimated ratios of information content (signal) to signal plus noise for each 1-hour interval during the typical trading day and corresponding 95% confidence intervals. (Note: we do not estimate signal-to-signal plus noise ratio for 07:00-08:00 interval due to small number of observations (28 valid observations out of 602 trading days).

The results suggest that the highest value of this ratio occurs at the beginning of the trading day (between 08:00 and 09:00). This means that this trading interval is characterised by a relatively low level of trading noise and that most price changes are related to the incorporation of new information. Thereafter, the level of noise starts to increase, with the lowest values of the signal to signal-to-signal plus noise ratio observed at the end of the trading day, indicating that these hours are the noisiest (meaning that the price discovery process during this period is relatively more informationally inefficient than the other periods).

The dynamics of the signal-to-signal plus noise ratio we observe here, differs slightly to what was previously found for the EU ETS secondary market by Ibikunle et al. (2013). First, the estimated ratio in our case is higher compared to the EU ETS secondary market, suggesting that noise level is relatively lower in the case of the UK ETS secondary market: in Ibikunle et al. (2013), the estimated signal noise ratios ranged from 0.37 to 0.78 during the normal trading hours.

Second, in the findings of Ibikunle et al. (2013), the ratio increases from the beginning of the trading day until 11:00 and then decreases, reaching its minimum at 13:00 (the nosiest hour of the day). In our case, the ratio decreases from the beginning of the trading day to the end, reaching its minimum at 17:00.

Third, in the findings of Ibikunle et al. (2013), the ratio peaks at the end of the trading day, while our estimates suggest that the highest value of the ratio is observed at the beginning of the trading day.

However, it is worth noting the analysis in Ibikunle et al. (2013) is based on the data for the period February 2009 to November 2009, which differs from the period we consider in this analysis. This differences in timeframe could potentially explain the variations observed in the results. Consequently, in Section 4.3.3.2.4, we assess the performance of the UK ETS secondary market in comparison to that of the EU ETS secondary market in terms of the signal-to-signal plus noise ratio, using data that covers a period common to both markets.

**Table 7.The results of information content (signal) to signal plus noise ratios estimation for 1-hour trading intervals (Sample 1).**

| Trading interval | Estimate | P-value |
|---|---|---|
| 08:00 – 09:00 | 0.9348 | 0.0001 *** |
| 09:00 – 10:00 | 0.9033 | 0.0001 *** |
| 10:00 – 11:00 | 0.7845 | 0.0006 *** |
| 11:00 – 12:00 | 0.7511 | 0.0001*** |
| 12:00 – 13:00 | 0.7126 | 0.0001*** |
| 13:00 – 14:00 | 0.6877 | 0.0001*** |
| 14:00 – 15:00 | 0.6508 | 0.0001*** |
| 15:00 – 16:00 | 0.6452 | 0.0001*** |
| 16:00 – 17:00 | 0.6071 | 0.0001*** |

**Notes**: The table displays the signal-to-signal plus noise ratios estimates based on the unbiasedness regressions for 1-hour intervals of the trading day. Signal-to-signal plus noise ratio is defined as a slope coefficient from the regression model $ret_{cc} = \alpha + \beta ret_{ck} + \varepsilon_k$, where $ret_{cc}$ is a close-to-close returns, $ret_{ck}$ is a returns from the close to the end of 1-hour trading interval $k$. The p-values are based on the Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) covariance matrix of regression residuals. The estimates are based on the daily data for the period 19 May 2021 to 15 September 2023. The normal trading day runs from 07:00 to 17:00 London time. The estimate is not computed for the interval 07:00-08:00 due to relatively low number of observations. '***' denotes the statistical significance of the estimate at 0.01 level.

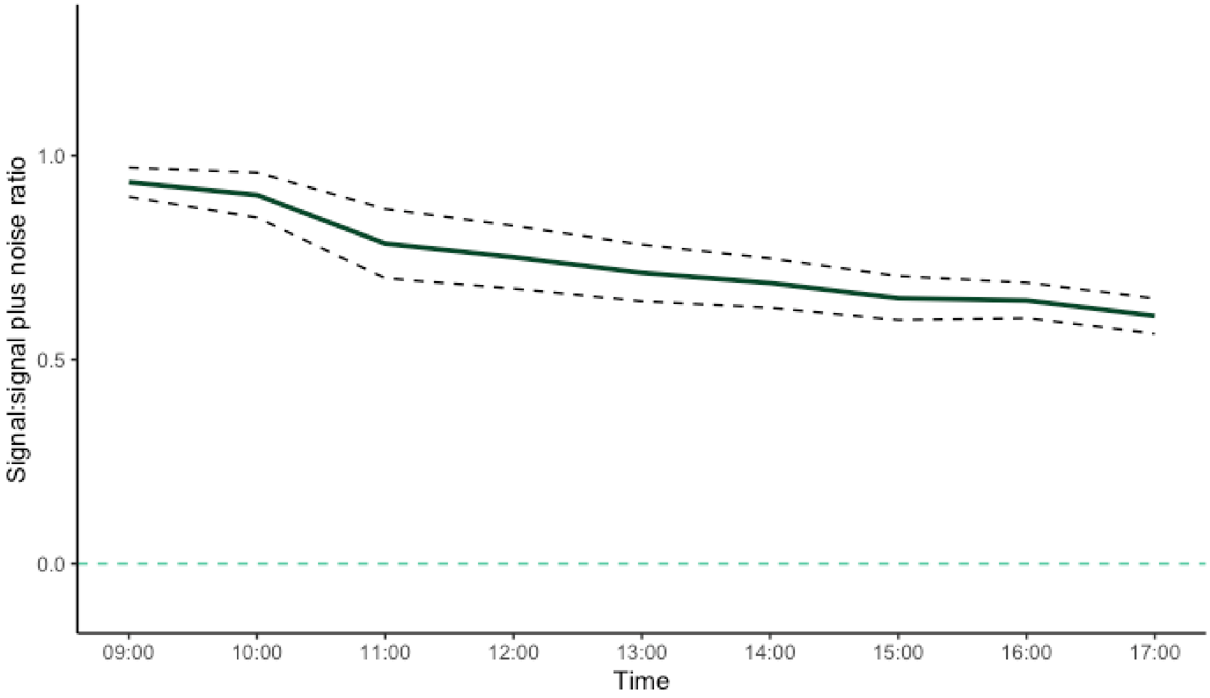


**Figure 5. Signal-to-signal plus noise ratios estimated based on the unbiasedness regressions for 1-hour trading intervals (Sample 1).**

**Notes**: The figure displays the signal-to-signal plus noise ratios estimates based on the unbiasedness regressions for 1-hour intervals of the trading day (green line) and corresponding upper bound and lower pound of the 5% confidence interval (dashes lines). Light green dashed line is horizontal line y=0. Signal-to-signal plus noise ratio is defined as a slope coefficient from the regression model $ret_{cc} = \alpha + \beta ret_{ck} + \varepsilon_k$, where $ret_{cc}$ is a close-to-close returns, $ret_{ck}$ is a returns from the close to the end of 1-hour trading interval $k$. The p-values are based on the Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) covariance matrix of regression residuals. The estimates are based on the daily data for the period 19 May 2021 to 15 September 2023. The normal trading day runs from 07:00 to 17:00 London time. The estimate is not computed for the interval 07:00-08:00 due to relatively low number of observations.

## 4.2 Evidence on liquidity in the UK ETS secondary market.

This section analyses the liquidity in the UK ETS secondary market based on two high frequency liquidity proxies (the effective and the relative traded spreads) and one low frequency liquidity proxy-the Amihud (2002) price impact ratio.

### 4.2.1 Liquidity based on high frequency spread measures.

Following the discussion in Section 3.2.2, the main part of the report considers two spread measures, namely the effective spread and the relative traded spread.

The trends in the daily averages of spread measures are presented in Figure 6, while the descriptive statistics for the estimated spreads are presented in Table 8. On average, liquidity has improved slightly over the period 22 May 2023 to 15 September 2023. During the first 10 trading days of the sample, the average effective spread was around £0.14, compared to £0.11 during the last 10 trading days of the sample. However, the trend is not constant over time and there are some spikes in the spread between the first 10 days and the last 10 days of the sample.

The size of the effective spread is ranged between £0.03 and £0.26 with the mean value of £0.12 (see Table 8). The relative traded spread is ranged between 0.05% and 0.64% with an average of 0.21%. We observe a slight narrowing of the spread over the period analysed. The highest levels of spread are observed on 3 July 2023 (£0.25 effective spread and 0.64% relative traded spread), 22 August 2023 (£0.26 effective spread and 0.51% relative traded spread), and 23 August 2023 (£0.22 effective spread and 0.63% relative traded spread). The spike on 3 July 2023 may be related to the UK ETS Authority's announcement of plans for future changes to the scheme on that date. Spikes in the spread on 22 August 2023 and 23 August 2023 may be related to the auction on 23 August 2023. In particular, the widening of the spread on these dates may be related to market participants' uncertainty about the outcome of auctions.

The effective spread and traded spread estimates are highly cor'elated with a Pearson correlation coefficient of 0.7 (statistically significant at the 0.01 significance level)[5].

In Section 4.3.3.2.5, we undertake additional analysis to compare the spread in the UK ETS secondary market with that of the EU ETS. This comparison is performed using data that encompasses a timeframe common to both markets.

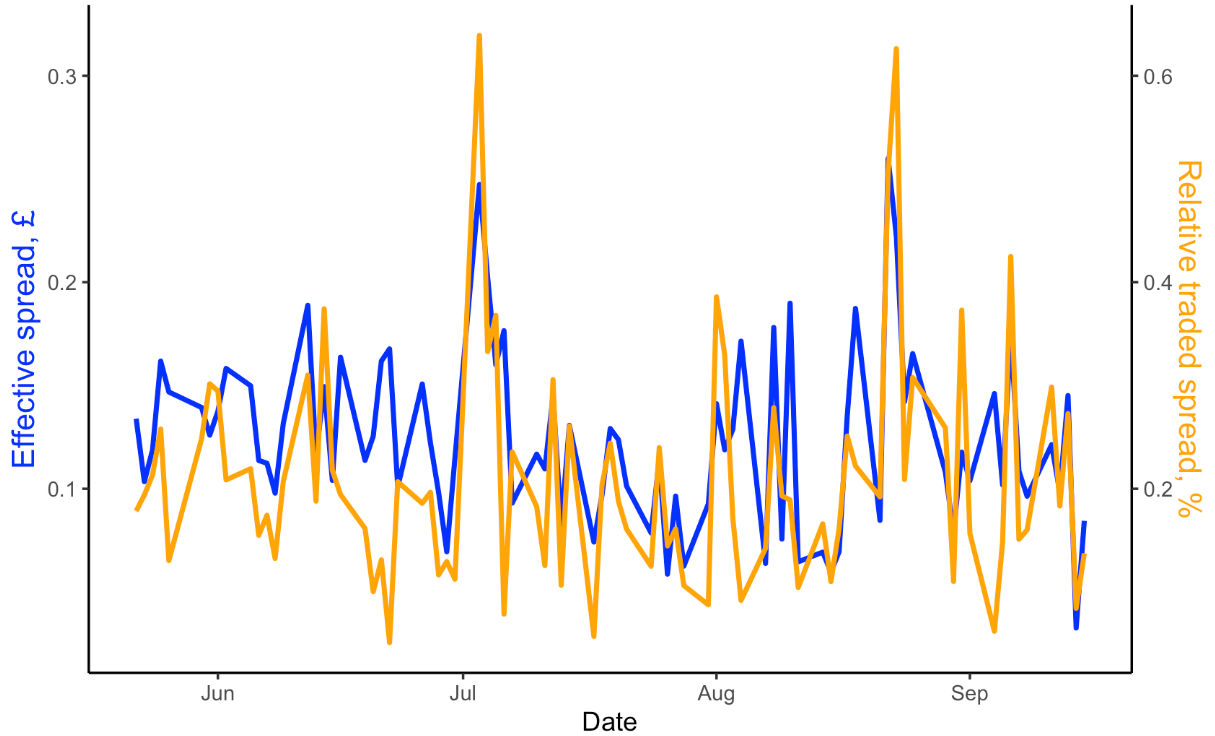


**Figure 6.The dynamics of relative traded spread and effective spread (Sample 2).**

**Notes**: The figure displays daily averages of the effective spread and relative traded spread during the period 22 May 2023 to 15 September 2023. Spread measures are calculated for 5-minute trading intervals and then averaged for each trading day. The effective spread is defined as the double of the difference between the trading

[5] The detailed results of the correlation analysis for spread measures and other market quality proxies considered in this report are presented in Appendix A2.6.

price of the k-th trade and the midpoint of the consolidated BBO (best bid and offer) (in £). Relative traded spread is defined as a difference between the best price of the buyer-initiated trades and the best price of the seller-initiated trades, divided by the average of these two prices (in %).

**Table 8. Descriptive statistics for the effective spread and relative trade spread (Sample 2).**

| Market quality proxy | Minimum | Median | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|
| Effective spread, £ | 0.0326 | 0.1188 | 0.1241 | 0.2598 | 0.0427 |
| Relative traded spread, % | 0.0511 | 0.1880 | 0.2097 | 0.6391 | 0.1109 |

**Notes**: The table shows the descriptive statistics of the daily averages of the effective spread and the relative traded spread for the period 12 May 2023 to 15 September 2023. Spread measures are calculated for 5-minute trading intervals and then averaged for each trading day. The effective spread is defined as the double of the difference between the logarithm of the trading price of the k-th and the logarithm of the midpoint of the consolidated BBO (best bid and offer) (in £). Relative traded spread is defined as a difference between the best price of the buyer-initiated trades and the best price of the seller-initiated trades, divided by the average of these two prices (in %).

### 4.2.2 Liquidity based on the Amihud (2002) price impact ratio.

Figure 7 and Figure 8 (below) show the dynamic of the daily Amihud (2002) price impact ratio, while the descriptive statistics are presented in Table 9. Panel A of Table 9 and Figure 7 corresponds to the Amihud (2002) price impact ratio calculated using data over the period 19 May 19 2021 to 15 September 2023 (Sample 1). We also present the results of Amihud (2002) price impact ratio analysis for the period covered by Sample 2 (22 May 2023 to 15 September 2023). This is to facilitate the comparison of this indicator with those proxies for market quality that can only be calculated for the period covered by Sample 2. These results are presented in Figure 8 and Table 9 (Panel B).

In line with the liquidity measures based on the two bid-ask price spread measures discussed above, the results of Amihud (2002) price impact ratio calculation suggest that the liquidity in the UK ETS secondary market has improved over the course of the period (19 May 2021 to 15 September 2023) considered in the analysis (meaning that the value of Amihud (2002) price impact ratio has generally declined over time). Specifically, liquidity was comparably low during the initial stages of the UK ETS secondary market but has enhanced as the market has evolved and matured. The average value of Amihud (2002) price impact ratio, for the period 19 May 2021 to 31 December 2021, is approximately 40% higher compared to the average value of this measure for the period 3 January 2023 to 15 September 2023.

The results therefore suggest that the market has become more capable of executing large orders without triggering price changes, since the start of trading in May 2021.

**Table 9. Descriptive statistics for the Amihud (2002) price impact ratio.**

| Variable/ Market quality proxy | Minimum | Median | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|
| Panel A. 19 May 2021 – 15 September 2023 (Sample 1) | | | | | |
| Amihud (2002) price impact ratio | 0.0000 | 0.0413 | 0.0638 | 0.6803 | 0.0701 |
| Panel B. 22 May 2023 – 15 September 2023 (Sample 2) | | | | | |
| Amihud (2002) price impact ratio | 0.0000 | 0.0537 | 0.0711 | 0.2316 | 0.0570 |

**Notes**: The table contains descriptive statistics of the daily of Amihud (2002) price impact ratio. Amihud (2002) price impact ratio is defined as an average ratio of the daily absolute return (in %) to the trading volume on that day (in £). Panel A corresponds to the period 19 May 2021 to 15 September 2023, while Panel B corresponds to the period 22 May 2023 to 15 September 2023.

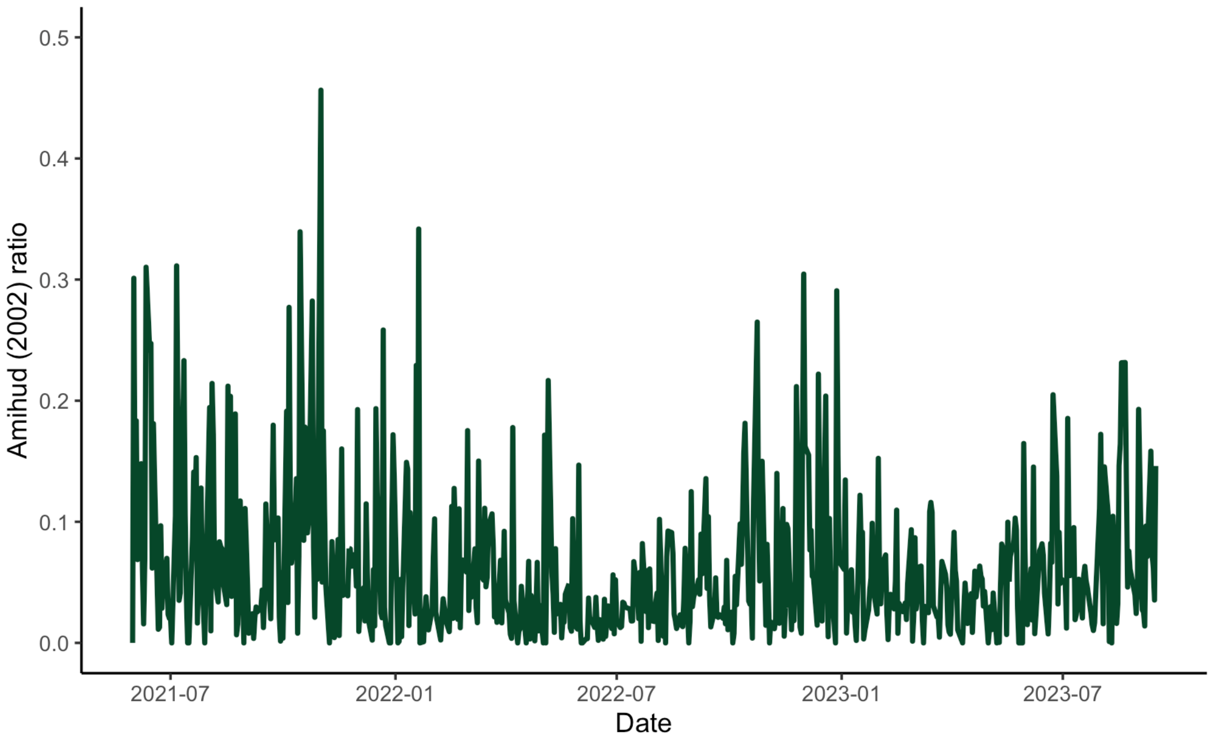


**Figure 7. The dynamics of Amihud (2002) price impact ratio (Sample 1).**

**Notes**: The figure displays the daily dynamics of Amihud (2002) price impact ratio over the period 19 May 2021 to 15 September 2023. This is based on data for futures contracts to be delivered in December 2021, December 2022, and December 2023 rolled into a single time series as described in Section 3.1. Amihud (2002) price impact ratio is defined as an average ratio of the daily absolute return (in %) to the trading volume on that day (in £).

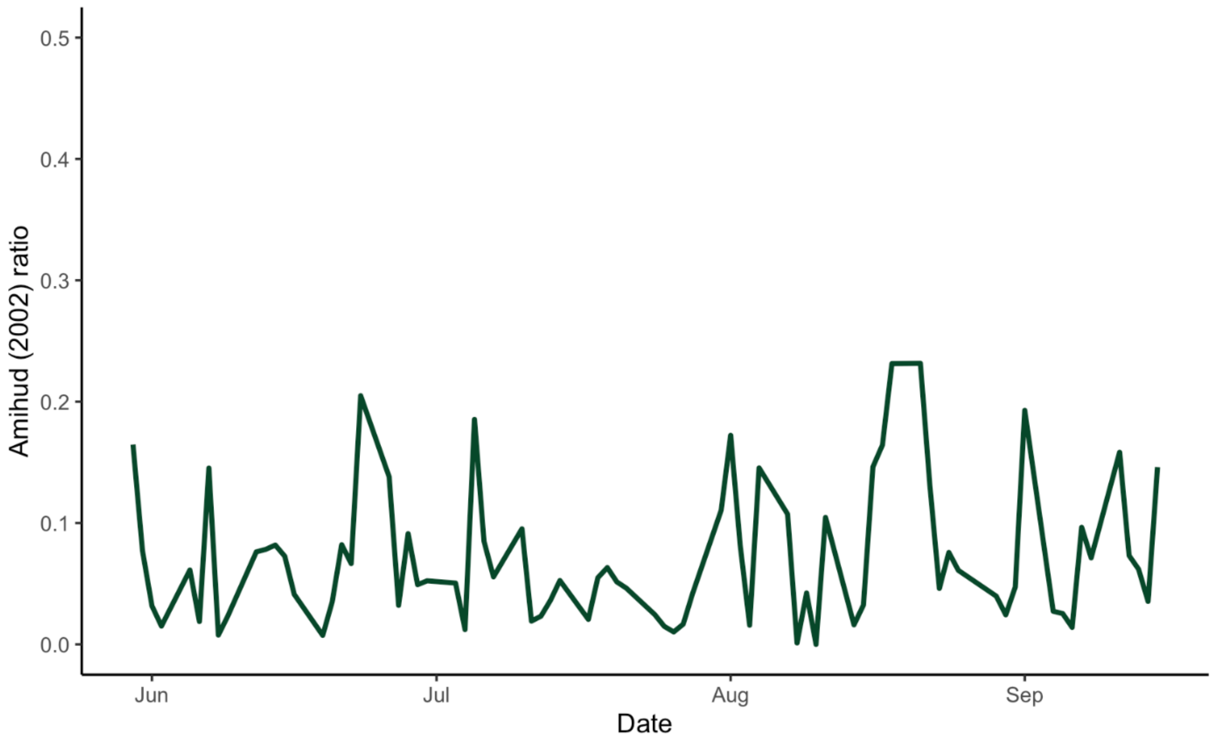


**Figure 8. The dynamics of Amihud (2002) price impact ratio (Sample 2).**

**Notes**: The figure displays the daily dynamics of Amihud (2002) price impact ratio over the period 22 May 2023 to 15 September 2023. This is based on data for futures contracts to be delivered in December 2023. Amihud (2002) price impact ratio is defined as an average ratio of the daily absolute return (in %) to the trading volume on that day (in £).

## 4.3 Further analysis of market quality proxies

This section further analyses market quality proxies presented in Section 4.1 and Section 4.2. This analysis comprises 3 parts.

- First, we examine whether there are differences in the proxies for market quality in weeks when UK allowances are auctioned compared to non-auctioning weeks (Section 4.3.1). (Auctioning is the primary mean of introducing allowance into the market. The UKA auctions are hosted by ICE Futures Europe. Auctions are held every 2 weeks.)
- Second, we analyse the relationship between market quality proxies related to liquidity and price discovery based on the regression analysis (Section 4.3.2).
- Third, we compare the results of our liquidity analysis with the liquidity of the EU ETS secondary market. This provides a benchmark against which the magnitude of the liquidity measures can be interpreted (Section 4.3.3).

### 4.3.1. Liquidity and price discovery on auction and non-auction weeks

The purpose of this section is to relate the results of the secondary market analysis to the primary introduction of the UK allowance through auctioning. Specifically, we test the hypothesis that trading days in auction weeks differ significantly from those in non-auction weeks in terms of price discovery and liquidity proxies. This hypothesis is based on the results of the interviews with market participants. Specifically, it was suggested by some trader interviewees that trading is currently more active in auction weeks, with a relatively inactive market in non-auction weeks.

We test this hypothesis based on the Welch two-sample t-tests. The results of these tests are presented in Table 10. The analysis for the relative traded spread, the coefficient of determination from returns predictability model, and the share of information-driven volatility is based on Sample 2 (22 May 2023 to 15 September 2023), comprising 83 trading days. Of these 83 days, 39 are trading days in auction weeks and 44 are trading days in non-auction weeks. The t-tests for the trading volume, price standard deviation, and Amihud (2002) price impact ratio are based on Sample 1, which comprises 602 trading days and covers the period 19 May 2021 to 15 September 2023. Of these 602 days, 291 are trading days in auction weeks and 313 are trading days in non-auction weeks.

There are two primary points worth emphasising from the table. First, the trading activity (in terms of trading volume) is higher during the auction weeks than the non-auction weeks, on average. This difference is statistically significant (at the 1% level of significance). The magnitude of this difference is within the interval of 80,868 UKA to 166,866 UKA (95% confidence interval).

Second, auction weeks are characterised by slightly higher level of liquidity in terms of effective spread and Amihud (2002) price impact ratio. However, these differences are not statistically significant. The same is true for the price discovery measures. None of them is characterised by statistically significant differences between auction and non-auction weeks.

It is worth noting that the limited sample size could account for the lack of statistical significance in the observed differences in the mean of market quality proxies between auction and non-auction days. As discussed in Section 3.1, most market quality proxies used in the analysis are based on bid and ask price data. In our case, this data is only available for the period 22 May 2023 to 15 September 2023.

**Table 10. Welch two-sample t-test results for the means of market quality proxies in auction and non-auction weeks (Sample 1 and Sample 2).**

| Variable/ Market quality proxy | Sample size (trading days) | Auction weeks (mean) | Non-auction weeks (mean) | t-statistic for difference between the two means | 95% confidence interval for difference between the two means | |
|---|---|---|---|---|---|---|
| | | | | | Lower bound | Upper bound |
| Trading volume | 602 | 539.7285 | 415.8617 | 5.6597*** | 80.8681 | 166.8655 |
| Price standard deviation | 602 | 0.0803 | 0.0765 | 0.8837 | -0.0047 | 0.0123 |
| Amihud (2002) price impact ratio | 602 | 0.0614 | 0.0659 | 0.7851 | -0.0158 | 0.0067 |
| Relative traded spread | 83 | 0.2016 | 0.2188 | 0.4651 | -0.0184 | 0.0296 |
| Coefficient of determination from return predictability model (R2) | 83 | 0.0454 | 0.0398 | 0.4651 | -0.0184 | 0.0296 |
| Share of information-driven volatility | 83 | 0.7058 | 0.7335 | 1.0323 | -0.0812 | 0.0257 |

**Notes**: The table presents the results of the Welch two-sample t-tests for the means of market quality proxies in auction and non-auction weeks. This test ascertains whether there are differences in the mean of considered market quality proxies between trading days in auction weeks and non-auction weeks. The null hypothesis of the test is that the difference in means in auction and non-auction weeks is equal to 0, meaning that there are no significant differences between the considered market quality proxies between trading days in auction weeks and non-auction weeks. The test statistics for the trading volume, price standard deviation, and Amihud (2002) price impact ratio are calculated based on the data from 19 May 2021 to 15 September 2023. For all other indicators tests statistics are calculated based on the data from 22 May 2023 to 15 September 2023. "***" indicates the statistical significance at the 0.01 level of significance. The trading volume is calculated based on the data for the 1-minute trading intervals by summing up all the trades during each trading day. Price standard deviation is defined as standard deviation of the 1-minute return over a single trading day. Amihud (2002) price impact ratio is defined as an average ratio of the daily absolute return (in %) to the trading volume on that day (in £). Relative traded spread is defined as a difference between the best price of the buyer-initiated trades and the best price of the seller-initiated trades, divided by the average of these two prices (in %). The coefficient of determination (R2) is defined as a share of the variance of the 15-minute returns that can be explained by the variance of the 15-minute order imbalance ratio for each trading day. The share of information-driven volatility ($Q$) is defined as $Q = 1 - \frac{2\sigma_s^2}{\sigma_r^2}$, where $\sigma_s^2$ is a pricing error variance (computed based on the procedure described in Section 4.1.2), $\sigma_r^2$ is a variance of the observed returns.

To check the robustness of the results presented above, we compared the average values of the market quality proxies on auction days and non-auction days[6]. The results of this daily level analysis (see Appendix A2.5) confirm the findings presented in Table 10. Moreover, when comparing auction and non-auction trading days, the difference in trading volume is even more pronounced (912,172 UKAs on auction days vs. 429,206 UKAs on non-auction days).

Therefore, based on the limited data available for this analysis, we can conclude that auctions are associated with a significant increase in trading activity in the secondary market. However, the differences in the proxies for market quality (both liquidity and price discovery) are not statistically significant, which may be explained by the limited sample size. Longer time series are likely to provide more robust evidence.

### 4.3.2 Regression analysis of the relationship between liquidity and price discovery in the UK ETS secondary market.

This section analyses the relationship between liquidity and price discovery in the UK ETS secondary market. Specifically, we estimate the effect of liquidity on the evolution of market efficiency using the approach employed by Ibikunle et al. (2016)[7]. This approach is based on the regression analysis, where 15-minute returns are regressed on the order imbalance ratio in the previous period and on the order imbalance ratio in the previous period interacted with the dummy variable that takes the value of 1 for the trading days with relatively high level of liquidity. The methodological details of this approach are presented in Appendix A1.10.

To analyse the effect of liquidity on price efficiency, we need to consider the coefficients of the lagged order imbalance ratio ( $\beta_1$) and that of the interaction term ( $\beta_2$). The coefficient $\beta_1$ reflects the predictability of returns irrespective of the liquidity level, while $\beta_2$ shows whether this predictability increases or decreases with liquidity. If, for example, both coefficients ($\beta_1$ and $\beta_2$) are statistically significant and if $\beta_1$ is positive, the interpretation of the results would depend on the sign of the coefficient $\beta_2$. If $\beta_2$ is negative, this means that the predictability of returns decreases when liquidity is high (spreads are narrow).

The results of the regression analysis are presented in Table 11 (below). We observe that the lag order imbalance is a statistically significant predictor of short-term returns, similar to the

[6] In this robustness check, we compare market quality proxies on auction and non-auction trading days, while the main results in Table 12 are based on the comparison of auction and non-auction weeks.

[7] The descriptive analysis of the relationship between market quality proxies based on correlation coefficients can be found in Appendix A2.6.

results presented in Section 4.1.3. However, this predictability decreases as market liquidity improves, as indicated by the statistically significant negative coefficient of the interaction term ($\beta_2$). This suggests that as market liquidity improves, information efficiency also improves. In other words, improvements in liquidity generate positive effects on market efficiency. This result is line with Ibikunle et al. (2016) who found a similar relationship for the EU ETS secondary market.

Nevertheless, we note that this finding is not robust to the use of alternative liquidity measures used to identify illiquid trading days. Specifically, if the relative traded spread measure is replaced by the effective spread, the coefficient $\beta_2$ loses its statistical significance. Therefore, the results presented in Table 11 can only be considered as preliminary evidence on the relationship between liquidity and price discovery in the UK ETS secondary market.

Appendix 2 provides further analysis of the relationship between market quality proxies considered in this report. Specifically, Appendix A2.6 contains the results of the correlation analysis of market quality proxies, while Appendix A2.7 presents the results of the relationship based on the VAR model.

**Table 11. The results of the regression analysis of the relationship between liquidity and price discovery (Sample 2).**

| Variable | Estimate (x100) | P-value |
|---|---|---|
| Intercept | 0.0041 | 0.6123 |
| $\mathrm{OrderImbalance}_{t-1}$ | 0.0252 | 0.0231 ** |
| $\mathrm{OrderImbalance}_{t-1}$ x $LIQ$ | -0.0582 | 0.0853 * |
| R2: 0.0048<br>F-statistic: 5.9920 (p-value: 0.0025) | | |

**Notes**: The table shows the results of the regression analysis of relationship between liquidity and price discovery in the UK ETS secondary market. The regression model is estimated based on the data for the period 22 May 2023 to 15 September 2023. The dependent variable is a UKA futures contract returns calculated for each 15-minute trading interval. $\mathrm{OrderImbalance}_{t-1}$ is a order imbalance ratio defined as $OrderImbalance_{t-1}(£) = \left(\frac{BUY_{t-1}-SELL_{t-1}}{BUY_{t-1}+SELL_{t-1}}\right)$, where $BUY_{t-1}$ and $SELL_{t-1}$ are the volumes (in £) traded within buyer-initiated and seller-initiated trades respectively during the period $t-1$. Order imbalance ratio is calculated for each 15-minute trading interval. $LIQ$ is a binary variable that takes value of 1 for the high liquidity trading days and 0 for low liquidity trading days. A high liquidity day is defined as a day on which the effective spread is below the period average plus 1 standard deviation. Low liquidity day is defined as a day when the effective spread is above the whole period average of this spread plus 1 standard deviation. The effective spread is defined as the double of the difference between the logarithm of the trading price of the k-th trade and the logarithm of the midpoint of the consolidated BBO (best bid and offer) (in £) The regression model is estimated using ordinary least squares with Newey and West (1997) heteroscedasticity and autocorrelation consistent (HAC) estimator of the residual's covariance matrix. '*' and '**' Indicate the statistical significance of the parameter at 0.10 and 0.05 levels of significance respectively.

### 4.3.3 Benchmarking the price discovery and liquidity of the UK ETS secondary market against that of the EU ETS secondary market.

In this section, we assess the price discovery process and liquidity in the UK ETS secondary market in comparison with that of the EU ETS secondary market. The aim of this comparative analysis is to benchmark the performance of the UK ETS secondary market against that of the EU ETS secondary market.

The EU ETS secondary market was chosen as the benchmark for evaluating the performance of the UK ETS secondary market for the following reasons. First, the UK participated in the initial phases (Phases 1, 2 and 3) of the EU ETS before exiting in January 2021 due to Brexit. Second, the design of the UK ETS closely aligns with that of the EU ETS, owing to the UK's pivotal role in the development of the EU ETS. Third, the EU ETS secondary market serves as an established and a mature market, having been in operation since 2005, and is characterised by a relatively high level of trading activity.

Subject to data availability for the EU ETS market, in this comparative analysis we consider five market quality proxies, namely standard deviation of 1-minute returns, the share of information-driven volatility based on the price volatility decomposition, the coefficient of determination from the return predictability model, signal-to-signal plus noise ratio, and the relative traded spread.[8]

As in the case of the UK ETS secondary market, ICE Connect platform provides two types of data for the EUA futures contracts. The first type of data includes summary information for 1-minute trading intervals (traded volumes, opening and closing prices). At the time of conducting this analysis, this type of data is available for the period 1 December 2021 to 15 September 2023 (452 trading days – Sample 3). This sample is used to compare EU ETS and UK ETS secondary markets in terms of price volatility (Section 4.3.3.2) and signal-to-signal plus noise ratio (Section 4.3.3.5).

The second type of data includes bid and ask prices, as well as the prices of executed trades. This information is available for the period 28 July 2023 to 15 September 2023 (36 trading days – Sample 4). This dataset is used to calculate share of information-driven volatility (Section 4.3.3.3), price efficiency as measured by the coefficient of determination from return predictability model (Section 4.3.3.4), and relative traded spread (Section 4.3.3.6).

For both markets, we use the data for the futures contracts expiring in December 2022 and 2023. For these contracts, the average daily trading activity in the UK ETS secondary market was 500,000 UKAs compared to 14,157,000 EUAs, based on the data for the period 1 December 2021 to 15 September 2023. The descriptive statistics for the samples used for the benchmarking analysis are presented in Table A-10 (Appendix A2.8).

[8] Relative traded spread is preferred to other spread measures as it is independent of the currency of the trade prices.

The following Section 4.3.3.1 provides a brief description of the EU ETS secondary market background, while Section 4.3.3.2 presents the results of the benchmarking analysis for each market quality proxy.

### 4.3.3.1 Background to the EU ETS secondary market

The EU ETS is arguably the world's largest carbon market, being launched in 2005, and is currently in its fourth phase (2021-2030). Like the UK ETS, the EU ETS operates as a 'cap and trade' system, where the regulator allocates a certain (capped) number of European Union Allowances (EUAs) through the primary market (auctions), after which the EUA futures contracts are traded on the secondary market via ICE platform.

The EUA futures contract is a deliverable contract where each Clearing Member with a position open at cessation of trading for a contract month is obliged to make or take delivery of EUAs to or from a Trading Account within the EUA delivery period and in accordance with the Rules[9]. Each traded lot in the EU ETS secondary market includes 1,000 EUAs. Each EUA is an entitlement to emit one tonne of carbon dioxide equivalent gas. The minimum trading size on the UK ETS secondary market is 1 lot (1 contract) with a minimum tick size of €0.01 per EUA or €10.00 per contract. The normal trading day runs from 07:00 to 17:00 (London time) with a pre-open period of 06:45-07:00. At the time of conducting this analysis, there were 19 futures contracts with different expiration dates traded in the EU ETS secondary market.

### 4.3.3.2 Results of the benchmarking analysis

4.3.3.2.1 Price volatility in the EU ETS secondary market vis-à-vis the UK secondary market

In this section, we present the results of the price volatility measured as the standard deviation of 1-minute returns. We computed the price standard deviation for two distinct periods: one spanning from 1 December 2021 to 15 September 2023 (Sample 3), and the other from 28 July 2023 to 15 September 2023 (Sample 4).

Panel A of Table 12 (below) presents summary statistics of the daily volatility of 1-minute returns for the EU ETS and UK ETS secondary markets for Sample 3, while the dynamics of price volatility over the same period is shown in Figure 9. The results suggest that on average, the price volatility in the UK ETS secondary market is slightly lower than that of the EU ETS (0.0882 in the UK ETS versus 0.1016 in the EU ETS) over the period from 1 December 2021 to 15 September 2023. However, the averages for two markets may differ substantially in different sub-periods. For example, EU ETS secondary market experienced more significant spikes in 2022, particularly at the end of February 2022 when the Russian invasion of Ukraine began.

At the same time, we observe a marked difference in price volatility in the two markets from the end of July to mid-September 2023, as shown in Figure 10. There is a relatively more consistent and stable trend in the EU-ETS secondary market when compared to the UK ETS during this period. On average, the price volatility in the UK ETS secondary market was approximately 30% higher than in the case of EU ETS. However, it's important to emphasise

[9] https://www.ice.com/products/197/EUA-Futures

that higher price volatility doesn't necessarily signify a deterioration in market quality, as this can be influenced by information or noise.

**Table 12. Summary statistics for the daily volatility of the 1-minute returns in the UK ETS and EU ETS secondary markets.**

| Variable/ Market quality proxy | Minimum | Median | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|
| Panel A. 1 December 2021 – 15 September 2023 (Sample 3) | | | | | |
| UK ETS | 0.0000 | 0.0825 | 0.0882 | 0.3308 | 0.0519 |
| EU ETS | 0.0519 | 0.0919 | 0.1016 | 0.4601 | 0.0100 |
| Panel B. 28 July 2023 – 15 September 2023 (Sample 4) | | | | | |
| UK ETS | 0.0302 | 0.0944 | 0.1034 | 0.2231 | 0.0518 |
| EU ETS | 0.0519 | 0.0672 | 0.0668 | 0.0987 | 0.0099 |

**Notes**: The daily volatility is computed as the standard deviation of the 1-minute return over a single trading day. The 1-minute returns are calculated as the difference between the opening price and the closing price of each 1-minute trading interval, divided by the opening price of the interval and multiplied by 100%. Panel A is based on the data for the EUA and UKA futures contracts to be delivered in December 2022 and December 2023 over the period 1 December 2021 to 15 September 2023. Panel B is based on the data for the EUA and UKA futures contracts to be delivered in December 2023 over the period 28 July 2023 to 15 September 2023.

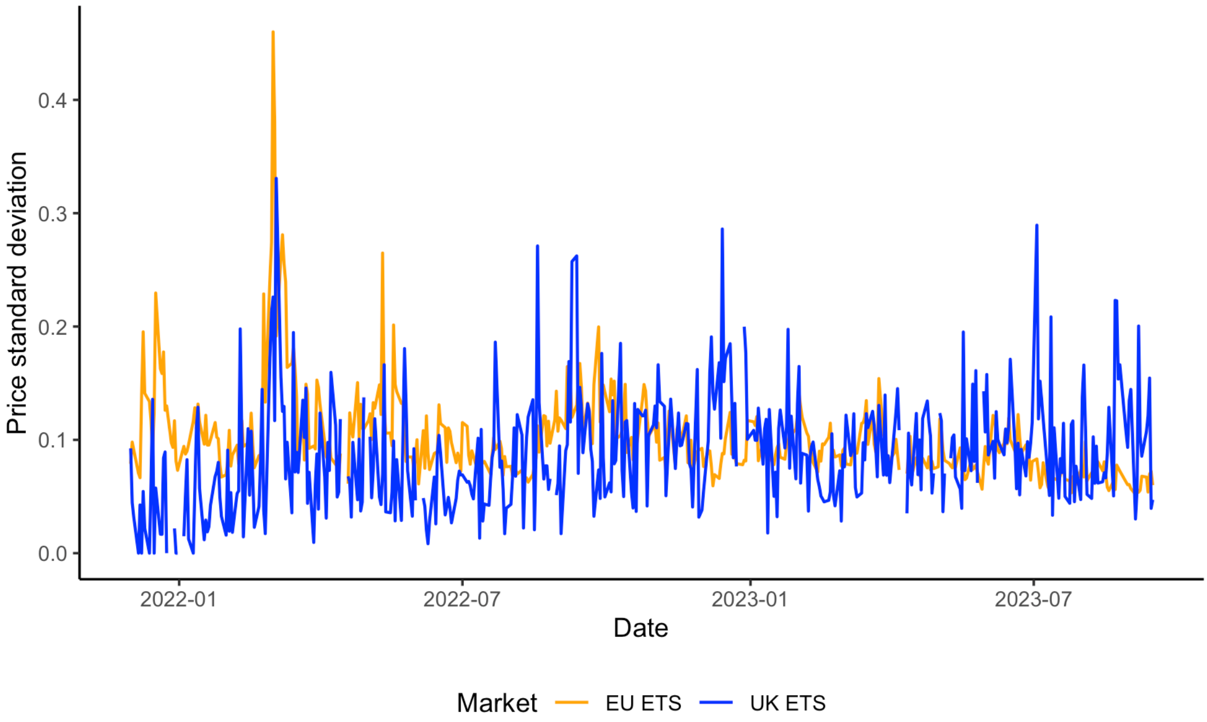

**Figure 9. The dynamics of daily volatility of 1-minute returns in the EU ETS and UK ETS secondary markets (Sample 3).**

**Notes**: The daily volatility is computed as the standard deviation of the 1-minute return over a single trading day. The 1-minute returns are calculated as the difference between the opening price and the closing price of each 1-minute trading interval, divided by the opening price of the interval and multiplied by 100%. This is based on the data for UKA and EUA futures contracts to be delivered in December 2022 and December 2023 rolled into a single time series over the period 1 December 2021 to 15 September 2023 (Sample 3). The data for the futures contract expiring in December 2023 is used for the period 1 December 2021 to 30 November 2022, while data for futures contracts expiring in December 2023 is used for the period 1 December 2022 to 15 September 2023.

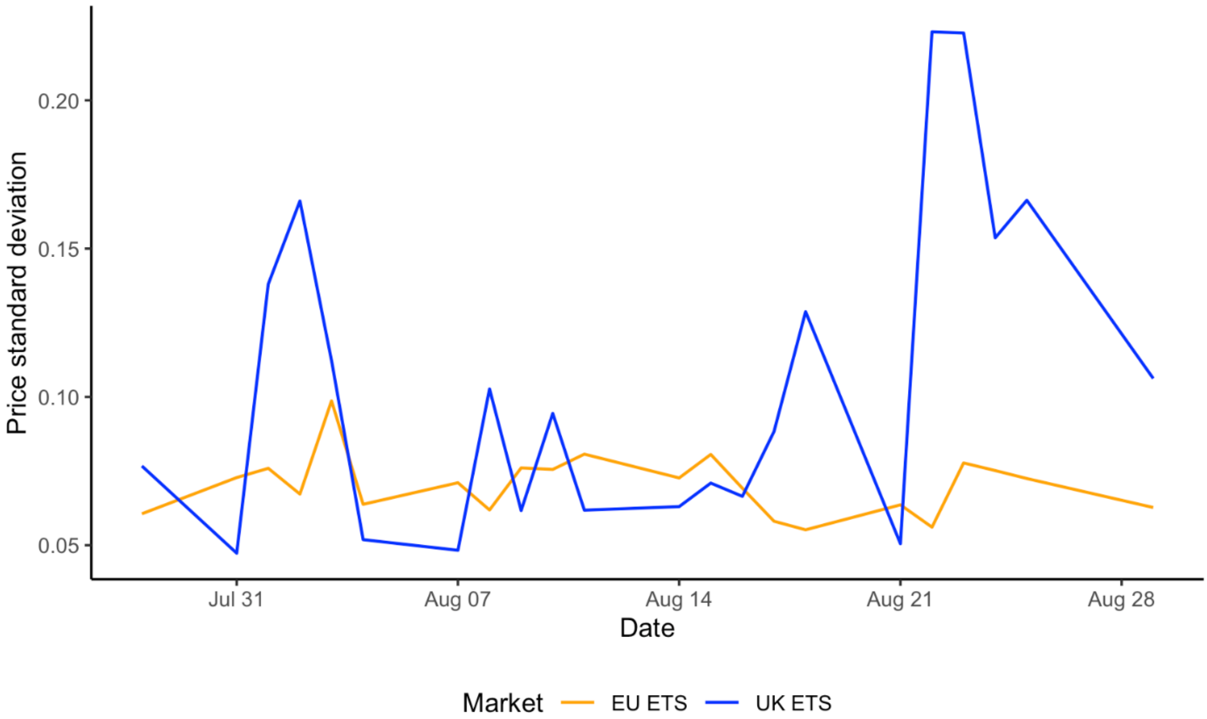


**Figure 10.The dynamics of daily volatility of 1-minute returns in the EU ETS and UK ETS secondary markets (Sample 4).**

**Notes:** The daily volatility is computed as the standard deviation of the 1-minute return over a single trading day. The 1-minute returns are calculated as the difference between the opening price and the closing price of each 1-minute trading interval, divided by the opening price of the interval and multiplied by 100%. This is based on the UKA and EUA futures contracts to be delivered in December 2023 over the period 28 July 2023 to 15 September 2023 (Sample 4).

#### 4.3.3.2.2 Price volatility decomposition

Figure 11 and Table 13 (below) present the share of information-driven volatility estimates for the EU ETS and UK ETS secondary markets for the period 28 July 2023 to 15 September 2023 (Sample 4). This is based on the volatility decomposition approach proposed by Hasbrouck (1993).

The findings from the volatility decomposition analysis reveal that, on average, approximately 60% of price volatility in the EU ETS secondary market from 28 July 2023 to 15 September 2023 can be attributed to the incorporation of new information into prices, with the remaining 40% being attributed to noise.

In contrast, the share of information-driven volatility in the UK ETS secondary market averaged around 75% during the same period.  This difference may be explained by the much higher level of trading activity in the EU ETS market, as increased trading activity may lead not only to faster incorporation of new information, but also to higher levels of trading noise.

However, it is crucial to emphasise that this divergence in information-driven volatility doesn't necessarily imply a superior level of informational efficiency in the UK ETS secondary market compared to the EU ETS market in terms of the price discovery process. This is due to the fact that  the level of price volatility varied between the two markets during the observed period - it was substantially lower for the period 28 July 2023 to 15 September 2023, in the EU ETS secondary market than in the UK ETS secondary market (see Figure 10).

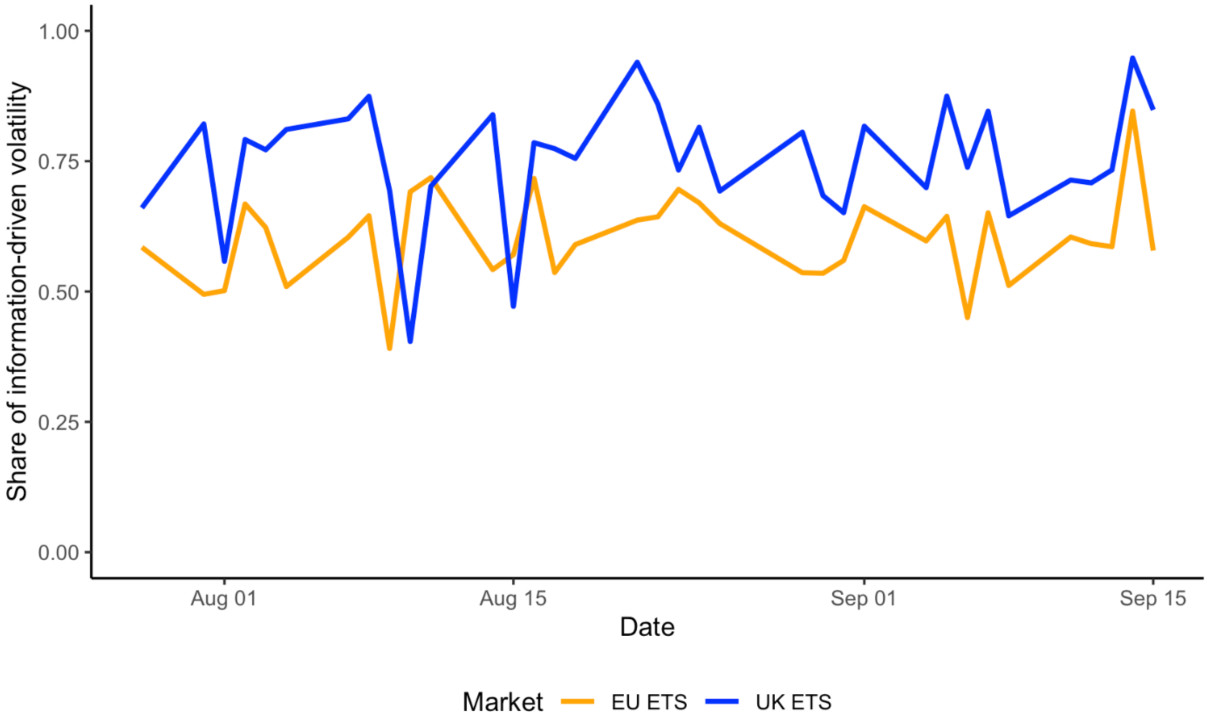


**Figure 11. The dynamics of the share of price volatility driven by information ( $Q$) estimated based on Hasbrouck's (1993) approach for the UK ETS and EU ETS secondary markets (Sample 4).**

**Notes**: The figure shows the dynamics of the market quality measure $Q$ estimated based on the Hasbrouck's (1993) approach for the period 28 July 2023 to 15 September 2023. This is based on data for the EUA and UKA futures contracts to be delivered in December 2023. $Q$ is defined as $Q = 1 - \frac{2\sigma_s^2}{\sigma_r^2}$, where $\sigma_s^2$ is a pricing error variance, $\sigma_r^2$ is a variance of the observed returns. Relatively high values of $Q$ correspond to the high level of market quality in terms of price discovery process. Estimates of the pricing error variance ($\sigma_s^2$) were multiplied by the number of trades during the corresponding trading day to make them comparable (Medina et al., 2014).

**Table 13. Summary statistics for the share of information-driven volatility in the UK ETS and EU ETS secondary markets (Sample 4).**

| Market | Minimum | Median | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|
| UK ETS | 0.4042 | 0.7719 | 0.7514 | 0.9480 | 0.1161 |
| EU ETS | 0.3907 | 0.5971 | 0.6005 | 0.8462 | 0.0863 |

**Notes**: The table displays the descriptive statistics for the market quality measure $Q$ (share of information-driven volatility). The estimates are obtained for each trading day during the period 28 July 2023 to 15 September 2023. This is based on data for the EUA and UKA futures contracts to be delivered in December 2023. Share of information-driven volatility is defined as $Q = 1 - \frac{2\sigma_s^2}{\sigma_r^2}$ where $2 \times \sigma_s^2$ is a double variance of the pricing error calculated according to the procedure described in Appendix A1.2, . $\sigma_r^2$ is a volatility (variance) of continuously compounded returns computed directly from the data. Relatively high values of $Q$ correspond to the high level of market quality in terms of price discovery process. To make the volatility estimates comparable across trading days, we multiply each volatility estimate by the number of trades on the corresponding trading day as was done in Medina et al. (2014).

It is also worth noting that shares of information-driven volatility in the two markets are positively correlated[10], suggesting that the same underlying factors may be driving the volatility dynamics in the UK ETS and EU ETS secondary markets, as one would anticipate. In other words, a positive correlation between the shares of information-driven volatility in the two markets suggests that the same information can drive the prices of both UKAs and EUAs. This is not surprising considering that the UK was originally a part of the EU ETS until its departure in January 2021 due to Brexit.

4.3.3.2.3 Price efficiency

Figure 12 and Table 14 (below) show the results of the return predictability analysis for each trading day during the period 28 July 2023 to 15 September 2023 (Sample 4).

The average level of return predictability in the UK ETS secondary market (0.05) is slightly higher than in the EU ETS secondary market over the period considered in this analysis. This suggests that the observed prices in the EU ETS secondary market are relatively more efficient than in the UK ETS secondary market, on average. Also, just like the other market quality proxies presented above, the coefficient of determination from the return's predictability model in the EU ETS market is characterised by a relatively lower degree of variability compared to the UK ETS secondary market.

[10] The correlation coefficient is equal to 0.3 and is statistically significant at the 0.1 level of significance.

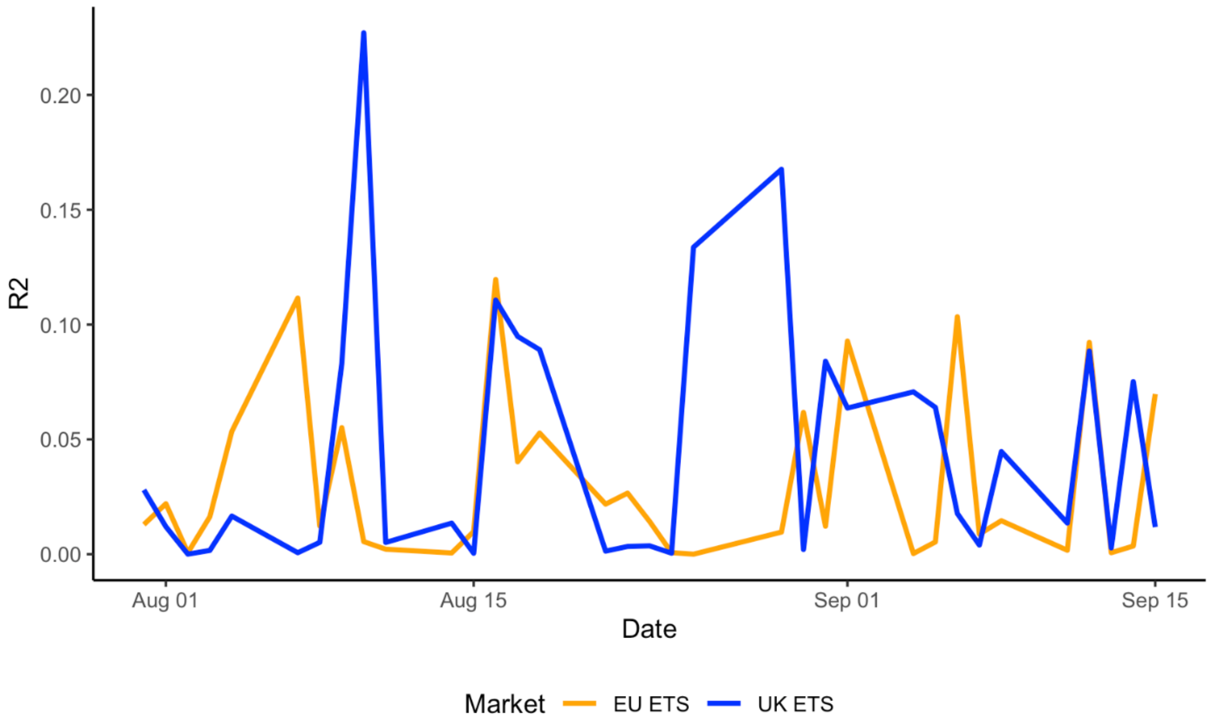


**Figure 12. The dynamics of the coefficient of determination from 15-minute return predictability models for each trading day in the UK ETS and EU ETS secondary markets (Sample 4).**

**Notes**: The figure displays the trend in the coefficients of determination that were estimated using the 15-minute return predictability model for each trading day from 28 July 2023 to 15 September 2023. This is based on data for EUA and UKA futures contracts to be delivered in December 2023. The coefficient of determination (R2) is defined as a share of the variance of the 15-minute returns that can be explained by the variance of the 15-minute order imbalance ratio for each trading day.

**Table 14. The descriptive statistics for the coefficient of determination (R2) from the 15-minute return predictability models for each trading day in the UK ETS and EU ETS secondary markets (Sample 4).**

| Market | Minimum | Median | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|
| UK ETS | 0.0000 | 0.0151 | 0.0453 | 0.2271 | 0.0555 |
| EU ETS | 0.0000 | 0.0136 | 0.0311 | 0.1196 | 0.0366 |

**Notes**: The table shows the descriptive statistics of the coefficients of determination (R2) that were estimated using the 15 minutes return predictability model for each trading day from 28 July 2023 to 15 September 2023. This is based on data for EUA and UKA futures contracts to be delivered in December 2023. Coefficient of determination (R2) is defined as a share of variance of the 15-minute returns that can be explained by the variance of the 15-minute order imbalance ratio for each trading day.

4.3.3.2.4 Signal-to-signal plus noise ratio estimated from unbiasedness regressions.

Figure 13. (below) displays the estimated signal-to-signal plus noise ratios and corresponding 95% - confidence intervals for each trading hour. (We do not estimate signal-to-signal plus noise ratio for 07:00-08:00 interval due to small number of observations for the UK ETS secondary market (28 valid observations out of 465 trading days)). Table 15 (below) shows the values of estimated coefficients and their statistical significance. The signal-to-signal plus noise ratios are calculated based on the data for the period 1 December 2021 to 15 September 2023 (Sample 3).

The results presented in Figure 13 and Table 15 suggest that the signal-to-signal plus noise ratio trends are very similar in both markets. The highest levels of signal-to-signal plus noise ratio are observed at the beginning of the trading day. This observation is unsurprising because the market seeks to integrate information from the overnight period (since the last trade of the previous day) at the start of the trading day. This suggests that price changes are associated with a relatively higher incorporation of new information in the early hours of the trading day in both markets.

Also, in both markets, we observe that the signal-to-signal plus noise ratios fall steadily over the course of the trading day with the lowest values recorded just before the end of the day. This means that the highest levels of trading noise are observed between 16:00 and 17:00.

It is worth noting that the signal-to-signal plus noise ratios throughout the trading day are comparatively higher in the EU ETS secondary market than in the UK ETS secondary market (see Table 15). This implies that the noise level is relatively lower in the EU ETS secondary market compared to the UK ETS (meaning that the price discovery process over a typical trading day is more informationally efficient in the EU ETS secondary market than in the UK ETS market).

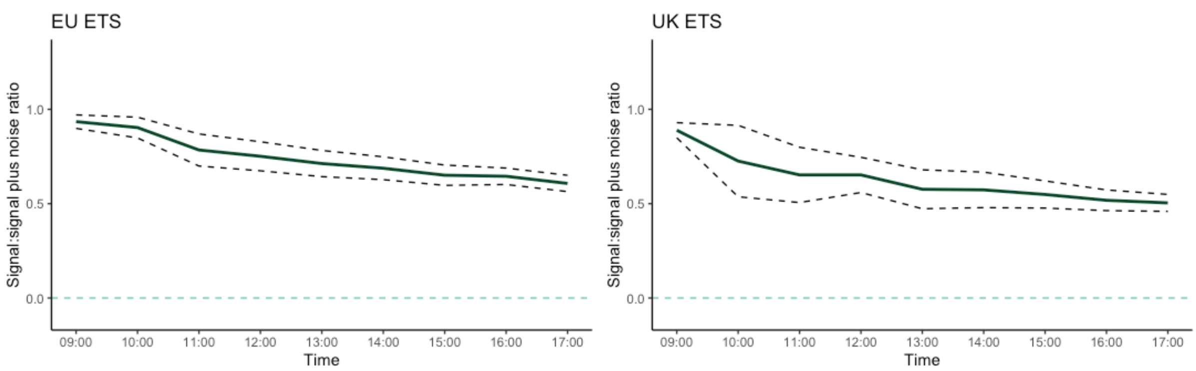


**Figure 13. Signal-to-signal plus noise ratios estimated based on the unbiasedness regressions for 1-hour trading intervals (UK ETS and EU ETS secondary markets, Sample 3).**

Notes: The figure displays the signal-to-signal plus noise ratios estimates based on the unbiasedness regressions for 1-hour intervals of the trading day (green lines) and corresponding upper bound and lower pound of the 5% confidence interval (dashes lines). Light green dashed line is horizontal line y=0. Signal-to-signal plus noise ratio is defined as a slope coefficient from the regression model $ret_{cc} = \alpha + \beta ret_{ck} + \varepsilon_k$, where $ret_{cc}$ is a close-to-close returns, $ret_{ck}$ is a returns from the close to the end of 1-hour trading interval $k$. The p-values are based on the Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) covariance matrix of regression residuals. The estimates are based on the daily data for the period 1 December 2021 to 15 September 2023. This is based on data for EUA and UKA futures contracts to be delivered in December 2023. The normal trading day runs from 07:00 to 17:00 London time. The estimate is not computed for the interval 07:00-08:00 due to relatively low number of observations.

**Table 15. The results of information content (signal) to signal plus noise ratios estimation for 1-hour trading intervals (UK ETS and EU ETS secondary markets, Sample 3)**

| Trading interval | UK ETS | EU ETS |
|---|---|---|
| 08:00 - 09:00 | 0.8892*** | 0.9362*** |
| 09:00 - 10:00 | 0.7257*** | 0.9127*** |
| 10:00 - 11:00 | 0.6523*** | 0.7974*** |
| 11:00 - 12:00 | 0.6524*** | 0.7130*** |
| 12:00 - 13:00 | 0.5763*** | 0.6619*** |
| 13:00 - 14:00 | 0.5731*** | 0.6636*** |
| 14:00 - 15:00 | 0.5486*** | 0.6339*** |
| 15:00 - 16:00 | 0.5179*** | 0.6219*** |
| 16:00 - 17:00 | 0.5040*** | 0.5954*** |

**Notes**: The table displays the signal-to-signal plus noise ratios estimates based on the unbiasedness regressions for 1-hour intervals of the trading day. Signal-to-signal plus noise ratio is defined as a slope coefficient from the regression model $ret_{cc} = \alpha + \beta ret_{ck} + \varepsilon_k$, where $ret_{cc}$ is a close-to-close returns, $ret_{ck}$ is a returns from the close to the end of 1-hour trading interval $k$. The p-values are based on the Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) covariance matrix of regression residuals. The estimates are based on the daily data for the period 1 December 2021 to 15 September 2023. This is based on data for EUA and UKA futures contracts to be delivered in December 2023. The normal trading day runs from 07:00 to 17:00 London time. The estimate is not computed for the interval 07:00-08:00 due to relatively low number of observations. '***' denotes the statistical significance of the estimate at 0.01 level.

#### 4.3.3.2.5 Liquidity based on the relative traded spread.

Figure 14 and Table 16 (below) present the results of the relative traded spread estimation in the UK ETS and EU ETS secondary markets. These results suggest that the level of liquidity based on the relative traded spread in the UK ETS secondary market is, on average, relatively slightly higher than in the EU ETS secondary market (as can be seen from the median[11] reported in Table 16) over the period considered in the analysis (28 July 2023 to 15 September 2023). However, the relative traded spread in the UK ETS secondary market is characterised by significantly higher levels of volatility. Specifically, the standard deviation of this spread measure over the period is 0.13 in the UK ETS secondary market compared to 0.04 in the EU ETS secondary market. For instance, the relative spread ranges from 0.16 to 0.31 in the EU ETS secondary market while it ranges from 0.06 to 0.63 in the UK ETS secondary market. This high level of variability can also be observed in Figure 14, where the relative traded spread in the EU ETS is relatively stable over the period considered in the analysis compared to that of the UK ETS. This implies that, over the time considered in this analysis, liquidity in the EU ETS market tends to remain relatively stable, although, on average, it is relatively slightly lower in comparison to the UK ETS. It is important to note, however, that this analysis is based on data for a limited period (36 trading days), and thus not conclusive.

The variation of the spread over time, in addition to its size, can also be important to market participants. For example, Bessembinder and Venkataraman (2010) point out that it is important for market participants to accurately estimate and incorporate the impact of trading costs. Also, Comerton-Forde (2010) argued that fluctuations in liquidity over time matters to market participants who worry about the cost of trading into or out of a desired position in a short period of time. Thus, substantial variation in the liquidity over time can make trading costs less predictable and impact trader's risk exposure. Thus, although the UK ETS secondary market is characterised by a slightly lower average spread (for the period 28 July 2023 to 15 September 2023), the relatively stable liquidity observed over the period under consideration in the EU ETS secondary market allows market participants to plan their trading costs and assess risks more accurately.

[11] In cases where the data distribution is skewed, the median becomes a more valuable measure because outliers can significantly distort the mean. We, thus, note that the median provides a better measure of the central tendency in this case because of the high variation in the relative traded spread in the UK ETS market over the period under consideration.

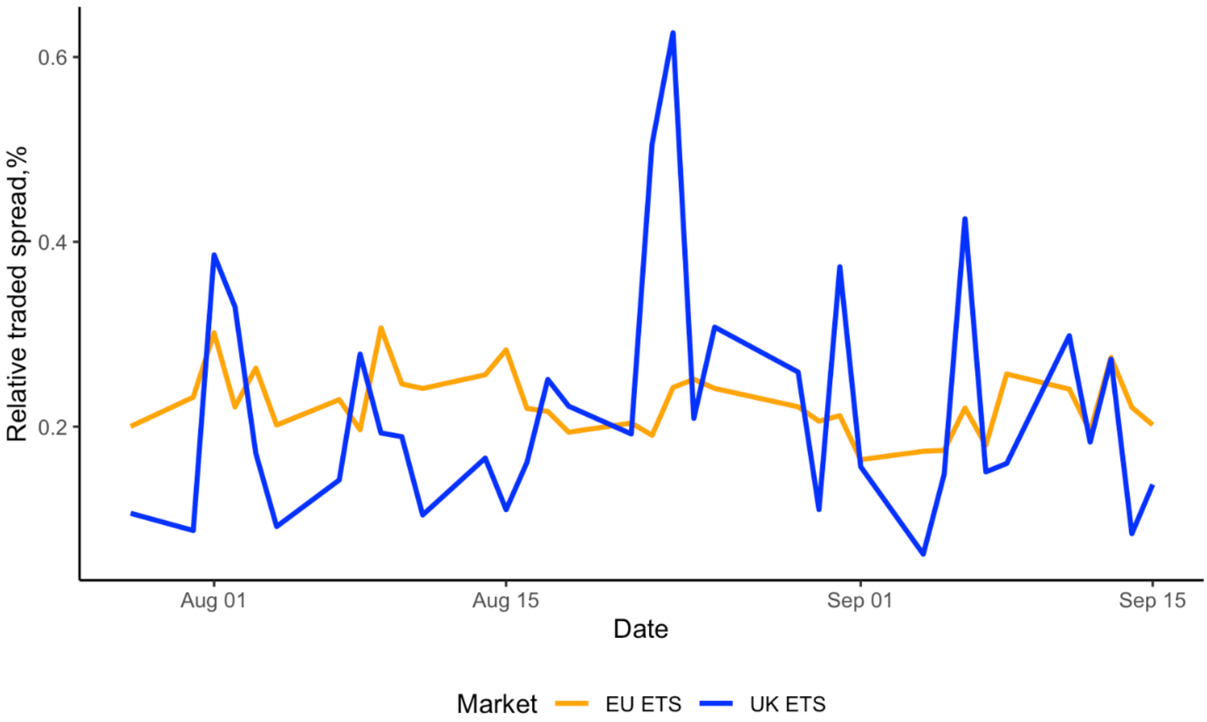


**Figure 14.The dynamics of relative traded spread in the UK ETS and EU ETS secondary markets (Sample 4).**

**Notes**: The figure displays daily averages of the relative traded spread during the period 28 July 2023 to 15 September 2023. This is based on data for the EUA and UKA futures contracts to be delivered in December 2023. Spread measures are calculated for 5-minute trading intervals and then averaged for each trading day. Relative traded spread is defined as a difference between the best price of the buyer-initiated trades and the best price of the seller-initiated trades, divided by the average of these two prices (in %).

**Table 16. Descriptive statistics for the relative trade spread in the UK ETS and EU ETS secondary markets (Sample 4).**

| Market | Minimum | Median | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|
| UK ETS | 0.0619 | 0.1833 | 0.2187 | 0.6262 | 0.1266 |
| EU ETS | 0.1643 | 0.2209 | 0.2252 | 0.3068 | 0.0351 |

**Notes**: The table shows the descriptive statistics of the daily averages of the relative traded spread for the period 28 July 2023 to 15 September 2023. This is based on data for the EUA and UKA futures contracts to be delivered in December 2023. Spread measures are calculated for 5-minute trading intervals and then averaged for each trading day. Relative traded spread is defined as a difference between the best price of the buyer-initiated trades and the best price of the seller-initiated trades, divided by the average of these two prices (in %).

# 5. Conclusion

The analysis presented in this report represents an attempt to assess the quality of the secondary market for the UK ETS in terms of price discovery/information efficiency and liquidity. The analysis made use of data from the ICE Connect portal and is based on the selected set of market quality proxies informed by the literature review conducted by (Ibikunle, 2023). The following conclusions can be drawn from this analysis.

- The results show that from the start of operations in May 2021 to 15 September 2023, the performance of the UK ETS secondary market in terms of trading activity has improved over time.
- The allocation of the allowances through the primary market (auctions) is associated with higher trading activity in the secondary market (meaning that trading activity is significantly higher (by 30%) in auction weeks than in non-auction weeks).
- There was a considerable increase in price volatility, as measured by the standard deviation of returns, between 19 May 2021 and 15 September 2023. Although the level of volatility has increased, around 80% (as estimated for the period 22 May 2023 to 15 September 2023) is information-driven. The remaining 20% of price volatility is related to trading noise. This suggests that the observed price variations are largely due to the incorporation of new information.
- On average, the price evolution closely follows a ‘random walk’ process, meaning that the observed UKA price is close to efficient. This is because only 0.4% of the variation in returns can be explained by trading activity over the period considered in the analysis. However, we observe variations in the degree of predictability between different trading days.
- The findings also reveal that, on average, the lowest level of noise is observed during the morning trading hours. After that, the level of noise increases steadily until the end of the trading day. This suggests that the price discovery process tend to be more informationally efficient in the early hours of the trading day than the later hours of the trading day.
- In addition, we find that liquidity in the market based on the high frequency spread measures has improved over the period (22 May 2023 to 15 September 2023) considered in the analysis, suggesting a reduction in the round-trip cost of the transaction for market participants, as the market matures.
- Consistent with this finding, the low frequency liquidity measure based on the Amihud (2002) price impact ratio, which considers the influence of large trades capable of inducing price shocks larger than the spread measures can convey, reaffirms that liquidity has indeed improved over the period considered in the analysis (19 May 2021 to 15 September 2023). This suggests that as the market develops and matures, it gains the ability to handle large orders without causing significant price fluctuations.
- Moreover, information efficiency in the market tends to improve as liquidity improves.

- In general, the performance of the UK ETS secondary market is somewhat similar to that of the EU ETS secondary market in certain aspects. Both markets exhibit similar price volatility in returns, on average, over the period 1 December 2021 to 15 September 2023. It's worth noting, nevertheless, that a substantial divergence in price volatility between the two became apparent towards the end of this period, specifically from 28 July 2023 to 15 September 2023. During this latter period, the price volatility was largely information-driven in both markets.
- Additionally, the efficiency of the price discovery process unfolds in a very similar manner in both markets throughout a typical trading day.
- However, there are notable differences when it comes to the predictability of short-term returns with trading activity. The extent to which trading activity explains variations in returns is relatively higher in the UK ETS compared to the EU ETS market during the analysed period (28 July 2023 to 15 September 2023). This suggests that the observed prices in the UK ETS secondary market are relatively less efficient than in the EU ETS secondary market.
- This finding aligns with the analysis of signal-to-signal-plus-ratio, revealing that the noise level in the UK ETS secondary market is comparatively higher than in the EU ETS. This again suggest that the price discovery process during a typical trading day is more efficient in the EU ETS secondary market than in the UK ETS market.
- Furthermore, while the average liquidity level is relatively slightly higher in the UK ETS market, it exhibits less stability in contrast to the EU ETS market, over the period considered in the analysis (28 July 2023 to 15 September 2023). This finding is, however, based on data covering a limited period and, thus, not conclusive.

It is worth pointing out a few of the potential limitations of the analysis we have undertaken. First, trading activity may be relatively low at the beginning of the period considered. This makes it difficult to estimate some of the market quality proxies. Second, considering the data on bid and ask prices used in the analysis covers only 83 trading days, liquidity proxies based on the bid-ask prices data can be calculated only for this period. Thus, the market proxies based on the spread measures does not cover the initial stages of the UK ETS secondary market. Third, an important limitation of the comparative analysis of the UK ETS and EU ETS secondary markets is that the market quality proxies based on the bid and ask prices are limited to the period 28 July 2023 to 15 September 2023. This restricted time frame could potentially influence our findings. This is because the EU ETS secondary market had lower auction volumes in August 2023, mainly due to the European holiday period, followed by higher auction volumes in September 2023. These fluctuations in auction volumes might have impacted trading behaviour in the EU ETS secondary market during the period considered in the analysis.

# 6. References


1. Amihud, Y. (2002) Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets, 5(1), 31-56.

2. Bessembinder, H., & Venkataraman, K. (2010). Bid-ask spreads: Measuring trade execution costs in financial markets. Encyclopedia of quantitative finance, 184-190.

3. Biais, B., Hillion, P., & Spatt, C. (1999). Price discovery and learning during the preopening period in the Paris Bourse. Journal of Political Economy, 107(6), 1218-1248.

4. Chordia, T., Roll, R., & Subrahmanyam, A. (2008). Liquidity and market efficiency. Journal of Financial Economics, 87(2), 249-268.

5. Comerton-Forde, C., Hendershott, T., Jones, C. M., Moulton, P. C., & Seasholes, M. S. (2010). Time variation in liquidity: The role of market-maker inventories and revenues. The journal of finance, 65(1), 295-331

6. Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The journal of Finance, 25(2), 383-417.

7. Frino, A., Kruk, J. & Lepone, A. (2010) Liquidity and transaction costs in the European carbon futures market. Journal of Derivatives and Hedge Funds, 16(2), 100-115

8. Goyenko, R. Y., Holden, C. W. & Trzcinka, C. A. (2009) Do liquidity measures measure liquidity? Journal of Financial Economics, 92(2), 153-181.

9. Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. Econometrica: journal of the Econometric Society, 424-438.

10. Hasbrouck, J. (1993). Assessing the quality of a security market: A new approach to transaction-cost measurement. The Review of Financial Studies, 6(1), 191-212.

11. Huang, R. D., & Stoll, H. R. (1996). Dealer versus auction markets: A paired comparison of execution costs on NASDAQ and the NYSE. Journal of Financial economics, 41(3), 313-357.

12. Ibikunle, G., Gregoriou, A., & Pandit, N. R. (2013). Price discovery and trading after hours: new evidence from the world’s largest carbon exchange. International Journal of the Economics of Business, 20(3), 421-445.

13. Ibikunle, G., Gregoriou, A., Hoepner, A. G. F. & Rhodes, M. (2016) Liquidity and market efficiency in the world's largest carbon market. The British Accounting Review, 48(4), 431- 447.

14. Ibikunle, G (2023). Market quality in emissions trading schemes: a literature review.

15. Hintermann, B. (2017) Market Power in Emission Permit Markets: Theory and Evidence from the EU ETS. Environmental and Resource Economics, 66 (2017), 89–112.

16. Lee, C. M., & Ready, M. J. (1991). Inferring trade direction from intraday data. r, 46(2), 733-746.

17. Medina, V., Pardo, Á., & Pascual, R. (2014). The timeline of trading frictions in the European carbon market. Energy Economics, 42, 378-394.

18. Newey, W. K., & West, K. D. (1987). Hypothesis testing with efficient method of moments estimation. International Economic Review, 777-787.

19. O'Hara, M. (2003). Presidential address: Liquidity and price discovery. The Journal of Finance, 58(4), 1335-1354.

# Appendix 1. Detailed methodology

This appendix provides methodological details on the market quality proxies used in the analysis.

## A1.1 Price volatility

Following (Frino et al., 2010), we measure price volatility as a standard deviation of the observed returns. This measure is aimed at capturing excess volatility, that is volatility unlikely to be driven by the incorporation of new information. Excess volatility may dissipate at low trading frequencies; hence, we calculate 1-minute returns and then calculate standard deviation over a single trading day. We calculate simple return measures according to (1) and standard deviation according to (2).

$$Ret_t = \frac{(P_{t,c} - P_{t,o})}{P_{t,o}} \times 100 \;\; (1)$$

Where $P_{t,o}$ is the opening price of the 1-minute interval t, $P_{t,c}$is the closing price of the 1-minute interval t.

$$SD_{ret} = \sqrt{\frac{1}{m}(Ret_{t,c} - Ret_c)^2} \;\; (2)$$

Where m is the number of 1-minute periods in the trading day,$Ret_t$ is a return for a contract during the trading interval t, $Ret_c$ is an average return for the contract over all 1-minute intervals of the trading day.

## A1.2 Price volatility decomposition

The decomposition of price volatility is based on the autoregressive (VAR) model (3):

$$y_t = \sum_{j=1}^{p} \Phi_j y_{t-j} + \varepsilon_t \; (3)$$

Where $y_t = \{r_t . \overline{x_t}\}$, $r_t$ is a continuously compounded return, $\overline{x_t} = \left\{x_t . x_t^S . x_t^{S^{\frac{1}{2}}}\right\}$, $x_t$is trade indicator (takes value of 1 for buyer-initiated trades and -1 for seller-initiated trades), $x_t^S = x_t * \vartheta_t$, $\vartheta_t$ is a trade size, $x_t^{S^{\frac{1}{2}}} = x_t \sqrt{\vartheta_t}$, $\Phi_j$ are matrices containing VAR model coefficients, $\varepsilon_t$ is error term.

Thus, the VAR model (3) is estimated based on the data on prices of executed trades and the corresponding trading volumes (in lots). Continuously compounded returns are calculated based on trade prices and reflect the return on the UKA futures contract between 2 adjacent trades. The trade indicator is obtained through the simple tick test (Lee & Ready, 1991)[12]. Following Medina et al. (2014), VAR model (3) is truncated at $p = 3$ (model includes 3 lags of the explanatory variables).

Having estimated model (3), we aim to obtain its vector moving average (VMA) representation (4):

$$y_t = \Psi(L)\varepsilon_t \ (4)$$

Where $\Psi(L)$ is a lag polynomial. Matrices $\Psi_j$ are calculated based on the VAR model coefficients according to (5):

$$\Psi_n = \sum_{k=1}^{n} \Phi_k \Psi_{n-k}\, , \Psi_0 = I_4 \ (5)$$

The lower bound of the pricing error variance can be computed based on the parameters of the equation for $r_t$ in the VMA (4). If we assume that $r_t = \alpha(L)\varepsilon_{rt} + \beta(L)\overline{\varepsilon_{xt}}$ where $\alpha(L)$ and $\beta(L)$ are lag polynomials, then the pricing error variance can be defined as a noisy component of returns volatility and computed according to (6):

$$\sigma_s^2 = \sum_{j=0}^{\infty} [\alpha_j . \beta_j] \Omega \begin{bmatrix} \alpha_j \\ \beta_j \end{bmatrix} (6)$$

Where $\alpha_j = -\sum_{k=j+1}^{\infty} \alpha_k$, $\beta_j = -\sum_{k=j+1}^{\infty} \beta_k$.

Based on the pricing error variance estimated according to the formula (6), we follow Medina et al. (2014) and consider a proxy for market quality defined by (7):

$$Q = 1 - \frac{2\sigma_s^2}{\sigma_r^2} \ (7)$$

Where $\sigma_r^2$ is a variance of the continuously compounded returns that is computed directly from the data. $Q$ quantifies the proportion of return volatility driven by information (public and private). A value of $Q$ close to 1 corresponds to a high level of market quality with respect to the price discovery process, so an increase in $Q$ signifies improved market quality, indicating that price volatility is largely a result of information rather than noise (namely not driven by information).

## A1.3 Price efficiency

According to Chordia et al. (2008), the coefficient of determination from the regression model (8) can be considered as a measure of short-horizon market efficiency.

$$ret_t = \alpha + \beta_1 OrderImbalance_{t-1} + \epsilon_t \ (8)$$

[12] Trades at a price higher than the prevailing midpoint are classified as buyer-initiated and as seller-initiated otherwise.

Where $ret_t$ is contract return over a 15-minute interval, $OrderImbalance_{t-1}$ is an order imbalance measure over the previous 15-minute interval, $\epsilon_t$ is a random error, $\alpha$ and $\beta_1$ are regression parameters.

Order imbalance ratio is defined by the formula (9):

$$OrderImbalance_t(£) = \left(\frac{BUY_t - SELL_t}{BUY_t + SELL_t}\right) (9)$$

Where $BUY_t$ and $SELL_t$ are the volumes (in £) traded within buyer-initiated and seller-initiated trades respectively during the trading interval t.

## A1.4 Signal to signal plus noise ratio estimated from unbiasedness regressions.

The signal-to-signal plus noise ratio measure allows analysis of how price efficiency evolves during a typical trading day. This approach is based on estimating an extent to which price change is due to the incorporation of information (efficient price change) (Ibikunle, 2023).

This measure of price efficiency was used previously, for example, by Ibikunle et al. (2013) in the context of the EU ETS secondary market.

The basis for signal-to-signal plus noise ratio is an unbiasedness regression of the following form (10).

$$ret_{cc} = \alpha + \beta ret_{ck} + \varepsilon_k \ (10)$$

Where $ret_{cc}$ is a close-to-close return, $ret_{ck}$ is a return over the period from close to the end of time interval $k$, $\varepsilon_k$ is a random error, $\alpha$ and $\beta$ are regression parameters. As demonstrated in (Barclay and Hendershott, 2003) and (Ibikunle et al., 2013), the slope coefficient $\beta$ from the regression model (10) measures the ratio of information content (signal) to signal plus noise in prices at interval $k$.

## A1.5 Relative quoted spread

The relative quoted spread is calculated based on the bid and ask prices data and is defined as a difference between the best bid and the best offer divided by the average of the best-traded bid and the best-traded ask for a particular period (11):

$$RQS = \frac{P_{bb} - P_{ba}}{Midpoint} \ (11)$$

Where $P_{bb}$ is the best bid price, $P_{ba}$ is the best ask price, $Midpoint$ is the average of the best-traded bid and the best-traded ask. The relative quoted spread is calculated for each 5-minute trading interval, and then averaged across each trading day.

## A1.6 Relative traded spread

Relative traded spread is based on the data on prices of executed trades and was used, for example, by Ibikunle et al. (2016) as an alternative to the relative quoted spread when data on the bid and ask prices is not available. Relative traded spread is calculated similarly to the relative quoted spread by substituting bid and ask quotes with buyer-initiated and seller-initiated prices (12):

$$RTS = \frac{P_{bb} - P_{ba}}{Midpoint} \quad (12)$$

Where $P_{bb}$ is the best price of buyer-initiated trades, $P_{ba}$ is the best price of seller-initiated trades, $Midpoint$ is the average between these two prices. The relative traded spread is calculated for each 5-minute trading interval and then averaged across each trading day.

## A1.7 Effective spread

Following Huang & Stoll (1996), we define effective spread as follows (13):

$$Effective\ spread_k = 2 \times |P_k - M_k| \quad (13)$$

Where $P_k$ is the price of k-th trade, $M_k$ is the midpoint of the consolidated BBO (best bid and offer) prevailing at the time of the k-th trade. Therefore, the effective spread measure incorporates both the data on bid and ask prices and data on the prices of executed trades. The effective spread is calculated for each 5-minute trading interval and then averaged across each trading day.

## A1.8 Realised spread.

Realised spread measure is based on the executed trades data and is defined by (14).

$$RS = \begin{cases} 2 \times (\ln(P_t) - \ln(P_{t+5})), when\ trade\ is\ a\ buy \\ 2 \times (\ln(P_{t+5}) - (\ln(P_t)), \quad when\ trade\ is\ a\ sell \end{cases} \quad (14)$$

The same definition of the realised spread was used, for example, by Goyenko et al. (2009). Like previous measures, we calculate this spread for each 5-minute trading interval and averaged across the trading day.

# A1.9 Amihud (2002) price impact ratio

The price impact ratio as defined by Amihud (2002) is a low-frequency liquidity measure that is calculated as an average ratio of the daily absolute return to the trading volume on that day (15):

$$RtoV_{it} = \frac{1}{D_{it}} \sum_{i=1}^{D_{it}} \frac{|R_{itd}|}{V_{itd}} \ (15)$$

Where $\mathrm{R_{itd}}$and $\mathrm{V_{itd}}$ are, respectively, the return and monetary volume (in £) of contract i on day d. $\mathrm{D_{it}}$is the number of valid observations days in month t.

# A1.10 Regression analysis of the relationship between liquidity and price discovery

To estimate the effect of liquidity on price efficiency, we estimate the following regression model (16):

$$ret_t = \alpha + \beta_1 OrderImbalance_{t-1} + \beta_2 OrderImbalance_{t-1} \times LIQ + \varepsilon_t \ (16)$$

Where $ret_t$ is a futures contract return over a 15-minute trading interval. $OrderImbalance_{t-1}$ is an order imbalance measure over the previous 15-minute trading interval defined as $OrderImbalance_t(£) = \left(\frac{BUY_t - SELL_t}{BUY_t + SELL_t}\right)$, where $BUY_t$ and $SELL_t$ are the volumes (in £) traded within buyer-initiated and seller-initiated trades respectively during the trading interval $t$. $LIQ$ is a binary variable that takes value of 1 if the trading day is characterised by high liquidity level and 0 in case of low liquidity. A high liquidity day is defined as a day on which the effective spread is below the period average plus 1 standard deviation. Low liquidity day is defined as a day when the effective spread is above the whole period average of this spread plus 1 standard deviation. $\epsilon_t$ is a random error. $\alpha$ and $\beta_1$ are regression parameters.

Following Ibikunle et al. (2016), we estimate regression model (18) using ordinary least squares with Newey and West (1997) heteroscedasticity and autocorrelation consistent (HAC) estimator of the residual's covariance matrix.

To estimate the effect of liquidity on price efficiency, we need to take the partial derivative of $ret_t$ by $OrderImbalance_{t-1}$. If both coefficients ($\beta_1$ and $\beta_2$) are statistically significant and if $\beta_1$ is positive, the interpretation of the results would depend on the sign of the coefficient $\beta_2$. If $\beta_2$ is negative, this means that the predictability of returns decreases when liquidity is high (spreads are narrow).

# Appendix 2. Additional tables and results

## A2.1 Descriptive analysis of the sample used in the analysis.

This appendix provides the description of the sample used in the analysis presented in the main section of the report.

Table A-1 presents the average trading activity for UKA futures contracts with different expiry dates. These averages shows that the highest level of trading activity is observed for the futures contracts expiring in December. These specific contracts were therefore selected for the analysis.

**Table A-1: Descriptive statistics of the real-time tick-by-tick UKA futures contracts data (Sample 2).**

| UKA futures contract | Average number of trades per day, 1000 UKA | Average value of trades per day, £ '000 |
|---|---|---|
| July 2023 | 11 | 605 |
| August 2023 | 0 | 0 |
| September 2023 | 0 | 0 |
| December 2023 | 1,272 | 70,367 |
| March 2024 | 9 | 463 |
| December 2024 | 53 | 3,163 |
| March 2025 | 0 | 0 |
| December 2025 | 1 | 55 |
| March 2026 | 0 | 0 |
| Daily futures contracts | 23 | 1,484 |

**Notes**: The averages are calculated based on the data for the period from 22 May 2023 to 15 September 2023, and based on real-time tick-by-tick data aggregated to a daily level.

Figure A-1 (below) presents the dynamics of trading activity for the futures contract expiring in December 2023. Trading activity is at a very low level before December 2022. This justifies the implementation of roll-over procedures (see Section 3.1) for the futures contracts expiring in December 2021, December 2022, and December 2023.

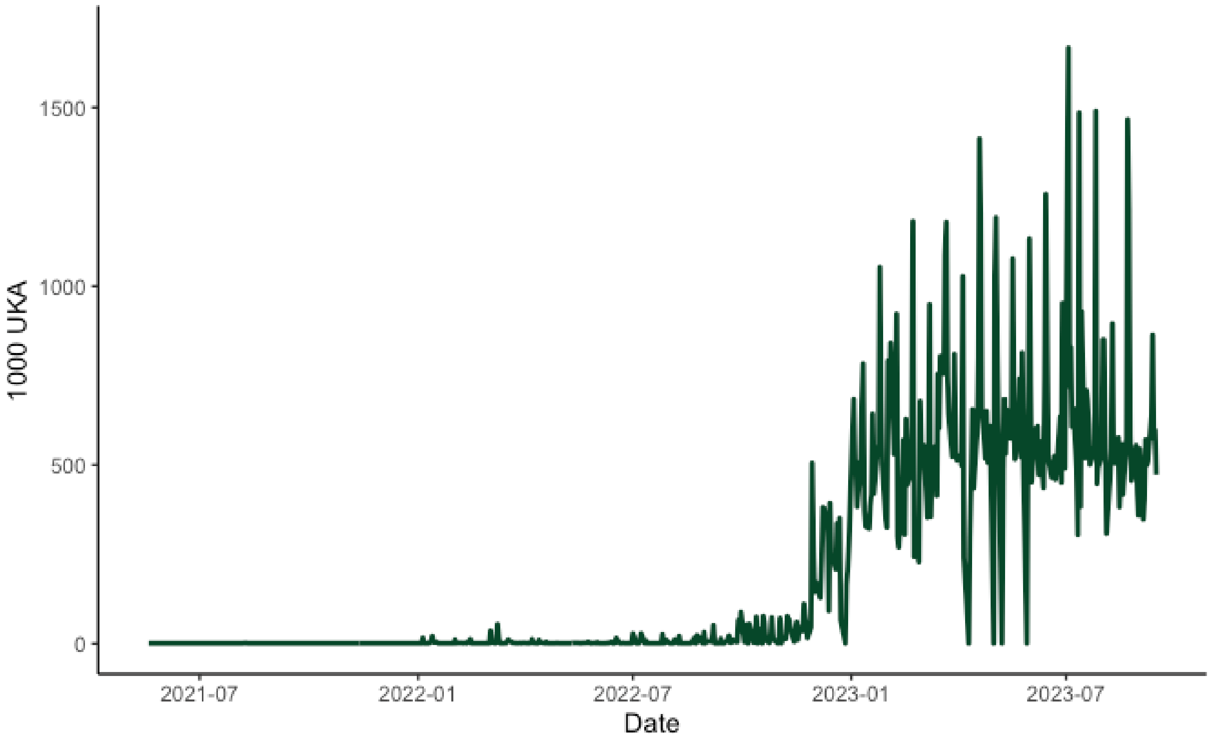


**Figure A-1: Daily trading volume of futures contracts to be delivered in December 2023, 19 May 2021 to 15 September 2023 (Sample 1).**

**Notes**: The figure displays daily trading volume of futures contracts to be delivered in December 2023, 19 May 2023 to 15 September 2023.

The following descriptive analysis is carried out for the final time series which combines data on futures contracts expiring in December 2021, December 2022, and December 2023.

Figure A-2 (below) presents the dynamics of daily closing prices and daily trading volumes for the period considered in the analysis. The dynamics of daily closing prices exhibits a parabolic form with a maximum of almost £100 per UKA in September 2022. The lowest prices of around £50 per UKA is observed just after the UK ETS secondary market inception in May 2021 and at the end of the considered period in August-September 2023. In August 2022, UKA price rose from £78 (August 1) to its historic high of £98 (August 19). On September 9, the price fell back to £76 per UKA.

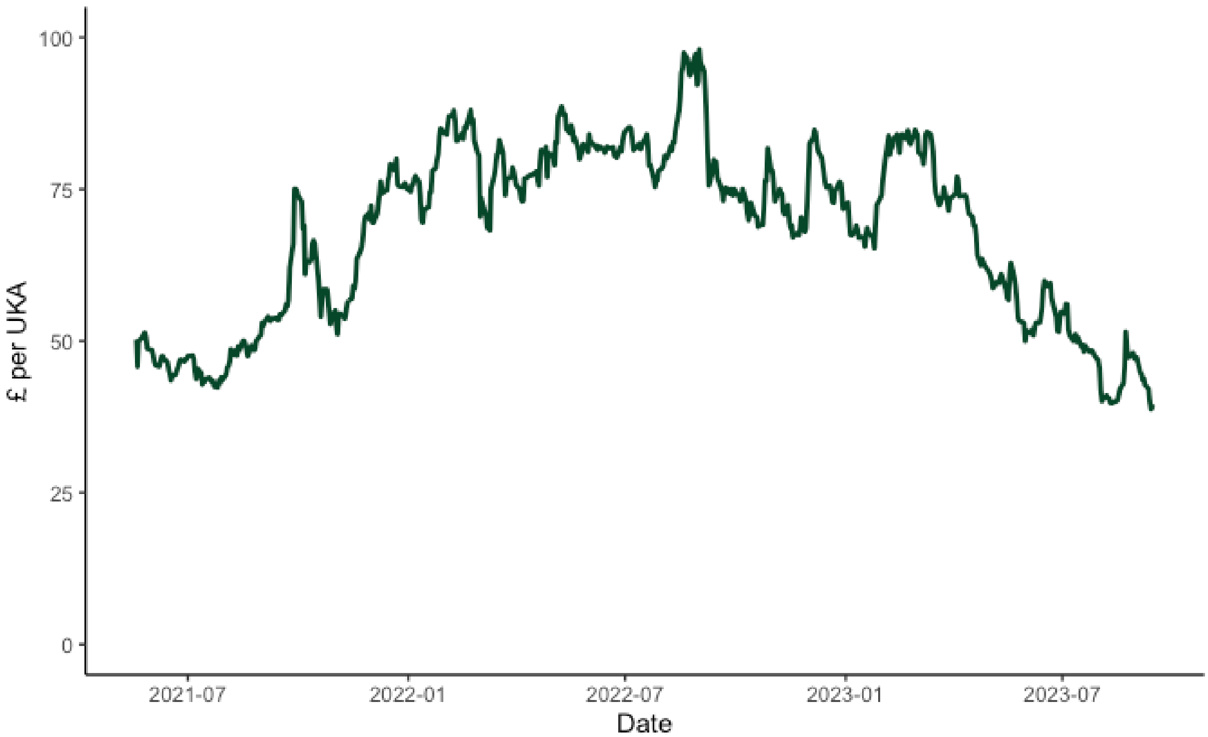


**Figure A-2. The dynamics of UKA futures contract daily closing price (Sample 1).**

**Notes**: The figure shows the dynamics of the UKA closing price, which is the last price at which the futures contract trades during the trading day. This is based on data for futures contracts to be delivered in December 2021, December 2022, and December 2023 rolled into a single time series as described in Section 3.1. The data spans from 19 May 2021 to 15 September 2023.

Table A-2 presents the average daily number and value of trades for the whole period and for the subperiods represented by futures contracts with different expiry dates.

It can be observed that the average trading activity (in terms of the average number of traded UKAs per day) for the futures contract expiring in December 2023 is, on average, more than 25% higher than the trading activity observed for the futures contract expiring in December 2021.

**Table A-2. The average number of trades and average values of trades per day for a final time series (Sample 1).**

| UKA futures contract | Sample period | Average number of trades per day, 1000 UKA | Average value of trades per day, £ '000 |
|---|---|---|---|
| December 2023 | December 1, 2022 – 15 September 2023 | 493 | 35,948 |

| UKA futures contract | Sample period | Average number of trades per day, 1000 UKA | Average value of trades per day, £ '000 |
|---|---|---|---|
| December 2022 | December 1, 2021 – 30 November 2022 | 447 | 35,304 |
| December 2021 | 19 May 2021 – 30 November 2021 | 394 | 21,246 |
| Combined time series | 19 May 2021 – 15 September 2023 | 476 | 31,965 |

**Notes**: The daily number of trades and the daily value of the trades are calculated based on the data for the 1-minute trading intervals by summing up all the trades and all the values of the trades during each trading day. Combined time series includes data for futures contracts to be delivered in December 2021, December 2022, and December 2023 rolled into a single time series as described in Section 3.1.

This improvement in the trading activity can also be seen in Figure A-3 (below), which shows the dynamics of the daily trading volume. In general, this trend shows an increasing pattern. The average trading volume in July 2023 reached 720,000 UKAs, compared to the 305,700 UKAs traded in May-June 2021, shortly after the secondary market trading began. It is also worth noting that despite positive trend over the whole period, trading activity is not stable. Trading days with a trading volume of around 1,500,000 UKA may be followed by days with a trading volume of less than 500,000 UKA.

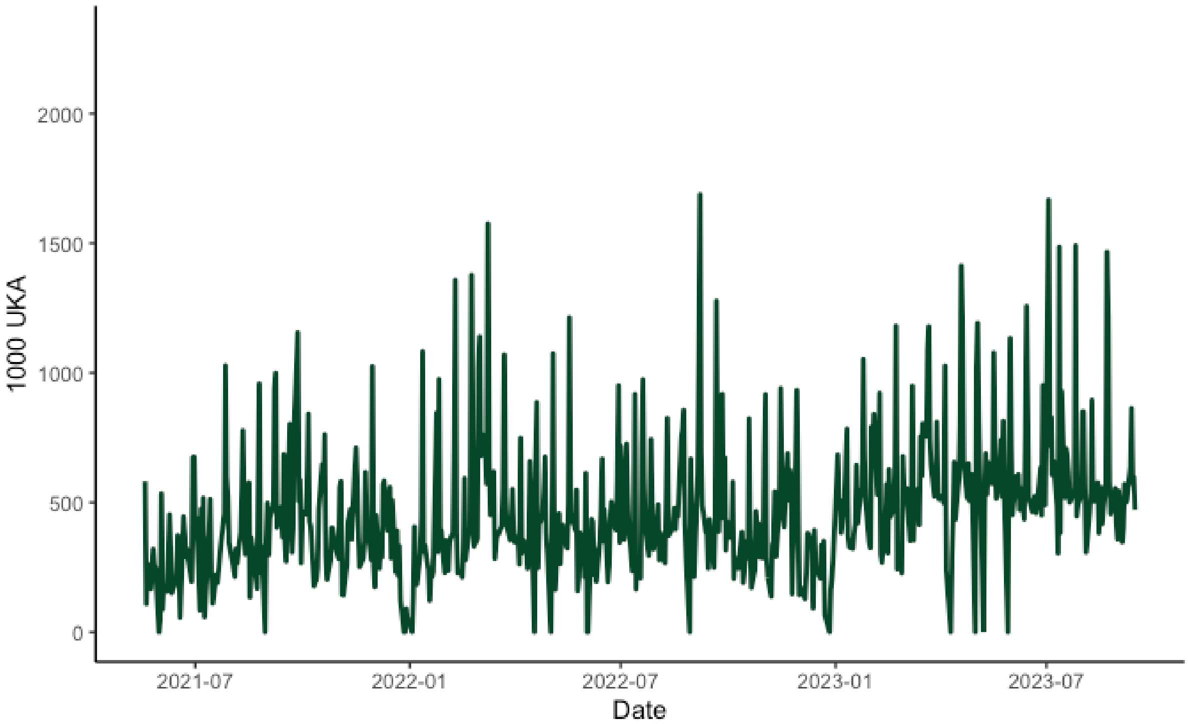


**Figure A-3. The dynamics of UKA futures contract daily trading volume (Sample 1).**

**Notes**: The figure shows the dynamics of the total number of UKAs traded during each trading day. This is based on data for futures contracts to be delivered in December 2021, December 2022, and December 2023 rolled into a single time series as described in Section 3.1. The data spans from 19 May 2021 to 15 September 2023.

The dynamics of daily price range presented in Figure A-4 (below) shows that the highest spike in price volatility is observed at the end of February 2022 just after the Russian invasion of Ukraine which is explained by the significant level of market uncertainty caused by this event.

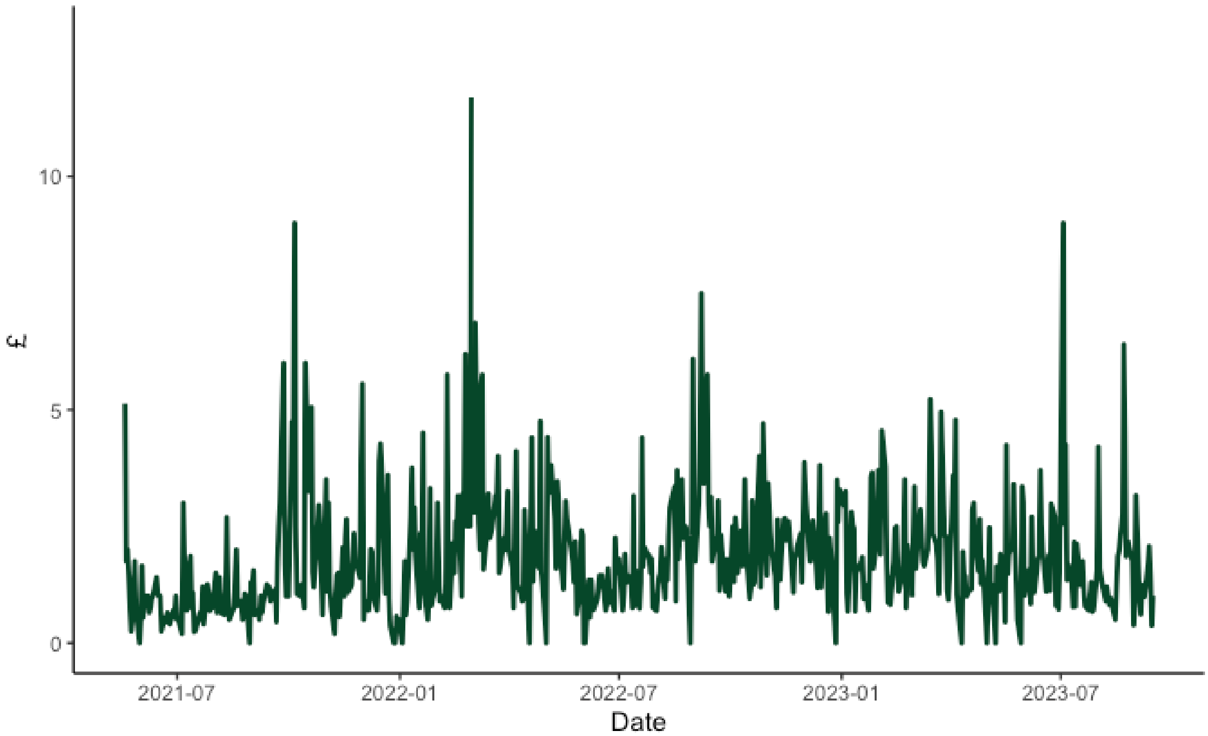


**Figure A-4. The dynamics of the daily price range (Sample 1).**

**Notes**: This is based on data for futures contracts to be delivered in December 2021, December 2022, and December 2023 rolled into a single time series as described in Section 3.1. Daily price range is calculated as a difference between the highest and the lowest prices observed during the trading day. The data spans from 19 May 2021 to 15 September 2023.

The dynamics of the daily close-to-close returns presented in Figure A-5 (below) suggests that the volatility of returns on average diminishes over the course of the considered period.

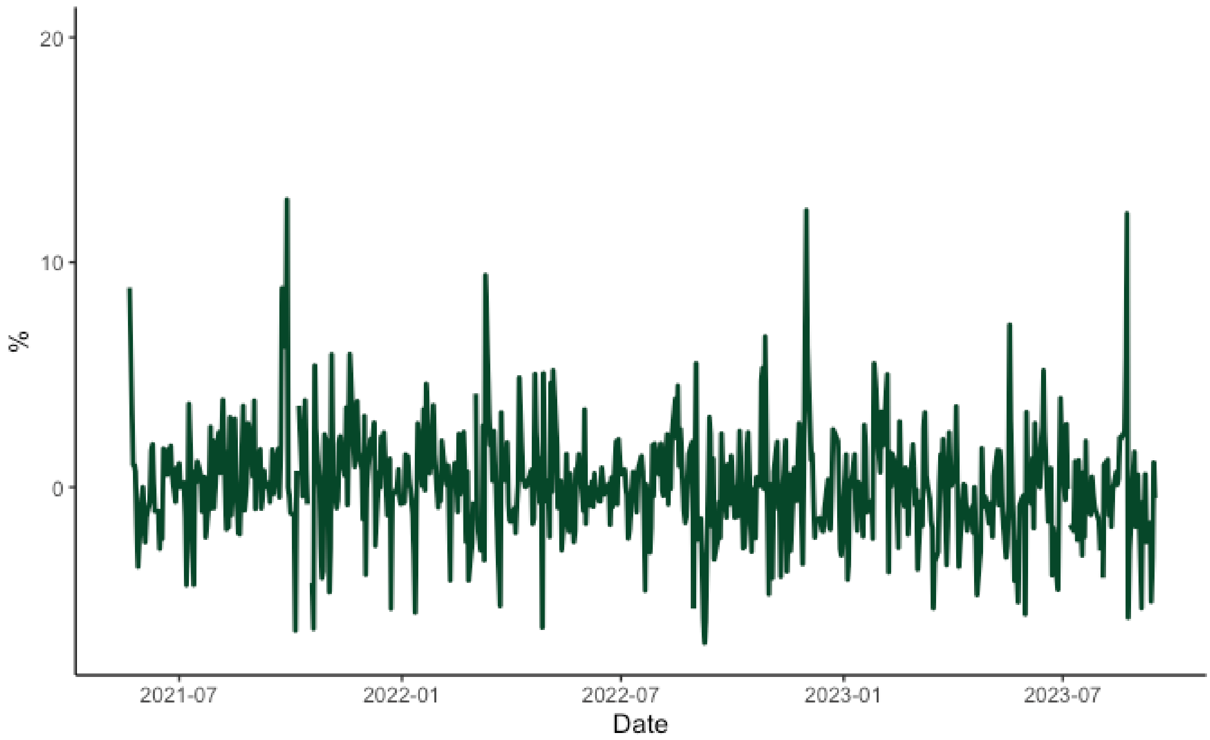


**Figure A-5. The dynamics of close-to-close returns (Sample 1).**

**Notes**: The close-to-close returns are calculated as the difference between the closing price on day t and the closing price on day t-1, divided by the closing price on day t and multiplied by 100%. This is based on data for futures contracts to be delivered in December 2021, December 2022, and December 2023 rolled into a single time series as described in Section 3.1. The data spans from 19 May 2021 to 15 September 2023.

# A2.2 Detailed results of the price volatility decomposition.

Table A-3 (below) presents the estimates of pricing error variance ($\mathbf{2 \times \sigma_s^2}$) and share of information driven volatility ($\boldsymbol{Q}$) for each trading day in the sample.

**Table A-3. Volatility components estimated based on Hasbrouck's (1993) approach for each trading day during the period 22 May 2023 to 15 September 2023 (Sample 2).**

| Date | # of observations | $2 \times \sigma_s^2$ | $\sigma_r^2$ | $Q$ |
|---|---|---|---|---|
| 2023-05-22 | 328 | 0.2088 | 0.5827 | 0.6416 |
| 2023-05-23 | 494 | 0.1400 | 0.8834 | 0.8416 |
| 2023-05-24 | 778 | 0.7199 | 1.8971 | 0.6205 |

| Date | # of observations | $2 \times \sigma_s^2$ | $\sigma_r^2$ | $Q$ |
|---|---|---|---|---|
| 2023-05-25 | 508 | 0.5226 | 2.0443 | 0.7444 |
| 2023-05-26 | 205 | 0.0646 | 0.1883 | 0.6569 |
| 2023-05-30 | 372 | 0.1717 | 0.9361 | 0.8166 |
| 2023-05-31 | 1644 | 1.5833 | 3.5398 | 0.5527 |
| 2023-06-01 | 381 | 0.3175 | 1.1300 | 0.7190 |
| 2023-06-02 | 328 | 0.1334 | 0.6353 | 0.7900 |
| 2023-06-05 | 522 | 0.8398 | 1.6639 | 0.4953 |
| 2023-06-06 | 1044 | 0.6115 | 2.2377 | 0.7267 |
| 2023-06-07 | 488 | 0.2607 | 1.1586 | 0.7750 |
| 2023-06-08 | 298 | 0.1779 | 1.0877 | 0.8364 |
| 2023-06-09 | 394 | 0.3735 | 1.2037 | 0.6897 |
| 2023-06-12 | 215 | 0.4792 | 0.8640 | 0.4454 |
| 2023-06-13 | 899 | 0.4983 | 1.9372 | 0.7428 |
| 2023-06-14 | 704 | 1.6269 | 3.3066 | 0.5080 |
| 2023-06-15 | 723 | 0.1542 | 1.2847 | 0.8800 |
| 2023-06-16 | 352 | 0.4893 | 2.1255 | 0.7698 |
| 2023-06-19 | 327 | 0.1987 | 0.5872 | 0.6617 |
| 2023-06-20 | 245 | 0.4563 | 0.8391 | 0.4562 |

| Date | # of observations | $2 \times \sigma_s^2$ | $\sigma_r^2$ | $Q$ |
|---|---|---|---|---|
| 2023-06-21 | 177 | 0.0453 | 0.3454 | 0.8689 |
| 2023-06-22 | 287 | 0.0701 | 0.7454 | 0.9060 |
| 2023-06-23 | 676 | 0.4399 | 2.5614 | 0.8283 |
| 2023-06-26 | 317 | 0.1337 | 0.6097 | 0.7808 |
| 2023-06-27 | 255 | 0.1968 | 0.5514 | 0.6431 |
| 2023-06-28 | 899 | 0.2344 | 1.3517 | 0.8266 |
| 2023-06-29 | 657 | 0.2833 | 0.9171 | 0.6911 |
| 2023-06-30 | 531 | 0.4774 | 1.2161 | 0.6074 |
| 2023-07-03 | 2015 | 4.1341 | 12.5932 | 0.6717 |
| 2023-07-04 | 377 | 0.6549 | 2.5762 | 0.7458 |
| 2023-07-05 | 614 | 0.2434 | 1.9590 | 0.8757 |
| 2023-07-06 | 206 | 0.0442 | 0.5624 | 0.9213 |
| 2023-07-07 | 488 | 0.4075 | 1.0761 | 0.6213 |
| 2023-07-10 | 377 | 0.1782 | 0.4955 | 0.6405 |
| 2023-07-11 | 280 | 0.2926 | 0.5920 | 0.5057 |
| 2023-07-12 | 901 | 1.4184 | 4.3009 | 0.6702 |
| 2023-07-13 | 740 | 0.1653 | 0.5162 | 0.6797 |
| 2023-07-14 | 865 | 0.5925 | 1.5357 | 0.6142 |

| Date | # of observations | $2 \times \sigma_s^2$ | $\sigma_r^2$ | $Q$ |
|---|---|---|---|---|
| 2023-07-17 | 228 | 0.2239 | 0.5080 | 0.5593 |
| 2023-07-18 | 720 | 0.5487 | 1.3557 | 0.5953 |
| 2023-07-19 | 639 | 0.3946 | 1.5306 | 0.7422 |
| 2023-07-20 | 344 | 0.1032 | 0.4870 | 0.7881 |
| 2023-07-21 | 1058 | 0.4941 | 1.7481 | 0.7174 |
| 2023-07-24 | 190 | 0.0427 | 0.1232 | 0.6537 |
| 2023-07-25 | 333 | 0.4189 | 0.9164 | 0.5429 |
| 2023-07-26 | 2791 | 0.2716 | 1.5221 | 0.8216 |
| 2023-07-27 | 321 | 0.1779 | 0.4639 | 0.6164 |
| 2023-07-28 | 250 | 0.0554 | 0.1632 | 0.6604 |
| 2023-07-31 | 309 | 0.0633 | 0.3544 | 0.8214 |
| 2023-08-01 | 790 | 1.4563 | 3.2944 | 0.5579 |
| 2023-08-02 | 415 | 0.3825 | 1.8349 | 0.7915 |
| 2023-08-03 | 216 | 0.1855 | 0.8132 | 0.7719 |
| 2023-08-04 | 181 | 0.0515 | 0.2723 | 0.8109 |
| 2023-08-07 | 243 | 0.0633 | 0.3747 | 0.8312 |
| 2023-08-08 | 553 | 0.1418 | 1.1294 | 0.8745 |
| 2023-08-09 | 652 | 0.1781 | 0.5817 | 0.6938 |

| Date | # of observations | $2 \times \sigma_s^2$ | $\sigma_r^2$ | $Q$ |
|---|---|---|---|---|
| 2023-08-10 | 311 | 0.2387 | 0.4007 | 0.4042 |
| 2023-08-11 | 332 | 0.1252 | 0.4199 | 0.7018 |
| 2023-08-14 | 262 | 0.0549 | 0.3414 | 0.8391 |
| 2023-08-15 | 232 | 0.3108 | 0.5881 | 0.4715 |
| 2023-08-16 | 389 | 0.1437 | 0.6696 | 0.7854 |
| 2023-08-17 | 370 | 0.2255 | 0.9978 | 0.7740 |
| 2023-08-18 | 300 | 0.2887 | 1.1798 | 0.7553 |
| 2023-08-21 | 391 | 0.0524 | 0.8709 | 0.9398 |
| 2023-08-22 | 943 | 0.6707 | 4.7692 | 0.8594 |
| 2023-08-23 | 1812 | 4.2771 | 16.0236 | 0.7331 |
| 2023-08-24 | 685 | 0.8466 | 4.5771 | 0.8150 |
| 2023-08-25 | 208 | 0.3479 | 1.1323 | 0.6927 |
| 2023-08-29 | 346 | 0.1835 | 0.9440 | 0.8057 |
| 2023-08-30 | 163 | 0.0556 | 0.1760 | 0.6839 |
| 2023-08-31 | 227 | 0.2599 | 0.7453 | 0.6512 |
| 2023-09-01 | 374 | 0.4121 | 2.2528 | 0.8171 |
| 2023-09-04 | 134 | 0.2139 | 0.7110 | 0.6992 |
| 2023-09-05 | 401 | 0.0772 | 0.6161 | 0.8748 |

| Date | # of observations | $2 \times \sigma_s^2$ | $\sigma_r^2$ | $Q$ |
|---|---|---|---|---|
| 2023-09-06 | 1331 | 2.5014 | 9.5545 | 0.7382 |
| 2023-09-07 | 235 | 0.0631 | 0.4094 | 0.8459 |
| 2023-09-08 | 711 | 0.2451 | 0.6909 | 0.6452 |
| 2023-09-11 | 359 | 0.2053 | 0.7171 | 0.7138 |
| 2023-09-12 | 725 | 0.3694 | 1.2669 | 0.7084 |
| 2023-09-13 | 740 | 0.6451 | 2.4180 | 0.7332 |
| 2023-09-14 | 291 | 0.0049 | 0.0941 | 0.9480 |
| 2023-09-15 | 183 | 0.0242 | 0.1598 | 0.8483 |

**Notes**: The table displays the results of volatility components estimation based on Hasbrouck's (1993) approach for each trading day separately. $2 \times \sigma_s^2$ is a double variance of the pricing error calculated according to the procedure described in Appendix A1.2. When the variance of pricing error is relatively high, the price discovery process in the market is deemed to be less efficient. $\sigma_r^2$ is a volatility (variance) of continuously compounded returns computed directly from the data. $Q$ is a market quality indicator defined by the formula (7). To make the volatility estimates comparable across subperiods, we multiply each volatility estimate by the number of trades in the corresponding subperiod as was done in Medina et al. (2014).

## A2.3 Unit-root tests for times series used in the unbiasedness regressions.

To estimate unbiasedness regression correctly, all the time series used for this analysis ($ret_{cc}$ and $ret_{ck}$) should be stationary. Table A-4 (below) presents the results of the augmented Dickey-Fuller tests for these time series. These results suggest that both $ret_{cc}$ and $ret_{ck}$ for all 1-hour trading intervals are stationary.

**Table A-4. The results of unit-root tests (augmented Dickey-Fuller test) for time series used in the unbiasedness regressions (Sample 1).**

| Time series | Dickey-Fuller statistics for $ret_{cc}$ | Dickey-Fuller statistics for $ret_{ck}$ |
|---|---|---|

| | | |
|---|---|---|
| Returns from close to 09AM | -5.5135 | -5.1813 |
| Returns from close to 10AM | -7.1591 | -6.9854 |
| Returns from close to 11AM | -7.8764 | -7.0121 |
| Returns from close to 12PM | -7.2251 | -6.6277 |
| Returns from close to 01PM | -7.3340 | -7.2945 |
| Returns from close to 02PM | -7.8374 | -7.4157 |
| Returns from close to 03PM | -7.6504 | -7.0608 |
| Returns from close to 04PM | -7.5901 | -7.2707 |
| Returns from close to 05PM | -7.5210 | -7.1521 |

**Notes**: The table shows the results of the unit root tests (augmented Dickey-Fuller test) for the time series used in the unbiasedness regressions. Test statistics are computed based on the daily data for close-to-close returns ($ret_{cc}$) and for returns from close to the end of time interval $k$ ($ret_{ck}$), where $k$ corresponds to 1-hour trading intervals. The null hypothesis of the test is that time series is non-stationary. Alternative hypothesis is that time series is stationary. P-value less than 0.05 means that the null hypothesis can be rejected at a 5% significance level.

## A2.4 Alternative spread measures

In this section we present two additional spread measures, namely realised spread and relative quoted spread. These spread measures are discussed in Section 3.2.2.

The trend in the average relative quoted spread and realised spread for each trading day over the period considered in the analysis is presented in Figure A-6, while the descriptive statistics are presented in Table A-5. The results show a general improvement in liquidity in the UK ETS secondary market during the period considered in the analysis, meaning that both spread measures have narrowed over time.

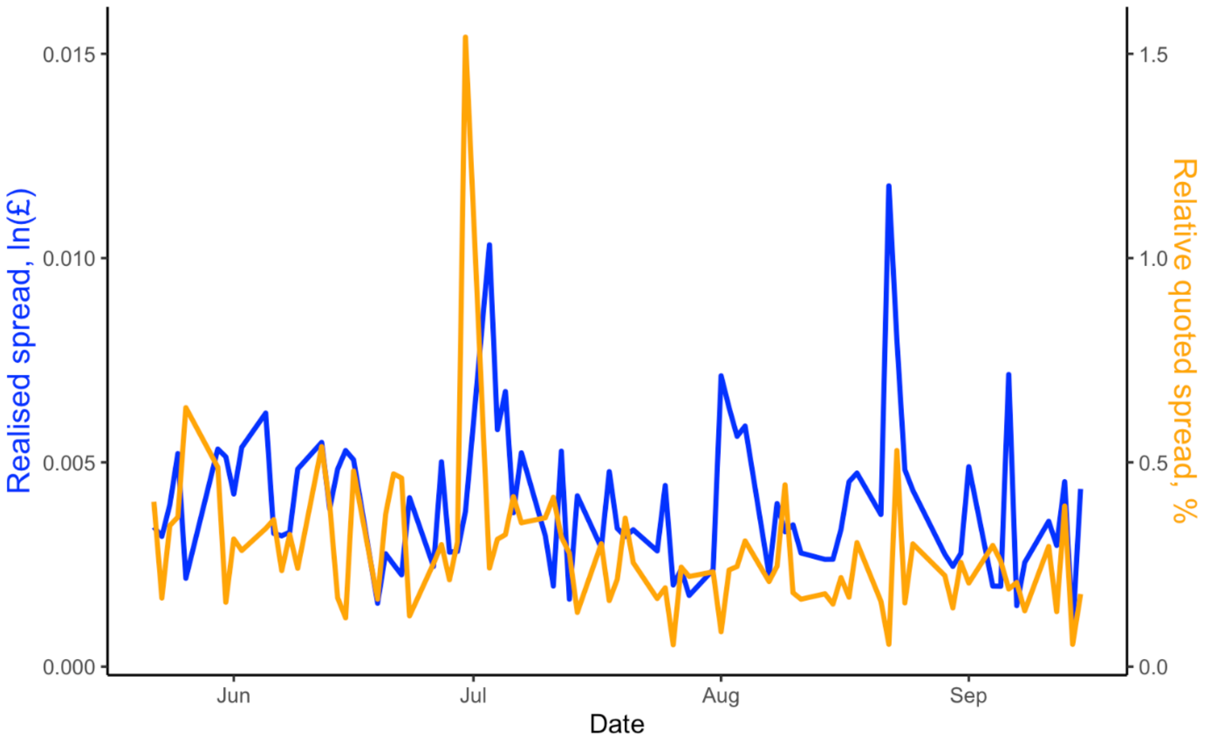


**Figure A-6. The dynamics of relative quoted spread and realised spread (Sample 2).**

**Notes**: The figure displays daily averages of the relative quoted spread and realised spread from 22 May 2023 to 15 September 2023. Spreads are calculated for 5-minute trading intervals and then averaged for each trading day. Relative quoted spread is defined as a difference between the best bid and the best ask divided by the average of the best-traded bid and the best-traded ask for a certain period (in £). The realised spread reflects the part of the effective spread realised by the trader and can be calculated according to the formula 14 (see Section A1.8).

**Table A-5. Descriptive statistics for the relative quoted spread and realised spread (Sample 2).**

| | Minimum | Median | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|
| Relative quoted spread, % | 0.0536 | 0.2459 | 0.2823 | 1.5409 | 0.1826 |
| Realised spread, ln (£) | 0.0009 | 0.0036 | 0.0040 | 0.0049 | 0.0018 |

**Notes**: The table shows the descriptive statistics of the daily averages of the relative quoted spread and realised spread for the period 22 May 2023 to 15 September 2023. The spreads are calculated for 5-minute trading intervals and then averaged for each trading day. Relative quoted spread is defined as a difference between the best bid and the best ask divided by the average of the best-traded bid and the best-traded ask for a certain period (in %). The realised spread reflects the part of the effective spread realised by the trader and can be calculated according to the formula 14 (see Section A1.8).

# A2.5 Liquidity and price discovery on auction and non-auction days

This section provides the results of the comparison of market quality proxies on auction to non-auction days (Table A-6).

**Table A-6. Average values of market quality proxies for auction and non-auction trading days (Sample 1 and Sample 2).**

| | Auction days | Non-auction days |
|---|---|---|
| Trading volume | 912.1724 | 429.2059 |
| Price standard deviation | 0.1123 | 0.0746 |
| Amihud (2002) price impact ratio | 0.0529 | 0.0649 |
| Effective spread | 0.1235 | 0.1313 |
| Coefficient of determination from return predictability model ($R^2$) | 0.0431 | 0.0423 |
| Share of information-driven volatility ($Q$) | 0.6930 | 0.7235 |

**Notes**: The table presents averages of average values of market quality proxies for auction and non-auction trading days. Averages of the trading volume, price standard deviation, and Amihud (2002) price impact ratio are calculated based on the data from 19 May 2021 to 15 September 2023. For all other indicators averages are calculated based on the data from 22 May 2023 to 15 September 2023. For indicators for which data is available from May 2021, we also test the statistical significance of the differences in averages. The only statistically significant difference is observed for the trading volume (at the 0.01 level of significance). The trading volume is calculated based on the data for the 1-minute trading intervals by summing up all the trades during each trading day. Price standard deviation is defined as standard deviation of the 1-minute return over a single trading day. Amihud (2002) price impact ratio is defined as an average ratio of the daily absolute return (in %) to the trading volume on that day (in £). The effective spread is defined as the double of the difference between the trading price of the k-th trade and the midpoint of the consolidated BBO (best bid and offer) (in £). The coefficient of determination ($R^2$) is defined as a share of the variance of the 15-minute returns that can be explained by the variance of the 15-minute order imbalance ratio for each trading day. The share of information-driven volatility ($Q$) is defined as $Q = 1 - \frac{2\sigma_s^2}{\sigma_r^2}$, where $\sigma_s^2$ is a pricing error variance (computed based on the procedure described in Section 4.1.2), $\sigma_r^2$ is a variance of the observed returns.

# A2.6 Correlation analysis of market quality proxies

This section presents the results of the descriptive analysis of the relationship between different market quality proxies based on correlation analysis. Considering different market quality proxies can be calculated for different periods, we split the correlation analysis into two parts.

Firstly, we calculate the coefficient of the correlation between Amihud (2002) price impact ratio (liquidity) and returns standard deviation (price discovery/informational efficiency). These proxies are based on the trading data for different time intervals; hence, we can calculate correlation using daily data from the period 19 May 2021 to 15 September 2023 (602 trading days). Considering that data on these indicators is available for a relatively long period of time, we calculate correlations both for the whole period as well as for the different subperiods. The results of this correlation analysis are presented in Table A-7.

All correlation coefficients presented in Table A-7 are positive; however, this correlation is statistically significant only for the last part of the considered period (1 December 2022 to 15 September 2023). Thus, at least during the period from December 2022 till July 2023 we observe positive and statistically significant link between liquidity and price discovery. In other words, the increase in returns standard deviation (noisiness of trading) corresponds to the higher levels of Amihud (2002) price impact ratio (lower level of liquidity). This finding coincides with the results of the previous studies. For example, Ibikunle et al. (2016) found a strong relationship between liquidity and market efficiency such that when spreads narrow, return predictability diminishes.

**Table A-7. Correlation between Amihud (2002) price impact ratio and returns standard deviation (Sample 1).**

| Period | Correlation coefficient | p-value |
|---|---|---|
| 19 May 2021 – 15 September 2023 | 0.0287 | 0.4894 |
| December 1, 2022 – 15 September 2023 | 0.2097 | 0.0039*** |
| December 1, 2021 – 30 November 2022 | 0.0612 | 0.3323 |
| 19 May 2021 – 30 November 2021 | 0.1324 | 0.1503 |

**Notes**: The table contains correlation coefficients and corresponding p-values for the Amihud (2002) price impact ratio and price standard deviation. Correlations are calculated for the period 19 May 2021 to 15 September 2023 and for different subperiods. Correlations are calculated on a daily level. "***" indicates that the correlation is statistically significant at the 1% significance level.

The second part of the correlation analysis is related to the indicators that are based on the trades/bid-ask prices and can only be calculated for the period 22 May 2023 to 15 September 2023 (83 trading days). However, we also include data on Amihud (2002) price impact ratio and returns standard deviation for this period. The computed correlation coefficients, as well as their significance level, are presented in Figure A- 7.

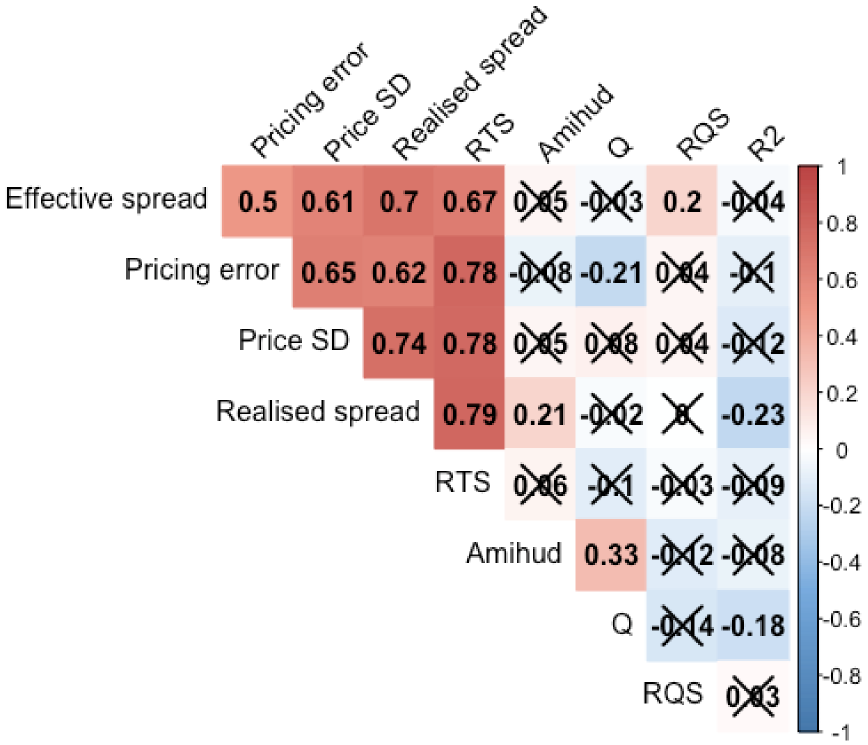


**Figure A-7. Person correlation coefficients between market quality proxies and their significance level (Sample 2).**

**Notes**: The figure displays the results of correlation analysis for all market quality proxies considered in the report. The correlations are calculated on a daily level for the period 22 May 2023 to 15 September 2023. Crossed-out correlation coefficients mean that they are not statistically significant at the 5%-significance level. RQS – relative quoted spread, Amihud – Amihud (2002) price impact ratio, Price SD – price standard deviation, RTS – relative traded spread.

There are several statistically significant correlation coefficients in Figure A-7. First, except for the relative quoted spread, all the estimated spread measures are positively and statistically significantly correlated with each other. Second, price standard deviation is positively and significantly correlated with effective spread, realised spread, and relative traded spread. That is, greater levels of price volatility are associated with wider spreads or, to put it another way, greater levels of market quality with respect to price discovery correspond to greater levels of market quality with respect to liquidity. Third, the share of information-driven volatility is negatively correlated with return predictability (meaning that a higher share of information driven-volatility is associated with lower short run predictability).

The results of this part of the correlation analysis confirm the existence of a positive and statistically significant relationship between liquidity and price discovery/informational efficiency on the UK ETS secondary market.

## A2.7 Modelling the relationship between market quality proxies based on vector autoregressive (VAR) models.

In this section we analyse the relationship between different market quality proxies considered in the report. Specifically, we use VAR models to estimate the relationships between the following variables:

- R2 (coefficient of determination) estimated from predictive regressions.
- Price volatility measured as returns standard deviation.
- Share of information driven volatility
- Effective spread
- Amihud (2002) price impact ratio

In this section, we use only effective spread, as it is highly correlated with the relative traded spread (see Appendix A2.6).

As most of the market quality proxies mentioned above are calculated daily for the period 22 May 2023 to 15 September 2023, the length of each time series is 83 trading days. In view of this limited sample size, we estimate the VAR model separately for each pair of price discovery and liquidity indicators. This means that 2 regression equations are estimated per VAR model.

Specifically, we consider the following dynamic equation (17):

$$X_t = B(L)X_{t-1} + U_t \ (17)$$

Where $X_t$ is a vector of variables over which VAR model is estimated, $B(L)$ is a polynomial lag operator, $U_t$ is a vector of residuals. The number of lags is set to 2 based on Akaike information criterion (AIC) and considering limited sample size.

For one pair of market quality proxies (price standard deviation and Amihud (2002) price impact ratio), daily data are available for the entire period from the UK ETS secondary market launch on 19 May 2021 to 15 September 2023. The VAR model is therefore estimated for this period for these variables. Table A-8 presents the specifications of VAR models used for the analysis of the relationship between different market quality proxies.

**Table A-8. Specifications of the VAR models used for the analysis of the relationship between market quality proxies.**

| | Variable – price discovery | Variable – liquidity | Time period covered by the data |
|---|---|---|---|
| Model 1 | R2 (coefficient of determination) estimated from predictive regressions | Effective spread – (ES) | 22 May 2023 – 15 September 2023 |
| Model 2 | R2 (coefficient of determination) estimated from predictive regressions | Amihud (2002) price impact ratio - (API) | 22 May 2023 – 15 September 2023 |
| Model 3 | Price volatility (price standard deviation) – (Price SD) | Effective spread – (ES) | 22 May 2023 – 15 September 2023 |
| Model 4 | Price volatility (price standard deviation) – (Price SD) | Amihud (2002) price impact ratio – (API) | 19 May 2021 – 15 September 2023 |
| Model 5 | Share of information driven volatility (Q) | Effective spread – (ES) | 22 May 2023 – 15 September 2023 |
| Model 6 | Share of information driven volatility (Q) | Amihud (2002) price impact ratio – (API) | 22 May 2023 – 15 September 2023 |

**Notes**: The table shows the specifications of VAR models used for the analysis of relationship between market quality proxies. Considering the limited sample size for market quality proxies computed based on the bid-ask prices data (83 trading days), each model is estimated over a set of 2 variables one of which represents market quality in terms of price discovery, and another represents the market quality in terms of liquidity. The coefficient of determination ($R^2$) is defined as a share of variance of the 15-minute returns that can be explained by the variance of the 15-minute order imbalance ratio for each trading day. Price volatility is defined as the standard deviation of the 1-minute return over a single trading day. The effective spread is defined as the double of the difference between the trading price of the k-th trade and the midpoint of the consolidated BBO (best bid and offer) (in £). Amihud (2002) price impact ratio is defined as an average ratio of the daily absolute return (in %) to the trading volume on that day (in £). $Q$ is a market quality indicator (share of information-driven volatility) calculated according to the procedure described in Appendix A1.2.

The results of models 1-6 identification are presented in t . The first column in the table reflects the variables included in each model. The second and third columns give the estimated coefficients for each equation in the VAR model (2 equations per model in our case). Each equation in the VAR model is a regression where the dependent variable is regressed on its own lags and on the lags of the second variable included in the VAR. Considering that in our case each VAR includes 2 variables and 2 lags, we estimate 4 coefficients for each equation.

The estimation of VAR models allows the identification of two statistically significant relationships:

- The price standard deviation is positively related to the Amihud (2002) price impact ratio (meaning that higher price volatility is associated with lower liquidity levels).
- The effective spread is negatively related to the proportion of information-driven volatility (meaning that higher levels of liquidity are associated with a higher proportion of information-driven volatility).
- These results confirm our findings presented in Section 4.3.2 and suggest that improvements in the liquidity of the UK ETS secondary market are associated with improvements in the price discovery process.

**Table A-9. Results of VAR models estimation (Sample 1 and Sample 2).**

| **Model 1: relationship between coefficient of determination from returns predictability model and effective spread** | | |
|---|---|---|
| Variable | Dependent variable - R2 | Dependent variable - ES |
| $R2_{t-1}$ | -0.0039 | -0.0911 |
| $ES_{t-1}$ | -0.2759 | 0.1484 |
| $R2_{t-2}$ | -0.1323 | 0.1209 |
| $ES_{t-2}$ | 0.0891 | 0.1977 |
| Model 2: relationship between coefficient of determination from returns predictability model and Amihud (2002) price impact ratio | | |
| Variable | Dependent variable - R2 | Dependent variable - API |
| $R2_{t-1}$ | -0.0223 | 0.1375 |
| $API_{t-1}$ | -0.0237 | 0.3020 * |
| $R2_{t-2}$ | -0.1084 | -0.1619 |

| | | |
|---|---|---|
| $API_{t-2}$ | -0.1566 | -0.0518 |
| Model 3: relationship between price standard deviation and effective spread | | |
| Variable | Dependent variable – Price SD | Dependent variable - ES |
| $Price\ SD_{t-1}$ | 0.0751 | 0.0115 |
| $ES_{t-1}$ | 0.0785 | 0.1351 |
| $Price\ SD_{t-2}$ | 0.2403 * | 0.0249 |
| $ES_{t-2}$ | 0.2403 | 0.1012 |
| Model 4: relationship between price standard deviation and Amihud (2002) price impact ratio | | |
| Variable | Dependent variable – Price SD | Dependent variable - API |
| $Price\ SD_{t-1}$ | 0.3685 *** | -0.0036 |
| $API_{t-1}$ | 0.3203 | 0.0089 ** |
| $Price\ SD_{t-2}$ | 0.0253 | 0.0142 * |
| $API_{t-2}$ | -0.2415 | 0.1200 ** |
| Model 5: relationship between share of information driven volatility and effective spread | | |
| Variable | Dependent variable – Q | Dependent variable – ES |
| $Q_{t-1}$ | 0.0120 | 0.0480 |
| $ES_{t-1}$ | -0.6686 * | 0.1312 |

| | | |
|---|---|---|
| $Q_{t-2}$ | 0.0765 | 0.0055 |
| $ES_{t-2}$ | 0.2965 | 0.1811 |
| Model 6: relationship between share of information driven volatility and Amihud (2002) price impact ratio | | |
| Variable | Dependent variable – Q | Dependent variable - API |
| $Q_{t-1}$ | 0.0784 | 0.0104 |
| $API_{t-1}$ | 0.5077 | 0.2735 * |
| $Q_{t-2}$ | 0.0865 | 0.0564 |
| $API_{t-2}$ | 0.3311 | -0.0906 |

**Notes**: The table displays the results of VAR models estimation for different pairs of market quality proxies related to price discovery and liquidity. R2 is a coefficient of determination which reflects a share of variance of the 15-minute returns that can be explained by the variance of the 15-minute order imbalance ratio for each trading day. The effective spread is defined as the double of the difference between the trading price of the k-th trade and the midpoint of the consolidated BBO (best bid and offer) (in £). API is a Amihud (2002) price impact ratio is defined as an average ratio of the daily absolute return (in %) to the trading volume on that day (in £). PSD is a price volatility defined as the standard deviation of the 1-minute return over a single trading day. $Q$ is a market quality indicator (share of information-driven volatility) calculated according to the procedure described in Appendix A1.2. Considering the limited sample size for most market quality proxies computed based on the bid-ask prices data (50 trading days), each model is estimated over a set of 2 variables one of which represents market quality in terms of price discovery, and another represents the market quality in terms of liquidity. Each model is truncated at $p = 2$. Models 1,2,3,5,6 are estimated based on the data for the period 22 May 2023 - 15 September 2023. Model 4 is estimated for the period 19 May 2021 to 15 September 2023. "***", "**", "*" indicate the statistical significance of the parameter at 0.01, 0.05 and 0.10 levels of significance respectively.

## A2.8 Comparison of the EU ETS and UK ETS secondary markets

Figure A-8 shows the dynamics of UKA and EUA prices during the period 1 December 2021 to 15 September 2023.

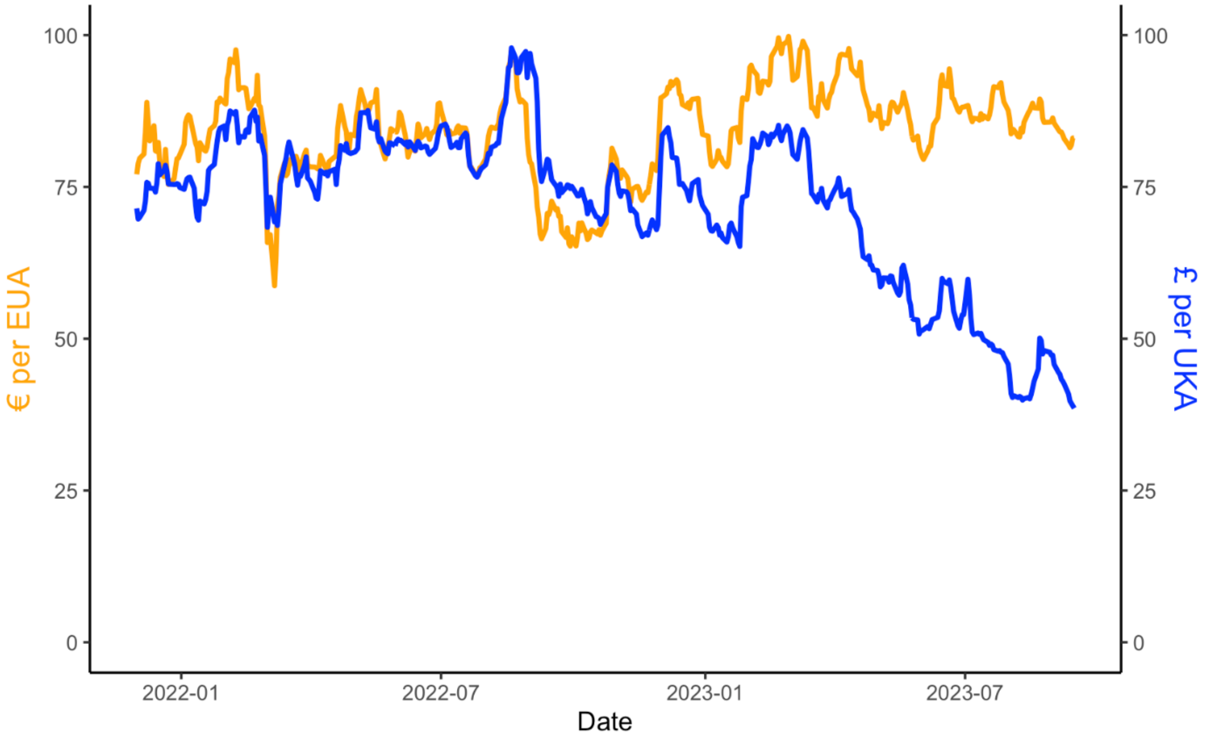


**Figure A-8. The dynamics of UKA and EUA futures contracts daily closing price.**

**Notes**: The figure shows the dynamics of the UKA and EUA futures contracts daily closing price, which is the last price at which the futures contract trades during the trading day. This is based on data for futures contracts to be delivered in December 2022 and December 2023, rolled into a single time series. Data on December 2022 contracts is used for the period 1 December 2021 to 30 November 2022. Data on December 2023 contracts is used for the period 1 December 2022 to 15 September 2023.

Table A-10 (below) shows the descriptive statistics for trading activity in the samples used for the comparative analysis of the UK ETS and EU ETS secondary markets quality.

**Table A-10. Trading activity in the UK ETS and EU ETS secondary markets based on the samples used for the benchmarking analysis (see Section 4.3.3)**

| | UK ETS | | EU ETS | |
|---|---|---|---|---|
| | Average number of trades per day, 1000 UKA | Average value of trades per day, £ ‘000 | Average number of trades per day, 1000 UKA | Average value of trades per day, € ‘000 |
| Sample 3 (1 December 2021 – 15 September 2023) | 500 | 35,202 | 14,157 | 1,188,614 |
| Sample 4 (28 July 2023 – 15 September 2023) | 588 | 25,550 | 14,116 | 1,202,700 |

**Notes**: The averages are calculated based on the data for futures contracts expiring in December 2023, and based on real-time tick-by-tick data aggregated to a daily level.

Table A-11 presents the descriptive statistics for the December 2022 and December 2023 EUA futures contracts the data on which is used to estimate market quality proxies for EU ETS secondary market.

**Table A-11. The average number of trades and average value of trades per day for the EUA.**

| EUA futures contract | Sample period | Average number of trades per day, 1000 EUA | Average value of trades per day, € '000 |
|---|---|---|---|
| December 2023 | 1 December 1 2022 – 15 September 2023 | 13,844 | 1,228,054 |
| December 2022 | 1 December 2021 – 30 November 2022 | 14,390 | 1,159,338 |
| Combined time series | 1 December 2021 – 15 September 2023 | 14,157 | 1,188,614 |

**Notes**: The daily number of trades and value of trades are calculated based on the data for the 1-minute trading intervals by summing up all trades, and all the values of the trades during each trading day. Combined time series includes data for futures contracts to be delivered in December 2022 and December 2023 rolled into a single time series.

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