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The Case of Fleeting Orders and Flickering Quotes

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ABSTRACT

The literature controversially discusses the ambiguous motives and driving forces behind quickly cancelled limit orders (fleeting orders), which are characteristic of high-frequency markets. In particular, manipulative and dysfunctional characteristics are feared. We analyze top-of-book fleeting orders—so-called flickering quotes—and show with an ultra-low latency derivative data set that none of these properties have to be dreaded. On the contrary, flickering quotes are associated with liquid market environments, for example: the prices of "flickering" order books improve by 3.90% before trades. The results reveal that flickering quotes are likely due to beneficial price discovery processes. Additionally, HFTs might offer their excess positions at a discount to other participants with these orders.

JEL Classification: G10, G13, G14, G18, G19

1 | Introduction

A distinctive feature of high-frequency markets is the rapid submission and cancellation of orders, often referred to as "fleeting orders" (Hasbrouck and Saar 2009) or "flickering quotes" (Baruch and Glosten 2013). While regulators have attempted to address this with restrictions on order-to-trade ratios, the underlying strategies and motives remain unclear. Our research aims to investigate the behavior and impact of fleeting orders, specifically flickering quotes, in high-frequency trading (HFT) within the equity options market.

Since the rise of HFT in 2005, spurred by the Regulation National Market System (Reg NMS), extensive research has explored the effects of faster trading on markets, market quality, social welfare, and associated risks. The consensus in both theoretical (Foucault et al. 2013) and empirical studies is that HFT generally enhances market liquidity, price efficiency, informativeness, and reduces trading costs under normal conditions (Hendershott et al. 2011; Hendershott and Riordan 2013; Carrion 2013; Brogaard et al. 2014; Hagströmer and Nordén 2013; Brogaard et al. 2015; Conrad et al. 2015; Malinova et al. 2012; Brogaard and Garriott 2019; van Kervel and Menkveld 2019). However, some theoretical models suggest potential drawbacks, such as harm to liquidity provision (Menkveld and Zoican 2017; Budish et al. 2015). Empirical studies indicate additional risks, including error propagation and excessive market comovement due to increased interconnectivity (Chaboud et al. 2014; Gerig 2012; Malceniece et al. 2019), and potential market dysfunction during certain conditions (Kirilenko et al. 2017; Madhavan 2012; Jarrow and Protter 2012; Ait-Sahalia and Saglam 2024; Egginton et al. 2016). Therefore, investigating the impact of fleeting orders adds to this strand of literature.

This article uses the term "fleeting orders" for the submission and immediate cancellation of orders across the entire order book, whereas "flickering quotes" specifically refers to rapid changes at the top-of-book prices without intervening trades. Consequently, a flickering quote is results in a flip-flopping movement between the old, the new (submission), and the old (after cancellation) best offer, seen as a "flicker."

One of the earliest empirical studies mentioning fleeting orders is Hasbrouck and Saar (2002), which analyzed 1999 stock data from the Island ECN, an early computerized marketplace. The study found that 27.7% of all visible limit orders were canceled within 2 s, mostly at prices within the pre-existing spread. Later studies, including (Roseman 2015), adopted the 2 s benchmark. With updated INET data (formerly Island ECN) from October 2004, Hasbrouck and Saar (2009) found that approximately one-third of limit orders were canceled within 2 s and 11.5% within 0.1 s, highlighting that fleeting orders are a recent phenomenon. This 2 s criterion was dropped for ultra-low latency data, as Hasbrouck and Saar (2013) presented TotalView-ITCH order book data from 2007 to 2008 showing flickering within milliseconds. These findings have been corroborated across various exchanges and locations, including Australia, Germany, the Taiwan futures market, and the EUR/USD FX market (Groth 2009; Chakrabarty and Tyurin 2011; Viljoen et al. 2015; Mandes 2016; Kuo and Lin 2018; Lin et al. 2018).

Hasbrouck (2018) addresses quote volatility in a more recent study, noting that traditional static market microstructure models fail to explain oscillating quotes at the sub-second level, as key determinants like interest rates and informed trade probability do not fluctuate that quickly.

Our research builds on Hasbrouck and Saar (2009) by expanding the hypotheses and incorporating insights from various publications and expert discussions, alongside additional analytical methods. While Hasbrouck and Saar (2009) uses a NASDAQ sub-sample from October 2004, we extend this research by utilizing derivative data, introducing a new segment for analysis.

Derivative data, particularly options, enable a detailed examination of the price discovery channel, leveraging the impact of information from different markets, both within options and the underlying assets. To date, options have not been utilized to investigate fleeting orders, despite their contribution of up to a quarter of all new information (Patel et al. 2020). This gap in research persists despite substantial evidence indicating the significant role options play in the dissemination of market information (Easley et al. 1998; Chakravarty et al. 2004). The underutilization of options in this context represents a missed opportunity for a deeper understanding of the dynamics of flickering quotes. We utilize high-frequency tick-by-tick data of equity options on German blue chips from January to February 2012 to analyze the price discovery channel and the relationship between underlying assets and derivatives in the context of flickering quotes.

Our findings suggest that approximately 20% of order book changes are due to top-of-the-book flickering quotes, which exhibit cyclical and highly automated behavior. This behavior varies significantly pre- and post-trade within the same option series and similar options. We find that flickering quotes enhance prices for liquidity-demanding traders and are likely used to incorporate new information (Menkveld 2016; Blocher et al. 2018; Li 2018; Bhattacharya and Saar 2020) and by HFTs to manage inventory (Hasbrouck and Saar 2002; Carrion 2013). Importantly, we find no evidence of illegal activities or negative impacts on market quality.

Our contributions to the field are manifold. Firstly, we extend existing literature by analyzing ultra-low latency derivative option data, offering a more comprehensive examination of fleeting orders and flickering quotes in a new asset class. Secondly, we provide strong evidence that flickering quotes are instrumental in price discovery, indicating their role in incorporating new information into market prices, thus enhancing market efficiency. Furthermore, our research rigorously tests and rejects several prevailing hypotheses regarding the drivers of fleeting orders and flickering quotes, including those suggesting these orders are primarily manipulative. Finally, we challenge the perception that HFT practices involving fleeting orders harm market quality, instead positing that these practices may enhance market efficiency in liquid markets. These contributions provide a nuanced understanding of flickering quotes, challenging established views and offering new insights into their role in modern financial markets.

2 | Hypotheses About the Fleeting Orders

In this section, we develop our hypotheses and discuss empirical approaches. The first three hypotheses address liquidity supply (market making). Subsequently, we present hypotheses related to liquidity demand (active trading), technical factors, and manipulative behaviors.

Hasbrouck and Saar (2009) formulate the chasing hypothesis, which describes the reaction of limit orders to market movements. When a limit order falls behind the current best offer, it is canceled and resubmitted to regain price priority.

Similarly, Liu (2009) presents a trading model involving a patient buyer, a news trader, and a liquidity trader. The model allows the buyer and seller to withdraw their orders to avoid being picked off by unfavorable news, leading to several hypotheses regarding order cancellations. These include the free option risk, where good (bad) news increases (decreases) the asset's value, which is equivalent to a free call (put) option. This free call (put) leads to limit sell cancellations to avoid being picked off. Additionally, the non-execution risk suggests that an increase in the free call (put) value leads to more limit buy cancellations to regain price priority. The model also predicts more cancellations with narrower spreads and higher-valued firms.

Fong and Liu (2010) empirically examine limit order revisions, identifying non-execution and free option risks as major reasons for cancellations, consistent with Hasbrouck's chasing hypothesis. Providers facing the free option risk will reduce price priority, with revisions related to monitoring costs. Liu (2009) also deduces that actively traded stocks and larger firms have more cancellations, while wider spreads result in fewer cancellations. The The CFTC (2001) notes that flickering quotes are "real quotes that are subject to immediate acceptance," which reduces market maker risks. Easley et al. (2012) describe a tactical liquidity provision algorithm where cancellations occur if the probability of adverse selection increases. Dahlström et al. (2024) show that short-lived limit orders are often explained by market makers' expected profit at execution.

Market participants, especially market makers, are generally risk-averse (Pratt 1964). This aversion leads to higher spreads and lower liquidity (O'Hara and Oldfield 1986; Subrahmanyam 1991), particularly in competitive markets (Dennert 1993). A decline in liquidity may result in more fleeting orders, as risk-averse market makers might cancel orders if no other quotes are near their limit order or use cancellations to protect against arbitrage strategies. This strategy, developed in consultation with market makers, introduces uncertainty into prices.

In summary, market makers constantly face the risk of their quotes being picked off by informed or faster traders. To mitigate this risk while maintaining their role as liquidity suppliers, they may quickly submit and cancel orders, leading to the following hypothesis:

Hypothesis 1 H1. *Liquidity suppliers use fleeting orders, and especially flickering quotes, to minimize the risk they face.*

The theoretical model of Roşu (2009) describes continuous trading with patient limit traders and impatient traders on opposite sides of the order book, where limit traders undercut each other until an equilibrium is reached. Building on this, Bhattacharya and Saar (2020) developed a model of a dynamic limit order market under asymmetric information, which leads to cancellations and resubmissions based on updated information.

In his meta-study on HFT, Menkveld (2016) extrapolates from the classical (Glosten and Milgrom 1985) model, predicting more quote updates and price discovery through quote updates in a high-frequency context. Blocher et al. (2018) identify cancellation clusters using an exponentially weighted moving average, interpreting these clusters as evidence of HFTs improving price discovery and processing information. When cancellation clusters clear a price level in the order book, the level is often refilled or the opposite side narrows the spread, indicating a true price change. Cartea and Penalva (2012) hypothesize that HFTs adapt their offers after a marketable order hits a limit order, leading to cancellations. Li (2018) finds no adverse effect of fleeting orders on liquidity measures, suggesting that fleeting orders, used mainly for market-making strategies, are beneficial for market quality. In a previous version of their paper (Baruch and Glosten 2019) also discuss flickering quotes in their repeated stage model, where liquidity suppliers randomly revise their limit orders to avoid undercutting, potentially leading to flickering quotes.

Fleeting orders may also be driven by other markets, as HFT leads to synchronized prices (Gerig 2012), which is particularly relevant for options that depend heavily on underlying prices.

In this context, derivative data is of considerable value, given that the options market is a significant contributor to the generation of new information (Easley et al. 1998; Chakravarty et al. 2004; Patel et al. 2020). Consequently, it serves as a crucial source of novel insights and plays a pivotal role in the process of price discovery.

In summary, market maker cancellations may result from market movements and new information, encompassing price discovery through quote updates, synchronization with different markets, clearing levels, immediate refilling, and adapting offers after a marketable order. This leads to the following hypothesis:

Hypothesis 2 H2. *Fleeting orders, and especially flickering quotes, are used for price discovery.*

Especially overnight, HFTs aim to minimize or eliminate their inventory (Carrion 2013). They may use fleeting orders to offer unwanted positions at a discount, allowing them to still earn a reduced spread compared to marketable orders. This strategy is employed in calm markets with predictable risks to further reduce adverse selection risk. HFTs leverage their speed advantage to gain profits, and holding positions increases their risks. Therefore, we hypothesize:

Hypothesis 3 H3. *HFTs use fleeting orders, and especially flickering quotes, to unwind their inventory.*

Roşu (2009) presents a dynamic model of continuous trading in an order book without a minimum tick size, where traders can freely modify and cancel their limit orders. He posits that in a competitive order book market, when the order book becomes full, a limit order on one side will be immediately accepted by a limit trader on the other side, resulting in a fleeting order. Correspondingly, Hasbrouck and Saar (2009) describe a dynamic strategy where traders replace limit orders with marketable orders as the cost of immediacy decreases. For example, a participant wanting to buy an option might cancel a buy limit order if the price of a sell limit order drops, resulting in a fleeting order, and then use a marketable order to buy the option. Also Kuo and Lin (2018) show that non-execution risk contributes to order cancellations. Hoffmann (2014) adds that slow traders, to avoid exploitation by fast HFTs, submit limit orders with lower execution probability, either by price or short-lived offers, resulting in fleeting orders. Baruch and Glosten (2013) support this by arguing that limit-order traders worried about being undercut use short-lived orders at random prices to hide their quotes. Therefore, we analyze the following hypothesis:

Hypothesis 4 H4. *Fleeting orders, and especially flickering quotes, are caused by liquidity demanding agents (traders).*

Hasbrouck and Saar (2009) emphasize that fleeting orders, driven by technological advancements in automated trading and low latency, are a recent phenomenon. According to Hasbrouck and Saar (2013), low-latency activities involve algorithms responding to each other, with submission, cancellation, and resubmission patterns reflecting attempts to trigger actions by other algorithms or to strategically position limit orders. Cartea and Penalva (2012) add that HFTs constantly adjust their bids and offers in relation to other HFTs, leading to rapid renewals of limit orders. Thus, we propose the following hypothesis:

Hypothesis 5 H5. *HFTs cause fleeting orders, and especially flickering quotes, when reacting to other algorithmic traders.*

Finally, fleeting orders can be used for "spoofing," a manipulative tactic where traders place visible orders opposite to their true intentions to create a false impression of supply or demand, thereby influencing prices before canceling the deceptive orders. Although this strategy might seem attractive, Hasbrouck and Saar (2002) doubt that the sheer volume of canceled limit orders can be attributed to spoofing due to the high risk of SEC detection and prosecution. Another related practice is quote stuffing, which involves overloading exchange bandwidth (Cartea and Jaimungal 2013).

A further potential manipulation involves influencing volatility indexes, such as the CBOE volatility index, as highlighted by The Wall Street Journal (29.09.2018). Traders may use limit orders to affect options prices and manipulate the volatility index without actual trades, exploiting the STOXX 50 volatility index (VSTOXX), which is based on mid prices. Our unique option dataset allows us to examine this manipulative tactic on the VSTOXX, leading to the following hypothesis:

Hypothesis 6 H6. *Fleeting orders, and especially flickering quotes, are caused by manipulative strategies.*

3 | Data

We investigate fleeting orders and flickering quotes using a novel high-frequency message-level option data set. This option data, previously unused for such analysis, offers new insights into the price discovery hypothesis. Our analysis uses quote data from EUREX, covering order books of over 15,000 American option series of 30 DAX-member German blue chips as of 2012. The data spans 43 trading days from January to February 2012. We have microsecond-level data on the first three bid and ask order book levels, including price, volume, and number of contributors. The sample includes submissions, cancellations, and trades. We obtain the option (Option Data EUROFIDAI 2017) and corresponding underlying data (Underlying Data EUROFIDAI 2017) from Deutsche Börse via EUROFIDAI, provided by the BEDOFIH database. EUREX offers two order types for options: limit and marketable orders.

We define a flickering quote as a limit quote that improves the price and is subsequently canceled without time restrictions. Lacking trader IDs, we use flickering quotes as a subset of fleeting orders. A flickering quote has no other equal or better offer on the same side between introduction and cancellation. We exclude limit offer adjustments coinciding with movements on the opposite order book side without a change in the absolute bid-ask spread, as these are simple price updates. An example of an order book dominated by flickering quotes is shown in Figure 1.

Some options, like very deeply out-of-the-money or long-expiration options, are very illiquid. We truncate our data set to include only order books that change on average at least once a minute (510 changes from 9 a.m. to 5:30 p.m.). This excludes about half of all options but less than one percent of all order book changes (see Table 1). The average order book changes for all options are 4724, well above this threshold, allowing us to analyze less liquid stocks alongside very liquid instruments.

3.1 | Preliminary Analysis

To better understand flickering quotes, we present distinct behaviors in the data. Order timing is rhythmic, with submissions peaking at the start of new seconds. Figure 2 shows a histogram of order book changes' timestamps, revealing peaks at 3, 14, and 27 ms, and smaller peaks every tenth of a second. A similar pattern is observed for all orderbook changes, but not for trades, indicating some detachment from trading activity. Furthermore, there are smaller peaks every tenth of a second, with the most distinct at 0.1 s and half a second after the start of the second. Bigger time scales like 1 min remainders only show a second-pattern, without a bigger peak at every minute start. Smaller time scales do not reveal any particular pattern.

The flickering quotes behave very similarly to the general order book changes regarding further measures. Figure 3 shows the number of changes for all options in five moneyness categories, revealing an inverted *U*-shape for order book changes, flickering quotes, and cancellations, independent of trade numbers. The relative number of flickering quotes forms a U-shape, suggesting that deep-in and deep-out-of-the-money options are less active and less liquid, confirming the fact that options are most liquid at-the-money (Etling and Miller 2000). We also analyze clusters based on option prices, trading volumes, underlying prices, market capitalizations, daily returns, and weekly patterns for both puts and calls. Generally, the number of order book changes and flickering quotes are similar and not closely related to trading volume.

Further analysis confirms the similarity between flickering quotes and order book changes. Figure 4 shows the log10 time between top-of-book changes with and without

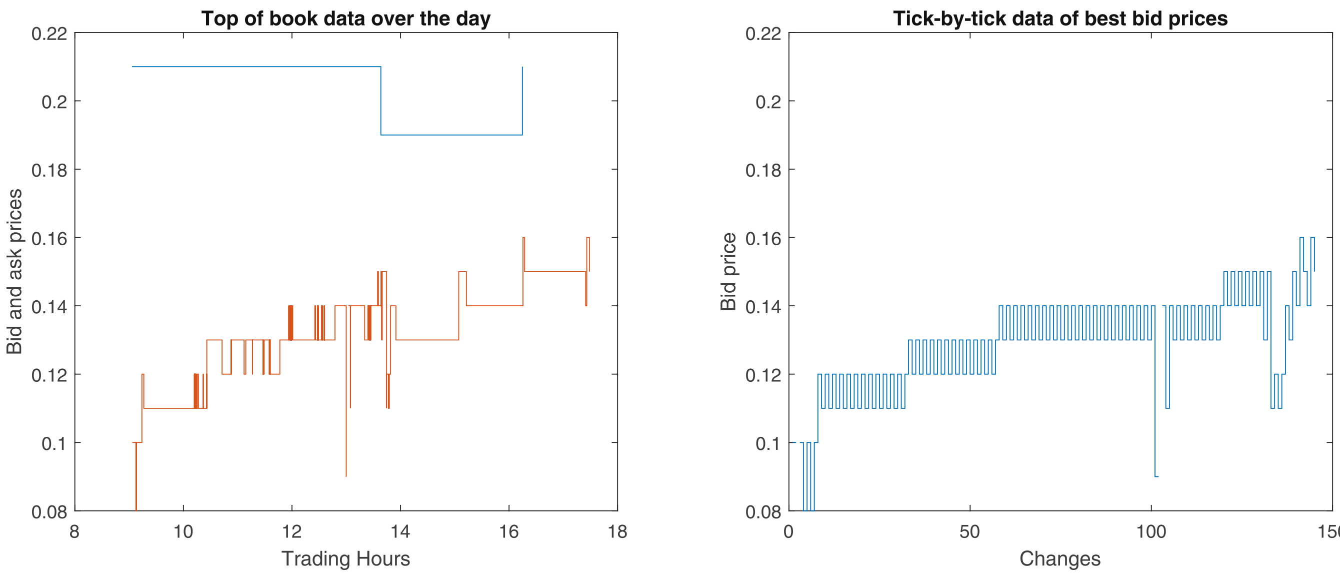

FIGURE 1 | Flickering quote dominated top-of-book prices. The example shows order book data from January 02, 2012 of a call option on BMW AG with expiration on June 15, 2012 and a strike price of 78 EUR. The underlying closing price on January, 02/2012 was around 53.16 EUR. The left side shows the top-of-book prices in clock-time, the right side the best bid price in tick-time (equidistant between ticks), to show the clustered flickering quotes.

TABLE 1 | Descriptive statistics: Full sample versus truncated sample.

	Options	Order book changes	Flickering quotes	Cancellations	Trades
Full sample	15,374	72,628,892	7,041,901	30,926,187	4430
Truncated	7505	72,325,321	7,002,537	30,708,548	4323
Truncated share	51.18%	0.42%	0.56%	0.70%	2.42%

Note: Daily average numbers comparing the full and truncated sample. Illiquid options (51.18% of all options) are sorted out, which only marginally affects the total order book changes (less than 1% of order book changes are truncated). One flickering quote consists of two order book changes (submission and cancellation); therefore, around 20% of all order book changes as well as cancellations can be attributed directly to the (top-of-book) flickering quotes.

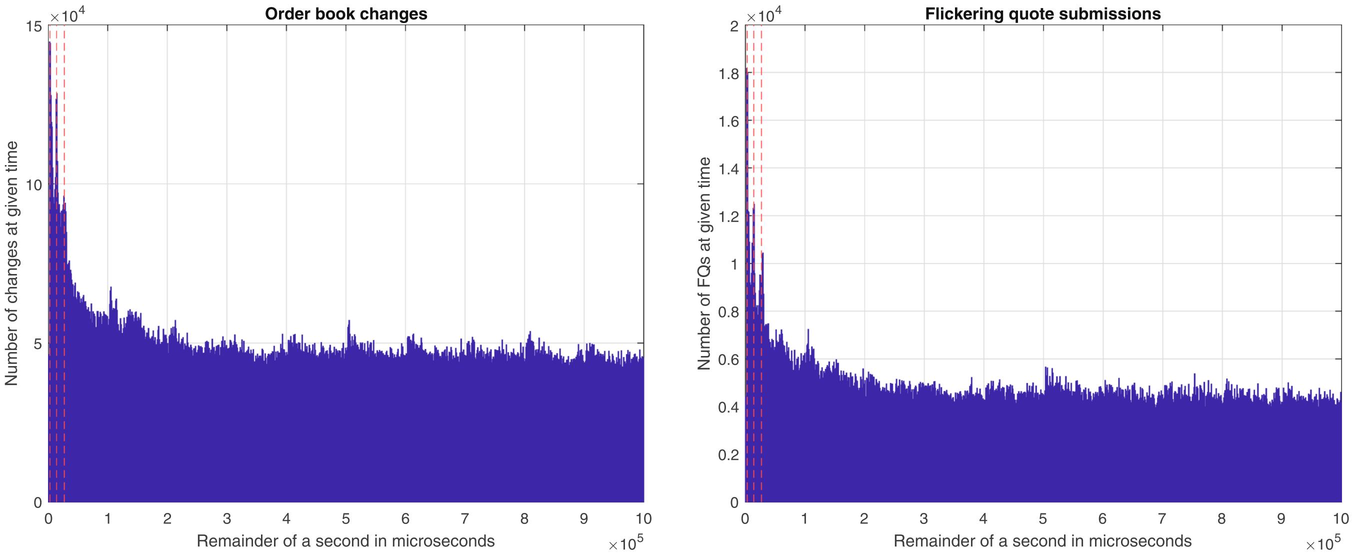

FIGURE 2 | Histogram of order book changes and flickering quotes over the remainder of a second. Histogram of one-second remainders of all timestamps of the order book changes (left) and flickering quote submissions (left), calculated as mod 1.000.000 over the timestamps in microseconds (clock-time). The first three vertical dotted lines are at the peaks 3, 14, and 27 ms.

flickering quotes and the time between submission and cancellation of flickering quotes, clustered by daytime. Peaks at around 20 ms, 30 ms, 1 s, and 15 s are consistent, with the last peak driven by flickering quotes during central trading hours. Some peaks can be linked to remote exchanges, with latency estimates for Frankfurt to various exchange locations around the world. For reference: the equivalent distance from Frankfurt to London, Paris, and Amsterdam is around 3.3 to 4.6 ms, to New York around 40 ms [1](CFTC 2014), and around 150 ms to the Asian markets (China Telecom 2018).

Latency is reported as one-way travel time, not round trip delay, with internal system latencies potentially adding a few milliseconds. We estimate co-location latency at around three milliseconds.

4 | Analysis of Flickering Quotes

For this chapter, to ascertain the impact on market quality we firstly use a bivariate analysis that focuses on the connection between flickering quotes and trades. Secondly, we deal with the causes of flickering quotes. Hereby, we use a regression analysis as in van Ness et al. (2015), whereby we are able to construct observations every minute, not just monthly (van Ness et al. 2015) or daily (Lin et al. 2018), and logistic as well as Cox regressions, as presented by Hasbrouck and Saar (2013), to make use of our tick-by-tick data.

4.1 | Bivariate Statistics: Pre and Post Trades

A primary concern about flickering quotes is their influence on market quality, for example, by initiating harmful trades or luring traders and algos into unfavorable trades. As a first step, we report a bivariate analysis of the behavior of flickering quotes before and after trades. Table 2 reports the number of order book changes, the number of flickering quotes, and the share of flickering quotes in the whole order book 5 min before and after trades. We define the flickering quote share as the ratio of the number of flickering quotes to the total number of order book changes within the specified timespan. Thereby, we truncate our sample to the trading hours from 10:00 a.m. until 04:00 p.m. (as the opening and closing sessions might work differently, following (Fong and Liu 2010)) and exclude all trades whose 5 min window overlap. However, even without truncating the sample, the results prevail. We observe that the numbers of flickering quotes spike after a trade. Especially on the trade-side we see a highly significant increase by about a quarter, from 5.99 flickering quotes in the 5 min leading to the trades to 7.46 flickering quotes post-trade. However, the share of flickering quotes within the order book, calculated as the number of

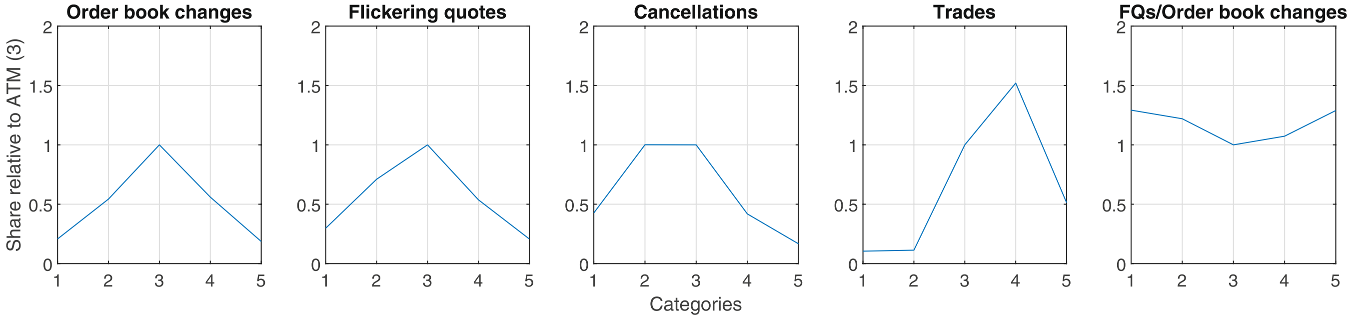

FIGURE 3 | Relative comparison of flickering quotes and other measures over moneyness. The plots show different measures over five moneyness categories. Category three (at-the-money) is the baseline, therefore always one. All other measures are relative to this category (e.g., the number of order book changes in category two are only 54% of the number of order book changes from the base at-the-money category). The inverted *U*-shape is prominent for all subplots, except for the far-right plot. This subplot gives the relative share of flickering quotes to all order book changes over the moneyness and has a slight *U*-shape, indicating relative to all order book changes more flickering quotes for deep-in- and deep-out-of-the money options.

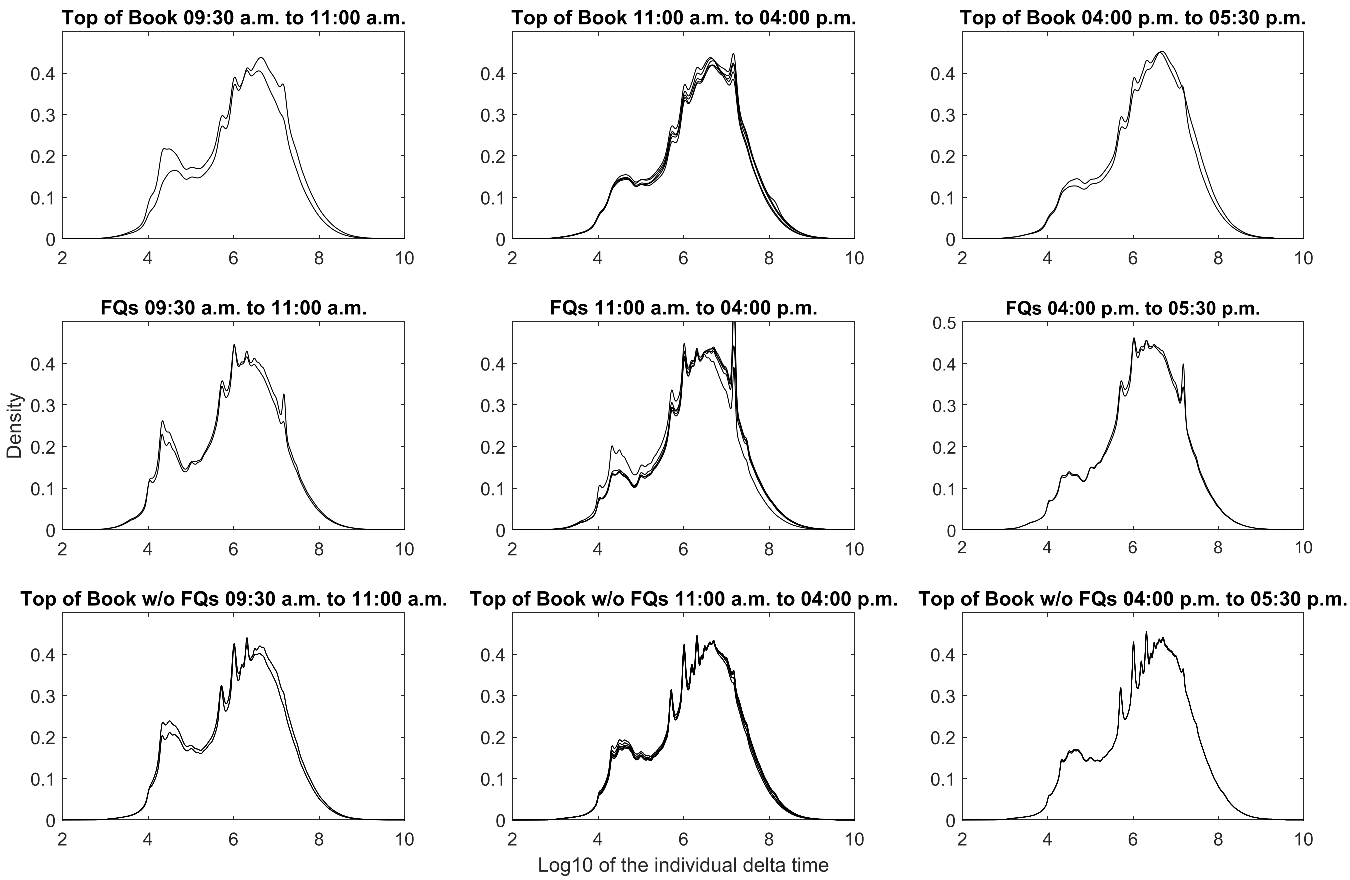

FIGURE 4 | Density plot of time between order book changes. Shown are the density plots of log10 delta times in microseconds. For the top-row, the delta times are the time between any top-of-book change on one order book side, for the mid-row, the time between submission and cancellation of a flickering quote (FQ), and for the bottom-row the time between the top-of-book changes on one order book side truncated by the orders encompassing flickering quotes (FQ). Peaks are especially visible at 20 to 30 ms, 1 s and 15 s. The morning and afternoon trading hours show similar patterns (left and right), whereas the main trading hours for flickering quotes differ slightly, due to the prominent 15 s peak. The densities are calculated separately for every day in our sample, which results in 43 individual lines in every subplot; however, as the densities are often very similar, only a few distinct lines are observable.

flickering quotes within 5 min times two divided by all top-of-book changes, declines significantly on the trade-side, while the non-trade-side is nearly unaffected. As one flickering quote consists of one order submission and one order deletion, a single flickering quote is accountable for two order book changes. Therefore, we include a factor of two for the share calculation. The majority of the top-of-book changes can be attributed to flickering quotes. While the number of flickering quotes on the trade- and non-trade-side are statistically different before the trade, they are statistically

TABLE 2 | Bivariate statistics of flickering quotes before and after trades.

	Flickering quotes			Flickering quote share		
	pre	**post**	**sig.**	**pre**	**post**	**sig.**
All	12.59	14.81	***	77.17%	68.72%	***
Trade-side	5.99	7.46	***	81.24%	64.45%	***
Non-trade-side	6.60	7.35	***	67.70%	66.49%	***

Note: The table compares the average sum of flickering quote submissions within a 5 min window before and after a trade on the left side. Additionally, we compute the flickering quote share as the total number of flickering quotes divided by the total number of top-of-book changes within the same 5 min window multiplied by two. The multiplication is done purely to show which share of all top-of-book changes can be attributed to flickering quotes, as one flickering quote results in two changes (submission and cancellation), and does not affect the significance. We exclude all trades that directly follow one another within a 1 min window. To gain further insights, in addition to the total number (top row), we calculate the results for the trade-side and non-trade-side separately. *** indicate a 1% significance of the null hypothesis, that the pre and post cases have the same mean and standard deviation.

TABLE 3 | Bivariate statistics of spread before and after trades.

	pre	**post**	**sig.**
Tick weighted	1.23%	1.38%	***
Time weighted	1.40%	1.51%	***

Note: The table compares the average relative spread within a 5 min window before and after a trade. Each spread is either calculated tick-weighted (top), or time weighted with an exclusion of any flickering quote related offer (bottom). Each relative spread is calculated as the absolute spread divided by the mid price. *** indicate a 1% significance of the null hypothesis, that the pre and post cases have the same mean and standard deviation.

indifferent afterward. Key takeaways from this are that new information is processed after a trade, leading to a clear peak in order book movements. However, the interesting part is that before the trade happens, the trade-side order book is "dried out" mainly on the trade-side leading to a high share of flickering quotes. As the number of flickering quotes pre-trade is less than post-trade, the spike in flickering quote share can be attributed to less general order book movement and not to an increase on the absolute amount of flickering quotes. This is a contradictory finding to the hypotheses of flickering quotes as a tool of active trading (H4), as we would expect less order activity from all these hypotheses after a trade happened. This can also lead to the assumption that the strategies behind flickering quotes do not lure participants into trades (H6, e.g., spoofing) but trades happen when we experience a quiet order book with small spreads (see Table 3), whereas the driving forces behind flickering quotes are not affected very much. The relative spread is calculated as the ratio of the absolute spread (the difference between the ask and bid prices) to the mid-price (the average of the ask and bid prices). We report the weighted relative spread for the 5 min intervals preceding and following trades. The spread is weighted either by the duration of time or by each tick when changes occur within the specified time span. Additionally, we compute the spreads with the exclusion of 1 min surrounding the trades (meaning from 5 to 1 min before the trade for the before-case and analogously for the post case). As the results do not differ substantially, we forgo to report them separately. Note that the reported average shares can not be calculated from the average flickering quotes and order book changes, nor can conclusions be drawn between the shares on the trade- and non-trade-side to the overall share (e.g., the overall flickering quote share after the trade is higher than any individual share on the trade-side and non-trade-side), as $\left(\sum^n FQ/n\right)/\left(\sum^n OrderBook/n\right) \neq \sum^n (FQ/OrderBook)/n$.

Most interestingly when comparing the instances before and after trades, these changes in flickering quote numbers are not only visible in the respective option series, in which the trade happened, but also in other closely related option series. Table 4 reports the impact of trades on the option series with the same characteristics but inverts puts to calls (left side), and series which have the nearest maturity date and otherwise the same characteristics (right side). In every case, the number of flickering quotes increases significantly post-trade, too. This indicates a connection to H2, as price discovery would involve not only one security but incorporate a broader set of instruments. This goes hand in hand with an increase in flickering quotes after a trade to adjust and find a true price with the new information due to the trade, resulting in more flickering quotes during the adjustment process.

The results are robust if we abandon the restrictions regarding trading hours and overlapping trades, as well as review additional time frames of one, three, or 10 min.

To analyze further if this clear difference in flickering quotes before and after trades negatively influences other participants, we review the instance that leads to a trade: if the trades happen at a favorable price (e.g., potential flickering quote submitted) or if the prices recently dropped (e.g., flickering quote canceled). Furthermore, the non-trade side might also influence the trades, which is why we also incorporate it. Of interest is the change in the best price leading to the trade. We define this measure referring to Hasbrouck and Saar (2009) as $p_i^{Bid} = \left(Price_t^{Bid} - Price_{t-1}^{Bid}\right)/Price_{t-1}^{Bid}$, where t is the instance before trade i and $t-1$ is the quote before t. A positive value of p is equivalent to a smaller spread. If flickering quotes can be attributed to an exploiting strategy, we would expect to see negative p-values on the trade side. The change on the ask-side p^{Ask} is defined analogously as $p_i^{Ask} = \left(-Price_t^{Ask} + Price_{t-1}^{Ask}\right)/Price_{t-1}^{Ask}$, which also results in a narrower spread for positive p's. Shown in Table 5 are the 0.25, 0.5, and 0.75 quantiles as well as the mean of the p's on the trade- and non-trade-side over all trades. The last column reports the significance for a mean greater zero. Throughout all specifications we have a significant positive p on the trade-side. This means that trades happen in general after a favorable price adjustment. Following this logic that traders wait for favorable price changes (on the trade side), we can try to distinguish automated from human trading. If we look at trades that happen right after an order book price change on the trade side (we choose 200 ms as cut off criteria which is even below the

TABLE 4 | Bivariate statistics of flickering quotes before and after trades with switched option series.

	Switched calls/puts			**Switched expiration**		
	pre	post	sig.	pre	post	sig.
All	23.01	24.32	***	12.41	13.10	***
Trade-side	11.65	12.34	***	6.25	6.44	***
Non-trade-side	11.36	11.98	***	6.16	6.65	***

Note: The table compares the average sum of flickering quote submissions within a 5 min window before and after a trade. Contrary to Table 2, we switch the option series. For any trade in the base series, we compute the sum of flickering quotes in the most related option series in two ways. On the right side, we summed the flickering quotes of the series with identical characteristics but swapped the payout profile from a call (put) base series to puts (calls). On the left side, we changed the expiration date from the base series to the nearest expiration relative to the base series. Besides the total number (top row), we calculate the results for the trade-side and non-trade-side separately. *** indicate a 1% significance of the null hypothesis, that the pre and post cases have the same mean and standard deviation.

TABLE 5 | Changes in spreads before trades.

	25% quantile	**50% quantile**	**75% quantile**	**mean**	**sig.**
I All					
Trade-side	0.28%	1.55%	4.00%	3.72%	***
Non-trade-side	−0.74%	0.33%	1.28%	0.40%	***
II Change on trade side < 200 ms					
Trade-side	0.51%	1.72%	4.09%	3.50%	***
Non-trade-side	−0.93%	0.25%	1.45%	0.29%	***
III Change on trade side < 200 ms & FQs on trade side					
Trade-side	0.52%	1.95%	4.62%	3.90%	***
Non-trade-side	−0.84%	0.21%	1.35%	−1.03%	
IV Change on trade side < 200 ms & FQs on trade side					
Trade-side	0.45%	1.45%	3.33%	2.63%	***
Non-trade-side	−0.52%	0.35%	1.32%	0.50%	***
V No change on trade side < 1 s & FQs on trade side					
Trade-side	0.44%	1.81%	3.80%	2.93%	***
Non-trade-side	−0.72%	0.42%	1.82%	0.50%	***
VI Change on non-trade side < 200 ms & No change on trade side 10 s & FQs on non-trade side					
Trade-side	−0.60%	0.32%	1.65%	1.21%	***
Non-trade-side	−0.18%	0.43%	1.32%	0.99%	***

Note: This table presents the changes in spreads before trades. Positive values indicate a narrowing of the spread before a trade, as the bid-side measure is calculated as $p_i^{Bid} = (Bid_t - Bid_{t-1})/Bid_{t-1}$, where t is the instance before trade i and $t-1$ is the quote before t. Analogously for the ask-side we compute $p_i^{Ask} = (-Ask_t + Ask_{t-1})/Ask_{t-1}$. The 25%-, 50%-, 75%-quantiles as well as the mean over all measures clustered in trade-side and non-trade side are given. Furthermore reported is the significance of the null hypothesis, that the mean is equal to zero. Hereby, *** indicate a 1% significance. To look into different aspects of potential flickering quote effects, we impose further criteria on the selected trades. Case **I** has no restriction. Case **II** demands a change on the trade-side within the last 200 ms. Case **III** demands a change on the trade-side within the last 200 ms and more than two flickering quotes on the trade-side within the last 10 s. Case **IV** demands a change on the trade-side within the last 200 ms and no flickering quotes on any side within the last 10 s. Case**V** demands a no change on the trade-side within the last second and more than two flickering quotes on the trade-side within the last 10 s. Case**VI** demands a change on the non-trade-side within the last 200 ms and no change on the trade side within the last 10 s, and more than two flickering quotes on the non-trade-side within the last 10 s.

reaction time of Formula 1 drivers), we can report a significant positive p on average. By incorporating flickering quotes (e.g., more than two on the trade side within 10 s) the average p rises further for the trade-side. The mean of the non-trade p is negative, probably because of outliers, as the median is positive. If we look for faster flickering (e.g., more than two flickering quotes within 500 ms on the trade-side), the p on the trade-side further rises with a mean of 8.06% (not shown in table). For trades without prevailing flickering quotes, p is smaller yet still significantly positive. Therefore, automated trades associated with flickering quotes are to the benefit of traders. Furthermore, all p's are significantly positive on average for order book changes within humanly accessible time frames (we chose 1 s based on a bill of indictment against human traders accused of spoofing (CFTC 2019)). Note that a submission cannot lead to a flickering quote if a trade happens, as the deletion criteria cannot be fulfilled anymore. Consequently, we find no sign that flickering quotes pose a danger for market quality, both within human and algorithm accessible time frames. Lastly, the non-trade-side behavior might also initiate an unfavorable trade. Spoofing is a primary example hereof. However, once again we are able to report a narrower spread movement right before the actual trade on both order book sides, with movement on the opposite trade side with preceding flickering quotes. All in all, with these results we find no support for any manipulative strategies (H6). Additionally, we review the relative spread, whereby the impact of trades is in general smaller if flickering quotes are present (not separately reported).

Apparently, flickering does not cause any disadvantages itself regarding trading, nor do we find any sign of manipulation in this regard based on our reviewed strategies. However, the share of flickering quotes rises drastically right before trades, as reported in Table 2. Therefore, next we want to analyze what factors drive this increased share.

4.2 | Regression: Flickering Quote Share

The formulated hypotheses suggest testable relationships between various options and underlying factors related to the share of flickering quotes. Consequently, we performed a multiple linear regression analysis on the flickering quote share. Calculating this share requires a specific time span, as tick-by-tick data are not directly usable. To utilize our data effectively and establish a sufficiently long time range for calculating meaningful shares, avoiding the predominance of zeros (e.g., no flickering quotes within the period), ones (order book changes consist solely of flickering quotes), or missing values (no change at all), we determined that a 1 min interval is suitable. The 1 min flickering quote share is calculated as the sum of all order submissions identified as flickering quotes within 1 min, divided by all top-of-book order book changes in the same period. This approach allows us to employ closely lagged variables, thus mitigating the endogeneity problem highlighted by van Ness et al. (2015) and obviating the need for a two-stage regression.

In the following paragraph, we introduce important determinants of the individual hypothesis. As our data does not allow identification of individual investors, we resort to operationalizations to capture the potential effects of our hypotheses, described in detail in the following. An overview of the factors used for the linear regression and the following analyses with corresponding hypotheses is given in the Appendix in Table A1.

In times of uncertainty (e.g., volatile prices), for market makers there is a very high risk in recovering costs or losses by buying low and selling high—especially when paired with a low bid-ask spread. Consequently, we would expect from volatility a positive influence and from the spread a negative influence on the flickering quote share if flickering quotes are a tool for market makers to reduce their risk (H1). To avoid potential endogenous problems, we use 1 min lagged data. We follow Hasbrouck and Saar (2009) and define $Vola_{t-1}^{Option}$ as the absolute return over—in our case—the preceding minute. $Spread_{t-1}^{Option}$ is the relative tick-weighted spread over the same time frame. Both measures are highly correlated with the non-lagged data. Furthermore, we would expect that market makers react to the state of the order book on different levels. If market makers can rely on deeper levels, their risk is smaller. A higher order book elasticity or slope, as proposed by Næs and Skjeltorp (2006) ($Slope_{t-1}$) should reduce the flickering quote share. Thereby, we use the last order book state before t and all three levels to calculate the slope, where $Slope = (Slope^{Ask} - Slope^{Bid})/2$ with $Slope^{Ask/Bid} = 1/3\left(\frac{Volume_{Level1}^{Ask/Bid}}{Price_{Level1}^{Ask/Bid} / Midquote - 1} + \sum_{\tau=2}^{3} \frac{Volume_{Level\tau}^{Ask/Bid} / Volume_{Level\tau-1}^{Ask/Bid} - 1}{Price_{Level\tau}^{Ask/Bid} / Price_{Level\tau-1}^{Ask/Bid} - 1}\right)$.

The usage of option data enables us to utilize the close connection with the underlying and to gain further insights. Thereby, the underlying volatility is important with regard to risks that market makers face. In uncertain times (e.g., high volatility, with the additional risk of fast arbitrage strategies), market makers could choose to pass the risk on by using blurring flickering quotes (H1). Furthermore, volatile times are also important for price discovery (H2). As prices need to be adjusted frequently and quickly, we would also expect a positive influence by the underlying volatility on the flickering quote share. To avoid potential endogeneity problems and achieve an uncoupling with regard to the option price volatility, we use an extended time frame of 10 min before t, over which we calculate the standard deviation of 1 min returns, expressed as $Vola_{t-10}^{Underlying}$ for the underlying volatility.

If the price discovery goes hand in hand with the underlying, we would expect a mirrored flickering quote share of the underlying (H2). Thereby, potentially out-of-money options might not be as prone to fleeting orders due to their lower option delta. We calculate the moneyness M as the strike price divided by the spot price (the instance before t) minus one (Dumas et al. 1998). Therefore, we further cluster not only for in- and out-of-money options but also for puts and calls (calls are in-the-money (out-of-the-money), if $M < 0$ ($M > 0$), and puts, if $M > 0$ ($M < 0$)). Thereby, the measure $|M|_{Call}^{InMoney}$ is the absolute of M as defined before, if the respective option is in-the-money and a call, and zero otherwise. All other indices ($OutMoney$, Put) act accordingly as dummies. The flickering quote share of the underlying itself ($\frac{FQ_t^{Underlying}}{OB_t^{Underlying}}$) is calculated in the same way as for the option. It measures a potential price discovery led by the underlying.

Prior trades should have a positive influence on HFTs wanting to unwind their inventory after a successful trade and offer their positions at a discount (H3). That is why we incorporate the number of successful trades in the preceding 10 min ($Trade_{t-10}$). Conversely, if active traders were successful in showing trading interest with fleeting orders and a trade occurred (H4), the share of flickering quotes should drop afterward. Additionally, we would expect slower traders, which are in general smaller traders, to reinforce odd lots. We refer to an odd lot if the submitted quantity is not a multiple of ten and compute the daily sum of odd lots relative to the number of daily trades per option as $OddLot_{daily}^{Option}$.

If flickering quotes are caused by algorithmic traders responding to each other (H4), flickering quote shares will be positively autocorrelated, which we test via the 1 min lagged flickering quote share $\frac{FQ_{t-1}}{OB_{t-1}}$. Lastly, if the manipulative tactic of influencing a volatility index (H6) holds, a sharp elevation of the flickering quote share for equities listed in a major volatility index, for example, the VSTOXX of the EURO STOXX 50 index, would occur. We test this with the $STOXX_{dummy}$, set equal to one if the underlying is listed in the EURO STOXX 50 index. Due to this dummy, we are not able to perform a firm-clustered fixed effects panel regression.

The final regression equation is given as

$$
\begin{aligned}
\frac{FQ_t}{OB_t} = \beta_0 &+ \beta_1 Vola_{t-1}^{Option} + \beta_2 Spread_{t-1}^{Option} + \beta_3 Slope_{t-1} \\
&+ \beta_4 Vola_{t-10}^{Underlying} + \beta_5 \frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \\
&\cdot |M|_{Call}^{InMoney} + \beta_6 \frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \\
&\cdot |M|_{Call}^{OutMoney} + \beta_7 \frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \\
&\cdot |M|_{Put}^{InMoney} + \beta_8 \frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \\
&\cdot |M|_{Put}^{OutMoney} + \beta_9 Trade_{t-10} + \beta_{10} OddLot_{daily}^{Option} \\
&+ \beta_{11} \frac{FQ_{t-1}}{OB_{t-1}} + \beta_{12} STOXX_{dummy} + \boldsymbol{\beta X} + \epsilon
\end{aligned} \tag{1}
$$

where $\boldsymbol{X}$ represents further control variables proposed by the literature that may have an influence on the cancellation rates, like stock price or relative tick-size, buyer-initiated trading volume (Chakrabarty and Tyurin 2011), capitalization (van Ness et al. 2015), bid-ask spread (Liu 2009), and price skewness (Hasbrouck 2018).

Corresponding to Hasbrouck and Saar (2009), we perform one regression for each of the 43 days individually and aggregate afterward because of the large size of the data sample. However, we report the median instead of the counts, as this analysis would require further clustering and the resulting big numbers cannot be easily compared. For further insights, we present the share of all highly significant estimates (p-value below 1%) greater than zero. This means that if an estimate is positive, this share should be around 100%, and around 0% if the estimates are negative. In our view, meaningful results should have a median p-value below 1% and a share of significant estimators in the same direction of at least 90%, and not more than 10%, respectively. In our approach we explicitly compute stock clustered standard errors (Petersen 2009) and implicitly day clustered errors. The residual plots of the regressions are not suspicious.

With regard to the regression results of Table 6, it is evident that the option volatility is highly significant and negative on each day, and likewise the spread is significantly positive for each day in our sample. This means that relatively more flickering quotes are associated with low volatility and wide spreads—in contrast to market maker risk minimization (H1). Here, the order book slope has no significant influence. The underlying volatility behaves precisely like the option volatility and has a negative influence on the flickering quote share, which is apparently even more distinctive. However, this can be attributed to the different calculation approaches. This finding is both inconsistent with the concept of liquidity suppliers reducing their risk with fleeting orders (H1) and the price discovery hypothesis (H2). Moreover, no penetration of the underlying fleeting order behavior can be observed. The deeper in the money the options are, the less the underlying flickering quotes positively or even negatively influence the flickering quote share of the option. For in-the-money call (put) options the median estimate is −2.65 (−1.52) and significant, while for out-of-the-money call (put) options, 13 (2) days result in a positive and 30 (41) days in a negative estimate—all significantly below the 1% threshold, resulting in 30.23% (4.65%) of significant estimates being negative. All this indicates no price discovery process (H2) driven by the underlying.

The positive estimate for preceding trades fits the scenario of unwinding inventories of HFTs (H3), but is contrary to liquidity demanders using flickering quotes (H4), even if not economically significant. Also, the estimate for the odd-lots dummy, indicating slower and presumably smaller traders, is not significant for our criteria and is also on average negative.

The lagged term has a negative impact on the current flickering quote share, which contradicts the hypothesis (H5) of algorithmic traders reacting to each other with fleeting orders. However, the 1 min time scale might be too long within a high-frequency context and will be revisited in the next subsection. Lastly, the volatility index dummy is inconclusive, as it is insignificant following our criteria and not economically relevant, revealing no such potential manipulative behavior of fleeting orders (H6).

The only significant result—not reported separately as it is only a control variable—is a negative dummy variable for calls with a median estimate of −0.01. This dummy is significant at the 1% threshold on 38 days. It indicates that call options have slightly smaller flickering quote shares.

At this point, we want to emphasize that some measures might influence the bid and ask sides differently. By running two regressions for the bid- and ask-sides separately, we find that a positive underlying return drives the flickering quote share on the bid side and dampens the share on the ask side for calls while the opposite is true for puts. The underlying return $r_t^{Underlying}$ is computed as the mid-price of the underlying at the end of the considered minute t, divided by the mid-price at the start of the minute minus one. The dummy D_{Call} (D_{Put}) is one for calls (puts) and zero otherwise. As no other results change considerably, Table 7 only reports the bespoken estimates. Furthermore, we tested other volatility estimate definitions, like high and low prices, without any notable differences. Additionally, we split the data set along the minute-by-minute order book changes in four different quantiles. The regressions are reported in the Table A2 without a change of the general results.

The regression analyses provide valuable insights and facilitate the investigation of several hypotheses. However, they do not fully exploit the potential of the tick-by-tick high-frequency dataset, as calculating the flickering quote share requires a defined timespan. Consequently, the logical next step is to employ specific analyses designed to address this limitation. By adopting a tick-by-tick approach, we can introduce new variables related to each individual submission or cancellation, potentially yielding further insights.

4.3 | Logistic Regression: Flickering Quotes

To investigate the behavior of flickering quotes with tick-by-tick data, we apply a logistic regression following (Hasbrouck and Saar 2009) closely. However, we expand their model to reflect our hypotheses, as we are only interested in the likelihood of an order characterized as a flickering quote. In more detail, we look at order submissions and analyze what leads to flagging

TABLE 6 | Regression on the flickering quote share.

	Estimate	p-value	sig $\beta > 0$	Hypothesis	Expectation
(Intercept)	3.49E-01	0.00%	100.00%		
$Vola_{t-1}^{Option}$	−5.07E-01	0.00%	0.00%	H1	+
$Spread_{t-1}^{Option}$	2.22E-01	0.00%	100.00%	H1	−
$Slope_{t-1}$	2.49E-06	99.99%	–	H1	−
$Vola_{t-10}^{Underlying}$	−1.68E+01	0.00%	0.00%	H1, H2	+
$\frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \cdot \lvert M \rvert_{Call}^{InMoney}$	−2.65E+00	0.00%	0.00%	H2	+
$\frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \cdot \lvert M \rvert_{Call}^{OutMoney}$	−2.38E-01	0.00%	30.23%	H2	o
$\frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \cdot \lvert M \rvert_{Put}^{InMoney}$	−1.52E+00	0.00%	4.65%	H2	+
$\frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \cdot \lvert M \rvert_{Put}^{OutMoney}$	6.38E-01	0.00%	86.05%	H2	o
$Trade_{t-10}$	1.04E-03	0.02%	88.37%	H3, H4	+ (H3), −(H4)
$OddLot_{daily}^{Option}$	−2.17E-03	8.03%	23.26%	H4	+
$\frac{FQ_{t-1}}{OB_{t-1}}$	−5.26E-02	0.00%	4.65%	H5	+
$STOXX_{dummy}$	3.12E-03	0.76%	74.42%	H6	+
Control variables	yes				

Note: The table reports the results for the regression on the minutely flickering quote share: $\frac{FQ_t}{OB_t} = \beta_0 + \beta_1 Vola_{t-1}^{Option} + \beta_2 Spread_{t-1}^{Option} + \beta_3 Slope_{t-1} + \beta_4 Vola_{t-10}^{Underlying} + \beta_5 \frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \cdot \lvert M \rvert_{Call}^{InMoney} + \beta_6 \frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \cdot \lvert M \rvert_{Call}^{OutMoney} + \beta_7 \frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \cdot \lvert M \rvert_{Put}^{InMoney} + \beta_8 \frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \cdot \lvert M \rvert_{Put}^{OutMoney} + \beta_9 Trade_{t-10} + \beta_{10} OddLot_{daily}^{Option} + \beta_{11} \frac{FQ_{t-1}}{OB_{t-1}} + \beta_{12} STOXX_{dummy} + \boldsymbol{\beta X} + \epsilon$where $\boldsymbol{X}$ are control variables, which we do not report for the sake of brevity. We estimate the regression separately for the 43 days in our sample due to the large sample, as we compute minutely flickering quote shares for every considered option. The reported estimates and p-values are calculated as the median over all individual regressions, to control for potential outliers. For further insights we report the share of individual positive estimates below the 1% p-value threshold divided by the sum of estimates below the 1%. For a positive median estimate we require at least 90% of all individual significant estimates to be positive, while for a negative median estimate no more than 10%. Additionally, the table references the individual factors to the appropriate hypotheses as outlined in Section 2, with the expected estimate sign – either positive (+), negative (−), or without a clear expectation (o). Over all regressions, the average number of observations is 352, 808.77 with an average adjusted R^2 of 6.66%.

TABLE 7 | Excerpt of bid and ask side separate regressions.

		Estimate	p-value	sig $\beta > 0$
Ask side	$r_t^{Underlying} \cdot D_{Call}$	−2.85E+01	0.00%	0.00%
	$r_t^{Underlying} \cdot D_{Put}$	3.26E+01	0.00%	100.00%
	Further variables	yes		
Bid side	$r_t^{Underlying} \cdot D_{Call}$	3.23E+01	0.00%	100.00%
	$r_t^{Underlying} \cdot D_{Put}$	−3.48E+01	0.00%	0.00%
	Further variables	yes		

Note: The table reports an excerpt of the regression as in Table 6 for the estimates of the underlying returns. At the top, only the ask side data was used, at the bottom only the trade side data. The underlying returns are used as control variables and not reported in the original Table 6 for brevity. As these results do however change, if we separately regress the bid and ask side they are reported separately. No other estimate changed considerably. As before, we estimate the regression separately for the 43 days in our sample due to the large sample, as we compute minutely flickering quote shares for every considered option. The reported estimates and p-values are calculated as the median over all individual regressions, to control for potential outliers. For further insights we report the share of individual positive estimates below the 1% p-value threshold divided by the sum of estimates below the 1%. For a positive median estimate we require at least 90% of all individual significant estimates to be positive, while for a negative median estimate not more than 10%. For both regressions, the average number of observations (and adjusted R^2) is (nearly) identical with 352, 808.77 (6.67%) on average.

these orders as a flickering quote. To illustrate the transition from a time-period analysis to a point-in-time analysis, we use i as the index instead of t in the following analyses. A market participant who submitted an order i may decide before and after her submission to cancel the quote, resulting in a flickering quote, or leave her order as is. Therefore, not only information at the time of submission but also information after the submission are valuable.

In comparison to the linear regression Equation (1) we are able to use individual measures for each submission or cancellation (p_i^{Same} and q_i^{Opp}, in the following described in detail); however, we have to drop underlying dependent factors, because we are computationally bound and the drastically-increased sample size does not allow evaluating the order book state of the underlying for every order book change (over 72,000,000). To be independent of stock and option specific differences, we estimate individually for every stock, day, and further cluster in put/call, bid/ask, three expiration categories, and five moneyness categories. The clusters allow us to analyze if flickering quotes are differently distributed across these subgroups. Furthermore, smaller data sets have computational advantages regarding speed. To enable comparisons, the explanatory variables are standardized to have zero mean and a deviation of one. Like before, we report the median estimate and median p-value.

We use the same factor definitions as Hasbrouck and Saar (2009), where applicable for our purpose. $Vola_i^{before}$ is the absolute of the 5 min return before the respective submission of i, whereby we use the ask prices if the submission happens at the ask side, and bid prices otherwise. $Spread_{i-}$ is the relative spread of the option series the instant before i. Both measures are linked to the market maker risk (H1) as well as the volatility to the price discovery channel (H2), as before. Additionally, an HFT might wish to have (nearly) zero inventory if the markets are volatile, but will probably be more likely to unwind her trades when the markets are calm and the spread is small, to raise the probability of fulfillment (H3). As before, we add an order book slope measure $Slope_{i-}$ to capture the state of deeper order book levels before the submission i, relevant to market makers (H1). The trading volume $Volume_i^{before}$ ($Volume_i^{after}$) is the sum of the traded volume in the option series within the 5 min instant before (after) i. The volume is directly linked to active trading (H4), whereby we would expect the fleeting orders are positively influenced by active traders before trades occur (the trade volume after the flickering quote ($Volume_i^{after}$) has a positive influence), and not or negatively influenced by the volume before, regardless of whether traders use fleeting orders to show interest or traders choose to cancel with a lower cost of immediacy. Furthermore, we would expect the same behavior of the volume measures if fleeting orders are used in manipulative ways like spoofing (H6). To measure the relative change due to the submission i, we compute the bid-side $p_i^{Same} = \left(Price_i^{Bid} - Price_{i-}^{Bid}\right)/Price_{i-}^{Bid}$, where $Price_i$ is the price of the submitted quote and $Price_{i-}$ the price of the instant before (similar to p_i^{Bid} and p_i^{Ask} in Section 4.1). The ask-side is constructed analogously so that positive values of p_i^{Same} indicate a smaller spread. We only use submissions, therefore, p_i^{Same} is strictly positive. The active trading tactic of searching for hidden liquidity is associated with a positive regression coefficient, as the spread would get narrower and narrower until a hidden order is found. However, this tactic is not possible to be used with the reviewed options, as no hidden orders can be placed. That is why we expect no significance in this context. The change after order i on the opposite order book side is defined for a submission on the bid-side as $q_i^{Opp} = \left(Price_{i+}^{Ask} - Price_i^{Ask}\right)/Price_i^{Ask}$, where $Price_{i+}$ is the price of the first change after the submission. A positive q_i^{Opp} is associated with a wider spread, and the q_i^{Opp} for submissions on the ask-side is defined accordingly. As the spread represents the costs of immediacy for liquidity demanding agents (H4), a negative q_i^{Opp} is expected for this hypothesis. We exclude the same-side measure q_i^{Same}, because a flickering quotes leads inevitably to a negative value, which is a potential bias of the logistic regression. Lastly, if HFTs react to other algorithmic traders (H5), a burst of flickering quotes leading to the cancellation decision (a positive $\#FQ_i^{before}$) is to be expected. The hypothesis only involves HFTs initiating fleeting orders due to fleeting orders before. Hereby, $\#FQ$ is defined as the sum of flickering quotes within a certain timespan. Therefore, no re-reaction measured with $\#FQ_i^{after}$ is part of H5. The associated estimators $\#FQ_i^{before}$ and $\#FQ_i^{after}$ are measured within 500 ms before and after the submission, respectively, to narrow down HFTs responding to one another. We do not log-transform the number of flickering quotes because we obtain zero flickering quotes for some observations, for which the logarithm is undefined. The behavior of the order book may differ during the opening and closing hours, as these periods are proximate to auctions, another form of market design that may alter effects. Consequently, Hasbrouck and Saar (2009) employ time-related controls. Additionally, the connection between derivatives and the underlying market is stronger for shorter times until expiration and should therefore also be considered. In summary, further control variables include a measure for the days until expiration of the option ($\Delta Expiration_i$) as well as dummy variables for the opening time from 09:30 a.m. to 11:00 a.m. ($Open_i$) and closing time from 04:00 p.m. to 05:30 p.m. ($Close_i$). These time frames are selected based on the results of the density plots shown in Figure 4.

Due to the large number of order book changes (over 72 million), we are unable to include underlying data due to computing restrictions. This restriction will be lifted at a later stage.

In summary, we analyze whether a submission at the top-of-book results in a flickering quote ($FQ = 1$) or not ($FQ = 0$) by using the following logistic regression model:

$$
\begin{aligned}
Logit\,(FQ = 1|X = x_i) = {} & \beta_0 + \beta_1 Vola_i^{before} + \beta_2 Sprea\\
& d_{i-} + \beta_3 Slope_{i-} + \beta_4 Volume_i^{before}\\
& + \beta_5 Volume_i^{after} + \beta_6 p_i^{Same}\\
& + \beta_7 q_i^{Opp} + \beta_8 \#FQ_i^{before} + \beta_9 \#FQ_i^{after}\\
& + \beta_{10} \Delta Expiration_i + \beta_{11} Open_i + \beta_{12} Close_i
\end{aligned}
\tag{2}
$$

We report the results in Table 8.

We show that even though the median p-values of most measures are highly significant, significant estimates with the same direction are sparse. Only the positive p_i^{Same} (order book movement before the submission on same side), negative q_i^{Opp} (order book movement after the submission on opposite side) and positive $\#FQ_i^{before}$ estimates fall within our outlined significance criteria. All three factors fit into the picture of the price discovery hypothesis H2. The results of the latter two determinants would also be plausible for liquidity demanding agents (H4) and algorithms that react to each other (H5). However, the other results do not support these two hypotheses (e.g., the volume and $\#FQ^{after}$ factors).

The results are generally robust to most clusters (put/call, bid/ask, and time until expiration) and the inclusion of the absolute of q_i^{Same}. Besides the correlation of volatility and spread with

TABLE 8 | Flickering quote probability.

	Estimate	p-value	Sig $\beta > 0$	Hypothesis	Expectation
(Intercept)	5.08E-01	0.00%	79.00%		
$Vola_i^{before}$	−4.76E-02	1.00%	16.75%	H1, H2, H3	+(H1, H2), −(H3)
$Spread_{i-}$	−3.82E-01	0.00%	11.91%	H1, H3	−
$Slope_{i-}$	−5.04E-02	0.01%	31.37%	H1	−
$Volume_i^{before}$	4.28E-03	5.87%	56.74%	H4, H6	o/ −
$Volume_i^{after}$	−5.35E-03	29.20%	43.15%	H4, H6	+
p_i^{Same}	2.70E-01	0.00%	95.71%	(H4)	o
q_i^{Opp}	−3.91E-01	0.00%	2.45%	H4	+
$\#FQ_i^{before}$	1.36E-01	0.00%	99.84%	H5	+
$\#FQ_i^{after}$	−1.50E-01	0.00%	16.36%	H5	o
$\Delta Expiration_i$	2.43E-02	0.00%	56.31%		
$Open_i$	−6.53E-02	0.13%	34.44%		
$Close_i$	8.90E-03	0.46%	51.33%		

Note: The table reports the results of the logistic regression on submissions to be part of a flickering quote ($FQ = 1$) (one flickering quote consists of a submission and a cancellation as defined in Section 3). The regression is given as $Logit(FQ = 1|X = x_i) = \beta_0 + \beta_1 Vola_i^{before} + \beta_2 Spread_{i-} + \beta_3 Slope_{i-} + \beta_4 Volume_i^{before} + \beta_5 Volume_i^{after} + \beta_6 p_i^{Same} + \beta_7 q_i^{Opp} + \beta_8 \#FQ_i^{before} + \beta_9 \#FQ_i^{after} + \beta_{10} \Delta Expiration_i + \beta_{11} Open_i + \beta_{12} Close_i$ We estimate individual regressions per day, underlying, put/call, bid/ask side, five moneyness categories and three expiration categories for computational advantages and cluster robustness. The reported estimates and p-values are the median over all individual regressions to control for outliers. For further insights we report the share of individual positive estimates below the 1% p-value threshold divided by the sum of estimates below the 1%. For a positive median estimate we require at least 90% of all individual significant estimates to be positive, while for a negative median estimate not more than 10%. Additionally, the table references the individual factors for the appropriate hypotheses, as outlined in Section 2, with the expected estimate sign: either positive (+), negative (−), or without a clear expectation (o). The average number of observations per cluster is 17,714.00.

TABLE 9 | Excerpt of moneyness clustered logistic regressions.

	$Vola_i^{before}$			$Spread_{i-}$		
Moneyness	**Estimate**	**p-value**	**sig $\beta > 0$**	**Estimate**	**p-value**	**sig $\beta > 0$**
Deep In	−2.54E-01	0.02%	5.31%	−2.09E-01	0.00%	37.90%
In	−4.72E-02	2.43%	21.92%	−5.81E-01	0.00%	3.82%
At	−2.81E-02	2.70%	31.54%	−4.78E-01	0.00%	3.72%
Out	−4.86E-02	3.35%	29.39%	−5.33E-01	0.00%	3.81%
Deep Out	−1.46E-01	0.10%	9.00%	−3.48E-01	0.00%	25.92%

Note: The table reports an excerpt of the regression as in Table 8 for the volatility and spread. From top to bottom, we separate the regressions in five moneyness categories, from deep-in-the-money to deep-out-of-the-money. No other estimates change considerably. As before, we estimate the regression separately for every day, underlying, put/call, bid/ask side, moneyness category and expiration category for computational advantages and cluster robustness. The reported estimates and p-values are calculated as the median over all individual regressions, in order to control for potential outliers. For further insights we report the share of individual positive estimates below the 1% p-value threshold divided by the sum of estimates below the 1%. For a positive median estimate we require at least 90% of all individual significant estimates to be positive, while for a negative median estimate not more than 10%. The average number of observations per cluster from deep-in to deep-out is 14,540.74, 17,255.36, 19,640.84, 19,179.15, and 17,076.64, respectively.

p_i^{Same} and q_i^{Opp} (up to 67.9% [$Vola_i^{before}$ and p_i^{Same}] and −45.9% [$Spread_{i-}$ and q_i^{Opp}]) we see only a small correlation between the variables with an average maximum correlation of $\#FQ_i^{before}$ and $\#FQ_i^{after}$ of 28.3% and an average minimum of −33.8% between the $Open_i$ and $Close_i$. However, separate regressions without the volatility and spread, or without p and q, do not change the remaining estimates considerably. The average residual first-order autocorrelation was well below 0.1. Other model specifications with, for example, underlying determinants, did not reveal any interesting or significant findings and are not reported.

Most interestingly, the clustering for different moneyness categories reveals that the significance of the volatility and spread depends on the moneyness. For at-the-money options, a narrow spread increases the probability of a flickering quote significantly. The coefficient for the volatility is negative and significant for deep-in and out-of-the-money options (see Table 9). As before, we split the data set into four different quantiles, based on the number of order book changes for each option series. The regressions are reported in the Table A3 without a change of the general results.

Ultimately, canceled quotes are not seen as a hazard to the market per se. However, very rapid bursts of fleeting orders with a very short time between submission and cancellation cause suspicion.

4.4 | Cox Hazard Rate: Flickering Quote Duration

We analyze what drives short intervals between submission and cancellation of orders that result in flickering quotes with a Cox hazard rate model. A faster cancellation is associated with a higher hazard rate $h(t|X = x_i)$ relative to an unspecified and unknown base hazard rate $h_0(t)$. As before, we include $Vola_i^{before}$, $Spread_{i-}$, $Slope_{i-}$, as well as $\Delta Expiration_i$, $Open_i$, and $Close_i$ for general market conditions. If market makers would ration their monitoring capacity and costs to reduce their risk (H1), they would probably prefer to monitor volatile options, which lead to faster cancellations. The same is true if the market maker quotes a relatively large price improvement (p^{Same} positively expected). As the options market does not offer hidden orders, p_i^{Same} should not be significant if it is only associated with a search for hidden liquidity (Hasbrouck and Saar 2009). If the market does not support a top-of-book quote with other orders in deeper levels, as a potential hedge for market makers (H1), we would expect a positive q_i^{Same}. This means that a participant reacts quicker if no near quotes support his offer. The same logic is true for the price discovery (H2) and the unwinding of HFT inventory (H3) hypotheses. The cost-of-immediacy for active traders (H4) is depicted by q_i^{Opp}. A lower spread due to movements on the opposite side (a negative q_i^{Opp}) would encourage traders to cancel their quote to trade right away. The last two measures describe the relation to the underlying order book behavior. Not only can we associate them with the price discovery hypothesis (H4), moreover, these measures open the field of lead-lag-relationships between underlying and derivatives markets in a high-frequency context. Our qs capture most of the evolution of the order book after the initial submission. As we only see the first three order book levels, a more detailed view of the order book evolution as done by Dahlström et al. (2024) would potentially lead to false conclusions. To account for the short position of puts, we multiply the underlying q-measures with minus one for puts. For flickering quotes on the bid-side, we compute $q_i^{UnderlyingSame} = (-1)^{(Put_{Dummy})}\left(Underlying_i^{Bid} - Underlying_{i+}^{Bid}\right)/Underlying_i^{Bid}$. Analogously, $q_i^{UnderlyingOpp}$ is also constructed to be positive for calls when the spread widens. For the case of calls on the bid-side, a falling price on the underlying bid-side should be priced by canceling the call-quote. The more severe the underlying change is, the faster the quote should be canceled. Alternatively, there is no incentive to cancel a quote if the underlying ask price rises, which should result in a negative $q_i^{UnderlyingOpp}$. These considerations can also be reversed (rising underlying bid price and falling underlying ask price) and transferred to the ask-side of the option without a change in the direction of the independent variables. For puts, the effects naturally reverse. However, due to the definition of our underlying q-values, the signs of the estimates should not change. Lastly, in the previous analysis, we linked $\#FQ_i^{before}$ to the response of algorithmic traders to each other (H5). While the probability and share of flickering quotes might be affected, there should be no dependency of the time till cancellation on previous flickering quote bursts.

Based on the outlined factors, our hazard rate model is given by

$$h(t|X = x_i) = h_0(t)\exp\begin{bmatrix}\beta_1 Vola_i^{before} + \beta_2 Spread_{i-} + \beta_3 Slope_{i-} + \beta_4 p_i^{Same} + \\ \beta_5 q_i^{Same} + \beta_6 q_i^{Opp} + \beta_7 q_i^{UnderlyingSame} \\ \quad + \beta_8 q_i^{UnderlyingOpp} + \\ \beta_9 \#FQ_i^{before} + \beta_{10}\Delta Expiration_i + \beta_{11} Open_i \\ \quad + \beta_{12} Close_i\end{bmatrix} \tag{3}$$

Compared to the factors of the logistic regression Equation (2), we remove factors causing potential endogenous problems ($\#FQ_i^{after}$, $Volume_i^{after}$), and $Volume_i^{before}$, as it has no economic reasoning regarding the speed of the flickering quotes. Furthermore, we add q_i^{Same}, as we do not have the restriction of the logistic regression, and the underlying measures $q_i^{UnderlyingSame}$ and $q_i^{UnderlyingOpp}$, because our sample now is smaller than before we are no longer computationally bound. We perform individual analysis of our hazard rate model in the same manner as the logistic regression, aggregate the results afterward, and normalize all regression factors analogously. The results of the proportional hazard analysis presented in Table 10 are robust to any clustering. However, it should be noted that with a longer time till expiration, the estimate of p_i^{Same} becomes more negative and significant on average. The scaled Schoenfeld residuals plotted over the time of a random sample of regressions, without open and close dummies, are not suspicious. As before, we once again split the data set in four different quantiles, based on the number of order book changes for each option series. The regressions are reported in the Table A4 without a change of the general results. Solely noteworthy is the increasing significance of both option qs for higher quantiles, which may be caused by an increased sample size, and a decrease of both underlying qs, indicating that price discovery effects from the underlying are more pronounced for less liquid options.

In line with market maker risk (H1), volatility drives fast cancellations. Furthermore, the relevant q measures (according to our significant criteria) show a faster cancellation if the relative price drop on the submission side of the flickering quote is larger—which is also in line with the price discovery hypothesis (H2). As the underlying behavior is especially relevant for the price discovery, we want to point out that the underlying q measures further support the hypothesis H2. The positive significant p_i^{Same} variable is also in line with HFT unwinding their inventories (H3). Even if q_i^{Opp} is not highly significant, the widening spread on the opposite side of the submission has, on average, an accelerating influence on the time till cancellation, in contrast to the expectation of the active trading hypothesis H4. More flickering quotes leading to the current flickering quote submission i also speed up cancellations, which is not covered by a response to other algorithmic traders (H5). The last significant factor is a positive dummy for the opening hours that underlines the findings of the density plot in Figure 4, where the middle part of the trading day has a shift to longer cancellation times (e.g., as seen with the 15-second peak).

5 | Discussion of the Hypotheses About the Flickering Quotes

Fleeting orders and flickering quotes are commonly associated with high-frequency trading. However, the rapid up-and-down

TABLE 10 | Cox hazard rate of flickering quotes.

	Estimate	*p*-value	sig $\beta > 0$	Hypothesis	Expectation
$Vola_i^{before}$	6.09E-02	0.01%	99.37%	H1	+
$Spread_{i-}$	1.72E-02	0.04%	58.11%		
$Slope_{i-}$	1.06E-03	1.04%	50.51%		
p_i^{Same}	−2.67E-02	0.65%	38.26%	H1	+
q_i^{Same}	1.56E-01	0.00%	96.34%	H1, H2, H3	+
q_i^{Opp}	2.93E-02	1.97%	86.36%	H4	−
$q_i^{UnderlyingSame}$	9.15E-02	0.00%	92.66%	H2	+
$q_i^{UnderlyingOpp}$	−9.26E-02	0.00%	6.25%	H2	−
$\#FQ_i^{before}$	1.32E-01	0.00%	99.98%	H5	*o*
$\Delta Expiration_i$	−4.96E-02	0.00%	27.45%		
$Open_i$	7.88E-02	0.00%	93.53%		
$Close_i$	4.20E-02	0.07%	82.01%		

Note: The table presents the results of the Cox proportional hazard rate analysis of flickering quote cancellation duration times. The hazard rate is modeled as $h(t|X = x_i) = h_0(t)\exp[\beta_1 Vola_i^{before} + \beta_2 Spread_{i-} + \beta_3 Slope_{i-} + \beta_4 p_i^{Same} + \beta_5 q_i^{Same} + \beta_6 q_i^{Opp} + \beta_7 q_i^{UnderlyingSame} + \beta_8 q_i^{UnderlyingOpp} + \beta_9 \#FQ_i^{before} + \beta_{10}\Delta Expiration_i + \beta_{11} Open_i + \beta_{12} Close_i]$ where $h_0(t)$ is the unspecified baseline hazard rate. For every flickering quote submission i, we compute the volatility as the absolute value of return over the preceding 5 min. The relative spread is calculated using prices at the instant before the submission that leads to the flickering quote. As for the logistic regression, for flickering quote submissions on the bid-side we use $p_i^{Same} = \left(Price_i^{Bid} - Price_{i-}^{Bid}\right)/Price_{i-}^{Bid}$ and $q_i^{Opp} = \left(Price_{i+}^{Ask} - Price_i^{Ask}\right)/Price_i^{Ask}$, where $-i$ depicts the instant before the submission i. q_i^{Same} is calculated analogously. Furthermore, $q_i^{UnderlyingSame} = (-1)^{(Put_{Dummy})}\left(Underlying_i^{Bid} - Underlying_{i+}^{Bid}\right)/Underlying_i^{Bid}$ and based on the calculation before, $q_i^{UnderlyingOpp}$, are used. In summary, p measures the change before the submission i, and is positive if the spread gets narrower, the q factors represent the next change after the submission and are positive if the spread widens. To allow for the same effect mechanism and expected estimate with puts, the underlying q is multiplied by minus one. To capture the high-frequency nature of our data set, the number of flickering quotes leading to i are summed over 500 ms. No logarithm transformation is used, as the short time span results in many zero measurements. To capture further general market conditions, we add the time until expiration and dummies for the opening and closing hours. Positive estimates indicate a higher hazard rate, and therewith a higher risk of faster cancellations of flickering quotes. We apply the model individually per day, underlying, put/call, bid-/ask-side, five moneyness and three expiration categories for computational advantages and cluster robustness. The reported estimates and p-values are the median over all individual regressions to control for outliers. For further insights we report the share of individual positive estimates below the 1% p-value threshold divided by the sum of estimates below the 1%. For a positive median estimate we require at least 90% of all individual significant estimates to be positive, while for a negative median estimate not more than 10%. Additionally, the table references the individual factors to the appropriate hypotheses, as outlined in Section 2, with the expected estimate sign: either positive (+), negative (−), or without a clear expectation (*o*). The average number of observations per cluster is 7095.45.

movements within one side of the order book might also be attributed to slower traders. Notably, we frequently observe flickering quotes persisting for several seconds before being deleted, suggesting a potential involvement of non-HFT participants. Conversely, patterns observed within fractions of a second indicates that automated trading is the primary driver. The magnitude of flickering quotes and cancellations within our dataset is consistent with existing literature (Hasbrouck and Saar 2009; Fong and Liu 2010; Hasbrouck and Saar 2013; van Ness et al. 2015; Blocher et al. 2018; Hasbrouck 2018; Kuo and Lin 2018), despite the fact that the EUREX options market does not permit hidden liquidity, which is often cited as a major cause of fleeting orders. Importantly, our study utilizes options data, offering unique insights into the behavior of flickering quotes. This analysis is systematically structured around six hypotheses concerning the dynamics of flickering quotes.

Contrary to previous studies, our analysis finds no evidence that flickering quotes mitigate liquidity suppliers' risk (H1) (Liu 2009; Fong and Liu 2010). Key risk factors such as volatility, spread, and order book depth present a different picture. Additionally, the control for tick-grid size is irrelevant to the flickering quote share, which is therefore not reported separately. The processing of news, as described by Liu (2009) and Fong and Liu (2010), suggests a dependency on grid size and monitoring costs. However, in an ultra-low latency environment, competition and low monitoring costs appear to decouple these relationships. The use of derivative data in our study may amplify this decoupling effect, leading to clearer results. Instead, liquidity suppliers leverage their speed advantage to minimize risk rather than utilizing fleeting orders.

The hypothesis that fleeting orders are used for price discovery (H2) receives strong support from our findings. Classic market mi crostructure literature, such as Roll (1984), explains price formation through new information (Madhavan 2000). Typically, trades are viewed as news and therefore drivers of price shifts. Correspondingly, the number of flickering quotes increases post-trade, indicating active price formation processes. This pattern is observed on both the non-trade side and related options, reflecting the interconnected nature of markets within a low latency environment. Furthermore, this behavior not only focused on the respective option series where the trade happened, but also detectable across other options. Flickering quotes exhibit characteristics like clustered occurrences and alignment with general order book changes, fitting into the price discovery framework. Ultimately, we would expect the underlying effects to penetrate through to the options market, though this is not always observed. The measures need to be highly specific and temporally precise to capture these effects accurately. Time-spanning measures, even those recorded over just 1 min, tend to lose their connection, similar to how the volatility measure behaves in logistic regression analysis. This highlights the critical importance of ultra-low latency in today's market structure. The finer the temporal reference, the more meaningful and significant the results become, aligning with findings from comparable studies, such as those by Hasbrouck and Saar (2009). In the context of options, it is essential to consider both the order book dynamics and the payout profile. The shift in significance within the logistic regression from the spread for near at-the-money options to the volatility for deep in- and out-of-the-money options supports this perspective. The spread measured immediately before an event is more relevant for generally liquid and frequently traded options. In contrast, options that are further out-of-the-money, which are less frequently updated, show a deeper connection to the relatively sluggish and lagged volatility. When fleeting orders are used as a price discovery tool, they enhance overall market quality by contributing to price efficiency. Our options dataset allows for a nuanced analysis of the price discovery channel, providing insights beyond those possible with simple equity time series.

We find robust evidence for the hypothesis linking flickering quotes to the inventory risks of HFTs (H3). Trade volume positively influences the flickering quote share, as shown in the linear regression, although this appears contrary to the bivariate results comparing pre- and post-trade characteristics. However, HFTs likely use flickering quotes to adjust their inventories, offering holdings at a discount to mitigate risk, consistent with pre-trade price movements. The behavior on the non-trade order book side may reflect convergence to the true mid-price, driven by the price discovery channel, especially in calm markets. Thus, HFTs appear to manage their portfolios during low volatility periods with flickering quotes.

Despite the association of fleeting orders with HFTs (Baruch and Glosten 2013; Hoffmann 2014), our data suggests that slow traders may also utilize these orders due to the cost of immediacy (Hasbrouck and Saar 2009; Kuo and Lin 2018) (H4). The time between submission and deletion of orders often exceeds 1 s, as indicated by density plots, with longer durations during peak European trading hours. This aligns with cost-driven strategies by slower traders. Our analysis demonstrates that the flickering quote environment changes both before and after trades. In contrast to the findings of Hasbrouck and Saar (2009), we do not observe a significant influence of movements in the opposite order book side on the duration hazard of flickering quotes. They suggested that changes in the opposing side could either lead to cancellations by impatient traders (the cost-of-immediacy effect) or motivate traders to retain their orders, increasing their chances of execution due to the closer proximity of the opposite order book side. Our narrower approach, focusing solely on top-of-book data, likely captures the latter effect, as price priority can be directly observed in this data. The theoretical model proposed by Bhattacharya and Saar (2020) predicts a pattern of cancellation and resubmission driven by the arrival of new information from informed traders. This is consistent with our observation of increased flickering quotes following trades. However, this model does not account for the majority of flickering quotes that occur without a trade connection, nor does it explain the repeated and rapid resubmissions at the same price levels, as the model anticipates repricing to achieve price priority. Bhattacharya and Saar (2020) explicitly state that in their model, no repricing occurs in the absence of informed trading.

Our study supports the hypothesis that algorithmic participants cause flickering quotes by reacting to each other (H5). Periodic quote updates observed every second or tenth of a second indicate algorithmic behavior, corroborated by quote clusters similar to those described by Hasbrouck and Saar (2013). The reaction times in our 2012 data are faster compared to the 2007–2008 data of Hasbrouck and Saar (2013), possibly reflecting advancements in trading technology. However, there are significant doubts about this straightforward explanation. The negative autocorrelation of flickering quotes and the dependency of the hazard rate on past flickering quotes do not support this approach. Additionally, the extremely short reaction times observed in our data do not align with the timing patterns seen during the flash crash (Kirilenko et al. 2017), which are often attributed to algorithmic behavior.

The primary concern regarding fleeting orders is their potential impact on market quality and the risk of being used as manipulative tools to adversely affect other market participants (H6). Our analysis demonstrates that all traders, regardless of speed, utilize marketable orders following a favorable price change. Even though faster traders can secure trades after an even more favorable adjustment, slower traders also benefit from these movements; for instance, slower traders can execute trades after a relative 3% price improvement. Flickering quotes, in fact, contribute to tightening the spread and adding liquidity to the market, consistent with the literature on algorithmic trading (Hendershott et al. 2011). The prevalence of flickering quotes is closely associated with general order book behavior rather than actual trading volume. Furthermore, in line with Hasbrouck and Saar (2002), our findings show no involvement of fleeting orders in spoofing activities. Contrary to expectations of a market withdrawal post-manipulative trade, the number of flickering quotes actually increases after a trade. Additionally, our study does not indicate signs of volatility index manipulation. Although we did not conduct an extensive analysis of flickering quote volume in relation to VIX sensitivity as done by Griffin and Shams (2018), our clustering approach allows us to implicitly analyze VIX sensitivity, revealing no such pattern. Options on EURO STOXX 50 (volatility) index members do not exhibit a significantly higher share of flickering quotes.

Exploring various relationships between the regression factors and hypotheses is conceivable. Our focus, however, centers on crucial aspects pertinent to each hypothesis. Furthermore, we emphasize that our dataset allows us to concentrate on flickering quotes as a distinct subset of fleeting orders. Although this approach may exclude some potential fleeting orders, the majority of order book changes occur at the best quote, enabling us to capture most orders of interest. Additionally, the proportion of flickering quotes relative to all order book changes in our sample aligns with figures reported in other studies.

Future research should leverage more detailed data that enables the identification of different traders. This would facilitate distinguishing between slow and fast traders and the various strategies they employ, providing a more granular view of market dynamics. Such detailed data would allow for a deeper investigation into the impact of different trading strategies. Additionally, extending the dataset to examine whether fleeting orders behave differently during calm versus volatile market phases could yield significant insights, particularly in understanding the relationship between price discovery and fleeting orders. Furthermore, analyzing the impact of changes to market design, such as the introduction of specific order-to-trade ratios, could be approached as an event-driven study. This would enable a comparison of the behavior of fleeting orders before and after such changes, and their corresponding effects on market quality. Moreover, we catch a brief glimpse of a potential lead-lag relationship between derivative and underlying markets in a high-frequency context, which provides interesting indications for further research. This comprehensive approach would significantly enhance our understanding of the nuanced behaviors within high-frequency trading and inform better regulatory practices. Regarding the latter, we conclude that fleeting orders and therefore HFTs are in general beneficial for the market quality. Any regulatory interventions should therefore be made very deliberately and include a subsequent analysis of their impacts. An increase in transparency and strengthening of risk management frameworks should be enforced in any case to achieve a deeper understanding of the risks of the strategies as well as their positive aspects.

As a final thought, we want to emphasize that the knowledge and understanding of flickering quotes goes beyond just market quality and manipulation concerns. In the spirit of high-frequency data and modern statistical methods like deep learning algorithms that are often not able to be understood completely, flickering quotes can lead to presumably extraordinary results that have, however, no economic significance. Choudhry et al. (2012) achieve with their neural network very good directional accuracies in-sample of up to above 90% and are also able to predict the direction of the next price move out-of-sample with 80% in some of the cases correctly. However, these works measure only the characteristic behaviors of flickering quotes, which can often affect the mid-quote by one (half) tick after submission and simply results in the mid-quote jumping back on cancellation. This shows up as a superior directional accuracy. When these models, like the behavior of the neural networks, can no longer be understood and insufficient comparative measures are used, a lack of knowledge about fleeting orders and flickering quotes can lead to serious problems.

6 | Conclusion

The literature has proposed numerous potential causes for fleeting orders and flickering quotes–rapid submissions and deletions of limit orders. Prior studies have predominantly focused on stocks or low-frequency data. In contrast, our research advances this field by utilizing ultra-low latency derivative data of options, encompassing puts and calls, different moneyness categories, and underlying instruments. This approach enables a more precise and comprehensive analysis of hypotheses related to fleeting orders. Our findings indicate that approximately 20% of all orders in our sample are classified as flickering quotes, a proportion similar to other studies on fleeting orders, and suggest that regulatory intervention may be necessary. Despite the introduction of regulations like the German high-frequency law (Hochfrequenzhandelsgesetz), our analysis shows that these regulations have not significantly impacted the prevalence of flickering quotes.

These flickering quotes are often linked with high-frequency trading and are sometimes viewed as potential threats to market efficiency. However, our study demonstrates that flickering quotes are not detrimental to market quality; rather, they are positively associated with liquid markets. It remains to be determined whether flickering quotes contribute to market liquidity or simply occur more frequently in liquid markets.

By leveraging ultra-low latency option data, we explored six hypotheses regarding the drivers of fleeting orders and flickering quotes. We concluded that market maker risk, liquidity demand, manipulation, and algorithmic traders' reactions to each other are not the primary causes of these rapid order activities. Nonetheless, flickering quotes exhibit highly automated and periodic behavior. Our analysis revealed that flickering quotes serve as a price discovery tool, facilitating the incorporation of new information into the market through both the introduction of new quotes and the withdrawal of existing ones. This finding is further substantiated by the dependency on trades within related option series and underlying movements, underscoring the unique insights provided by our option data.

Employing linear regressions on flickering quote share, logistic regressions on flickering quote probability, and Cox proportional hazard rate analysis on flickering quote duration, we identified a positive correlation between flickering quotes and high-quality markets. Additionally, high-frequency traders (HFTs) appear to use flickering quotes to manage their inventories by offering positions at a discount for short periods. This is supported by the positive correlation between trading volume and flickering quote share and the higher probability of flickering quotes during relatively calm market conditions.

Future research should aim to leverage detailed trader identification data to distinguish between different trader types and strategies. It should also examine the behavior of fleeting orders across various market conditions, explore the lead-lag relationship between derivative and underlying markets, and analyze the impact of market design changes. Such efforts will enhance our understanding and regulation of high-frequency trading.

Even if we are able to show that the markets are highly interconnected and automated, quote adjustments do not happen very fast most of the time. Therefore, slower traders are also able to profit. Regulatory interventions should be approached cautiously, ensuring that both slow and fast traders can continue to benefit from these rapid order activities. Increasing transparency and strengthening risk management frameworks will further our understanding of the risks and benefits associated with these strategies, ultimately contributing to more efficient and robust financial markets.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The authors have nothing to report.

Endnotes

[1]Note that the reference point was Zurich; however, an archived article used the same values for Frankfurt.

References

Ait-Sahalia, Y., and M. Saglam. 2024. "High Frequency Traders: Taking Advantage of Speed." *Journal of Econometrics* 239, no. 2: 105421. https://doi.org/10.1016/j.jeconom.2022.12.015.

Baruch, S., and L. R. Glosten. 2013. "Fleeting Orders." *SSRN Electronic Journal* 13: 43. https://doi.org/10.2139/ssrn.2278457.

Baruch, S., and L. R. Glosten. 2019. "Tail Expectation and Imperfect Competition in Limit Order Book Markets." *Journal of Economic Theory* 183: 661–697. https://doi.org/10.1016/j.jet.2019.07.008.

Bhattacharya, A., and G. Saar. 2020. "Limit Order Markets Under Asymmetric Information." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3688473.

Blocher, J., R. Cooper, J. Seddon, and B. van Vliet. 2018. "Phantom Liquidity and High-Frequency Quoting." *Journal of Trading* 3, no. 4: 119–128. https://www.cftc.gov/sites/default/files/idc/groups/public/@aboutcftc/documents/file/acinterimmarketaccessreport.pdf.

Brogaard, J., and C. Garriott. 2019. "High-Frequency Trading Competition." *Journal of Financial and Quantitative Analysis* 54, no. 4: 1469–1497. https://doi.org/10.1017/S0022109018001175.

Brogaard, J., B. Hagströmer, L. Nordén, and R. Riordan. 2015. "Trading Fast and Slow: Colocation and Liquidity." *Review of Financial Studies* 28, no. 12: 3407–3443. https://doi.org/10.1093/rfs/hhv045.

Brogaard, J., T. Hendershott, and R. Riordan. 2014. "High-Frequency Trading and Price Discovery." *Review of Financial Studies* 27, no. 8: 2267–2306. https://doi.org/10.1093/rfs/hhu032.

Budish, E., P. Cramton, and J. Shim. 2015. "The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response *." *Quarterly Journal of Economics* 130, no. 4: 1547–1621. https://doi.org/10.1093/qje/qjv027.

Carrion, A. 2013. "Very Fast Money: High-Frequency Trading on the NASDAQ." *Journal of Financial Markets* 16, no. 4: 680–711. https://doi.org/10.1016/j.finmar.2013.06.005.

Cartea, Á., and S. Jaimungal. 2013. "Modelling Asset Prices for Algorithmic and High-Frequency Trading." *Applied Mathematical Finance* 20, no. 6: 512–547. https://doi.org/10.1080/1350486X.2013.771515.

Cartea, Á., and J. Penalva. 2012. "Where Is the Value in High Frequency Trading?" *Quarterly Journal of Finance* 2, no. 3: 1250014. https://doi.org/10.1142/S2010139212500140.

CFTC. 2001. "Market Access Subcommittee: Best Practices for Organized Electronic Markets." *Interim Report* 8: 1–22. https://www.cftc.gov/sites/default/files/idc/groups/public/@aboutcftc/documents/file/acinterimmarketaccessreport.pdf.

CFTC. 2014. Foreign Board of Trade Application for Registration (in Order to Permit Direct Access to Members and Other Participants) - Eurex Zürich AG 1–142. https://www.cftc.gov/sites/default/files/groups/public/@otherif/documents/ifdocs/orgfbotezagncfdsub161207.pdf.

CFTC. 2019. 19 CR 669: Conspiracy to Conduct or Participate in an Enterprise Engaged in a Pattern of Racketeering Activity) 1: 45. https://www.justice.gov/opa/press-release/file/1202466/download.

Chaboud, A. P., B. Chiquoine, E. Hjalmarsson, and C. Vega. 2014. "Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market." *Journal of Finance* 69, no. 5: 2045–2084. https://doi.org/10.1111/jofi.12186.

Chakrabarty, B., and K. Tyurin. 2011. "Market Liquidity, Stock Characteristics and Order Cancellations: The Case of Fleeting Orders." In *Financial Econometrics Modeling: Market Microstructure, Factor Models and Financial Risk Measures*, edited by G. N. Gregoriou and R. Pascalau, 33–65. Palgrave MacMillan.

Chakravarty, S., H. Gulen, and S. Mayhew. 2004. "Informed Trading in Stock and Option Markets." *Journal of Finance* 59, no. 3: 1235–1257. https://doi.org/10.1111/j.1540-6261.2004.00661.x.

China Telecom. 2018. Ultra Low Latency. Retrieved from https://www.chinatelecomglobal.com/static/learn-file/ULTRA%20LOW%20LATENCY.pdf.

Choudhry, T., F. McGroarty, K. Peng, and S. Wang. 2012. "High–Frequency Exchange–Rate Prediction With an Artificial Neural Network." *Intelligent Systems in Accounting, Finance and Management* 19, no. 3: 170–178. https://doi.org/10.1002/isaf.1329.

Conrad, J., S. Wahal, and J. Xiang. 2015. "High-Frequency Quoting, Trading, and the Efficiency of Prices." *Journal of Financial Economics* 116, no. 2: 271–291. https://doi.org/10.1016/j.jfineco.2015.02.008.

Dahlström, P., B. Hagströmer, and L. Nordén. 2024. "Determinants of Limit Order Cancellations." *Financial Review* 59, no. 1: 181–201. https://doi.org/10.1111/fire.12363.

Dennert, J. 1993. "Price Competition Between Market Makers." *Review of Economic Studies* 60, no. 3: 735. https://doi.org/10.2307/2298133.

Dumas, B., J. Fleming, and R. E. Whaley. 1998. "Implied Volatility Functions: Empirical Tests." *Journal of Finance* 53, no. 6: 2059–2106. https://doi.org/10.1111/0022-1082.00083.

Easley, D., M. M. López de Prado, and M. O'Hara. 2012. "The Volume Clock: Insights into TheHigh-Frequency Paradigm." *Journal of Portfolio Management* 39, no. 1: 19–29. https://doi.org/10.3905/jpm.2012.39.1.019.

Easley, D., M. O'Hara, and P. S. Srinivas. 1998. "Option Volume and Stock Prices: Evidence on Where Informed Traders Trade." *Journal of Finance* 53, no. 2: 431–465. https://doi.org/10.1111/0022-1082.194060.

Egginton, J. F., B. F. van Ness, and R. A. van Ness. 2016. "Quote Stuffing." *Financial Management* 45, no. 3: 583–608. https://doi.org/10.1111/fima.12126.

Etling, C., and T. W. Miller. 2000. "The Relationship Between Index Option Moneyness and Relative Liquidity." *Journal of Futures Markets* 20, no. 10: 971–987. https://doi.org/10.1002/1096-9934(200011)20:10%3C971::AID-FUT5%3E3.0.CO;2-8.

Fong, K. Y., and W. -M. Liu. 2010. "Limit Order Revisions." *Journal of Banking & Finance* 34, no. 8: 1873–1885. https://doi.org/10.1016/j.jbankfin.2009.12.010.

Foucault, T., O. Kadan, and E. Kandel. 2013. "Liquidity Cycles and Make/Take Fees in Electronic Markets." *Journal of Finance* 68, no. 1: 299–341. https://doi.org/10.1111/j.1540-6261.2012.01801.x.

Gerig, A. 2012. "High-Frequency Trading Synchronizes Prices in Financial Markets." *SSRN Electronic Journal* 8: 1–6. https://doi.org/10.2139/ssrn.2173247.

Glosten, L. R., and P. R. Milgrom. 1985. "Bid, Ask and Transaction Prices in a Specialist Market With Heterogeneously Informed Traders." *Journal of Financial Economics* 14, no. 1: 71–100. https://doi.org/10.1016/0304-405X(85)90044-3.

Griffin, J. M., and A. Shams. 2018. "Manipulation in the VIX?" *Review of Financial Studies* 31, no. 4: 1377–1417. https://doi.org/10.1093/rfs/hhx085.

Groth, S. S. 2009. "Further Evidence on Technology and Liquidity Provision: The Blurring of Traditional Definitions." *SSRN Electronic Journal*: 1–25. https://doi.org/10.2139/ssrn.1539990.

Hagströmer, B., and L. Nordén. 2013. "The Diversity of High-Frequency Traders." *Journal of Financial Markets* 16, no. 4: 741–770. https://doi.org/10.1016/j.finmar.2013.05.009.

Hasbrouck, J. 2018. "High-Frequency Quoting: Short-Term Volatility in Bids and Offers." *Journal of Financial and Quantitative Analysis* 53, no. 2: 613–641. https://doi.org/10.1017/S0022109017001053.

Hasbrouck, J., and G. Saar. 2002. "Limit Orders and Volatility in a Hybrid Market: The Island ECN." *SSRN Electronic Journal* 1, no. 25: 1–48. https://doi.org/10.2139/ssrn.310940.

Hasbrouck, J., and G. Saar. 2009. "Technology and Liquidity Provision: The Blurring of Traditional Definitions." *Journal of Financial Markets* 12, no. 2: 143–172. https://doi.org/10.1016/j.finmar.2008.06.002.

Hasbrouck, J., and G. Saar. 2013. "Low-Latency Trading." *Journal of Financial Markets* 16, no. 4: 646–679. https://doi.org/10.1016/j.finmar.2013.05.003.

Hendershott, T., C. M. Jones, and A. J. Menkveld. 2011. "Does Algorithmic Trading Improve Liquidity?" *Journal of Finance* 66, no. 1: 1–33. https://doi.org/10.1111/j.1540-6261.2010.01624.x.

Hendershott, T., and R. Riordan. 2013. "Algorithmic Trading and the Market for Liquidity." *Journal of Financial and Quantitative Analysis* 48, no. 4: 1001–1024. https://doi.org/10.1017/S0022109013000471.

Hoffmann, P. 2014. "A Dynamic Limit Order Market With Fast and Slow Traders." *Journal of Financial Economics* 113, no. 1: 156–169. https://doi.org/10.1016/j.jfineco.2014.04.002.

Jarrow, R. A., and P. Protter. 2012. "A Dysfunctional Role of High Frequency Trading in Electronic Markets." *International Journal of Theoretical and Applied Finance* 15, no. 03: 1250022. https://doi.org/10.1142/S0219024912500227.

Kirilenko, A., A. S. Kyle, M. Samadi, and T. Tuzun. 2017. "The Flash Crash: High-Frequency Trading in an Electronic Market." *Journal of Finance* 72, no. 3: 967–998. https://doi.org/10.1111/jofi.12498.

Kuo, W. -Y., and C. -T. Lin. 2018. "Trader Types and Fleeting Orders: Evidence From Taiwan Futures Exchange." *Journal of Futures Markets* 38, no. 12: 1443–1469. https://doi.org/10.1002/fut.21963.

Li, K. 2018. "Do High-Frequency Fleeting Orders Exacerbate Market Illiquidity?" *Electronic Commerce Research* 18, no. 2: 241–255. https://doi.org/10.1007/s10660-017-9273-8.

Lin, Z., B. F. van Ness, and R. A. van Ness. 2018. "Canceled Orders and Executed Hidden Orders." *Journal of Trading* 13, no. 2: 5–19. https://doi.org/10.3905/jot.2018.13.2.005.

Liu, W. -M. 2009. "Monitoring and Limit Order Submission Risks." *Journal of Financial Markets* 12, no. 1: 107–141. https://doi.org/10.1016/j.finmar.2008.04.003.

Madhavan, A. 2000. "Market Microstructure: A Survey." *Journal of Financial Markets* 3, no. 3: 205–258. https://doi.org/10.1016/S1386-4181(00)00007-0.

Madhavan, A. 2012. "Exchange-Traded Funds, Market Structure, and the Flash Crash." *Financial Analysts Journal* 68, no. 4: 20–35. https://doi.org/10.2469/faj.v68.n4.6.

Malceniece, L., K. Malcenieks, and T. J. Putniņš. 2019. "High Frequency Trading and Comovement in Financial Markets." *Journal of Financial Economics* 134, no. 2: 381–399. https://doi.org/10.1016/j.jfineco.2018.02.015.

Malinova, K., A. Park, and R. Riordan. 2012. "Do Retail Traders Suffer From High Frequency Traders?" *SSRN Electronic Journal*: 1–42. https://doi.org/10.2139/ssrn.2183806.

Mandes, A. 2016. "Algorithmic and High-Frequency Trading Strategies: A Literature Review: MAGKS Papers on Economics." Working Paper. Retrieved from https://EconPapers.repec.org/RePEc:mar:magkse:201625.

Menkveld, A. J. 2016. "The Economics of High-Frequency Trading: Taking Stock." *Annual Review of Financial Economics* 8, no. 1: 1–24. https://doi.org/10.1146/annurev-financial-121415-033010.

Menkveld, A. J., and M. A. Zoican. 2017. "Need for Speed? Exchange Latency and Liquidity." *Review of Financial Studies* 30, no. 4: 1188–1228. https://doi.org/10.1093/rfs/hhx006.

Næs, R., and J. A. Skjeltorp. 2006. "Order Book Characteristics and the Volume–Volatility Relation: Empirical Evidence From a Limit Order Market." *Journal of Financial Markets* 9, no. 4: 408–432. https://doi.org/10.1016/j.finmar.2006.04.001.

O'Hara, M., and G. S. Oldfield. 1986. "The Microeconomics of Market Making." *Journal of Financial and Quantitative Analysis* 21, no. 4: 361. https://doi.org/10.2307/2330686.

Patel, V., T. J. Putniņš, D. Michayluk, and S. Foley. 2020. "Price Discovery in Stock and Options Markets." *Journal of Financial Markets* 47: 100524. https://doi.org/10.1016/j.finmar.2019.100524.

Petersen, M. A. 2009. "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches." *Review of Financial Studies* 22, no. 1: 435–480. https://doi.org/10.1093/rfs/hhn053.

Pratt, J. W. 1964. "Risk Aversion in the Small and in the Large." *Econometrica* 32, no. 1/2: 122. https://doi.org/10.2307/1913738.

Roll, R. 1984. "A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market." *Journal of Finance* 39, no. 4: 1127–1139. https://doi.org/10.1111/j.1540-6261.1984.tb03897.x.

Roseman, B. 2015. "More Depth to Depth: Liquidity of Fleeting and Static Orders." Working Paper. University of Mississippi, 8: 1–32. http://faculty.bus.olemiss.edu/rvanness/speakers/presentations%202015-2016/brianroseman-memphispresentation.pdf.

Roşu, I. 2009. "A Dynamic Model of the Limit Order Book." *Review of Financial Studies* 22, no. 11: 4601–4641. https://doi.org/10.1093/rfs/hhp011.

Subrahmanyam, A. 1991. "Risk Aversion, Market Liquidity, and Price Efficiency." *Review of Financial Studies* 4, no. 3: 417–441. https://doi.org/10.1093/rfs/4.3.417.

The Wall Street Journal. 29.09.2018. "Investors Say They Were Harmed by Manipulation in Volatility Products: A Complaint Alleges That Market Players Consistently Manipulated Prices of Derivatives Tied to The VIX." The Wall Street Journal.

van Kervel, V., and A. J. Menkveld. 2019. "High–Frequency Trading Around Large Institutional Orders." *Journal of Finance* 74, no. 3: 1091–1137. https://doi.org/10.1111/jofi.12759.

van Ness, B. F., R. A. van Ness, and E. D. Watson. 2015. "Canceling Liquidity." *Journal of Financial Research* 38, no. 1: 3–33. https://doi.org/10.1111/jfir.12051.

Viljoen, T., J. Westerholm, H. Zheng, and D. Gerace. 2015. "Fleeting Orders and Dynamic Trading Strategies: Evidence From the Australian Security Stock Exchange (ASX)." *Journal of Accounting and Finance* 15, no. 4: 108–134.

Option Data: EUROFIDAI. 2017. XETRA Intra-Day Tick Data for DAX 30 Firms for the Year 2012.

Underlying Data: EUROFIDAI. 2017. EUREX Intra-Day Tick Data for DAX 30 Firms for the Year 2012.

Appendix A

Table A1

TABLE A1 | Overview of the explanatory variables and operationalizations with corresponding hypothesis and analysis methods.

Operationalization		Corresponding hypotheses to each analysis method		
Symbol	**Description**	**Linear reg.**	**Logistic reg.**	**Cox hazard rate**
$Vola_{t-1}^{Option}\left(Vola_i^{before}\right)$	One (Five) minute absolute preceding mid-quote (quote) return	H1	H1, H2, H3	H1
$Spread_{t-1}^{Option}(Spread_{i-})$	One minute tick-weighted (Instant) preceding relative spread	H1	H1, H3	
$Slope_{t-1}(Slope_{i-})$	Observation preceding order book elasticity or slope of order book	H1	H1	
$Vola_{t-10}^{Underlying}$	Ten minute preceding standard deviation of minutely mid-quote returns	H1, H2		
$\frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \cdot \lvert M \rvert_{Call\ (Put)}^{InMoney\ (OutMoney)}$	One minute underlying flickering quote share multiplied with	H2		
	moneyness dummy for in-the-money (out-of-the-money), and call (put)			
$Trade_{t-10}$	Number of trades of the respective option series within the preceding 10 min	H3, H4		
$OddLot_{daily}^{Option}$	Daily number of trades with a volume not being a multiple of ten options	H4		
$\frac{FQ_{t-1}}{OB_{t-1}}$	One minute flickering quote share, lagged by 1 min	H5		
$STOXX_{dummy}$	Dummy controlling for an underlying listed in the EURO STOXX 50 index (=1), or not (=0)	H6		
$Volume_i^{before}\left(Volume_i^{after}\right)$	Sum of traded volume 5 min before (after) submission i		H4, H6	
p_i^{Same}	Relative offered price change due to submission i,		H4	H1
	positive values indicate a smaller spread			
q_i^{Same}	Relative offered price change after submission i on the same			H1, H2, H3
	order book side, positive values indicate a wider spread			
q_i^{Opp}	Relative offered price change after submission i on the opposing order book side, positive values indicate a wider spread		H4	H4
$q_i^{UnderlyingSame}$	Relative underlying offered price change after submission i on the same (puts: opposing) order book side,			H2
$q_i^{UnderlyingOpp}$	Relative underlying offered price change after submission i on the opposing (puts: same) order book side, positive values indicate a wider spread			H2
$\#FQ_i^{before}$	Sum of flickering quotes within the 500 ms before the submission i		H5	H5
$\#FQ_i^{after}$	Sum of flickering quotes within the 500 ms after the submission i		H5	

Note: The table presents an overview of the operationalizations used to capture the effects assumed to result from the different hypotheses H1 to H6, as outlined in Section 2 for every analysis used in Section 4. We have to revert to operationalizations, as our data does not identify individual traders, and some hypotheses act indirect.

Table A2

TABLE A2 | Regression on the flickering quote share with different quantiles.

	Quantile 1			Quantile 2			Quantile 3			Quantile 4		
	Estimate	p-value	sig $\beta > 0$	Estimate	p-value	sig $\beta > 0$	Estimate	p-value	sig $\beta > 0$	Estimate	p-value	sig $\beta > 0$
(Intercept)	3.73E-01	0.00%	100.00%	2.64E-01	0.00%	100.00%	2.20E-01	0.00%	100.00%	2.54E-01	0.00%	100.00%
$Vola_{t-1}^{Option}$	−4.35E-01	0.00%	0.00%	−5.06E-01	0.00%	0.00%	−2.54E-01	0.00%	4.65%	−8.44E-02	0.00%	27.91%
$Spread_{t-1}^{Option}$	1.75E-01	0.00%	100.00%	2.26E-01	0.00%	100.00%	2.08E-01	0.00%	97.67%	2.10E-01	0.00%	95.35%
$Slope_{t-1}$	2.09E-06	100.00%	–	2.56E-06	100.00%	–	3.19E-06	100.00%	–	5.04E-06	100.00%	–
$Vola_{t-10}^{Underlying}$	−2.91E+01	0.00%	0.00%	−1.49E+01	0.00%	0.00%	−1.02E+01	0.00%	0.00%	−6.98E+00	0.00%	2.33%
$\frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \cdot \lvert M\rvert_{Call}^{InMoney}$	−2.54E+00	0.00%	0.00%	−2.63E+00	0.00%	2.33%	−2.46E+00	0.00%	2.33%	−1.65E+00	0.00%	2.33%
$\frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \cdot \lvert M\rvert_{Call}^{OutMoney}$	−4.63E-01	0.00%	25.58%	−3.19E-01	0.00%	20.93%	−4.74E-02	0.00%	44.19%	4.08E-01	0.00%	67.44%
$\frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \cdot \lvert M\rvert_{Put}^{InMoney}$	−1.68E+00	0.00%	6.98%	−1.36E+00	0.00%	2.33%	−1.89E+00	0.00%	6.98%	−1.65E+00	0.00%	4.65%
$\frac{FQ_t^{Underlying}}{OB_t^{Underlying}} \cdot \lvert M\rvert_{Put}^{OutMoney}$	3.57E-01	0.00%	72.09%	4.19E-01	0.00%	79.07%	7.00E-01	0.00%	93.02%	1.63E+00	0.00%	97.67%
$Trade_{t-10}$	1.29E-03	0.01%	74.07%	1.59E-03	0.00%	90.00%	8.83E-04	0.30%	92.00%	9.48E-04	0.02%	96.00%
$OddLot_{daily}^{Option}$	−6.62E-03	0.73%	8.70%	−2.17E-03	7.58%	20.00%	−4.40E-04	20.49%	33.33%	7.12E-04	14.61%	50.00%
$\frac{FQ_{t-1}}{OB_{t-1}}$	−1.44E-01	0.00%	0.00%	−3.82E-02	0.00%	4.76%	2.39E-02	0.00%	87.80%	9.14E-02	0.00%	100.00%
$STOXX_{dummy}$	−5.43E-03	0.23%	20.00%	1.30E-03	6.42%	66.67%	2.59E-03	3.44%	80.95%	3.68E-03	0.03%	82.14%
$r_t^{Underlying} \cdot D_{Call}$	−2.71E-01	0.00%	48.84%	2.13E+00	0.00%	69.77%	1.48E+00	0.00%	79.07%	8.72E-01	0.00%	62.79%
$r_t^{Underlying} \cdot D_{Put}$	−3.98E+00	0.00%	27.91%	−2.74E+00	0.00%	27.91%	−9.23E-02	0.00%	48.84%	7.84E-01	0.00%	60.47%
$\Delta Expiration_i$	1.00E-05	100.00%	–	6.03E-05	99.99%	–	9.57E-05	99.98%	–	1.48E-04	99.95%	–
$Volume_{daily}^{Option}$	2.41E-06	100.00%	–	1.26E-06	100.00%	–	1.28E-06	100.00%	–	1.21E-06	100.00%	–
Market capitalization	1.30E-02	75.45%	–	1.45E-02	61.87%	–	1.32E-02	60.26%	–	6.31E-03	75.62%	–
$Price_t^{Option}$	−9.10E-03	86.20%	–	−9.16E-03	65.32%	–	−9.39E-03	49.56%	–	−9.23E-03	32.47%	–
$Price_{close}^{Underlying}$	−7.39E-04	99.75%	–	−4.35E-04	99.81%	–	−4.08E-04	99.78%	–	−3.69E-04	99.73%	–
$Vola_{daily}^{Underlying}$	−1.19E+01	0.00%	27.91%	6.66E+00	0.00%	69.77%	8.51E+00	0.00%	65.12%	−9.22E+00	0.00%	23.26%
$Skew_{daily}^{Option}$	8.72E-04	40.38%	57.14%	1.13E-03	13.59%	78.57%	4.79E-04	4.26%	62.50%	6.23E-04	0.02%	52.00%
Remaining day time	−4.71E-04	93.35%	–	−7.35E-04	93.96%	–	−1.03E-03	91.44%	–	−1.25E-03	88.92%	–
$Call_{dummy}$	−1.16E-02	0.00%	0.00%	−1.03E-02	0.00%	0.00%	−9.44E-03	0.00%	0.00%	−7.85E-03	0.00%	0.00%

(Continues)

TABLE A2 | (Continued)

	Quantile 1			Quantile 2			Quantile 3			Quantile 4		
	Estimate	***p*-value**	**sig $\beta > 0$**	**Estimate**	***p*-value**	**sig $\beta > 0$**	**Estimate**	***p*-value**	**sig $\beta > 0$**	**Estimate**	***p*-value**	**sig $\beta > 0$**
$Orderflow_{Daily} \cdot D_{Call}$	1.64E-06	100.00%	–	1.11E-06	100.00%	–	5.06E-07	100.00%	–	3.58E-07	100.00%	–
$Orderflow_{Daily} \cdot D_{Put}$	1.23E-06	100.00%	–	−1.06E-07	100.00%	–	−1.85E-08	100.00%	–	−1.60E-07	100.00%	–
Average Adj. R^2	6.30%			5.91%			9.18%			17.68%		
Average No. of observations	85,149.00			88,977.07			89,481.40			89,201.30		
Average minutely order book changes	10.27			25.56			46.94			104.86		

Note: The table reports the results for the regression on the minutely flickering quote share divided into quantiles (along the number of order book changes). The regression itself is carried out exactly as done in Table 6 but the observations were cluster into four quantiles using the number of order book changes of each observation. For completeness we report the whole regression results with the control variables. If no estimate of a explanatory variable is significant, we report—in the third column of each quantile.

Table A3

TABLE A3 | Logistic regression on the flickering quote share with different quantiles.

	Quantile 1			Quantile 2			Quantile 3			Quantile 4		
	Estimate	***p*-value**	**sig $\beta > 0$**	**Estimate**	***p*-value**	**sig $\beta > 0$**	**Estimate**	***p*-value**	**sig $\beta > 0$**	**estimate**	***p*-value**	**sig $\beta > 0$**
(Intercept)	−7.30E-01	0.00%	24.90%	4.36E-01	0.00%	64.74%	6.71E-01	0.00%	83.65%	4.39E-01	0.00%	81.59%
$Vola_i^{before}$	−9.40E-02	13.80%	11.11%	−8.67E-02	7.16%	11.46%	−5.01E-02	10.00%	16.97%	−1.92E-02	6.02%	30.37%
$Spread_{i-}$	−4.27E-03	0.04%	50.89%	−4.54E-01	0.00%	15.84%	−5.47E-01	0.00%	4.10%	−5.25E-01	0.00%	1.67%
$Slope_{i-}$	−3.43E-01	0.00%	22.57%	−9.72E-02	0.34%	29.66%	−4.28E-02	0.96%	36.96%	−4.54E-02	0.04%	31.65%
$Volume_i^{before}$	2.21E-02	16.05%	65.50%	1.16E-02	12.38%	59.11%	4.43E-04	10.52%	51.99%	2.72E-03	4.26%	52.71%
$Volume_i^{after}$	−7.78E-03	31.28%	42.02%	−1.80E-02	34.99%	28.29%	−1.81E-02	31.08%	24.90%	−6.79E-03	26.07%	35.58%
p_i^{Same}	9.39E-02	3.73%	64.71%	2.55E-01	0.14%	89.75%	3.11E-01	0.00%	95.72%	3.13E-01	0.00%	98.38%
q_i^{Opp}	4.70E-02	0.95%	57.19%	−2.78E-01	0.00%	7.18%	−4.56E-01	0.00%	1.28%	−5.34E-01	0.00%	0.42%
$\#FQ_i^{before}$	1.60E-01	4.03%	99.32%	1.42E-01	2.15%	99.32%	1.25E-01	0.72%	99.21%	1.29E-01	0.00%	99.83%
$\#FQ_i^{after}$	1.07E-01	4.27%	81.85%	3.75E-02	0.97%	54.71%	−1.05E-01	0.01%	26.28%	−2.10E-01	0.00%	10.65%
$\Delta Expiration_i$	−5.03E-02	0.00%	45.87%	−3.65E-03	0.00%	49.97%	−3.56E-02	0.01%	44.78%	1.31E-02	0.00%	53.21%
$Open_i$	−9.10E-02	1.69%	40.00%	−8.09E-02	2.76%	36.89%	−5.86E-02	2.76%	38.34%	−1.79E-02	0.30%	45.53%
$Close_i$	3.08E-02	5.26%	58.11%	4.28E-02	4.32%	56.56%	1.79E-02	4.50%	53.06%	−1.29E-02	1.06%	45.93%
Average No. of observations	1164.17			2206.34			4165.45			16,174.91		
Average order book changes per option series	1363.66			4288.32			9634.79			25,798.57		

Note: The table reports the results for the logistic regression on the flickering quote probability divided into quantiles. The estimation itself is carried out exactly as done in Table 8 but the observations were cluster into four quantiles using the daily number of order book changes of each option.

Table A4

TABLE A4 | Cox hazard rate of flickering quotes with different quantiles.

	Quantile 1			Quantile 2			Quantile 3			Quantile 4		
	Estimate	***p*-value**	**sig $\beta > 0$**	**Estimate**	***p*-value**	**sig $\beta > 0$**	**Estimate**	***p*-value**	**sig $\beta > 0$**	**Estimate**	***p*-value**	**sig $\beta > 0$**
$Vola_i^{before}$	5.4%	27.6%	82.6%	6.4%	16.2%	94.1%	6.0%	3.1%	98.5%	6.5%	0.0%	99.6%
$Spread_{i-}$	13.3%	13.9%	64.4%	7.7%	6.4%	66.5%	6.2%	2.2%	69.9%	4.7%	0.2%	73.3%
$Slope_{i-}$	2.7%	25.2%	57.7%	0.3%	19.1%	50.2%	−0.2%	14.1%	48.0%	−1.0%	5.5%	39.4%
p_i^{Same}	7.6%	17.0%	28.3%	−6.9%	9.7%	27.0%	−5.3%	6.4%	35.5%	1.6%	1.4%	55.9%
q_i^{Same}	34.7%	14.5%	84.5%	14.3%	6.8%	89.2%	11.5%	0.7%	93.4%	15.4%	0.0%	95.3%
q_i^{Opp}	13.0%	22.8%	64.5%	2.2%	18.7%	70.3%	2.8%	10.7%	77.8%	2.5%	3.8%	86.1%
$q_i^{UnderlyingSame}$	16.1%	0.8%	96.9%	13.4%	0.1%	96.3%	10.5%	0.0%	94.9%	8.2%	0.0%	89.2%
$q_i^{UnderlyingOpp}$	−16.4%	0.8%	2.4%	−13.6%	0.0%	3.2%	−10.3%	0.0%	5.1%	−8.2%	0.0%	9.2%
$\#FQ_i^{before}$	18.8%	7.2%	98.5%	13.2%	0.5%	99.4%	12.8%	0.0%	99.9%	12.7%	0.0%	100.0%
$\Delta Expiration_i$	−4.0%	11.4%	38.8%	−5.0%	4.3%	35.8%	−4.4%	1.2%	34.6%	−3.9%	0.0%	30.5%
$Open_i$	9.5%	9.9%	88.3%	8.7%	2.7%	90.4%	8.0%	0.3%	91.0%	8.1%	0.0%	92.4%
$Close_i$	6.2%	16.4%	83.5%	5.1%	8.4%	82.6%	4.3%	3.3%	80.2%	3.9%	0.1%	77.8%
Average No. of observations	412.87			994.41			2193.68			8038.79		
Average order book changes per option series	1363.66			4288.32			9634.79			25,798.57		

Note: The table reports the results for the Cox proportional hazard rate analysis of flickering quote cancellation duration times divided into quantiles. The estimation itself is carried out exactly as done in Table 10 but the observations were cluster into four quantiles using the daily number of order book changes of each option. We excluded individual regressions, with constant explanatory vectors due to estimation issues. However, the results if we exclude the respective explanatory variable do not change drastically.