Evaluation of the UK Emissions Trading Scheme: Phase 1 report – Annex 3

Literature review on market quality in emissions trading schemes

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December 2023

Acknowledgements

A report prepared for the UK ETS Authority by Gbenga Ibikunle of the University of Edinburgh, RoZetta Institute (Sydney, Australia) and the European Capital Markets Cooperative Research Centre (Italy). Research assistance was provided by Katie Warren and Jasmine Porter of the University of Edinburgh Business School.

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Abstract

This report reviews the economics literature investigating the market quality characteristics of emission allowances. The review covers an 18-year period (2005 to 2023). It commences with an introductory background into the key theoretical issues underpinning the evolution of the two fundamental market quality characteristics, liquidity, and price discovery/informational efficiency. It then reviews the literature investigating these and associated characteristics in the context of emissions allowances trading. It concludes with a list of suggested market quality proxies that could be employed in evaluating the quality of the trading process on the market platform(s) facilitating the exchange of allowances and associated financial instruments within the UK Emissions Trading Scheme (UK ETS).

1. The economics of market quality characteristics: background and theory

This section provides a background review of the literature on the market quality characteristics in financial markets, it does so to provide a necessary context for the review of the literature on market quality in emissions trading schemes. Hence, while the concepts introduced in the section are revisited in the subsequent sections, a progression from this section into the next should not be expected. Where relevant, in section 2, references are made to sub-sections of section 1.

1.1 Defining market quality

In facilitating the transfer of instruments between buyers and sellers, markets perform two fundamental functions: the provision of liquidity and price discovery. Liquidity is defined as the ability to trade large quantities of an instrument quickly and with little or no price impact (see Campbell et al., 1997), while price discovery is the process through which relevant information is incorporated into the price of an instrument, with the goal of this process being to achieve informational efficiency – a state where all relevant information is impounded into price. Consistently, theoretical, and empirical evidence also show that liquidity and price discovery/informational efficiency are inextricably linked (see as examples, O'Hara, 2003; Chordia et al., 2008; Ibikunle et al., 2016), irrespective of whether they facilitate the trading of conventional instruments, such as company shares, or unconventional instruments, such as the permission to pollute (for example emission/carbon allowances/credits). The market for a financial instrument is only informationally efficient to the extent to which its price reflects all the information, both public and private, relevant to its pricing (see Fama, 1970). Thus, the evolution of price should only be informed by a change in belief regarding the risk-adjusted value of an instrument. However, price movements are susceptible to the effects of factors other than innovation in beliefs. One of these factors is illiquidity risk; hence, the liquidity-informational efficiency link and the importance of liquidity for the price discovery process.

In addition to liquidity and informational efficiency, there is a third market quality characteristic that is often overlooked in the academic literature given the difficulty of objectively measuring it, this is market integrity. As most regulator mandates are to ‘ensure fair and efficient markets’ (concerning insider trading, market manipulation and broker-client conflicts and so on), this is nevertheless a crucial characteristic to consider on an ongoing basis. Complicating the regulator mandate is the conflict that exists between market integrity and informational efficiency. For example, while insider trading may be beneficial for driving price discovery, and thus, informational efficiency, it is not desirable from a fairness perspective. An example of insider trading in the emissions trading context could be an insider trading on yet-to-be-released information on whether the market for emission allowances for a given compliance year is net long or short.

1.2 Liquidity

Trading primarily occurs in financial markets for two reasons: to exploit private information, namely profit motivation reasons, and for needs that arise beyond the market itself, not primarily driven by the fundamental value of the instrument they are trading. Value traders, technical traders, dealers, and arbitrageurs would be considered to be those who trade to exploit private information. In line with the market microstructure literature, these are all hereafter referred to as ‘informed traders’, while those whose trading is not primarily driven by the need to profit from the movement in price are uninformed traders (see O'Hara, 2003). An example of the latter would be an electricity producer trading in emission permits to offset its carbon footprint in accordance with the law. A non-renewable electricity generator must purchase natural gas and so on to generate electricity and trade emission allowances should it have compliance responsibilities under an emissions trading scheme – this is the generator’s primary purpose for trading, not trading on information. The electricity generator in this context is the classic ‘liquidity trader’ because they provide liquidity that could be ‘taken’ by informed traders exploiting their information when trading. This does not imply that electricity generators, who are compliance traders under the UK-ETS, are uniformly ‘uninformed’ in practical terms; the designation refers to their motivation for trading in relation to the value of the instrument they are trading. If in a narrow sequence of trading, an electricity generator’s motivation for trading switches to altering its inventory due to its foreknowledge of an impending price change, then for that period, the producer is an informed trader. This is plausible given that trading desks of electricity producers may continually analyse emission permits’ price movements and the fundamentals that influence them (for example economic activity) to optimise their inventory.

Both informed and uninformed/liquidity traders are crucial for the normal functioning of markets. Informed traders acquire information (often at a cost) with which they trade by taking advantage of uninformed trading positions. The informed trader’s activity is critical for price discovery and informational efficiency because they are the ones who possess the information needed to ensure that the instrument they trade is fairly priced. However, the presence of informed traders in financial markets is only made possible by the presence of uninformed traders – without a party to adversely select, in other words ‘take advantage of’, there is no incentive to acquire information in aid of the price discovery process (see Kyle, 1985; Glosten and Milgrom, 1985).

The implication of this is that the presence of uninformed traders in markets is as important as that of informed traders. Thus, in a market like the secondary trading platforms of the UK-ETS, market quality would not only depend on the presence of compliance traders, such as the emission-intensive energy installations, but also profit-seeking arbitrageurs, such as commodity trading desks of investment banks. I should note again that compliance traders are not permanently condemned to being uninformed, they may exploit information during sequences of trading as much as sophisticated trading desks of investment house could.

In practical terms, the presence of informed traders is hazardous for uninformed/liquidity traders, making them perhaps reluctant to supply the liquidity crucial for maintaining informational efficiency in the market. To appreciate why uninformed traders should be wary of providing liquidity, consider Kyle's (1985) starker description of the informed trader as the 'risk neutral insider' trader in his seminal 1985 paper. Analogous to this insider is perhaps a 'house that always wins' in a casino game. This is essentially what an informed trader represents – she is in a position that makes losing in a game of trading based on information practically impossible. The 'reluctance' to supply liquidity yields liquidity constraints or inventory pressures, which price reflects. Price is a combination of an efficient price component, which captures information, and a noise component that is an amalgam of microstructure impacts, overreaction and underreaction to information, imperfect liquidity, and price impacts of noise trading, meaning trading at prices divorced from fundamental value and so on. As an example, where the shortage of orders is on the buyers' side of the market, we should expect a reduction in the number of buy orders (bids) submitted to the market and thus a fall in bid prices. The consequence of this decline in bids is a widening of the 'spread' between the bid and ask/offer prices. Thus, the larger the spread between the bid and ask prices the larger the cost of trade. The spread is a non-zero economic necessity encapsulating the transaction costs borne by traders and the economic gain for a market intermediary, such as the market maker[1] or a dealer. Therefore, in quote-driven markets, the market maker quotes are a proxy for measuring transaction costs, such as inventory holding costs and order processing costs. Inventory holding and order processing costs are not the only components of the spread. Indeed, the reluctance of uninformed traders to trade is linked to the risk of being adversely selected by informed traders. As earlier suggested, if a house 'always wins' then those from outside the house must abhor some concerns or even fear about engaging in a (trading) game with the house. Yet, liquidity traders must trade for reasons not linked to profit making and market makers have a statutory responsibility to provide liquidity/trade; hence, they demand compensation for taking the risk of trading with informed traders, meaning

[1] A classic market marker is a designated economic agent that provides liquidity and is compensated by an exchange for doing so, as an example, the European Energy Exchange (EEX) designates RWE AG as a market maker for its EUA financial instruments.

information risk. This is priced as adverse selection cost, and it is the most important component of the bid-ask spread (see Glosten and Milgrom, 1985).

Thus, the extent of ‘tightness’ or ‘narrowness’ of the bid-ask spread is a proxy for liquidity, it is indeed the most popular and most intuitive liquidity proxy in the financial economics literature because they reflect at least three of the five dimensions of liquidity; however, they only fully capture the distance between the ask and bid prices (namely the tightness or width dimension). The other dimensions are breadth, resilience, depth, and immediacy. 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. Resilience captures the time it takes for prices to move back to equilibrium after a large trade, and breadth corresponds to the number of participants who do not wield significant power. These characterisations are relevant to whether orders can be executed promptly without generating significant or enduring price impacts. Variants of the bid-ask spread include the quoted bid-ask spread, the relative quoted bid-ask spread, the effective bid-ask spread, and the realised spread. They, theoretically, represent the round-trip cost of a transaction, at least for regular-sized transactions. The quoted spread is computed as the ask price minus the bid price, while the relative quoted spread is the quoted spread scaled by the midpoint (the average of the ask and bid prices). Both the quoted and relative quoted spreads could overstate or understate the execution costs for liquidity demanding trades when orders execute within or beyond prevailing bid and ask quotes/prices. The effective spread accounts for these issues, it is defined as twice the absolute value of the difference between the prevailing execution transaction price and its corresponding midpoint.

As explained above, the spread is often interpreted as the profit earned by a liquidity provider for facilitating a trade (the cost of trading with that liquidity provider). But trades typically have positive price impact (quotes tend to move up following buyer-initiated trades and vice versa), hence, effective spreads overstate liquidity provider profits and the trade’s true ‘execution cost’ if defined as the price at which a transaction is conducted, relative to the true value of the asset. To account for these effects, we can use an alternative spread estimate, the relative realised spread. In contrast to the effective spread, the realised spread compares the trade price to the mid-quote at a future point in time once the trade’s price impact has been realised (for example five milliseconds in the future).

However, many trades are block (large) trades that induce price shocks larger than the spread components can convey (see Kraus and Stoll, 1972; Chiyachantana et al., 2004 among others); hence, the need to account for order sizes in estimating liquidity (see as an example, Brennan and Subrahmanyam, 1996). Block trades typically induce large price shocks even when they are liquidity-driven as they may be seen as conveying information, and despite the literature suggesting that informed traders are more likely to disguise their trades using other trade sizes (see Barclay and Warner, 1993). Disguising trading intentions is a ‘stealth trading’ practice that is now the norm in the age of algorithmic/high frequency trading (AT/HFT) (see Ibikunle, 2018). The liquidity effects of block trades are particularly important in a market like the UK-ETS given that compliance traders are institutional trading entities expected to trade in large quantities.

Two of the earliest studies to establish the essence of the price impact of block trades include Kraus and Stoll (1972) and Holthausen et al. (1990) (see also Chan and Lakonishok, 1993). Kraus and Stoll (1972) propose two channels explaining the short-run liquidity impact of block trades. The first channel is linked to order imbalance, which induces buyers initiating trades to pay a premium or sellers to offer a discount, while the second channel reflects similar discounting and charging of premia on account of non-substitutability of tradeable instruments. Holthausen et al. (1990) offers evidence consistent with the payment of premia in the execution of buyer-initiated block trades; however, there is no evidence of the predicted discount for seller-initiated block trades in their analysis. This is consistent with Kraus and Stoll’s (1972) finding that price impact is higher for block purchases than sales because concession or an implicit commission paid are usually higher for purchases than sales. Measures such as the Amihud price impact ratio (see Amihud, 2002) are volume-based and thus reflect the price impact of transactions in the aggregate over time series. Therefore, they are suited for long-term analysis of the state of liquidity in markets.

1.3 Price discovery and informational efficiency

As price discovery involves the incorporation of information into price, the process is driven by the informativeness or otherwise, namely noisiness, of the trading. Endogenously, trading platforms that successfully attract liquidity/uninformed traders become attractive to informed traders and are thus likely to offer more informationally efficient prices than platforms that are less attractive to liquidity traders. This implies that being able to attract informed and uninformed orders are essential for the price discovery process (see Kyle, 1985; Glosten and Milgrom, 1985). Furthermore, in modern financial markets, the speed of execution and other factors, such as lack of pre-trade transparency, the defining characteristic of dark pools (see Comerton-Forde and Putnins, 2015), have also become vital factors for attracting different classes of traders. In an environment where extracting and exploiting private information has become increasingly costly due to the 24-hr nature of the financial news cycle and the ubiquity of mobile news apps providing timely updates, the ability of informed traders to take advantage of their information at high speeds is critical to their obtaining compensation for sourcing trading-relevant information. Speed of trading, as encapsulated by the emergence of AT/HFT, has become an important factor in the price discovery process. In modern markets, this factor has a significance that encompasses all three market quality characteristics. While many studies show that it has improved liquidity (for example Hendershott et al., 2011) and price discovery (for example Brogaard et al., 2014), it is also responsible for a recent upsurge in latency arbitrage trading strategies, defined by Budish et al. (2015) as the use of speed by fast traders to exploit new symmetrically observable public information ahead of slower traders. This implies that the type of information that latency arbitrageurs exploit is distinct from the asymmetrically observable private information the classic informed trader described above exploits. Essentially, latency arbitrageurs exploit public information by using superior speed technological infrastructures instead of conducting the type of analyses that that underpin the private information used by, for example, technical and fundamental analysts. Aquilina et al. (2022) estimate that the deployment of latency arbitrage strategies results in losses of approximately $5 billion per year in global equity markets. This may not be a significant issue for the UK-ETS at this time; nevertheless, as the market becomes more mainstream and more sectors of the UK economy become involved, it is logical to expect that latency arbitrageurs may come to view UK-ETS carbon financial instruments (CFIs) as fair targets.

Notwithstanding the potentially negative effects of latency arbitrage, trading at high speeds may help enhance market quality. This is because if market makers, who are obligated liquidity providers in a market, are fast in updating their quotes such that they can use it to avoid being adversely selected by latency arbitrageurs, they will be motivated to provide more liquidity to the market. In addition, this is expected to positively impact price discovery (for example Brogaard et al., 2014; Hendershott et al., 2011; Hoffmann, 2014). Should the liquidity consumers be the fastest traders in the market, they may deploy their speed advantage to pick off slow traders' orders, thereby imposing adverse selection costs on them and reducing their incentive for information acquisition (for example Biais et al., 2015; Foucault et al., 2016; Weller, 2018). This negatively impacts price discovery. Hence, who holds the speed advantage in markets factor into the efficiency of the price discovery process. A further factor is the nature of the latency arbitrage opportunity that liquidity-consuming high frequency traders (HFTs) exploit. Rzayev et al. (2023) show that when such opportunities are toxic, meaning linked to information, AT/HFT impairs liquidity. It, however, enhances price discovery by facilitating incorporation of information into price. And when HFTs exploit non-toxic latency arbitrage opportunities, meaning opportunities arising due to liquidity constraints, they enhance liquidity and reduce transaction costs. A consequence of this effect is that traders are incentivised to acquire information and engage in informed trading activity in service of the price discovery function of markets.

1.4 Liquidity and informational efficiency

Informational efficiency is not a binary concept; rather it exists as a continuum. Specifically, to determine whether a price is informationally efficient, we should need to first define what an informational efficient price is – this is the joint hypothesis challenge that makes it impossible to define price efficiency as an either or concept (see Campbell et al., 1997). If we do not know what an efficient price looks like, then any test we conduct to ascertain whether price is efficient will fall short of expectations. Therefore, we define informational efficiency in terms of the extent to which price reflects all relevant information to the instrument being priced (see, for example, Fama, 1970). Furthermore, since the impounding of each new set of relevant information will take time to complete (informed traders need to extract information and incorporate it into their strategies and so on), markets are not routinely highly efficient throughout the average trading day. Indeed, we should expect a fluctuation in the degree to which the price of an instrument reflects all the information relevant to it (see for example Epps, 1979; Hillmer and Yu, 1979; Patell and Wolfson, 1984; Chordia et al., 2008). This expectation is consistent with the findings from an extensive streams of the market microstructure literature such as Cushing and Madhavan (2000) and Chordia et al. (2005), who show that order flow (the balance/imbalance of the flow of buy and sell orders to the market) is a predictor of short-horizon returns. According to Chordia et al. (2008), this predictability diminishes as a market becomes more liquid. Specifically, the study validates one of three candidate hypotheses on whether there exists a relationship between liquidity and informational efficiency and establishes a path to estimating informational efficiency.

The channel linking liquidity to informational efficiency in Chordia et al.'s (2008) framework captures the liquidity constraint often faced by market makers/liquidity providers daily in financial markets. When market makers are faced with a challenging inventory scenario, for example brought on by dealing with over-exposure, the provision of liquidity, their statutory responsibility, becomes impossible. This scenario creates the environment for price pressures and allows for the evolving order flow to cause a pricing strain that induces a deviation of prices from the value of the instruments they are meant to capture, an arbitrage opportunity thus arises. This strain creates the perfect condition for order flow to predict returns, at least over short, intraday horizons (see also Stoll, 1978; Chordia and Subrahmanyam, 2004). Observant market participants, such as watchful HFT algorithms trained on large datasets to observe the emergence of this predictability may readily observe the violation of the random walk hypothesis, and tender market orders that allow them to profit from the arbitrage opportunity. Using market orders to take advantage of arbitrage opportunities is necessitated by the fleeting nature of such opportunities given the level of competition among arbitrageurs. Incidentally, the submission of such orders is instrumental in eliminating the arbitrage opportunities by relieving the pressure on market makers' inventories and inducing a correction in pricing. Once the price correction is achieved the predictability of return from order flow, and thus the arbitrage opportunity, is erased (see also Chordia et al., 2005). Since arbitrage traders are more likely to tender these orders when the spreads are narrow (see for example Peterson and Sirri, 2002; Brennan and Subrahmanyam, 1998 for the influence of liquidity on trading tactics), we should expect reduced return predictability when the market is fairly liquid than otherwise – recall that narrow spreads imply greater liquidity. Chung and Hrazdil (2010) and Rzayev and Ibikunle (2019) also provide evidence of the diminishing predictability proposition based on large sample analyses of US-listed stocks.

Other studies have also addressed the linkages between liquidity and informational efficiency by exploring other potential channels of connection. The main channel explored has been how illiquidity constitutes risk and therefore commands premia; the insights offered based on this channel are varied. Pástor and Stambaugh (2003) find the existence of a relationship in the cross-section of stock returns and illiquidity risk. This finding is consistent with Datar et al. (1998) and Acharya and Pederson (2005). Likewise, Amihud (2002) shows that expected market liquidity is a predictor of stock excess return, which suggests that excess return encapsulates illiquidity premia (see also Chang et al., 2010).

2. The literature on market quality in emissions trading schemes

This section is divided into four distinct but related parts focusing on the methodological approaches employed in the literature on market quality and price volatility dynamics of emissions trading. In some cases, the findings of studies are summarised or stated where relevant to the discussion on methodologies, but this is not the standard applied throughout.

Section 2.1 reviews the literature on the price drivers of emission allowances/permits and the CFIs they underpin, sections 2.2 and 2.3 discuss the literature on the two key market quality characteristics studied in the literature, price discovery/informational efficiency and liquidity respectively. Section 2.4 briefly considers the lone reviewed literature on market integrity issues.

2.1 Emission allowances: price drivers and volatility

The earliest studies addressing the factors driving carbon financial instrument (CFI)[2] price formation in emissions trading schemes (carbon markets) focus exclusively on EU Emission Allowance (EUA) price formation and characterisation of the volatility of its price. Christiansen and Arvanitakis (2004), Mansanet-Bataller et al. (2007) and Alberola et al. (2008) using daily data, explore the effects of changes in energy fundamentals on daily EUA returns during the opening phase of the EU-ETS (2005 – 2007). Bredin and Muckley (2011) extend their investigation of price determinants to Phase II of the EU-ETS. All four studies report that pricing in the EU-ETS is driven by fundamentals. However, it is equally plausible that EUA price drives energy fundamentals rather than the reverse. Fezzi and Bunn (2009), using a vector autoregressive (VAR) framework, show that electricity prices are jointly influenced by shocks in carbon prices. Their findings suggest that, despite allowances being freely allocated, a 1% increase in the price of emission permits elicits a 0.32% increase in UK electricity prices during Phase I of the EU-ETS (see also Nazifi and Milunovich, 2010; Hintermann, 2012). Koch (2014) investigate the price driver question in the context of the precipitous fall in EUA price from almost 30€/tCO2 in mid-2008 at the start of the EU-ETS's Phase II to less than 5€/tCO2 in mid-2013 at the start of its Phase III. Their analysis focuses on the contributory effects of the three commonly identified EUA price explanatory factors: macroeconomic fundamentals, renewable policies, and the use of international credits. Their findings, however, fail to support the popular view that negative demand shocks (as would be encapsulated by a fall in

[2] CFI is used interchangeably with terms, such as emission allowance or allowance.

the demand for emission-intensive goods and services) lead to reductions in EUA price. Indeed, they find moderate interaction effects between the overlapping EU-ETS and renewable policies (see also Ibikunle and Okereke, 2014). Crucially, they find that 90% of the variations in EUA price changes remains unexplained by the abatement-related fundamentals, such as energy. This is consistent with more recent evidence, based on Phase III data, by Batten et al. (2021) showing that their best performing model, based on energy prices, explains only 12% of EUA price variation. Nevertheless, the role of aggregate emissions as a driver of CFIs is hardly disputed in the case of the EU-ETS. For example, Hitzemann et al. (2015) show that annual announcements of realised emissions in the EU-ETS consistently elicits significant absolute abnormal returns associated with increased trading volumes and high intraday volatilities on the announcement days.

New sets of evidence from this stream of the literature increasingly focus on the world's largest carbon market, the Chinese Emissions Trading Scheme (CETS), and its predecessor pilot schemes. Wen et al. (2022) employ data from three of the largest Chinese pilot schemes (Guangdong, Shenzhen, and Hubei) to investigate the role of macroeconomic risk and uncertainty, energy fundamentals and environmental factors in the pricing of Chinese CFIs and find that all three are CFI price drivers (see also Fan and Todorova, 2017). Interestingly, however, different factors dominate the price discovery processes in each of the three schemes examined, suggesting the heterogeneous determination of allowance price drivers. Chang et al. (2019) and Ji et al. (2021) also report the pilot scheme location-dependent heterogeneous effects of CFI price drivers in the Chinese schemes. Chang et al. (2017; 2018a), using a series of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models (see Engle, 1982) to characterise the pricing dynamics of allowances' prices, also find heterogeneous effects related to general pricing. Indeed, the use of GARCH-type models to characterise the pricing process or price volatility in carbon markets qualifies as a 'minor cottage industry'. However, these studies mainly aim to understand the econometric properties of price, not whether price reflects some expectation of quality, and they frame their questions in the context of model fit. The outputs nevertheless hold value for investment-focused questions, such as value-at-risk forecasting (see also Paolella and Taschini, 2008; Benz and Trück, 2009; Daskalakis et al., 2009; Cong and Lo, 2017; Chang et al., 2018; Dai et al., 2022).

Another stream of the economics of emissions trading schemes literature focus on policy factors. Mansanet-Bataller and Pardo (2007), and Miclăuş et al. (2008) use event study to examine the impact of regulatory events, such as national action plan (NAP) announcements on EUA prices. Their findings suggest that the announcements are key EUA price drivers in Phase I of the EU-ETS – this is unsurprising given the informational nature of the announcements. We should expect new information to spur new trading activity through which it can be impounded into price (see also Mansanet-Bataller and Sanin, 2014). Equally noteworthy is the finding by Mansanet-Bataller and Pardo (2007) showing that information routinely leaks to the market prior to the announcement days; nonetheless, the effects of the announcements on their official release days remain statistically significant. However, Hintermann (2010), suggests that prior to the April 2006 price crash in EUA price, policy, and not the expected marginal abatement costs of one tonne of CO2e was the dominant driver EUA price. The outsized role of policy in the price discovery process in the early days of the EU-ETS appears consistent with the trajectory of a market yet to mature. However, Conrad et al. (2012), using a GARCH framework with high frequency data, find that the EU Commission's NAP decisions continue to have immediate and substantial impacts on EUA pricing. And Koch et al. (2016), exploiting a framework that addresses parameter instability and model uncertainty investigate the news-implied price impact of 29 announcements regarding the EU-ETS supply schedule, and document a high level of market responsiveness. Furthermore, Dai et al. (2022), exploiting a longer time series covering all the first three phases of the EU-ETS finds that both European and global policy uncertainty can be used to forecast EUA price volatility.

International evidence also strongly suggests that policy is the dominant driver of pricing in emissions trading schemes. Using data from the Shanghai Emissions Trading Scheme pilot, Song et al. (2018) show that, in line with Koch et al. (2016), policy drives allowance price in the pilot through its effect on the fundamentals of supply and demand, effectively suggesting that pricing relies on authorities tweaking the rules to make the market work. This view is consistent with the EU Commission introducing the backloading policy in 2014 and the market stability reserve (MSR) in 2019 to prop up EUA price in the EU-ETS (see Kollenberg and Taschini, 2016; Perino and Willner, 2016). Further international evidence, from New Zealand, underscore the complexity of the price formation process in emissions trading schemes. Diaz-Rainey and Tulloch (2018), based on allowance importation and exportation data, show that the imports of offsets, rather than fundamentals (for example energy prices, weather, and economic conditions), are the major price drivers of emission allowances in the New Zealand Emissions Trading Scheme (NZ-ETS). This is instructive given that until 2013, the NZ-ETS, a comparatively small carbon market, allowed for an unlimited use of Kyoto allowances. The case thus underscores the necessity of small schemes reserving the right of imposing restrictions on the importation of international allowances, especially in cases where they are linked with larger schemes, to avoid pricing distortions, meaning the reflection of non-fundamental price drivers. The complexity of the rules governing various schemes have generally been known to induce pricing distortions, and this is not limited to the NZ-ETS. In the case of the EU-ETS, Daskalakis et al. (2009) and Daskalakis and Markellos (2009) find that inter-phase banking restrictions engender pricing distortions during Phase I (see also, Alberola and Chevallier, 2009).

Furthermore, on price volatility, Frino et al. (2010) and Ibikunle et al. (2013) directly estimate price volatility as an evolving characteristic. Although Frino et al. (2010) focus on Phase I of the EU-ETS, their analysis offers a useful reference for capturing how price volatility evolves in the market for emission allowances over the long-term. Their approach to estimating volatility is also important because it can be related to increasing transaction costs – transaction costs increase in times of price volatility. Frino et al. (2010) employ two measures of price volatility: the daily standard price range measured in ticks and the standard deviation of daily returns to estimate volatility at a quarterly frequency. The former is a poor estimate of intraday volatility given that it ignores the intraday transactions. However, the latter can be adapted for intraday estimations or for daily frequency by using trade-to-trade/midpoint-to-midpoint/clock time returns as Ibikunle et al. (2013) do. They estimate intraday volatility for half-hour intervals by estimating the standard deviation of trade-to-trade returns over half hour intervals for each CFI and then compute panel averages over each interval. Their results demonstrate how volatility relates to trading volume; they also use variations in the relationship as an indicator of noise in the price discovery process.

2.2 Emission allowances: price discovery and informational efficiency

The early studies on price discovery for traded emission allowances are undermined by the quality of the datasets available to them. This implies that their relevance is impacted by the immature nature of the scheme (EU-ETS) they examine at the time, and they often focus on conducting horse races among the emerging trading platforms of the period. As an example, in an unpublished manuscript, Benz and Hengelbrock (2009) present the first intraday analysis of liquidity and price discovery in the European carbon futures market by using a vector error correction model (VECM) (see as examples, Schwarz and Szakmary, 1994; Hasbrouck, 1995; Gonzalo and Granger, 1995) to identify which platform between the London-based European Climate Exchange (ECX, now ICE) and Oslo-based Nord Pool leads the price discovery process during Phase I of the EU-ETS. Estimating common factor weights (as in Schwarz and Szakmary, 1994) and information shares (as in Hasbrouck, 1995), they find that ECX leads price discovery during the phase. Similarly, Rittler (2012) and Mizrach and Otsubo (2014) investigate price leadership between two platforms, but with focus on the now defunct Paris-based BlueNext spot market in Paris and the derivatives trading-focused ECX. Crucially, both studies' analyses focus on the more mature Phase II of the EU-ETS. Consistent with Benz and Hengelbrock (2009), Rittler (2012) and Mizrach and Otsubo (2014) find ECX responsible for up to 79.4% and 88% of the EUA price discovery driven by both platforms – different estimates appear linked to variations in intraday data sampling frequencies. While their findings offer important insights on the large role futures trading plays in the price discovery process for CFIs, the VECM approach employed by these three studies is only useful from the perspective of determining price leadership, because it offers no indication of the 'quality' of the information in itself.

The question it answers is simply: ‘which price moves first subject to controlling for a set of assumed short-term pricing frictions?’

As discussed in section 1, the quality of the price discovery process lies in how much price reflects information rather than noise. Hence, approaches based on isolating the information content of transactions and estimating the extent to which price efficiently reflects information are more appropriate for investigating price discovery in emissions trading schemes. A number of studies attempt to achieve this by using low frequency/daily data from the EU-ETS and exploiting approaches developed for characterising price discovery and volatility dynamics in the financial economics literature. These include, among others Daskalakis and Markellos (2008), Joyeux and Milunovich (2010), Montagnoli and de Vries (2010), Chevallier (2011),[3] Crossland et al. (2013), Daskalakis (2013), Feng et al. (2011), Lee et al. (2020) employing a series of low frequency frameworks. The use of (low frequency) daily data is a limitation for at least three reasons.

The first relates to the nonsynchronous trading or nontrading effect. Employing daily data assumes that CFI prices are recorded at time intervals of one length when they are recorded at irregular intervals – that is the nature of trading in financial markets, the closing price used in many studies are simply the last price in a series of prices recorded during on a trading day. These closing prices generally do not occur at the same time each day, but referring to them as closing prices implicitly assumes a 24-hour sampling frequency. As explained by Campbell et al. (1997), this assumption creates a false impression of predictability in price changes and returns even when they are statistically independent. Specifically, the nontrading effect instigates serious biases in the moments and co-moments of asset returns (for example means, variances, covariances, betas, and autocorrelation, and cross-autocorrelation coefficients). Campbell et al. (1997) present a mathematically elegant motivation of this issue, which, inexplicably, is still often overlooked in some areas of the broader financial economics literature. Secondly, serial dependence across the trading day is effectively zero for dynamically traded instruments (see Chordia et al., 2005); therefore, an intraday/high frequency analysis is required to detect informational efficiency or otherwise. This is also a logical choice given that the prices that traders obtain emerge upon order execution and not necessarily at the end of the day; hence, the use of daily closing prices to investigate the efficiency of the price discovery process appears to be an anomaly driven by the lack of access to high frequency data in the past. High frequency (tick-by-tick) data is now easily accessible and the trading frequency on platforms has quickened since the early days of trading on EU-ETS platforms. Thirdly, the information content of transactions can only be reliably extracted from data capturing the evolution of the transactions themselves intraday.

[3] A section of Chevallier’s (2011) analysis involves the use of intraday data.

These issues and the additional challenge of thin trading on trading platforms also affect the preponderance of the non-EU-ETS evidence. For example, although Zhou et al., (2019) estimate variance ratios in a test of the random walk hypothesis a la Lo and MacKinlay (1988) for eight regional schemes in China. If an instrument's price follows a random walk, the variance of its returns is a linear function of the measurement frequency, the variance ratio exploits this property to measure inefficiency as a price series' deviation from the characteristics that would be expected under a random walk. Their analysis employs only daily and weekly observations due to lack of sufficient trading activity for intraday-driven analysis. Their study also mischaracterises trading volume as liquidity; this mischaracterisation appears common in the studies focused mainly on econometric portrayals of CFI price characteristics (see as an example, Cong and Lo, 2017). Wang et al. (2022), handicapped by thin trading on Chinese platforms, also employ weekly data in their test of the efficient market hypotheses (EMH) on six regional pilot schemes. Indeed, studies, such as Chang et al. (2018b) emphasise the severe nature of the lack of trading activity on these platforms. In their paper, they note that although trading in the emission allowance instrument from the Chongqing pilot had been operation for 764 days at the time of their data collection in July 2017, (limited) trading activity was recorded for only 164 days.

Some studies, however, implement a series of high frequency data-focused methodological choices that are relevant to investigating price discovery and informational efficiency dynamics in a market like the UK-ETS. These studies typically focus either on estimating the informativeness of trading activity on carbon trading platforms (for example Ibikunle et al., 2013; Kalaitzoglou and Maher Ibrahim, 2013; Medina et al., 2014; Mizrach and Otsubo, 2014, Kalaitzoglou and Maher Ibrahim, 2016) or the efficiency of the price discovery process (for example Ibikunle et al., 2013; Mizrach and Otsubo, 2014; Ibikunle et al., 2016).

In computing the informativeness of trading activity on EU-ETS platforms, Ibikunle et al. (2013), Medina et al. (2014), Mizrach and Otsubo (2014) all hinge their analyses on market microstructure models that decompose the bid-ask spread into its components (see section 1.2.). As stated in section 1.2, a key component of the spread, adverse selection cost, is a common proxy for informed trading activity and information asymmetry in the market microstructure literature because it reflects the risk of the market maker trading with an informed trader. Hence, Ibikunle et al. (2013) employ the Huang and Stoll (1997) spread decomposition framework, which exploits portfolio trading pressure, while Benz and Hengelbrock (2009), Medina et al. (2014) and Mizrach and Otsubo (2014) conduct a Generalised method of Moments (GMM) estimation of the Madhavan et al. (1997) trade indicator model. Medina et al. (2014) also employ additional robustness estimates based on the Hasbrouck (1993) VAR model for decomposing price into its efficient and noise components (see section 1.2). In addition, to estimating a time series of intraday price discovery measures, Ibikunle et al. (2013) compute modified versions of the weighted price contribution (WPC) and weighted price contribution per trade (WPCT) measures in the spirit of Cao et al. (2000), Barclay and Hendershott (2004) and van Bommel (2011). The WPC and WPCT are, however, only useful in the context of identifying the relative proportion of price discovery occurring at various periods of the trading day. Finally, Kalaitzoglou and Maher Ibrahim (2013) employ the Engle and Russell (1998) Autoregressive Conditional Duration (ACD) framework and Kalaitzoglou and Maher Ibrahim (2016) use a dynamic joint expectation model building on the microstructure trade indicator models, such as those of Madhavan et al. (1997) and Huang and Stoll (1997). The findings from these studies are largely compatible with the preceding papers' findings in that they present evidence of strategic information-driven trading activity on EU-ETS platforms. Kalaitzoglou and Maher Ibrahim (2013) and Medina et al. (2014) also suggest that learning speed improves in Phase II of the EU-ETS, which is consistent with Ibikunle et al.'s (2013) finding of a level of trading sophistication in line with that of traditional financial instruments.

Studies explicitly estimating informational efficiency measures based on high frequency CFI data are rarer and are largely focused on the EU-ETS due to thin trading on the platforms of other emerging schemes. Ibikunle et al. (2013) are the first to compute a time series of an intraday-focused proxy for measuring informational efficiency from high frequency data by estimating the signal-to-signal plus noise ratio observed in returns using the so-called 'unbiasedness regressions', first proposed by Biais et al. (1999). Their analysis exploring the comparative evolution of informational efficiency of CFIs during the trading day and after-hours trading show evidence of higher trading volume per minute and greater price efficiency for trading after hours in comparison with regular trading hours. They also find that due to a higher proportion of informed trades during the after-hours trading period, adverse selection risk is higher during the period than during the regular trading day. Ibikunle et al. (2016), however, conduct perhaps the most extensive high frequency analysis of the evolution of informational efficiency during Phase II of the EU-ETS. Their analysis is based on ICE-provided data spanning the first 40 months of trading of the phase. Their analysis assumes a theoretical link between liquidity and informational efficiency (as in Chordia et al., 2008, please see section 1.4), it, however, also includes an explicit examination of how informational efficiency evolves over the 40-month period. Hence, it offers a template for analysing the short- to long-term development of informational efficiency using high frequency data. Their main framework uses short-horizon (15-minute)[4] return predictability as an inverse indicator of market efficiency. Specifically, the extent to which lag order imbalance predicts short-horizon return indicates a violation of the random walk hypothesis, and thus is a sign of the extent to which the price discovery process is informationally

[4] 15-minute intervals are selected to reduce instances of missing observations for the computed variables, especially in the cases of the CFIs with lower trading activity. To implement this procedure today in a market such as the EU-ETS, a higher frequency would be more appropriate.

inefficient. They then show that return predictability is lower when the market for CFIs is relatively more liquid; they find a clear statistically significant relationship between liquidity and informational efficiency, such that as the market becomes more liquid, informational efficiency improves. They also show that liquidity and informational efficiency improve consistently over the sample period. Mizrach and Otsubo (2014) also estimate similar predictive regressions without the liquidity component; however, their estimation makes use of day-level observations for just one CFI.

In a further test of the randomness of the 15-minute returns, Ibikunle et al. (2016) estimate ratios of 15-minute return variance to open-to-close return variance as a test of the random walk hypothesis. Zhou et al., (2019) also estimate variance ratios using daily and weekly observations.

2.3 Emission allowances: liquidity

The mischaracterisation of liquidity as a market quality characteristic is common in the emissions trading literature, with studies often depicting trading volume as 'liquidity' (see as examples, Cong and Lo, 2017; Zhou et al, 2019). This depiction is incorrect. Johnson (2008), for example, show that volume and liquidity are weakly related (see also Jones, 2002; Fujimoto, 2004). Others, such as Foster and Viswanathan (1993), Lee et al. (1993), and Danıelsson and Payne (2010) provide evidence of a negative relationship between the two. Based on the foregoing, this section reviews only studies accurately characterising liquidity based on its five dimensions – tightness, breadth, resilience, depth, and immediacy (see section 1.2).

Frino et al. (2010), in their analysis of liquidity and transaction costs in Phase I of the EU-ETS, employ two of the liquidity proxies most commonly used with tick-by-tick data in the market microstructure literature, namely the effective and quoted spread metrics – the others include the relative and realized spread measures (see as examples, Ibikunle, 2018; Malceniece et al., 2019). Ibikunle et al. (2016)[5] modify these measures for use with the ECX CFI data provided by ICE. Typically, the relative and quoted spread measures are estimated using bid and ask quotes, and the effective spread estimated with execution price and the quotes (see section 1.2). However, due to the constraints of the data provided by ICE (dataset has execution prices with buyer-initiated and seller-initiated indicators and does not include quotes), the so-called relative traded spread and the traded spread based on execution prices are computed instead. The bid and ask quotes/prices are substituted for the buyer-initiated and seller-initiated prices respectively. Hundreds, perhaps thousands, of studies in the financial economics literature deploy the

[5] Both Frino et al. (2010) and Ibikunle et al. (2016) report improving liquidity conditions over the course of their sample periods in the EU ETS.

standard spread-based liquidity measures as proxies for liquidity. This is not surprising given their consistency as proxies for market liquidity. For example, Goyenko et al. (2009) conduct a horse race of commonly used liquidity proxies in the financial economics literature and find that, when measured against benchmarks, bid-ask spread-based proxies typically win the race.

Other studies (for example Benz and Hengelbrock, 2009; Ibikunle et al., 2013; Mizrach and Otsubo (2014) employ more econometrically robust approaches to estimate the effective spread or the 'liquidity/temporary/noise component' of price. A by-product of the attempts by these studies to estimate the informed trading component of price (see section 2.2), is an estimation of the liquidity component, since the approaches either require spread decomposition (spread must thus be robustly estimated first) or price to be split into its informed (public and private) and noise trading components in order to extract the informed trading proxies.

Studies employing daily and other low frequency data to measure liquidity (see as examples, Chang et al., 2018a; 2018b) generally employ the most popular low frequency liquidity measure in the market microstructure literature, the Amihud price impact ratio (see Amihud, 2002). The Amihud price impact ratio is defined as the ratio of the absolute return to trading volume over a given interval. Although, given its low frequency nature, it is a poor substitute for high frequency data-based estimates, 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 illiquid state (see section 1.2). Furthermore, Ibikunle et al. (2016), who also estimate the ratio, show that its evolution and that of a similar ratio, the Florackis et al. (2011) price impact ratio, is highly identical to that of the high frequency proxies over the course of Phase II of the EU-ETS.

2.4 Emission allowances: market integrity issues

While some of the studies reviewed above allude to potential market integrity issues, none directly investigates them. This is because, as stated in section 1.1, it is difficult to objectively measure market integrity with a single or combination of metrics. Nevertheless, Hintermann (2017) addresses market power dynamics, which takes in issues, such as strategic price manipulation and speculation, in Phase I of the EU-ETS. The study employs excess allowance holdings as an indicator of strategic price manipulation. It finds evidence consistent with strategic price manipulation, which cannot be explained by price speculation or precautionary purchases to insure against uncertain future emissions, by some compliance traders/companies. It is important to note that this study does not claim to offer a proxy for market integrity.

3. Recommended market quality proxies and sources

This section recommends market quality proxies for use in secondary market data analysis within the UK ETS evaluation, drawing on the findings from sections 1 and 2 of this literature review.

3.1 Price discovery and informational efficiency

Recommended market proxies for price discovery and informational efficiency are shown in Table 1 below.

Table 1: Recommended market proxies for price discovery and informational efficiency

No	Market quality proxy	Notes and recommended guide(s)/source(s) for computation
1.	Efficient and noise components of price based on Hasbrouck (1993) vector autoregression (VAR) model	The microstructure VAR as advanced by Joel Hasbrouck over a number of papers (see as an example, Hasbrouck, 1993) is a well-established estimation approach for decomposing price (changes/volatility) into its efficient (public and private information-driven) and so-called noise components (not driven by information). It can be estimated for defined periods in a time series as is the case in Medina et al. (2014) who estimated this for each quarter of Phase I and Phase II (up to 2010) of the EU-ETS. They estimate the noise component; hence, when the component trends higher, the price discovery process in the market is deemed to be less efficient. See Medina et al. (2014) for a detailed motivation of the modelling framework.

2.	Signal to signal plus noise ratio estimated from unbiasedness regressions	As already discussed, 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 (efficient price change). Specifically, it is described as a ratio of signal (meaning information that leads to an enduring price change) to signal + noise (meaning a price change that reverses quickly). Ibikunle et al. (2013) outlines the process for computing this ratio in the ETS context.
3.	$\overline{R^2}$ (Coefficient of determination) estimated from predictive regressions	When prices are efficient, we should expect their evolution to be random; hence, they should not be predictable using other market variables, such as trading activity. This approach is based on this idea. It estimates the extent to which lagged order imbalance (between buy and sell orders/transactions) predicts short horizon returns. Ibikunle et al. (2016) defines short-horizon as 15-minutes based on Phase II trading activity level in EUA derivatives, a shorter horizon may be necessary for more recent data, depending on trading activity levels in UK-ETS secondary platform(s).
4.	Price volatility in time series: standard deviation of intraday returns	The variability of returns over a given window has often been used as a measure of excess volatility and an indicator of market quality. The idea is that information relevant to the pricing of an instrument is not typically routinely released over very short intervals across a trading day; hence, significant variations in its price is seen as an indicator reduced informational efficiency. This is what is estimating the standard deviation of short horizon returns over the course of a longer interval is

		expected to capture. Both Frino et al. (2010) and Ibikunle et al. (2013) employ the standard deviation of intraday returns as a measure of volatility.

3.2 Liquidity

Recommended market proxies for price discovery and informational efficiency are shown in Table 2 below.

Table 2: Recommended market proxies for liquidity

No	Market quality proxy	Notes and recommended guides/sources for computation
1.	Spread estimates from quotes and transactions: • Effective spread • Relative quoted spread • Realised spread • Relative traded spread	As explained in section 2 above, liquidity proxies based on the bid-ask spread are the most commonplace measures of liquidity in the market microstructure literature. They intuitively capture the probability that an economic agent will be able to execute a regular-sized order quickly and with little or no price impact. Frino et al. (2010) and Goyenko et al. (2009) outline how these measures can be estimated. Ibikunle et al. (2016) also provide a guide for estimating the measures using transaction prices in the absence of quotes data. Time-weighted daily averages of relative quoted spreads are usually computed, while the others are typically computed as currency weighted daily averages for each trade.
2.	Low frequency liquidity measure:	As explained in section 2, a key limitation of the standard spread metrics is that they only approximate the round-trip transaction costs for regular-sized orders, such sizes

	Amihud (2002) price impact ratio	are dependent on the level of trading activity pricing in an instrument. Although this would naturally be a concern for traders executing block volumes rather than for a regulator or a policymaker, for robustness, estimating alternative low frequency proxies are recommended. The Amihud (2002) price impact ratio is a well-established liquidity measure that will prove useful in this regard. Chang et al. (2018a), Chang et al. (2018b) and Ibikunle et al. (2016) all offer useful guides for computing the measure in the ETS context.

3.3 Market integrity

As stated in section 2, we have been unable to identify a proxy for market integrity in the ETS literature. In section 1, the difficulty of objectively measuring this market quality aspect is also discussed. It may, however, be helpful to consult Hintermann (2017), which is cited in section 2, for some contextual guidance on how excess emission allowances might provide some indication of price speculation and market manipulation.

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This publication is available from: www.gov.uk/government/publications/evaluation-of-the-uk-emissions-trading-scheme-phase-1