The Case of Fleeting Orders and Flickering Quotes *

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ABSTRACT

The literature controversially discusses the ambiguous motives and driving forces behind fleeting orders and flickering quotes. In particular, manipulative and dysfunctional characteristics are feared. We show with an ultra-low latency derivative data set that none of these properties have to be dreaded. Fleeting orders are associated with liquid market environments. The prices of fast flickering order books improve by 3.90% before trades. The results of our Cox proportional hazard rate, logistic, and linear regressions reveal that flickering quotes are likely due to beneficial price discovery processes and inventories of HFTs offered at a discount to other participants.

JEL classification: G10, G14, G18.

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With the flourish of the high-frequency trading (HFT) since 2005, driven unintentionally by the introduction of the Regulation National Market System (Reg NMS), a whole new strand of literature has developed. The intention is to reveal interrelations, comprehend how faster trading changes markets, quality, welfare, assess the risk of new developments, and how to cope with it. In general, the research community has come to the broad conclusion that HFT is beneficial to the market under normal conditions, both theoretical (Foucault et al., 2013) and empirical, regarding liquidity, price efficiency, informativeness, adverse selection, short term volatility, market stability, and trading costs (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). Potential drawbacks of HFT like harm to liquidity provision, are theoretically illustrated by Menkveld and Zoican (2017) and Budish et al. (2015), but are not backed by empirical results. However, empirical findings point out further risks, like the spread of local errors and excessive comovement due to increased interconnected markets (Chaboud et al., 2014; Gerig, 2012; Malceniece et al., 2019), and the fear of accelerated market failure and dysfunctionality in certain market conditions (Kirilenko et al., 2017; Madhavan, 2012; Jarrow and Protter, 2012; Ait-Sahalia and Saglam, 2013; Egginton et al., 2016)

One distinct behavior of HFT that has not been mentioned so far, but is of great concern to market quality, are very fast order submissions and cancellations, which can be seen in order book data. While regulators try to impose (or already have imposed) restrictions on this behavior with a maximum order-to-trade ratio, the motives, and strategies behind this phenomenon are not finally resolved. This brevity of quote lifetimes is known as 'fleeting orders' (Hasbrouck and Saar, 2009) or 'flickering quotes' (Baruch and Glosten, 2013). In this article 'fleeting orders' summarize the general fast order cancellation within the whole order book. In contrast, 'flickering quotes' only focus on the current best bid or ask price, which results in a flip-flopping movement between the old, the new (submission), and the old (after cancellation) best offer, seen as a flicker. A more detailed definition is given in Section II. By this approach we try to provide a deeper understanding of the mechanisms behind fleeting orders by analyzing the flickering in detail. Neither are the motives behind flickering quotes fully understood, nor is it clear, if fleeting orders adversely affect the markets. One of the earliest empirical works mentioning fleeting orders is Hasbrouck and Saar (2002). They analyze stock data from 1999 of the Island ECN, one of the earliest computerized marketplaces. They state that 27.7% of all visible limit orders are canceled within two seconds, which are mostly submitted at prices within the pre-existing spread. Also, other contributions like Roseman (2015) use the two seconds benchmark. With an updated dataset of INET orders (formerly Island ECN) of October 2004 Hasbrouck and Saar (2009) find that around one-third of all limit orders are canceled within two seconds or 11.5% within 0.1 seconds. They stress that the fleeting orders are a recent phenomenon. The two-second criterion was later dropped with ultra-low latency data. Hasbrouck and Saar (2013) present TotalView-ITCH order book data of October 2007 and June 2008 that flickers within the millisecond regime. Empirical results are also confirmed for other exchanges (Chakrabarty and Tyurin, 2011; Lin et al., 2018), different locations like Australia (Viljoen et al., 2015) or Germany (Groth, 2009), and further markets like the Taiwan futures market (Kuo and Lin, 2018) or EUR/USD FX market (Mandes, 2016).

In one of his most recent studies Hasbrouck (2018) addresses the quote volatility and he comments that classic static market microstructure models are inadequate to explain oscillating quotes at the subsecond horizon because their determinants like interest rates, risk aversion, and informed trade probability do not vary as fast. We aim at giving a conclusive answer to both the cause of fleeting orders and if they pose a potential market quality risk by analyzing the subcategory 'flickering quotes' in detail. We review the literature of fleeting orders and come up with potential hypotheses in the fields of liquidity supply and demand, manipulative, and technical. Closest to our paper is the article of Hasbrouck and Saar (2009), which uses in part analogous methods and weights three different trading strategies as causes with a NASDAQ subsample from October 2004. We add to this by expanding the analyzed hypotheses incorporating different publications and discussions with experts, by using additional analysis methods and a new market segment. Options have never been used to bring light to fleeting orders, therefore, we use high-frequency tick-by-tick option data of equity options of the German DAX index over the period from January to February 2012. With respect to Hasbrouck and Saar (2009), this dataset allows us to contribute new evidence on the interrelation between underlying and derivatives, as well as between different options on the same underlying with regard to flickering quotes. In particular, we investigate channels that involve trades, price discovery, and the chasing hypothesis with more depth. Besides this, also new conclusions about liquidity and market quality can be drawn.

We show that around 20% of all order book changes can be attributed to top-of-the book flickering quotes, which behave very cyclical and are seemingly highly automated. The behavior of flickering quotes changes significantly pre- and post-trade within the same option series and remarkably also within similar options. We find evidence that flickering quotes lead to an improved price for liquidity demanding traders, both for slow and fast traders. Empirical analysis reveals that it is most likely that high-frequency traders (HFTs) try to clear their inventory (Hasbrouck and Saar, 2002; Carrion, 2013) by offering fleeting orders. Additionally, we find weaker evidence that flickering quotes are used to incorporate new information (Menkveld, 2016; Blocher et al., 2018; Li, 2018). We do not find any support for a harmful behavior or a risk-aversion property of fleeting orders.

The paper is organized as follows: Section I introduces the literature related to fleeting orders and extracts hypotheses about possible channels and determinants driving this order book pattern. The following section II presents the data with descriptive statistics and visualizes flickering quotes. A profound analysis of motivations behind flickering quotes, including bivariate analyses, linear regressions, logistic regressions, and cox hazard rate analyses, is given in section III. The results are discussed in chapter IV and the last section V concludes.

I. Hypotheses about the Fleeting Orders

In this section, we develop our hypotheses and discuss the empirical approaches. The first three hypotheses refer to liquidity supply (market making). Additionally, liquidity demanding (active trading), technical and manipulative hypotheses are presented in the following. Fleeting orders are described by empirical as well as theoretical contributions.

Hasbrouck and Saar (2009) formulate the chasing hypothesis, which describes a reaction to market movement. A limit order, which has fallen behind the current best offer is canceled, and a new limit order resubmitted to regain price priority.

In line herewith, the theoretical work of Liu (2009) also encompasses a trading model with a patient buyer, news trader, and liquidity trader. The buyer and seller are allowed to withdraw their orders to avoid being picked off if unfavorable news arrives. The author deduces several hypotheses regarding order cancellations from his model. First, the free option risk: If good (bad) news arrive, the asset value is higher (lower) than the current market price, which is equivalent to a free call (put) option. An increase of the free call (put) value is associated with more limit sell cancellations, to avoid being picked off. Second, the non-execution risk: An increase of the free call (put) value is associated with more limit buy cancellations, to adjust the offer according to the increased asset value to regain price priority. Third, with a narrower spread, the number of order cancellations will increase. Fourth, larger stocks have more order cancellations.

Fong and Liu (2010) empirically analyze limit order revisions and work out the non-execution, which is in line with the chasing hypothesis of Hasbrouck and Saar (2009), and the free option risk as major reasons for order cancellations. If limit order providers face the risk of other traders exploiting the offered option to buy or sell a stock (free option risk), they will decrease the price priority. Thereby, revisions are not random but related to monitoring costs. Also Liu (2009) presents a model with free option and non-execution risks of liquidity suppliers and finds an increase in cancellations for actively traded stocks and firm size and a decrease with spread. The CFTC (2001) comes to the consensus that flickering quotes 'are real quotes that are subject to immediate acceptance', which reduces the risks, market makers are facing. The tactical liquidity provision algorithm outlined e.g., in Easley et al. (2012) will also lead to cancellations if the probability of adverse selection rises (with time).

Additionally, market participants are, in general, seen as risk-averse (Pratt, 1964). Especially for market makers, risk aversion leads to higher spreads and lower liquidity (O'Hara and Oldfield, 1986; Subrahmanyam, 1991), which is especially true for a competitive market (Dennert, 1993). Under the light of this paper, a decline in liquidity may be reflected as an increased number of fleeting orders. As O'Hara and Oldfield (1986) point out, the spread of a risk-averse market maker can widen depending on, e.g., the supply. In a modern limit-order-book market, this means that less supply e.g., no other quotes near the current limit order of the market maker might lead the market maker to use fleeting orders to cope with the risk. This strategy of market makers, namely to cancel a limit order after a specific time, if no other participant follows and quotes at the same level (against whom the market maker could unwind their trade) or to use cancellations as protection against arbitrage strategies, as fleeting orders introduce some level of uncertainty into the prices, was discussed and developed with market makers.

In summary market makers constantly face the risk of their quotes being picked off by an informed or faster trader. Therefore, they search for ways to reduce their risks while still acting as a liquidity supplier in terms of their market maker status. Submitting and canceling orders fast is a potential solution, which points 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 a continuous trading setting with patient limit traders on one side and only impatient traders on the other order book side, where the limit traders will undercut each other if no correct undercut level (equilibrium) is found.

In his meta-study on HFT Menkveld (2016) extrapolates from the classical Glosten and Milgrom (1985) model. Thereby, more quote updates in between trades and price discovery through quote updates are expected in a high-frequency context. Blocher et al. (2018) identify cancellation clusters with an exponentially weighted moving average. The authors construe these frequently occurring clusters as a sign for HFTs improving the price discovery and processing information because after clearing a price level in the order book with cancellation clusters either the level is mostly filled again or the opposite order book side moves to narrow the spread (true price change). This is directly linked to the liquidity concerns within HFT. Cartea and Penalva (2012) hypothesize that HFT will adapt their offers after a marketable order hits a limit order, which results in cancellations. Also Li (2018) finds no adverse effect of fleeting orders on liquidity measures. In his view, fleeting orders are mainly used for market making strategies (updates of old and stale quotes), which is beneficial for the market quality. In a previous version of their paper, Baruch and Glosten (2019) also elaborate on flickering quotes. In their repeated stage model, liquidity suppliers fill the order book, and then, either the game ends right away after a news trader arrives, or it continues. In the latter case, the liquidity suppliers randomly revise their limit orders to avoid undercutting, which potentially leads to flickering quotes, and the game repeats.

Another interesting aspect is that fleeting orders might be driven by other markets, as HFT leads to synchronized prizes Gerig (2012). This is especially important for options, which are highly dependent on the underlying prices.

All in all cancellations of market makers might be due to market movements and new information, which encompass price discovery through quote updates, synchronization and chasing of different market movements, clearing levels, and refilling right away or filling the other order book side, and adapting offers after a marketable order. Thus, both theoretical and empirical contributions lead to the following hypothesis:

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

Especially overnight, HFTs try to minimize their inventory or even have zero inventory (Carrion, 2013). To achieve this, they could use fleeting orders to offer their undesired positions at a discount to other participants. In contrast to marketable orders, they can hereby still earn the (now a little bit smaller) spread. If possible, they will do this in a calm market with foreseeable risks. With these short lived offers, they can further reduce their adverse selection risk. In short, the business model of HFTs is to utilize their speed advantage to gain profits and holding on to positions only increases their risks. Therefore, we hypothesize:

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

Additionally, Roşu (2009) presents a dynamic model of continuous trading in an order book setting without a minimum tick size. The novelty is that traders can modify and cancel their limit orders freely. He derives empirical implications from his model with patient and impatient buyers and sellers (general case). He posits that in a competitive order book market 'when the limit order book becomes full, a buyer or seller will place a limit order, and a limit trader on the other side will immediately accept it by canceling the limit order and placing a market order', which would result in a fleeting order. Corresponding, Hasbrouck and Saar (2009) set out a dynamic strategy in which traders want an immediate execution as the cost of immediacy decreases and replace their previous limit order (cancellation) with a marketable order. E.g., if a market participant wants to buy an option, she can use a buy limit order; if the price of a sell limit order drops, she can decide to cancel her buy limit order, which results in a fleeting order, and use a marketable order to buy the sell limit order. Also Kuo and Lin (2018) show that the non-execution risk of traders is a factor for order cancellations. Hoffmann (2014) mentions another tactical element which may lead to fleeting orders. Stale orders of slow traders are prone to be exploited by fast HFTs. Therefore, 'slow traders strategically submit limit orders with a lower execution probability'. This can be accomplished either by price or by short lived offers, which is reflected in fleeting orders. In line with this hypothesis, Baruch and Glosten (2013) argue that 'limit-order traders worried about being undercut can effectively hide their quotes by using short lived orders at random prices'. 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) stress that the fleeting orders as recent phenomena are driven by technology (automated trading and low latency). In the view of Hasbrouck and Saar (2013), the low-latency activity represents algorithms responding to each other. They attribute the submission, cancellation, and resubmission patterns to algorithms attempting to trigger actions of other algorithms or of algorithms alternately trying to position their limit orders strategically in response to each other. Additionally, Cartea and Penalva (2012) expresses, that HFTs position their offers and bids constantly with respect to the other HFTs, which also leads to quick renewals of limit orders. Thus, the following hypothesis is stated:

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

Finally, fleeting orders can be used as a manipulative tactic known as spoofing. This strategy involves the placement of visible orders in the opposite direction of the desired intention to create the illusion of supply or demand and consequently drive prices in a favored way before the actual trades are unwound and the deceptive orders finally canceled. While the manipulative spoofing is appealing the risk of detection and prosecution by the SEC let Hasbrouck and Saar (2002) doubt that the order of magnitude of canceled limit orders can be attributed to this. The act of exchange bandwidth overloading, or quote stuffing, should also be mentioned (Cartea and Jaimungal, 2013). Based on the alleged manipulation of the CBOE volatility index (The Wall Street Journal, 2018) another potential fraud comes to mind. Traders could influence the price of options with limit orders to drive a volatility index in the desired fashion. The calculation of, e.g., the STOXX 50 volatility index, is based on mid prices, which allows traders to drive the volatility index without actually trading options. Only our unique dataset enables us to review this special manipulative tactic of the VIX, so that we can hypothesize broadly:

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

II. Data

We investigate the case of fleeting orders and flickering quotes with a novel and rich high-frequency option dataset. Option data has not been used to analyze this matter and, therefore, allows for new conclusions. For our analysis, we use quote data from EUREX covering order books of over fifteen thousand American option series of 30 German blue chips, which are members of the DAX as of 2012. The observation horizon spans 43 trading days from January to February 2012. We know the first three bid and ask order book levels on a nanosecond base with price, volume, and the number of contributors. The sample is constructed from order book difference information, which contains submissions, cancellations, and trades. The option as well as the corresponding underlying data from the Deutsche Börse are obtained via the European Financial data Institue (EUROFIDAI) and provided by the BEDOFIH (Base Europenne de Donnes Financires Haute Frquence) database. The EUREX trading architecture offers two different order types for options, namely either limit or marketable orders.

As mentioned in the introduction, we define a flickering quote as a limit quote, which improves the price (e.g., for the case of bid a higher offer), and subsequently gets canceled, without any time restrictions. As we do not have trader IDs, we are not able to characterize every fleeting order as such and therefore use flickering quotes as a subset of fleeting orders. We demand a flickering quote to have no other equal offer or improved price on the same order book side between introduction and cancellation. Additionally, we exclude limit offer adjustments, that coincide with a movement on the other order book side, without a change in the absolute bid-ask spread. This order renewals can easily be attributed to a simple price update and is therefore not of interest to us, as the intention is clear and requires no further analysis. A prime example of a flickering quote dominated order book (here, on the bid side (red line)) is printed on the left side of Figure 1. The right side of the figure shows the single ticks of the bid-side (not scaled for clock-time, equidistant between ticks), where the 66 flickering quotes can be seen particularly easy.

Not all of the several thousand tradeable options are liquid, as some are, for example, very deep-out-of-the money or have a very long time till expiration. Therefore, we truncate our data set and demand on average an order book change at least every minute or 510 changes in the order book as trading starts at 9 a.m. and ends at 5:30 p.m. Around half of all options are sorted out, which is less than one percent of all order book changes (see Table I). The average (mean) order book changes for all options are with 4,724 well above that threshold.

A. *Preliminary Analysis*

To get a better understanding of flickering quotes, we present some very distinct behavior of the data. The timing of the orders is very rhythmical. Participants submit periodically mainly at the start of a new second (clock-time). Figure 2 shows the histogram of one-second remainders of all timestamps of the order book changes, calculated as mod 1,000,000 over the timestamps in nanoseconds. Besides the first most prominent peak around three milliseconds, two additional

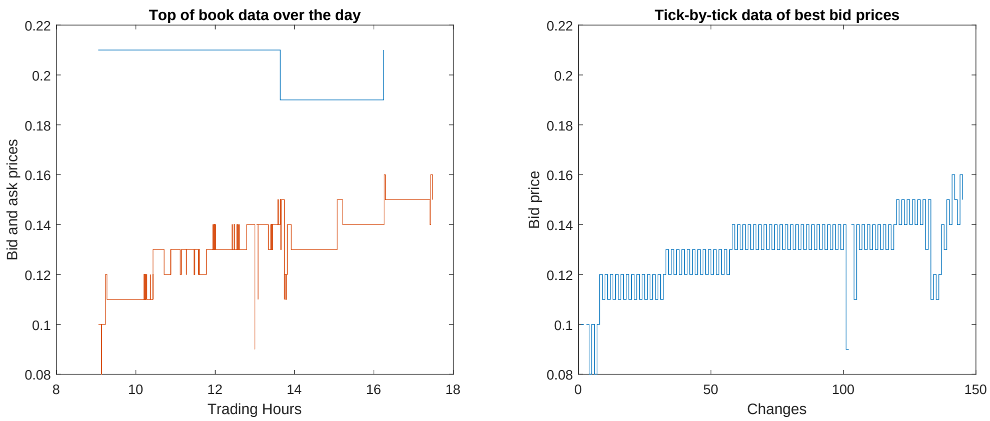

Figure 1. Flickering quote dominated top of book prices

The example shows order book data from 01/02/2012 of a call option on BMW AG with expiration on 06/15/2012 and a strike price of 78 EUR. The underlying closing price on 01/02/2012 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 see the clustered flickering quotes.

Table I Descriptive statistics: Full sample vs. truncated sample

	Options	Order book changes	Flickering quotes	Cancellations	Trades
Full Sample	15,374	72,628,892	7,041,901	30,926,187	4,430
Truncated	7,505	72,325,321	7,002,537	30,708,548	4,323
Truncated share	51.18%	0.42%	0.56%	0.70%	2.42%

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.

peaks at 14 ms and 27 ms can be detected (the peaks are marked with dotted vertical lines). Furthermore, there are smaller peaks every tenth of a second, with the most distinct at 0.1 seconds and half a second after the start of the second. The identical pattern is shown by the analogously constructed histogram of all flickering quotes. Bigger timescales like one-minute remainders only show a second-pattern, without a bigger peak at every minute start. Smaller timescales do not reveal any particular pattern. There is nearly no pattern observable in trades, which indicates, that order book changes or flickering quotes are detached from trades to a certain extend.

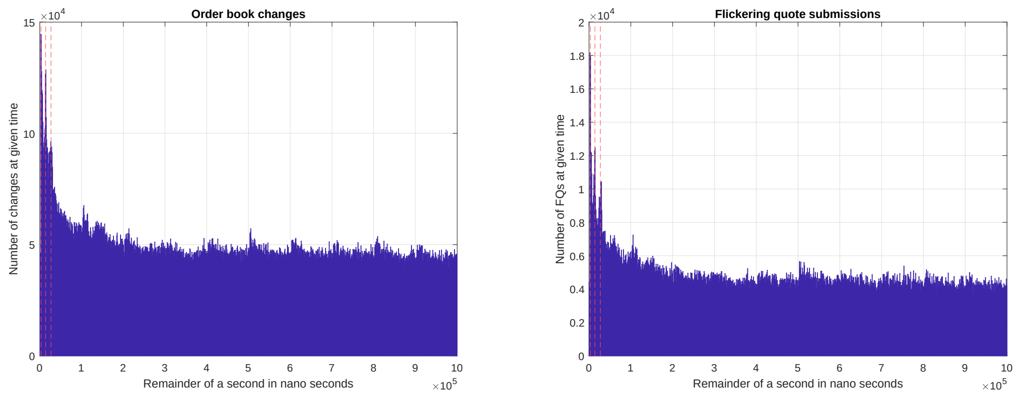

Figure 2. Histogram of order book changes and flickering quotes over the remainder of a second

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 nanoseconds (clock-time). The first three vertical dotted lines are at the peaks 3ms, 14ms, and 27 ms.

The flickering quotes behave very similarly to the general order book changes regarding further measures. For example, Figure 3 shows the number of changes for all options clustered in five moneyness categories, relative to the at-the-money cluster. The first three sub figures (from the left) display the order book changes, flickering quotes, and cancellations. All three sub figures show an inverted U-shape and are detached from the number of trades. Interestingly, the relative flickering quotes (the number of flickering quotes divided by the number of order book changes) have a U-shape and are even more detached from the number of trades or any other subplot. This means that deep-in- and deep-out-of-the money options have less order book activity and that they are in general less liquid. This confirms the stylized fact of options, which are in general most liquid at-the-money, where most volume is traded, too (Etling and Miller, 2000). Besides moneyness clusters, we analyze clusters of option prices, options trading volume, underlying prices, underlying trading volume, underlying market capitalization, underlying daily returns, and weekly patterns, for all options as well as separated in puts and calls. In general, the conclusions from above prevail: The number of order book changes and the number of flickering quotes are very identical, mostly not closely related to actual trading volume.

Also, in further analysis, the similarity between flickering quotes and order book changes is evident. In Figure 4, we plot the log10 time between the top of book changes with (top-row) and without (bottom-row) flickering quotes and the time between submission and cancellation

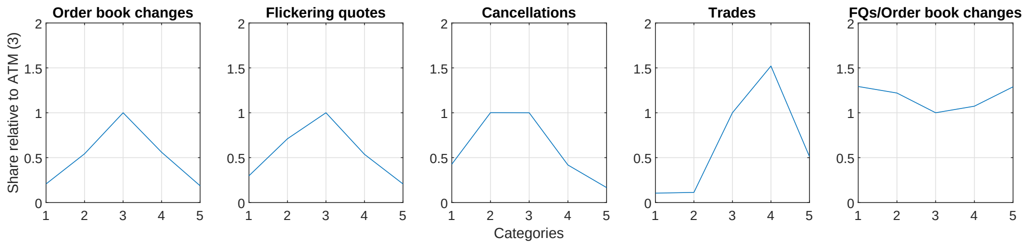

Figure 3. Relative comparison of flickering quotes and other measures over moneyness

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.

of flickering quotes (mid-row) in nanoseconds. The data is clustered for daytime and every line represents one day of our sample. The similarities of all subplots are evident with identically placed peaks. Major peaks are at around 20 and 30 milliseconds (4.34 and 4.5 in the plots), 1 second (6 in the plot), and around 15 seconds (7.17 in the plot), whereas especially the last data point is driven by flickering quotes around the central trading hours. Some peaks can also be attributed to certain remote exchanges. For reference, the equivalent distance from Frankfurt to London, Paris, and Amsterdam is around 3.3 to 4.6 milliseconds, to New York around 40 milliseconds (CFTC, 2014, note, that the refrence point was Zurich, however, an archived article used the same values for Frankfurt), and to the Asian markets around 150 milliseconds (China Telecom, 2018). Note that latency is normally expressed as round trip delay (RTD). However, we report the time needed for a one-way route for our purpose. Internal system latencies may well add a few milliseconds. We estimate the latency for co-location at around three milliseconds.

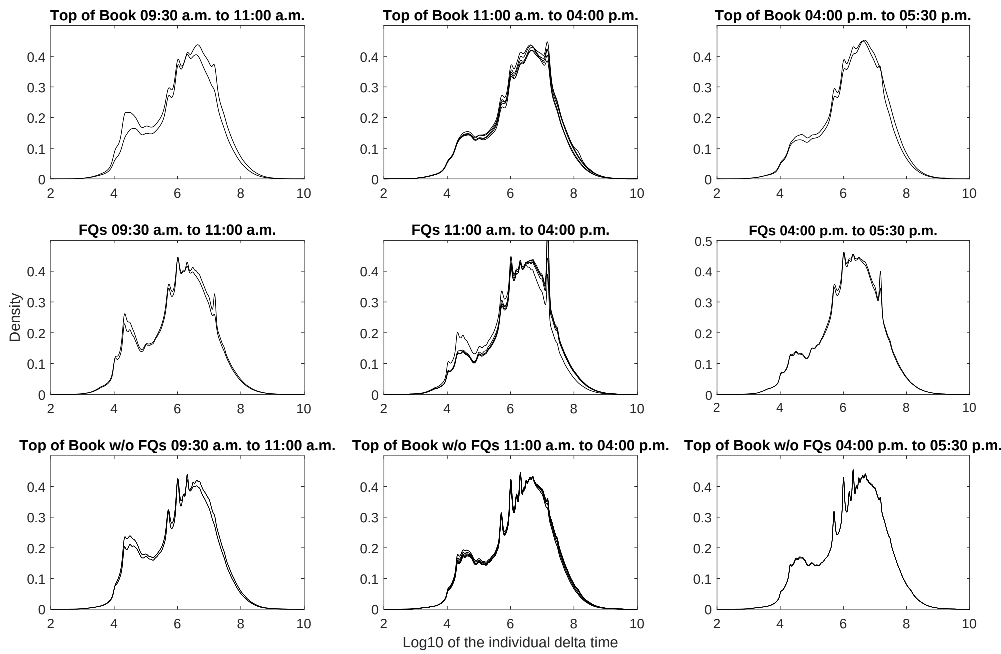

Figure 4. Density plot of time between order book changes

Shown are the density plots of log10 delta times in nanoseconds. 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 milliseconds, 1 second and 15 seconds. 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-second 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.

III. Analysis of Flickering Quotes

For this chapter, we firstly use a bivariate analysis, that focuses on the connection between flickering quotes and trades to grasp the impact on market quality. 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 data (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.

A. *Bivariate statistics: pre and post trades*

A primary concern about flickering quotes is their influence on market quality, e.g., 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. Tables II reports the number of order book changes, the number of flickering quotes, and the share of flickering quotes in the whole order book five minutes before and after trades. Thereby, we truncate our sample to the trading hours from 10:00 a.m. until 04:00 p.m. and exclude overlapping trades in the bespoken five-minute time window before and after a trade. We can 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 five minutes 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 flickering quotes within five minutes times two divided by all top of book changes, declines significantly on the trade-side, 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 need the factor 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 indifferent afterward. Key takeaways from this are that after a trade, the new information is processed, which leads 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 flickering quote share. 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 of flickering quotes itself. This is a contradictory finding to the hypotheses of flickering quotes as a tool of active trading (**H4**), as we would expect a lower 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 quite order book with small spreads (see Table III), whereas the driving forces behind flickering quotes are not affected very much. Additionally, we computed the spreads with the exclusion of one minute surrounding the trades (meaning from five minutes to one minute 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 flickering quote share over all after the trade is higher than any individual share on the trade-side and non-trade-side), as $(\sum^n FQ/n)/(\sum^n OrderBook/n) \neq \sum^n (FQ/OrderBook)/n$.

Most interestingly, these changes in flickering quote numbers comparing the instances before and after trades are not only visible in the respective option series, in which the trade happened, but also in other closely related option series. Table IV 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

Table II 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%	***

The table compares the average sum of flickering quote submissions within a five minute 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 five minute window multiplied by two. The multiplication is purely done 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 follow one another within a one minute window directly. Besides the total number (top row), we calculate the results for the trade-side and non-trade-side separately, to gain further insights. *** indicate a 1% significance of the null hypothesis, that the pre and post cases have the same mean and standard deviation.

Table III Bivariate statistics of spread before and after trades

	pre	post	sig.
tick weighted	1.23%	1.38%	***
time weighted	1.40%	1.51%	***

The table compares the average relative spread within a five minute 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.

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, which additionally 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, which results in more flickering quotes during the adjustment process.

Table IV 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	***

The table compares the average sum of flickering quote submissions within a five minute window before and after a trade. Contrary to Table II, 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.

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

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 incorporate it, too. Of interest is the change in the best price leading to the trade. We define this measure referring to Hasbrouck and Saar (2009) as $p_i^{Bid} = (Price_t^{Bid} - Price_{t-1}^{Bid})/Price_{t-1}^{Bid}$, 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 $p_i^{Ask} = (-Price_t^{Ask} + Price_{t-1}^{Ask})/Price_{t-1}^{Ask}$, which also results in a narrower spread for positive p's. Shown in Table V 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 milliseconds as cut off criteria which is even below the 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 seconds) the average p further rises for the trade-side. The mean of the non-trade p is negative, probably because of outliers, as the median is positive again. If we demand faster flickering (e.g., more than two flickering quotes within 500 milliseconds on the trade-side), the p on the trade-side further rises with a mean of 8.06%. For trades without prevailing flickering quotes, p is smaller, however still significantly positive. Therefore, automated trades associated with flickering quotes are to the benefit of traders. Furthermore, also for order book changes within humanly accessible time frames (we chose one second based on a bill of indictment against human traders accused of spoofing (CFTC, 2019)) all p's are significantly positive on average. 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 algo accessible time frames. Lastly, also the non-trade-side behavior might 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, for a 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 for manipulation in this regard. However, the share of flickering quotes rose drastically right before trades, as reported in Table II. Therefore, we want to analyze what factors drive this share, next.

Table V Changes in spreads before trades

	25%	50%	75%	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 < 200ms					
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 < 200ms & 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 < 200ms & No FQs on any 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 sec & 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 < 200ms & No change on trade side < 10 sec & 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%	***

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 milliseconds. Case **III** demands a change on the trade-side within the last 200 milliseconds and more than two flickering quotes on the trade-side within the last 10 seconds. Case **IV** demands a change on the trade-side within the last 200 milliseconds and no flickering quotes on any side within the last 10 seconds. 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 seconds. Case**VI** demands a change on the non-trade-side within the last 200 milliseconds and no change on the trade side within the last 10 seconds, and more than two flickering quotes on the non-trade-side within the last 10 seconds.

B. Regression: Flickering quote share

The deduced hypotheses imply testable relations of different option and corresponding underlying factors on the flickering quote share. Therefore, we conduct a multiple linear regression on the flickering quote share. To calculate a share, we need a timespan and cannot use tick-by-tick data as is. To make use of our data and simultaneously come up with a long enough time range to calculate useful shares that do not consist mainly of zeros (no flickering quote within timespan), ones (order book change consists only of flickering quotes), or no value (no change at all), we found one minute to be an appropriate timespan. The flickering quote share of one minute itself results in the sum of all order submissions characterized as flickering quotes within one minute divided by all order book changes at the top of book at the same time. As this allows us to use closely lagged variables, we have no potential endogenous problem and do not need a two-stage regression as van Ness et al. (2015).

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

In times of uncertainty (e.g., volatile prices), the risk for market makers is very high, especially paired with a low bid-ask spread to recover costs or losses by buying low and selling high. Consequently, we would expect a positive influence of the volatility and negative influence of the spread 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 one-minute 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.

The usage of option data enables us to utilize the close connection to the underlying and to gain further insights. Thereby, the underlying volatility is important with regard to risks that market makers face. Within an uncertain time (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**). Prices need to be adjusted frequently and fast, that is why we would also expect a positive influence of 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 minutes before t, over which we calculate the standard deviation of one minute 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, that want 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 ten minutes ($Trade_{t-10}$). Contrary, 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 (**H5**), flickering quote shares will be positively autocorrelated, which we test with the one minute 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, e.g., the VSTOXX of the EURO STOXX 50 index, would occur. We test this with the $STOXX_{dummy}$, which is 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

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

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

According to Hasbrouck and Saar (2009), we perform one regression for each of the 43 days individually and aggregate afterward because of the very big data sample. However, we choose to report the median instead of the counts itself, as with the following analysis, we cluster further and would have to report big numbers, which cannot be compared easily. For further insights, we present the share of all highly significant estimates (p-value below 1%) that are 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. We explicitly compute stock clustered standard errors (Petersen, 2009) and implicitly day clustered errors with our approach. The residual plots of the regressions are not suspicious.

With regard to the regression results of Table VI, it is evident that the option volatility is highly significant and negative for every day, and the spread likewise significantly positive for every day in our sample. This means that relatively more flickering quotes are associated with low volatility and wide spreads, which is in contrast to market maker risk minimization (**H1**). 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 liquidity supplier 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 the options are in the money, the less the underlying flickering quotes influence or even negatively influence the flickering quote share of the option, as for in-the-money call (put) options, the median estimate is -2.65 (-1.52) and significant. 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 so that 30.23% (4.65%) of all significant estimates are negative. All this indicates no price discovery process (**H2**), driven by the underlying.

The positive estimate for preceding trades fits for 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 as of our criteria and, additionally, on average, negative.

The lagged term has a negative impact on the current flickering quote share, which contradicts a reaction hypothesis (**H5**) of algorithmic traders to each other with fleeting orders. However, the time scale of one minute 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, which is not reported separately, as it is only a control variable, is a negative dummy 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 a have slightly smaller flickering quote share.

At this point, we want to emphasize that some measures might influence the bid and ask side differently. By running two regressions for the bid- and ask-side separately, we find out that a positive underlying return drives the flickering quote share on the bid side and dampens the share on the ask side for calls. 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

Table VI Regression on the flickering quote share

	estimate	p-value	sig $\beta > 0$	hypothesis	expectation
(Intercept)	3.49E-01	0.00%	100.00%		
$Vola^{Option}_{t-1}$	-5.07E-01	0.00%	0.00%	H1	$+$
$Spread^{Option}_{t-1}$	2.22E-01	0.00%	100.00%	H1	$-$
$Vola^{Underlying}_{t-10}$	-1.68E+01	0.00%	0.00%	H1, H2	$+$
$\frac{FQ^{Underlying}_t}{OB^{Underlying}_t} \cdot \lvert M\rvert^{InMoney}_{Call}$	-2.65E+00	0.00%	0.00%	H2	$+$
$\frac{FQ^{Underlying}_t}{OB^{Underlying}_t} \cdot \lvert M\rvert^{OutMoney}_{Call}$	-2.38E-01	0.00%	30.23%	H2	o
$\frac{FQ^{Underlying}_t}{OB^{Underlying}_t} \cdot \lvert M\rvert^{InMoney}_{Put}$	-1.52E+00	0.00%	4.65%	H2	$+$
$\frac{FQ^{Underlying}_t}{OB^{Underlying}_t} \cdot \lvert M\rvert^{OutMoney}_{Put}$	6.38E-01	0.00%	86.05%	H2	o
$Trade_{t-10}$	1.04E-03	0.02%	88.37%	H3, H4	$+$ (H3), $-$ (H4)
$OddLot^{Option}_{daily}$	-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				

The table reports the results for the regression on the minutely flickering quote share:

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

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 big 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 demand at least 90% of all individual significant estimates to be positive, for a negative median estimate, we no more than 10%. Additionally, the table references the individual factors to the appropriate hypotheses, as outlined in section I, 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%.

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 VII only reports the bespoken estimates. Furthermore, we tested other volatility estimate definitions, like high and low prices, without any notable differences.

Table VII 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		

The table reports an excerpt of the regression as in Table VI 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 VI for brevity. As these results do however change, if we separately regress the bid and ask side, we report them separately. No other estimate changed considerably. As before, we estimate the regression separately for the 43 days in our sample due to the big 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 demand at least 90% of all individual significant estimates to be positive, for a negative median estimate, we demand 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.

The regressions give interesting insights and allow us to investigate some hypotheses. Unfortunately, however, it does not make use of the tick-by-tick high-frequency dataset. Therefore, the logical next step is to use analyses, which overcome this issue and potentially bear further insights.

C. Logistic regression: Flickering quotes

To investigate the behavior of flickering quotes with tick-by-tick data, we apply a logistic regression and follow Hasbrouck and Saar (2009) closely. However, we expand their model to reflect our hypotheses, and 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 these orders as a flickering quote. 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 is valuable. 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:

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

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 the sample size increases drastically and we are computationally bound and therefore not able to evaluate 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 datasets have computational advantages regarding speed. The explanatory variables are standardized to have zero mean and a deviation of one, to enable comparisons. Like before, we report the median estimate and median p-value.

We use the same factor definitions as Hasbrouck and Saar (2009), if it is applicable for our purpose. $Vola_i^{before}$ is the absolute of the five-minute 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, a 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. The trading volume $Volume_i^{before}$ ($Volume_i^{after}$) is the sum of the traded volume in the option series within the five minutes 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 of 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 for the bid-side $p_i^{Same} = (Price_i^{Bid} - Price_{i-}^{Bid})/Price_{i-}^{Bid}$, 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 III.A). 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, but this tactic is not possible to be used with the reviewed options. That is why we expect no significance hereof. The change after order i on the opposite order book side is defined for a submission on the bid-side as $q_i^{Opp} = (Price_{i+}^{Ask} - Price_i^{Ask})/Price_i^{Ask}$, 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. 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 milliseconds before and after the submission, respectively, to narrow down HFTs responding to another. We do not log-transform the number of flickering quotes, because we often obtain zero flickering quotes for one observation, for which the logarithm is undefined. Further control variables consist of a measure for the days until expiration of the option ($\Delta Expiration_i$) as well as dummies 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. ($Close_i$), whereby we choose these time frames based on the results of the density plots from Figure 4.

We can show that, even though the median p-values of most measures are highly significant, the significant estimates with the same direction are sparse. Only the positive $Vola_i^{before}$, negative q_i^{Opp} and positive $\#FQ_i^{before}$ estimates fall within our outlined significance criteria. While the first result of $Vola_i^{before}$ is in contrast to **H1** (market makers using fleeting orders to mitigate their risk) the latter two are in line with the expected results of the cost of immediacy active trading hypothesis **H4** (however, the other results do not support **H4**) and the responding hypothesis **H5**.

The results are, in general, 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 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

Table VIII Flickering quote probability

	estimate	p-value	sig $\beta > 0$	hypothesis	expectation
(Intercept)	5.07E-01	0.00%	79.06%		
$Vola_i^{before}$	-4.68E-02	0.94%	17.82%	H1, H2, H3	$+$(H1, H2), $-$(H3)
$Spread_{i-}$	-3.54E-01	0.00%	13.30%	H1, H3	$-$
$Volume_i^{before}$	4.65E-03	5.34%	57.01%	H4, H6	$o/-$
$Volume_i^{after}$	-5.50E-03	29.11%	42.71%	H4, H6	$+$
p_i^{Same}	2.72E-01	0.00%	95.33%	(H4)	o
q_i^{Opp}	-3.88E-01	0.00%	2.55%	H4	$+$
$\#FQ_i^{before}$	1.37E-01	0.00%	99.84%	H5	$+$
$\#FQ_i^{after}$	-1.50E-01	0.00%	16.47%	H5	o
$\Delta Expiration_i$	1.68E-02	0.00%	54.72%		
$Open_i$	-6.43E-02	0.11%	34.41%		
$Close_i$	8.79E-03	0.41%	51.48%		

The table reports the results for 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 II). The regression is given as

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

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 demand at least 90% of all individual significant estimates to be positive, for a negative median estimate, we demand not more than 10%. Additionally, the table references the individual factors to the appropriate hypotheses, as outlined in section I, 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.

the remaining estimates considerably. The average residual first-order autocorrelation was well below 0.1. Other model specifications with, e.g., 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 IX).

Table IX 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	-2.56E-01	0.01%	6.13%	-1.73E-01	0.00%	40.85%
In	-4.75E-02	2.44%	22.28%	-5.46E-01	0.00%	4.23%
At	-2.75E-02	2.39%	32.63%	-4.54E-01	0.00%	3.76%
Out	-4.56E-02	3.12%	31.10%	-4.88E-01	0.00%	3.90%
Deep Out	-1.44E-01	0.11%	10.11%	-3.13E-01	0.00%	29.28%

The table reports an excerpt of the regression as in Table VIII 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 demand at least 90% of all individual significant estimates to be positive, for a negative median estimate, we demand not more than 10%. The average number of observation 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.

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.

D. 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 $Vola_i^{before}$, $Spread_{i-}$, $\#FQ_i^{before}$, as well as $Expiration_i$, $Open_i$, 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 choose to preferable monitor volatile options, which leads 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^{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^{Same}. This means that a participant is reacting 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^{Opp}. A lower spread due to movements on the opposite side (a negative q^{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 derivate markets in a high-frequency context. To account for puts and calls, we multiply the underlying q-measures with minus one for puts as they act herewith in the opposite direction as for calls. For flickering quotes on the bid-side, we compute $q_i^{UnderlyingSame} = (-1)^{(Put_{Dummy})}(Underlying_i^{Bid} - Underlying_{i+}^{Bid})/Underlying_i^{Bid}$. Analogously to the opposite q measure and $q_i^{UnderlyingSame}$, $q_i^{UnderlyingOpp}$ 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 responding 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

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

Compared to the factors of the logistic regression Equation 2, we remove factors, which cause 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 and we are not computationally bound anymore. We perform individual analysis of our hazard rate model in the same manner as the logistic regression and aggregate the results afterward and normalize all regression factors analogously. The results of the proportional hazard analysis presented in Table X are robust to any clustering. However, it should be noted that with a longer time till expiration, the estimate of p_i^{Same} gets 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.

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 price discovery (**H2**) and HFT unwinding their inventories (**H3**). 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**. Even if q_i^{Opp} is not highly significant, the widening spread on the opposite side to 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 the cancellation, which is not covered by a response to other algorithmic traders (**H5**). The last significant factor is a positive dummy for the opening hours, which 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).

Table X Cox hazard rate of flickering quotes

	estimate	p-value	sig $\beta > 0$	hypothesis	expectation
$Vola_i^{before}$	6.72E-02	0.02%	99.30%	H1	$+$
$Spread_{i-}$	1.73E-02	0.02%	59.40%		
p_i^{Same}	-4.17E-02	0.70%	37.31%	H1	$+$
q_i^{Same}	1.50E-01	0.00%	95.14%	H1, H2, H3	$+$
q_i^{Opp}	3.11E-02	2.62%	87.32%	H4	$-$
$q_i^{UnderlyingSame}$	8.98E-02	0.00%	92.55%	H2	$+$
$q_i^{UnderlyingOpp}$	-9.18E-02	0.00%	6.20%	H2	$-$
$\#FQ_i^{before}$	1.28E-01	0.00%	99.98%	H5	o
$\Delta Expiration_i$	-4.14E-02	0.00%	28.21%		
$Open_i$	7.94E-02	0.00%	92.88%		
$Close_i$	4.08E-02	0.10%	80.32%		

The table presents the results of the Cox proportional hazard rate analysis of flickering quote cancellation duration times. The hazard rate is modeled as

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

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 five minutes. The relative spread is calculated with the prices at the instant before the submission, that leads to the flickering quote. As for the logistic regression, we use for flickering quote submissions on the bid-side $p_i^{Same} = (Price_i^{Bid} - Price_{i-}^{Bid})/Price_{i-}^{Bid}$ and $q_i^{Opp} = (Price_{i+}^{Ask} - Price_i^{Ask})/Price_i^{Ask}$, where $-i$ depicts the instant before the submission i. q_i^{Same} is calculated analogously. Furthermore, $q_i^{UnderlyingSame} = (-1)^{(Put_{Dummy})}(Underlying_i^{Bid} - Underlying_{i+}^{Bid})/Underlying_i^{Bid}$ 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. Whereby, for the underlying q is multiplied by minus one, to allow for the same effect mechanism and expected estimate with puts. To capture the high-frequency nature of our data set, the number of flickering quotes leading to i are summed over 500 milliseconds. No logarithm transformation is used, as the short timespan results in a lot of zero measures. 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 for faster cancellations of flickering quotes.

We estimate 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 demand at least 90% of all individual significant estimates to be positive, for a negative median estimate, we demand not more than 10%. Additionally, the table references the individual factors to the appropriate hypotheses, as outlined in section I, with the expected estimate sign, either positive (+), negative ($-$), or without a clear expectation (o). The average number of observations per cluster is 7,095.45.

IV. Discussion of the Hypotheses about the Flickering Quotes

Fleeting orders and flickering quotes are widely associated with high-frequency trading. However, the fast up-and-down movement within one order book side might also be due to slow traders. In fact, we see flickering quotes lasting all too often several seconds before the order is deleted. On the other side, the pattern plotted as the remainder of a second suggests non-human but automated trading as the primary cause. The scale of flickering quotes and cancellations within our data is comparable to the literature so far (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 that, the EUREX options market does not allow for hidden liquidity, which is often mentioned as a prime cause of fleeting orders. The primary concern about fleeting orders is the impact on market quality and the risk of fleeting orders as a manipulative tool to select other market participants adversely. However, we can show that all traders use marketable orders after a favorable price change. Even if faster traders are able to ensure to trade after an even more favorable adjustment, also slow traders benefit from these movements. Slower traders can trade after a relative 3% price improvement. Flickering quotes instead improve the spread and add liquidity to the market, which is in line with the literature about algorithmic trading (Hendershott et al., 2011). The number of flickering quotes is closely linked to the general order book behavior and not to actual trading volume. We can also refute other market manipulation. In line with the conjecture of Hasbrouck and Saar (2002) we find no evidence for the involvement of fleeting orders in spoofing. After a successful manipulative trade, we would expect a withdrawal from the market for a while. In contrast, the number of flickering quotes rises after a trade. Furthermore, we do not find signs of volatility index manipulation. Even if we did not use an extensive analysis of (flickering quotes) volume concerning VIX sensitivity, like Griffin and Shams (2018), our clustering implicitly enables us to analyze VIX sensitivity, and it reveals no such pattern. Options on EURO STOXX 50 volatility index members have no significant or economically important higher flickering quote share. The logistic regressions support this conclusion, as we would expect a lower flickering quote probability after trades if these are caused by malicious flickering quotes, which is not the case.

Even if it seems contradictory that slow traders would use a tool like fleeting orders, which is associated with HFT (Baruch and Glosten, 2013; Hoffmann, 2014), the cost of immediacy (Hasbrouck and Saar, 2009; Kuo and Lin, 2018) may well lead to these orders. The time between submission and deletion of orders is not ultra-low latency per se, as we show several peaks in the density plots well above one second. Interestingly, the time until cancellation gets longer during the prime European trading hours. The major peaks are not directly related to the distances between other exchanges, however, smaller peaks may well be.

Moreover, we show that the flickering quote environment changes before and after trades. However, in contrast to Hasbrouck and Saar (2009), we find no significant influence of a movement of the opposite order book side on the duration hazard of flickering quotes. They state that the change in the opposing side could either lead to the cost-of-immediacy effect (cancellation by an impatient trader) or motivate a trader to be patient and hold on to her order, as her chance of execution increased with the now closer opposite order book side. Thereby, our narrower approach to use only top of book data probably captures the second effect more likely, as price priority for the trader is given herewith.

In general, the relative grid size of options and equities is not comparable, whereby the other estimates have similar magnitudes. Besides these findings, also the market reaction after a trade is not only focused on the respective option series with the trade, but the effect scatters across other options. Fleeting orders behave similarly to regular order book updates. Therefore, it seems evident that flickering quotes are caused by algorithmic participants reacting to each other. Quote clusters, also described by Hasbrouck and Saar (2013), can be seen in the data. Additionally, the periodic quote updates every second or tenth of a second support this thesis. These periodicities reveal a faster reaction of participants with our data of 2012 compared to the 2007 and 2008 data of Hasbrouck and Saar (2013). Nevertheless, there are doubts about this simple answer. Neither does the negative autocorrelation of flickering quotes or the dependency of the hazard rate on past flickering quotes support this approach, nor is the very short reaction time within our data in line with the timing of the flash crash Kirilenko et al. (2017), which supposedly reflects algorithmic behavior. More convincingly is the hypothesis that fleeting orders are used for price discovery, for which we find strong evidence. The classic market microstructure literature, like Roll (1984), encompasses price formation by new available information (Madhavan, 2000). Ordinarily, trades are viewed as bearer of such news that shifts prices. Appropriately, the number of flickering quotes rises after a trade, which is a sign of a price formation processes. Matching herewith, also the non-trade side and related options change and reflect the price formation with an increase in flickering quotes, which is to be expected in highly interconnected markets within a low latency environment. The stylized facts of flickering quotes, like clustered occurrence and cohesion to the general order book changes, fit into this picture, too. Ultimately, we would expect underlying effects to penetrate through to the option, which is not always the case. The measures have to be very specific and only work at the present. The time-spanning measures, even if only recorded for just one minute, lose the connection, like the volatility measure in the logistic regression. This underlines the ultra low latency environment of today's market structure. The closer the time reference is, the more meaningful and significant the results are, which is in line with comparable studies like Hasbrouck and Saar (2009). In the case of options, both the order book side, as well as the payout profile needs to be considered. The shift of 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 makes sense in this light. The spread measured at the instance before an event is more relevant for the in general liquid and often traded options, whereas the less frequently updated options away from the money have a deeper connection to the - in comparison - sluggish and lagged volatility. If fleeting orders are used as a price discovery tool, they are beneficial to the market quality as they contribute to efficient prices.

In contrast to previous contributions, we find no evidence for mitigation of liquidity suppliers' risk associated with flickering quotes (Liu, 2009; Fong and Liu, 2010). Factors measuring the risk, like volatility and spread, mirror a different picture. Also, a control for the tick-grid size is not relevant for the flickering quote share, which we do not report separately. The processing of news is inherent in the games described by Liu (2009) and Fong and Liu (2010), which argue for a grid size dependency and consequently, a dependency on monitoring costs. However, in an ultra-low latency environment, the competition and low monitoring costs apparently lead to an uncoupling. Liquidity suppliers do instead use their speed advantage to minimize risk, not fleeting orders. Whereas, we find strong evidence for the highly linked inventory risks of HFTs. The trade volume has a positive influence on the flickering quote share (see linear regression), which seems contrary to the bivariate results, where we compare pre and post-trade characteristics. However, if HFTs build up inventory, they might offer their holdings at a discount to reduce risk, which is in line with the price movements before a trade. Unexplained is the movement on the non-trade order book side, which might reflect a convergence to the true mid-price, propelled by the price discovery, especially during the case of calm markets. Following, HFTs seem to unwind their portfolio during low volatility times.

We want to point out that many other relations between the regression factors and the hypothesis could be drawn. However, we chose key aspects that are especially relevant for the particular hypothesis.

Last, we want to emphasize, that due to our data we focus on flickering quotes as a special subset of fleeting orders. Even if we truncate some potential fleeting orders herewith, most order book changes happen at the best quote, consequently we are able to capture most orders of interest. Furthermore, the flickering quote share with respect to all order book changes in our sample is similar to the reported numbers of other contributions.

V. Conclusion

The literature so far has come up with a lot of possible causes of fleeting orders and flickering quotes - the fast submissions and deletions of limit orders. So far, studies in this regard have mostly been carried out with stock or low-frequency data. We extend the literature by analyzing ultra-low latency derivative option data and analyze the hypotheses regarding fleeting orders comprehensively. Around 20% of all orders are classified as flickering quotes within our sample, which might require political interference. New regulations like a maximum order-to-trade ratio introduced with the German high-frequency law (Hochfrequenzhandelsgesetz) and specific implementations by the exchanges do not have a major influence on these numbers, as further analysis of our data showed that most order-to-trade ratios in the respective option series are well below the maximum threshold. Our flickering quote share of around 20% is similar to other contributions reviewing fleeting orders.

These effects are nearly always associated with high-frequency trading and are often seen as a potential market efficiency hazard. We can show that flickering quotes are not hazardous to market quality. Quite on the contrary, these orders have a positive connection to liquid markets. It remains to be clarified if flickering quotes contribute to liquid markets themselves or only happen when the markets are liquid.

We analyze six hypotheses about the drivers of fleeting orders and flickering quotes as a special subset, whereby, based on our results, we reject 1) market maker risk, 2) liquidity demand, 3) manipulation, and 4) pure reaction of algorithmic traders to each other as the root of these rapid limit order submissions and deletions. Nonetheless, flickering quotes are highly automated and behave periodically. We use linear regressions on the flickering quote share, logistic regressions on the flickering quote probability, and Cox proportional hazard rate analysis of the time till cancellation of flickering quotes. Thereby, we find evidence that flickering quotes are used as a price discovery tool, where new information is not only priced into the market with new quotes but also by the withdrawal of existing offers. A dependency on trades within related option series and on underlying movements confirms this explanation further. This would also mean that flickering quotes are not only apparent when the market quality is good, but that flickering quotes are an essential tool for efficient markets. Furthermore, we find strong evidence that HFTs try to unwind their inventories by offering their positions at a discount for a short time, which is supported, e.g., by a positive connection between trading volume and flickering quote share as well as a higher chance of a flickering quote when the markets are relatively calm.

Additionally, 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.

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. Political intervention should be undertaken with caution, as both slow and fast traders profit from fleeting orders.

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, which have, however, no economic significance. Choudhry et al. (2012) achieve with their neural network phenomenal 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, all that is measured herewith is the characteristic behavior of flickering quotes, which often changes the mid-quote by one (half) tick with the submission and lets the mid-quote jump back with cancellation. This shows up as a superior directional accuracy. When these models, like the behavior of the neural networks, can not be understood anymore, and insufficient comparative measures are used, a lack of knowledge about fleeting orders and flickering quotes can lead to serious problems.

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VI. Appendix

Table XI 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
$Vola_{t-1}^{Option}$ ($Vola_i^{before}$)	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	
$Vola_{t-10}^{Underlying}$	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 moneyness dummy for in-the-money (out-of-the-money), and call (put)	H2		
$Trade_{t-10}$	Number of trades of the respective option series within the preceding ten minutes	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 one minute	H5		
$STOXX_{dummy}$	Dummy controlling for an underlying listed in the EURO STOXX 50 index (=1), or not (=0)	H6		
$Volume_i^{before}$ ($Volume_i^{after}$)	Sum of traded volume five minutes before (after) submission i		H4, H6	
p_i^{Same}	Relative offered price change due to submission i, positive values indicate a smaller spread		H4	H1
q_i^{Same}	Relative offered price change after submission i on the same order book side, positive values indicate a wider spread			H1, H2, H3
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, positive values indicate a wider spread			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 milliseconds before the submission i		H5	H5
$\#FQ_i^{after}$	Sum of flickering quotes within the 500 milliseconds after the submission i		H5	

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 I for every analysis used in section III. We have to revert to operationalizations, as our data does not identify individual traders, and some hypotheses act indirect.