The Lasting Impact of Flickering Quotes*

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ABSTRACT

Short-lived limit orders, or flickering quotes, are widely viewed as transitory and therefore irrelevant for price discovery. Using proprietary order-level data from Euronext Amsterdam that identify each trading firm, we show that flickering quotes are frequent, clustered, and concentrated among a small set of high-frequency traders. They have persistent price effects and account for approximately 20% of limit order price discovery, despite comprising only 0.3% of the total lifetime of round-trip limit orders. Flickering quotes induce directional responses from other market participants, who trade in ways that leave a lasting imprint on prices. Rather than being transitory, flickering quotes have a consequential role in price formation.

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The rise of high-frequency traders (HFTs) has largely reshaped trading activity in the limit order book (see, e.g., O'Hara, 2015; Menkveld, 2016). One way HFTs have changed market dynamics is through the introduction of short-lived limit orders, also known as flickering quotes. We find that around 40% of all limit orders are cancelled within a second. While flickering quotes now frequently appear in limit order books, there is no consensus on their role in the price formation process. In this paper, we study whether these short-lived orders contribute to price discovery.

Price discovery occurs when traders revise their beliefs about the fundamental value of the asset through Bayesian learning. This revision occurs whenever there is a possibility that an incoming market order (see, e.g., Glosten and Milgrom, 1985; Kyle, 1985) or an incoming limit order (see, e.g., Kaniel and Liu, 2006) is from an informed trader. Similarly, if a limit order is strategically cancelled, then, all else being equal, there should be a Bayesian revision in beliefs that removes the initial effect of the limit order (see Williams and Skrzypacz, Forthcoming). Therefore, flickers should have a net price impact of zero.

Similarly, even though there is no consensus on the purpose of flickers, theoretical models generally agree that flickers are uninformed byproducts of quoting strategies in a limit order book, and that flickering quotes do not contribute to price discovery. Baruch and Glosten (2013) show that quotes flicker because players use mixed strategies to win price priority, while Yueshen (2025) shows that flickers arise when liquidity (book depth) overshoots due to queuing uncertainty. On the other hand, Bhattacharya and Saar (2021) show that quotes flicker when uninformed traders revise and reprice their outstanding limit orders.[1]

In our empirical testing of the theoretical literature, we find that flickers materially impact prices, and that the impact of flickers persists beyond the cancellation leg of the flicker. Moreover, flickers contribute substantially to price discovery and account for around 20% of the total price discovery of limit orders, even though they account for less than 0.3%

[1]The HFT literature also provides insights into flickering quotes. Baldauf and Mollner (2022) show that quotes flicker when HFTs race to set a new price, and losers of the race immediately cancel because HFTs are unwilling to provide excess liquidity. Li et al. (2021) show that quotes flicker when execution algorithms undercut HFTs. Similarly, in Cartea et al. (2025), quotes flicker when retail traders undercut HFTs.

of the total lifetime of all limit orders that are cancelled. To understand the mechanism by which flickers contribute to price discovery, we use proprietary data that identify each trading firm and all their orders. Our results show that the price impact of flickers is permanent because they induce other market participants to trade. Specifically, flickers induce both non-HFTs and other HFTs to take more liquidity in the direction of the flicker than against it. Following a flicker, 91% of market orders are by firms other than the flickerer.

We use proprietary data from Euronext Amsterdam, which contains all order entries, amendments, and cancellations for the month of January 2023. The sample covers all stocks listed in the Dutch large-cap, mid-cap, and small-cap index. Importantly, the data identify each market participant, which allows us to group activity by HFTs and non-HFTs.

The data show that flickers are pervasive and occur across market capitalization. Around 40% of all non-executed limit orders are cancelled within a second, and a large proportion of flickers occur at even shorter horizons. Any tenfold reduction in the time horizon used to define a flicker roughly halves the number of flickers observed. Thus, we adopt a one-second definition for a flicker because it captures a substantial share of fast cancellations and its economic implications do not materially differ from those of shorter-lived flickers.

Flickers tend to cluster in time. Around 94% of all flickers are in seconds with at least one other flicker, and the number of buy flickers minus sell flickers per second is mostly non-zero. This suggests that flickers carry a directional signal and that they are not symmetric noise from uninformed byproducts of quoting strategies. Furthermore, flicker activity follows a U-shaped intraday pattern and is essentially an HFT phenomenon. By flicker count, the top HFT accounts for 26.36% of all flickering quotes, while 56.79% and 77.76% of these flickers are by the top three and top five HFT firms, respectively. Flickering activity is also disproportionately concentrated at the top of the book.

We estimate a logistic regression to study the predictability of flickers. We find that recent price movements predict flickering: a positive return increases the likelihood of buy-side flickers and decreases the likelihood of sell-side flickers. This is consistent with flickers

being responsive to short-term information rather than being random. Furthermore, the effect is monotonic in the size of the price move: large upwards (downwards) price moves substantially increase the probability of a buy (sell) flicker. This affirms that flickering is state-dependent and information-linked.

Our analysis uses a signed price impact regression and a structural vector autoregression (SVAR; Fleming et al., 2018; Hasbrouck, 1991a,b, 1995) to study the impact of flickers posted at various price levels in the book. We find that the net price impact of flickers is non-zero regardless of where they are placed in the book. The price impact of flickers that improve the best quotes or that are posted at the best quotes is positive, while the price impact of flickers placed deeper in the limit order book is negative. In contrast, the price impact of non-flickers is positive regardless of where the orders are placed in the book; thus, the negative price impact of orders deep in the book applies only to flickers.

The magnitude of the price impact of flickers placed at different price levels is similar to that of non-flickers, where the price impact of orders placed at more aggressive price levels is higher. For both flickers and non-flickers placed at different price levels, the price impact of orders that improve the best quotes is the highest, followed by orders posted at the best quotes, and then by orders placed behind the best quotes.

In addition to the non-zero net price impact, flickers contribute substantially to price discovery. Although the resting time of flickers in the book is very short, their contribution to price discovery is disproportionally high. Flickers account for around 20% of the total price discovery of limit orders, even though they account for less than 0.3% of the total lifetime of all limit orders that are cancelled. This means that their information contribution to time-in-book ratio is very large compared to that of non-flickers. The disproportionate contribution of flickers to price discovery is further highlighted by the concentration of trading firms that use flickers. Since five HFTs account for around 75% of the flickers, this suggests that the flickers from five HFT firms account for around 15% of the total price discovery of limit orders.

We use the SVAR to study the activity in the order book following a flicker to understand the mechanism by which flickers have permanent price impact and contribute to price discovery. We find that spread-improving flickers trigger same-side non-flicker orders to enter at the best quote and deeper in the book, opposite-side non-flicker cancellations, and buyer-initiated trades. These reactions persist beyond the lifetime of the flicker, which explains how a short-lived order creates lasting price discovery. Specifically, flickers induce durable responses from other participants.

To verify these reactions, we use a regression to show that spread-improving and at best flickers are followed by transactions initiated in the direction of the flicker, while flickers deeper in the book are followed by transactions initiated in the opposite direction. This directional asymmetry confirms that the negative signed price impact for deep flickers is not noise, but rather reflects a genuinely different mechanism such as to avoid adverse selection or induce other trades to trade with remaining liquidity in the order book.

Finally, we study who (HFT or non-HFT) trades in the interval following a flickering quote, how much of their trading is liquidity taking and liquidity providing, and how much is in the direction of the flicker and opposite to it. We say that a buyer (seller)-initiated transaction following a buy (sell) flicker is in the direction of the flicker, and the other trades are in the opposite direction of the flicker. Similarly, liquidity-providing buy transactions following a flicker buy order are in the direction of the flicker, and passive sell transactions are in the direction opposite to the flicker.

We find that both HFT and non-HFT take more liquidity in the direction of the flicker than in the opposite direction. Their shares of directional liquidity taking are similar in magnitude, with each group accounting for roughly half of the total liquidity-taking trades in the direction of the flicker in the 10-second interval following a flicker. The most pronounced difference between HFT and non-HFT is in liquidity provision. HFTs supply liquidity in a largely symmetric manner, being equally active in the direction of the flicker and in the opposite direction. On the other hand, non-HFTs predominantly provide liquidity in the

direction opposite to the flicker. This suggests that HFT and non-HFT respond differently to flickers. Our results also show that 91% of liquidity-taking transactions following a flicker are by firms other than the flickerer itself, so transactions are not just by flickerers who decide to cross the spread. Finally, flickers dramatically increase the number of trades in the subsequent 1 or 10 seconds. Specifically, HFTs execute an average of 0.422 liquidity-taking trades in the second after a flicker, which is more than 100 times their rate in non-flicker seconds. Non-HFTs show an even stronger reaction, rising from a baseline of 0.006 to 0.544 trades. A similar pattern holds for liquidity provision.

Our results contribute to the understanding of flickering quotes. Theoretical models of flickering quotes suggest that flickers are uninformed byproducts of quoting strategies (see Baruch and Glosten, 2013; Bhattacharya and Saar, 2021; Yueshen, 2025). In contrast, we show that flickers contribute to price discovery, and in this sense are informative. Similar to theoretical papers on flickers, many empirical papers that rationalize flickering quotes assume that flickers are uninformative. Degryse et al. (2020) argue that flickers can result from ghost liquidity, where firms duplicate their limit orders in other venues and cancel the remaining duplicates upon execution of one of their orders. Ulze et al. (2021) find evidence that flickering quotes lead to better prices for liquidity taking traders, which is arguably a result of HFTs trying to clear their inventory. In contrast, we empirically show that flickers induce both non-HFTs and other HFTs to trade. This suggests that flickers are more consistent with the explanations of Hasbrouck and Saar (2009, 2013), who argue that flickers are components of strategies that demand liquidity, and strategic runs, respectively.[2]

Our results also contribute to the understanding of price discovery through limit orders. While limit orders are generally seen as a passive supply of liquidity that reflects public information, it is also understood that limit orders contribute to price discovery.[3] The

[2]Hasbrouck (2018) studies whether flickering quotes explain the high volatility of bids and offers, and he finds that Edgeworth cycles provide a better explanation than flickering quotes for the high volatility of bids and offers.

[3]A number of papers examine the role of limit orders in a limit order book. Cohen et al. (1981) study the tradeoff between the use of limit orders and market orders. The static equilibrium models of Glosten (1994), Biais et al. (2000), and Back and Baruch (2013) study the price and quantity placement of limit orders. The

empirical literature shows that limit orders contribute to price discovery (see, e.g., Fleming et al., 2018; Brogaard et al., 2019), and theoretical models of the limit order book also show that limit orders contribute to price discovery (see, e.g., Kaniel and Liu, 2006; Goettler et al., 2005, 2009; Hoffmann, 2014). Here, we show that short-lived limit orders can also contribute to price discovery by inducing others to act.

Finally, our results contribute to understanding the behavior of HFTs.[4] While flickers are not exclusively a HFT phenomenon, we find that HFTs account for the large majority of flickers. Our results complement those of Brogaard et al. (2019), who analyze the contribution to price disovery of HFT and non-HFT orders. Instead, we study the contribution to price discovery by flickering and non-flickering orders, and find that short-lived orders have permanent price impact and play a meaningful role in price discovery.[5]

1. Institutional Setting, Data, Methodology

The dataset was provided by the Dutch Authority for the Financial Markets (AFM) and contains all order entries, amendments, and cancellations on Euronext Amsterdam in January 2023.[6] The data include fields such as the trading date, microsecond-level timestamps, order type, order volume, and buy/sell indicator of the message. Importantly, the data identify the identity of each trading firm, which allows us to group activity by participant

dynamic equilibrium models of Parlour (1998), Foucault (1999), Foucault et al. (2005), and Roşu (2009) studies a range of tradeoffs such as non-execution risk, adverse selection, and waiting costs.

[4]The theoretical literature on HFTs largely focuses on their use of market orders to "pick off" stale limit orders (see, e.g., Budish et al., 2015; Biais et al., 2015; Foucault et al., 2017; Aquilina et al., 2021).

[5]Other papers examine trading by HFTs and their contribution to price discovery. Brogaard et al. (2014) show that HFTs contribute to price discovery with market orders by trading in the direction of future prices changes. Carrion (2013) finds that prices incorporate information more efficiently when HFT participation is high, while Conrad et al. (2015) find that high-frequency trading and high-frequency quoting correlate with more efficient prices. Chaboud et al. (2014) find that HFTs improve price efficiency through lower return autocorrelations and fewer arbitrage opportunities. Chordia et al. (2018) show that high-frequency market orders impound information quickly following macroeconomic announcements. Brugler and Hendershott (2025) show that the contribution to price discovery by HFTs is equally split between races and non-races for both trades and quotes.

[6]An amendment is a change to the price or volume of an order, while retaining the same order ID. As a result, an order may be amended multiple times before it is eventually cancelled. We exclude amendments from our analyses, because the cancellations ultimately apply to the original order ID.

type.

Institutional Setting The Netherlands has a number of equity markets on which trading is organized. Euronext Amsterdam is the largest trading venue for stock trading, and makes up more than 47% of volume traded in Dutch shares on exchange in the period of our study.[7] Euronext Amsterdam operates a central limit order book (CLOB) with price-time priority.

Data Our sample covers all stocks listed in the Dutch large-cap AEX index, the mid-cap AMX index, and the small-cap ASCX index at the time of writing this paper. Each index comprises 25 stocks. The final dataset consists of 25 AEX stocks, 21 AMX stocks, and 21 ASCX stocks, because eight of the current constituents were not yet listed on Euronext Amsterdam in January 2023.

On Euronext Amsterdam, members trade with a specific dealing capacity assigned by the exchange. This classification indicates whether a member trades on its own account or executes orders on behalf of clients, and specifies which trading behavior is allowed by the member when acting in that capacity. We exclude from our dataset all messages by members with dealing capacity "Retail Liquidity Provider" (retail LPs). Messages by retail LPs and transactions that involve retail LP's orders are visible only to members with dealing capacity "Retail". Retail can trade with both retail LPs and the rest of CLOB, which in effect creates two limit order books, one for retail members and one for all other members. We exclude retail LP messages so that the transactions, quoted spreads and depth we compute are not biased by factors unobservable to some market participants.

We also exclude from our dataset the cancellation leg of immediate-or-cancel orders because the resting time of these orders is zero microseconds, which would bias our results.[8] We also remove stop-loss orders and the non-displayed part of iceberg orders from our calcu-

[7] This percentage is calculated on MIFID II data reported to the supervisor, where we exclude all transactions off-exchange.

[8] We do include the entries of immediate-or-cancel orders, because these orders can result in transactions and have price impact.

lations of order count, best bid/ask prices and quote volumes because these volumes are not observable to market participants, and could bias our analyses. Finally, we exclude the first and last fifteen minutes of the trading day from our analyses because these periods might include parts of the open- and closing-auction. The open- and closing-auctions operate under a trading mechanism different from the CLOB, which could result in negative spreads and bias our calculations.

Methodology Members with dealing capacity "Liquidity Provider" have contractual quoting obligations imposed by the exchange.[9] Cartea et al. (2025) show that the trading behavior of Liquidity Providers on Euronext Amsterdam is consistent with that of traditional HFTs. Accordingly, in our analyses, we classify members trading with dealing capacity Liquidity Provider as HFTs. All remaining members are classified as non-HFTs. This group includes members with dealing capacity "Client", who enter orders on behalf of institutional investors; "House", who trade for their own account but do not qualify as Liquidity Providers; and "Retail", who handle retail orders.

We exclude small-cap stocks from our analyses unless stated otherwise because small-cap stocks have very limited activity. This limited activity often results in insufficient data points to estimate each variable in the structural vector autoregression. Finally, throughout the paper, we estimate regressions and a structural vector autoregression. Table 1 outlines and defines all the dependent and independent variables we use throughout the paper.

INSERT TABLE 1 ABOUT HERE

2. Prevalence, Patterns, and Market Conditions

In this section, we analyze the main characteristics of flickering quotes. Flickers are pervasive, cluster in time, and flicker activity follows a U-shaped intraday pattern. Also,

[9] See Euronext (2023) for details on dealing capacities on Euronext Amsterdam, and see Euronext (2024) for a list of exchange members.

flickering activity is disproportionately concentrated at the top of the book compared to non-flickers, and flickers that improve the spread are joined by orders at the same or better price levels. Most flickers are by HFTs, and flickers can be predicted by recent price movements.

Prevalence A flickering quote is an order that is cancelled shortly after entry. We analyze the prevalence of flickers using different time intervals to understand whether flickers are a universal feature in modern stock markets.

Table 2 reports statistics on order activity and cancellations for large-, mid-, and small-cap stocks traded on Euronext Amsterdam in January 2023. The table shows the number of orders, the number of cancellations, and the proportion of cancellations per stock-day for various time intervals: 1 second, 100 milliseconds, 10 milliseconds, 1 millisecond, and 100 microseconds.

INSERT TABLE 2 ABOUT HERE

For large-cap stocks (AEX constituents), the average daily number of orders per stock-day is 166,075, of which 96.1% are cancelled. A substantial portion of these cancellations occurs quickly after entry: 33.44% within 1 second, 18.25% within 100 milliseconds, 7.36% within 10 milliseconds, 2.89% within 1 millisecond, and 1.24% within 100 microseconds. These proportions highlight the prevalence of short-lived orders in liquid stocks.

On average, flicker activity in mid-cap (AMX) and small-cap (ASCX) stocks is lower than that in large-cap stocks. For mid-caps, on average, 23.07% of the orders are cancelled within 1 second, and 5.01% within 10 milliseconds. While there are fewer orders in small-cap stocks (average of 7,957 per day), the proportion of cancellations within 1 second is 16.01% and within 10 milliseconds is 5.71%, so there is also flickering in less liquid stocks.

The table shows that flickering is pervasive, and flickering persists across various market capitalizations. Furthermore, the percentage of flickers drops radically less quickly than the reduction in the time interval, which shows that a large share of flickering happens at very short horizons.

Figure 1 visualizes the distribution of resting times for orders that were cancelled. The distribution is heavily right-skewed, with a mass of cancellations at very short durations. This visually reinforces that flickering is not just an arbitrary cutoff. Rather, there is a natural concentration of extremely short-lived orders.

INSERT FIGURE 1 ABOUT HERE

The choice of flickering time interval varies in the literature, where the intervals range from microseconds to two seconds in Hasbrouck and Saar (2009). We adopt a one-second interval because it captures a substantial share of fast cancellations as highlighted in Figure 1, while the economic implications are similar to shorter time horizons.[10]

Another way to measure the prevalence of flickers is to compute their cumulative lifetime in the order book. The average resting time of a flicker is 0.21 seconds, and the average resting time of a non-flicker order that is subsequently cancelled is 53.22 seconds. In our dataset, flickers account for 39.5% of all orders that are subsequently cancelled in large-cap, mid-cap, and small-cap stocks.[11] This means that flickers account for less than 0.3% of the total time-weighted average lifetime of all limit orders that are cancelled. So although flickers account for a substantial share of all cancelled orders, their cumulative time in the order book is very small.

Patterns We study patterns in flickering quotes to understand whether flickers carry a directional signal. Also, we study the position where flickers enter the order book and leave the order book.

Figure 2 (left panel) shows the clustering of flickering quotes, measured as the number of flickers per second. There is at least one flickering quote in 24.54% of the one-second intervals in our sample. Within these one-second intervals with at least one flickering quote,

[10] Robustness analyses show that our findings are economically similar when applied to shorter flickering time intervals.

[11] The 39.5% is calculated on all cancelled orders in January 2023, and the percentages reported in Table 2 are per stock-day.

the average number of flickers is 5.44 per second, and in 42.38% of these one-second intervals there are four or more flickering quotes. Finally, 93.95% of the flickers are in seconds with at least one other flicker.

The right panel of Figure 2 shows the difference between the number of buy-side and sell-side flickers per second. The data show that 90% of seconds with at least one flicker are imbalanced, i.e., have a different number of buy-side flickers than sell-side flickers. Specifically, 44% of the seconds have one more buy-side flicker than sell-side flicker or the other way around.

INSERT FIGURE 2 ABOUT HERE

The figure shows that flickers cluster in time (most flickers occur in seconds with other flickers), and their buy-sell imbalance is almost always non-zero. Together, this means that flickers carry a directional signal and are not symmetric noise.

Figure 3 shows the distribution of flickering quotes throughout the trading day (Subfigure A) and across firms (Subfigure B). Flicker activity is most pronounced during the first hour of trading (13.56%), followed by the last hour (13.63%), with a relative decline in between (11.20% per hour). This pattern aligns with the known U-shape intraday market dynamics, where trading intensity and volatility typically peak at market open and close.

INSERT FIGURE 3 ABOUT HERE

Subfigure B of Figure 3 reports the percentage of flickers by HFTs and non-HFTs. HFTs account for around 90.89% of flickers, while the top 5 HFTs alone account for around 78% of flickers. The concentration of flicker behavior likely reflects superior technological capabilities of HFTs, so there is concentration of flicker behavior among those with the most sophisticated and fastest systems. Thus, flickering is essentially an HFT phenomenon and highly concentrated among a small subset of firms, which means any contribution to price discovery of flickers is attributable to a very small number of HFTs.

Table 3 shows the frequency of flicker and non-flicker activity at different price levels of the book. Flickers account for 39.1% of all messages, and appear most frequently in the best quotes of the book. Flickers that enter at the best quote and flickers that are cancelled at the best quote account for 10.85% and 10.88% of all messages, respectively. Flickers deeper in the book occur less frequently than flickers at the best; flickers that enter deeper in the book account for 7.32% of all messages, and flickers that are cancelled deeper in the book account for 7.59% of all messages. Flicker activity that changes the best quotes occur less frequently; flickers that enter and improve the spread account for 1.35% of all messages, while cancellations of flickers that worsen the spread account for 1.11% of all messages.

Interestingly, 54.38% of the activity at the top of the order book is flickers, while non-flickering messages often occur deeper in the book. Overall, 62.16% of flicker messages are inside the spread or at the best quotes, while 34.01% of the non-flicker messages are inside the spread or at the best quotes. Thus, relative to non-flickers, flickering activity is disproportionately concentrated at the top of the book.

INSERT TABLE 3 ABOUT HERE

Table 3 reports flicker messages at different price levels, but ignores the connection between the entry and exit of the same flicker. On the other hand, Table 4 studies the lifetime of the same flicker, and reports the frequency of where a flicker entered and exited the book.

Most flickers are entered at the best quote and eventually cancelled at the best quote. These account for 49.23% of all flickers. Another frequent combination is flickers entered deeper in book and eventually cancelled deeper in book (33.78%). This shows that most flickers are cancelled at the position in the book where they entered.

The exception is spread-improving flickers, where 52.59% of the flickers are cancelled without worsening the spread. This means that other orders joined at that price level (or better price levels) during the brief lifetime of the flicker. This is direct evidence of the mechanism where flickers attracts durable liquidity at its price level.

INSERT TABLE 4 ABOUT HERE

Market Conditions We estimate a logistic regression model to study which market conditions change the likelihood of flickers in large-cap and mid-cap stocks. Our approach resembles the framework of Hasbrouck and Saar (2009), who employ a multinomial logit model to analyze the outcomes of order submissions: executions, cancellations, and resting orders. Here, we focus on the binary outcome of whether a non-marketable limit order is cancelled within 1 second (i.e., is a flickering quote) or not.

We restrict our analysis to non-marketable limit orders, i.e., orders that do not immediately result in a transaction upon entry. We estimate the model

$$\text{logit}(\text{Flicker}_{i,t}) = \beta_0 + \beta_1 \cdot \text{Return}_{i,t-h} + \beta_2 \cdot \text{Spread}_{i,t} + \beta_3 \cdot \mathbb{1}_{\text{FirstHour}} + \beta_4 \cdot \mathbb{1}_{\text{MidDay}} + \epsilon_{i,t} \quad (1)$$

for each stock-day. We fit separate models on buy orders (columns (1)-(4)) and sell orders (columns (5)-(8)). Here, $\text{Flicker}_{i,t}$ is equal to 1 if an order that entered at time t in stock i is cancelled within 1 second after entry, and 0 otherwise. $\text{Return}_{i,t-h}$ is the midpoint price return of stock i over the $0.1, 1, 5, 10$ seconds prior to order entry, standardized to have zero mean and unit variance per stock-day. $\text{Spread}_{i,t}$ is the relative bid-ask spread, standardized to have zero mean and unit variance per stock-day. The indicator $\mathbb{1}_{\text{FirstHour}}$ is equal to 1 if the order is entered between 9:15 and 10:00, and the indicator $\mathbb{1}_{\text{MidDay}}$ is equal to 1 if the order is entered between 10:30 and 16:30. We include all non-marketable orders, regardless of their distance to the best bid/ask, and we exclude the bottom and top one percent $\text{Spread}_{i,t}$ to mitigate the influence of outliers. Finally, we remove the bottom and top one percent of the stock-day OLS coefficient estimates to mitigate the influence of outliers, compute the average of the coefficients, and cluster standard errors by stock-day, following the approach of Thompson (2011).

INSERT TABLE 5 ABOUT HERE

Table 5 shows averages of the coefficients of the logistic regression models with which we estimate the likelihood (in log-odds) that an order is cancelled within 1 second of entry. In all specifications, the intercept is negative and statistically significant, indicating a low baseline probability of flickering buy and sell quotes.

The table shows a statistically significant relationship between recent returns across all horizons and flickering quotes. All models show that a positive (negative) return in midpoint price prior to order entry is associated with an increased likelihood that a buy (sell) order is cancelled within 1 second of entry. Specifically, a one standard deviation increase in the midpoint return over the 100 milliseconds prior to order entry increases the log-odds of a buy order to flicker by 0.090. Conversely, the same increase in midpoint return reduces the log-odds of a sell order to flicker by 0.097.

To illustrate the effect of price movement on the likelihood of an incoming buy order to flicker, consider the mean probability $p = 0.3344$ of a flicker order in large-cap stocks. In this case, the odds are $\frac{0.3344}{1-0.3344} \approx 0.502$, which increase by a factor of 1.094 if there is a standard deviation increase in the midpoint return over the 100 milliseconds prior to order entry. The new odds become $0.502 \times 1.094 \approx 0.549$, so the probability of an incoming buy order to flicker increases from approximately 33.44% to 35.44% (i.e., $\frac{0.549}{1+0.549}$).

The effect of price changes on the likelihood of flickers over longer time intervals prior to order entry is positive and statistically significant, although the economic impact diminishes as the time interval lengthens. For example, a one standard deviation increase in the midpoint return over the 1-second interval prior to order entry increases the log-odds of a buy order to flicker by 0.075. Similarly, the effect of price changes over the 5- and 10-second windows prior to order entry is statistically significant (0.064 and 0.058, respectively).

These results show that recent price movements predict flickering: a positive return increases the likelihood of buy-side flickers and decreases the likelihood of sell-side flickers. This is consistent with flickers being responsive to short-term information rather than happening at random.

Time-of-day effects are robust across specifications. Orders submitted during the first hour of trading (9:15–10:00) and orders entered during 10:30–16:30 are significantly less likely to flicker than orders entered in the last hour of trading, with coefficients ranging from -0.098 to -0.045, all significant at the 1% level.

To further explore the effect of price movements on flickers, we use indicator variables for large and medium upward and downward price movements to estimate the logistic regression model

$$\begin{aligned}\text{logit}(\text{Flicker}_{i,t}) = \beta_0 &+ \beta_1 \cdot \mathbb{1}_{\text{LargePriceMoveUp}_{i,t-h}} + \beta_2 \cdot \mathbb{1}_{\text{MediumPriceMoveUp}_{i,t-h}} \\ &+ \beta_3 \cdot \mathbb{1}_{\text{MediumPriceMoveDown}_{i,t-h}} + \beta_4 \cdot \mathbb{1}_{\text{LargePriceMoveDown}_{i,t-h}} \\ &+ \beta_5 \cdot \text{Spread}_{i,t} + \beta_6 \cdot \mathbb{1}_{\text{FirstHour}} + \beta_7 \cdot \mathbb{1}_{\text{MidDay}} + \epsilon_{i,t}\end{aligned} \tag{2}$$

for each stock-day. We fit separate models on buy orders (columns (1)-(2) in Table 6) and on sell orders (columns (3)-(4)). $\mathbb{1}_{\text{LargePriceMoveUp}_{i,t-h}}$ is equal to 1 if the standardized return in the midpoint price in the h seconds prior to order entry is larger than 2 standard deviations, and 0 otherwise; $\mathbb{1}_{\text{MediumPriceMoveUp}_{i,t-h}}$ is equal to 1 if this value is between 1 and 2 standard deviations, and 0 otherwise; $\mathbb{1}_{\text{MediumPriceMoveDown}_{i,t-h}}$ is equal to 1 if this value is between -1 and -2 standard deviations, and 0 otherwise; $\mathbb{1}_{\text{LargePriceMoveDown}_{i,t-h}}$ is equal to 1 if this value is less than -2 standard deviations, and 0 otherwise. The remaining variables are as defined above.

INSERT TABLE 6 ABOUT HERE

Table 6 shows that large and medium upward price movements in the 1 second prior to order entry significantly increase the likelihood of buy orders to flicker, with coefficients of 0.414 and 0.325, which increase the odds of a buy order to flicker with a factor of approximately 1.51 and 1.38, respectively. This implies an increase in the probability of a buy order to flicker from an average of 33.44% to 43.19% following short-term large upward price movements. Downward price movements also increase the likelihood of buy-side flickers, but

less strongly: the coefficients are 0.176 and 0.162 for medium and large downward changes, respectively.

For sell orders, the pattern reverses. Large and medium downward movements in midpoint price significantly increase the likelihood of sell orders to flicker (coefficients of 0.435 and 0.339 respectively), while the effect of upward movements in the midpoint price is smaller (coefficients of 0.161 and 0.130 respectively).

These results affirm that recent price movements predict flickering. Also, the effect is monotonic in the size of the price move: large same-direction price moves increase the probability of flicker more than medium same-direction moves. This reinforces that flickering is state-dependent and information-linked.

3. Price Formation Effects: Do Flickering Quotes Move Prices?

In this section, we use a signed price impact regression and a vector autoregression (VAR; Hasbrouck, 1991a,b, 1995) to study whether flickering quotes have permanent price impact. Furthermore, we quantify the contribution of flickers to price discovery.

3.1. Price Impact Regression

We estimate

$$\begin{aligned}\text{PriceImpact}_{i,t} = \beta_0 + \beta_1 \cdot \text{SignedFlicker}_{i,t} + \beta_2 \cdot \text{FlickerVolumeImbalance}_{i,t} \\ + \beta_3 \cdot \text{OrderbookImbalance}_{i,t} + \beta_4 \cdot \text{Spread}_{i,t} + \epsilon_{i,t}\end{aligned} \tag{3}$$

per stock-day to quantify the price impact of flickers. Here, $\text{PriceImpact}_{i,t}$ is the midpoint price return of stock i at time t in basis points over the next 10 seconds. The return is measured from the moment immediately *before* the entry of the flickering quote. The

signed indicator SignedFlicker$_{i,t}$ is equal to $+1$ for a flicker buy order and is equal to -1 for a flicker sell order. FlickerVolumeImbalance$_{i,t}$ is the difference between the volume of flicker buy orders cancelled at the best bid in the previous 5 seconds and the volume of flicker sell orders cancelled at the best ask in the previous 5 seconds, divided by their sum. Orderbook Imbalance$_{i,t}$ is the difference between the volume at the best bid and the volume at the best ask at time t, divided by their sum. Spread$_{i,t}$ is the relative bid-ask spread standardized per stock-day as defined before.

We restrict our analysis to non-marketable limit orders, and exclude the bottom and top one percent Spread$_{i,t}$ to mitigate the effect of outliers. Finally, we exclude the bottom and top one percent of the OLS coefficient estimates to mitigate the influence of outliers, compute the average of the remaining coefficients, and cluster standard errors by stock-day, following the approach of Thompson (2011).

Table 7 reports the average coefficients of the OLS regressions estimating the signed price impact of flicker orders in the next 10 seconds. We estimate a baseline specification which includes only the Intercept and SignedFlicker$_{i,t}$, and a specification with control variables. We estimate these models separately for flicker orders entered inside the spread (columns (1) and (2) in Table 7), flicker orders entered at the best quote (columns (3) and (4)), and flicker orders entered deeper in the book (columns (5) and (6)).

INSERT TABLE 7 ABOUT HERE

The table shows that the signed price impact SignedFlicker$_{i,t}$ of flicker orders entered inside the spread is strongly positive and statistically significant (coefficients 1.211 and 1.090). This indicates that entry of buy (sell) flicker orders that improve the spread is associated with upward (downward) price movements in the next 10 seconds. The effect of order book imbalance and relative spread is positive and statistically significant (coefficients 0.565 and 1.271, respectively).

The price impact of flicker orders entered at the best quote is positive and statistically significant, but smaller than that of the spread-improving flickers (coefficients 0.174 and

0.230). The control specification shows that flicker volume imbalance and order book imbalance are positively associated with price impact. This reinforces the notion that increased (decreased) buy-side pressure via flickering quotes or non-flickering quotes anticipates upwards (downwards) price changes. The effect of relative spread is not statistically significant, which suggests that spread conditions play a lesser role for at-best flickers.

Interestingly, the price impact of flicker orders entered deeper in the book is negative and statistically significant (coefficients -0.269 and -0.184, respectively). The control specification shows that flicker volume imbalance and order book imbalance remain positive and are significantly related to price impact (coefficients 0.119 and 1.152, respectively).

These results show that prices move in the direction of spread-improving and at-best flickers, and against the direction of deep flickers.

INSERT TABLES 7 ABOUT HERE

3.2. Vector Autoregression

To investigate how flickering quotes affect price discovery, we estimate a Structural Vector Autoregression (SVAR) model, see Fleming et al. (2018) and Brogaard et al. (2019). The SVAR model uses past price movements and the arrival and cancellation legs of flicker and non-flicker orders to estimate movements in the efficient price. More specifically, the model dynamically estimates the relation between order entries and cancellations and future movements in the efficient price of the security. Causal interpretation in the SVAR arises from the temporal ordering of events. The model is estimated in event time, where each message (order, cancellation, or trade) is one observation.

The SVAR incorporates trades and limit order activity, both entries and cancellations, at various price levels into the standard price discovery SVAR. We extend this model by separating Flicker and Non-Flicker messages. For each stock-day, we estimate

$$
\begin{aligned}
r_t &= \sum_{i=1}^{5} \alpha_i^1 \, r_{t-i} + \sum_{j=1}^{13} \sum_{i=0}^{5} \beta_i^{1,j} \, X_{t-i}^j + \mu_t^1, \\
X_t^1 &= \sum_{i=1}^{5} \alpha_i^2 \, r_{t-i} + \sum_{j=1}^{13} \sum_{i=1}^{5} \beta_i^{2,j} \, X_{t-i}^j + \mu_t^2, \\
X_t^2 &= \sum_{i=1}^{5} \alpha_i^3 \, r_{t-i} + \sum_{j=1}^{13} \sum_{i=1}^{5} \beta_i^{3,j} \, X_{t-i}^j + \mu_t^3, \\
&\vdots \\
X_t^{13} &= \sum_{i=1}^{5} \alpha_i^{14} \, r_{t-i} + \sum_{j=1}^{13} \sum_{i=1}^{5} \beta_i^{14,j} \, X_{t-i}^j + \mu_t^{14}.
\end{aligned}
\tag{4}
$$

Here, α is the coefficient on the midpoint return series r, lagged one to five periods, and β is the coefficient on the limit order and trade variables, X^1 through X^{13}. The contemporaneous events can cause price changes: the return equation includes contemporaneous and five lag values of the limit order and trade variables, whereas the remaining equations do not include contemporaneous terms.

The thirteen X variables are: *Trade*, *Flicker Improving order*, *Flicker Order at best*, *Flicker Order deeper in book*, *Non-Flicker Improving order*, *Non-Flicker Order at best*, *Non-Flicker Order deeper in book*, *Flicker Worsening cancel*, *Flicker Cancellation at best*, *Flicker Cancellation deeper in book*, *Non-Flicker Worsening cancel*, *Non-Flicker Cancellation at best*, and *Non-Flicker Cancellation deeper in book*. *Order* variables take the value $+1$ for bids placed, -1 for offers placed, and 0 otherwise. *Cancel* variables follow analogous definitions, with -1 for bid-side cancellations and $+1$ for ask-side cancellations. The *Trade* variable takes the value $+1$ for buyer-initiated trades, -1 for seller-initiated trades, and 0 otherwise. If an order both executes and improves the quote, it is classified only as a trade to ensure mutual exclusivity between the two variables. This approach attributes the full price impact to the trade, potentially overstating its effect on the midpoint price.

Impulse Response Functions The Impulse Response Functions (IRFs) derived from our SVAR model quantify the cumulative impact of a one-unit shock in each message on midpoint returns over a 20-event horizon.[12] The SVAR is estimated for each stock-day. We exclude messages entered during the first and last 15 minutes of the trading day. The averages of the stock-day IRFs impact is reported in basis points.

The SVAR framework captures the linear dynamics between variables and returns. We invert the SVAR model into its vector moving average (VMA) to derive the IRFs. IRFs quantify the impact of an innovation on subsequent orders and price movements. Specifically, we compute IRFs in response to an unexpected buy message to measure its effect on returns. The IRFs reflect the price impact of all variables, commonly interpreted as their contribution to price discovery or informational content. For instance, consider the arrival of a *Flicker Improving order* order in the bid-side: traders swiftly react by sending *Non-Flicker Order at best* orders at the bid-side, and other traders react by sending *Non-Flicker Worsening cancel* cancellations on the ask-side, further influencing the midpoint price. The return IRF aggregates both the immediate and predictable price responses to the initial *Flicker Improving order*. So both the immediate price change and the lagged price change are attributed to the *Flicker Improving order*.

IRFs measure the cumulative effect of a one-unit change in the relevant variable on the midpoint return. By definition, the entry of a flicker is followed by the cancellation of the order, so the negative price impact of the cancellation is already incorporated in the effect of the flicker at entry.

INSERT TABLE 8 ABOUT HERE

Table 8 reports the estimates of the return IRFs from the SVAR, which can be interpreted as the average permanent price impact of flicker and non-flicker events. First, the results are consistent with the regression estimates from Section 3.1. As in Section 3.1, the price impact of flicker improving entries and flicker entries at best quotes is positive and statistically

[12] We choose 20 events such that our results can be compared to Brogaard et al. (2019).

significant. Also, the price impact of flicker improving entries is larger than the price impact of flicker entries at best quotes. Specifically, the average cumulative price impact of a spread-improving flicker entry is 0.38 basis points, and the average price impact of a flicker entry at best is 0.24 basis points. In contrast, the price impact of a flicker order entered deeper in the book is negative and statistically significant (–0.13 basis points), again consistent with the negative coefficient in the price impact regressions of Section 3.1.

The sign of the permanent price impact of flicker and non-flicker messages is the same for all messages except for orders entries deeper in the book. Specifically, a buy flicker entry deeper in the book is on average followed by a 0.13 basis points *decrease* in the midpoint price, and a buy non-flicker entry deeper in the book is on average followed by a 0.02 basis points *increase* in the midpoint price. This suggests that the price impact of flicker orders deeper in the book is driven by a different mechanism than that of non-flicker orders deeper in the book. Also, the price impact of non-flickers is larger than that of flickers, except for orders posted deeper in the book. We look further into the mechanism underlying the price impact of flickers and non-flickers in Section 4.1.

Overall, our results are consistent with the results of the SVAR of Brogaard et al. (2019), who report a large positive price impact of improving orders, a smaller positive price impact for orders placed at best, and a negative price impact of orders placed deeper in the order book. They do not separate flickers and non-flickers, so their price impact is a combination of flicker and non-flicker events. Our SVAR shows that the negative price impact of orders placed deeper in the book is a combination of the less frequent but strongly negative impact of deep flickers and the more frequent but only moderately positive price impact of non-flicker orders.

Finally, the sign and relative magnitude of price impacts for flickering quotes in the SVAR are similar to the signs and relative magnitude in the price impact regressions: spread-improving flickers have the largest and positive price impact, flickers at best have a smaller but positive impact, and flickers deeper in the book have a negative price impact.

Variance decomposition The price impact regressions and IRFs provide insights about the average price impact of flickering quotes. However, due to autocorrelation and cross-correlation in message activity, we cannot multiply the IRFs by message frequencies to estimate the contribution of each message type to overall price discovery. Instead, we use the variance decomposition of Hasbrouck (1991b) that weights the IRFs by the variance of innovations in each message type to calculate the total contribution to price discovery by message type for flicker and non-flicker orders.

INSERT TABLE 9 ABOUT HERE

The IRF captures the permanent price impact of a message type, while the variance of innovations in a message type indicates the magnitude of innovations. We square the IRF per message type and multiply it by the corresponding variance in innovation to obtain the contribution to the efficient price variance by message type. Table 8 reports the estimates to calculate the variance decomposition reported in Table 9.[13]

In total, market orders contribute 21.6% to price discovery, and limit orders contribute 20.92% to price discovery. Flickers account for around 20% of the total contribution of price discovery via limit orders, which challenges theoretical predictions that flickers do no contribute to price discovery. Furthermore, flickers contribute substantially to price discovery, despite representing less than 0.3% of total limit-order resting time. So their information contribution to time-in-book ratio is very large compared to that of non-flicker orders.

The table reports that flicker and non-flicker messages at the best quotes or that result in changes to the bid-ask spread contribute more to price discovery than activity deeper in the order book. So most price discovery occurs through flicker and non-flicker messages at the top of the book.

Non-flickers contribute more to price discovery than flickers for all order types, except

[13]The linear structure of the SVAR explains about 42% of the variance of the efficient price. The remainder is the variance of the innovation in the return equation. Following Hasbrouck (1991b), we use the amount of the efficient price that is explained as the denominator to calculate each message type's contribution to price discovery.

order entries deeper in the book. The difference in price discovery between flicker and non-flicker messages is at least partially explained by differences in their respective price impacts, as reported in Table 8.

Overall, the variance decomposition shows that the contribution of flickers to price discovery is large compared to their lifetime in the order book, and that more aggressively priced flickers contribute more to price discovery than less aggressively priced flickers.

4. Mechanisms and Heterogeneity

In this section, we study the mechanism by which flickers have permanent price impact. We show that flickers induce market participants to send orders that last beyond the lifetime of the flicker, and induce market participants to send cancellations that change the midpoint price. Flickers induce both non-HFTs and other HFTs to take more liquidity in the direction of the flicker than against it. Specifically, 91% of directional liquidity-taking is by firms other than the flickerer. Finally, the majority of trades in the limit order book follows shortly after a flicker.

4.1. Order-Book Responses and Subsequent Trades

We use the SVAR to study the activity in the order book following a flicker to understand why flickers have permanent price impact and contribute to price discovery.

Table 10 reports the average stock-day IRF estimates. The rows correspond to the message variable being shocked by one unit, while the columns represent message responses for flickers and non-flickers. For instance, the *Flicker ImpOrd* row provides IRF estimates for how flickers and non-flickers entries and cancellations respond to a flicker order placed inside the spread.

The table shows that flicker messages predominantly follow flicker messages. Specifically, a buy spread-improving flicker leads on average to 0.45 buy flickers entered at best and 0.07

buy flickers entered deeper in the book. In contrast, a buy improving non-flicker leads to 0.33 buy flickers entered at best and 0.04 sell flickers entered deeper in the book. Similarly, a buy flicker (non-flicker) entered at best leads to 0.18 (0.10) buy flicker entries at best and 0.02 (-0.01) buy flicker entries deeper in the book.

Conversely, non-flicker messages are primarily followed by non-flicker messages. A buy spread-improving non-flicker (flicker) is followed on average by 0.66 (0.19) buy non-flickers entered at the best bid and 0.50 (0.36) buy non-flickers entered deeper in the book. Similarly, a buy non-flicker (flicker) entry at best is on average followed by 0.38 (0.08) buy non-flicker entries at the best bid and 0.16 (0.12) buy non-flicker entries deeper in the book. These findings align with those in the literature, such as Biais et al. (1995), which document that orders tend to be followed by similar types of orders. The results are also consistent with those in Table 2, which shows that flicker activity tends to cluster.

Table 10 shows that flicker order entries are generally followed by cancellations at the same position in the book. Specifically, a flicker buy order at the best bid is followed by an average of 0.46 cancellations at the best bid. Similarly, flicker buy orders placed deeper in the book are followed by an average of 0.56 cancellations of buy orders at those deeper levels. These results are consistent with those in Table 4, which shows that flicker orders entered at the best quotes are typically cancelled at the same distance to the best bid/ask as they were entered, and those entered deeper in the book are cancelled deeper in the book. The impact of spread-improving flicker orders is less straightforward.

Interestingly, Table 10 shows that a $+1$ innovation in flicker spread-improving entries is followed, on average, by 0.19 non-flicker buy entries at the best bid, 0.36 non-flicker buy entries orders deeper in the book, and 0.29 non-flicker cancellations of sell orders at the best ask. So flicker improving orders are followed by order entries and cancellations that last beyond the duration of the flicker. Additionally, a spread-improving buy flicker is followed by an average of 0.34 buyer-initiated trades, i.e., buy orders that cross the spread. We study the relation between flickers and buyer (seller)-initiated trades further in Sections 4.2 and

4.3. This sequence of events explains the positive price impact of spread-improving flicker buy orders. Flicker entries at the best bid have similar effects, but to a lesser extent.

Flicker orders placed deeper in the book appear to follow a different mechanism. The number of flicker and non-flicker messages following an innovation in these flickers is lower than that for improving flickers and flickers at best. Although the effect is small, the entry of flicker buy orders deeper in the book is followed by spread-improving sell orders and buy-side cancellations that worsen the spread. Furthermore, these shocks are followed, on average, by 0.02 seller-initiated transactions, i.e., sell orders that cross the spread.

Overall, flickers trigger reactions that change the midpoint price beyond the lifetime of the flicker, which explains how a short-lived order has lasting price impact and contributes to price discovery.

INSERT TABLE 10 ABOUT HERE

4.2. Where in the Book do Flickers Matter the Most?

In this section we estimate a linear regression in calendar-time to reaffirm that spread-improving and flickers at best are on average followed by transactions initiated in the same direction, while flickers deeper in the book are on average followed by transactions initiated in the opposite direction.

The SVAR in Section 4.1 shows that spread-improving flickers are on average followed by transactions initiated in the same direction as the flicker, while flickers deeper in the book are on average followed by transactions initiated in the direction opposite to the flicker. This suggests that flickers deeper in the book anticipate adverse price movements, and are cancelled to avoid being adversely selected. Alternatively, the cancellation might invite other traders to adversely select remaining orders in the book.

If flicker orders deeper in the book anticipate adverse price movements, then we would expect a net number of sell (buy) liquidity taking transactions following a buy (sell) flicker

order deeper in the book. In contrast, we would expect a net number of buy (sell) liquidity taking transactions following a buy (sell) flicker spread-improving orders or orders at best.

We estimate the linear regression

$$\begin{aligned}\text{NetLiquidityTakingDirection}_{i,t} = \beta_0 &+ \beta_1 \cdot \text{SignedFlicker}_{i,t} + \beta_2 \cdot \text{FlickerVolumeImbalance}_{i,t} \\ &+ \beta_3 \cdot \text{OrderbookImbalance}_{i,t} + \beta_4 \cdot \text{Spread}_{i,t} \\ &+ \beta_5 \cdot \text{Return}_{i,t-10\text{sec}} + \epsilon_{i,t}\end{aligned} \tag{5}$$

to quantify the net number of buyer-initiated and seller-initiated trades following the entry of a flicker order.[14] Here, $\text{NetLiquidityTakingDirection}_{i,t}$ is the net number of buyer-initiated minus seller-initiated liquidity-taking transactions in the 10-second window following the entry of a flicker order for stock i at time t, while the other variables are defined as before.

Table 11 reports the average coefficients of the OLS regressions estimating the net number of buyer-initiated and seller-initiated trades after flicker orders in the next 10 seconds. We estimate a baseline specification which includes only the Intercept and $\text{SignedFlicker}_{i,t}$, and a specification with control variables. We estimate these models separately for flicker orders entered inside the spread (columns (1) and (2), flicker orders entered at the best quote (columns (3) and (4)), and flicker orders entered deeper in the book (columns (5) and (6)). We exclude the bottom and top one percent of the OLS coefficient estimates to mitigate the influence of outliers, compute the average of the remaining coefficients, and cluster standard errors by stock-day, following the approach of Thompson (2011).

Table 11 reports a positive and statistically significant coefficient β_1 for flicker orders that either improve the spread or are entered at the best quote in the baseline specification and the control specification. Specifically, on average, in the baseline specification a buy flicker is followed by respectively 0.042 and 0.065 more buyer-initiated than seller-initiated trades in the 10-second window after its entry, which reaffirms their positive price impact documented

[14] If a buy (sell) liquidity taking order executes against multiple sell (buy) liquidity providing orders, we count this as one buyer (seller)-initiated trade, because we are only interested in the direction of the trade for the purposes of this analysis.

in Section 3.

Interestingly, the coefficients associated with flicker orders placed deeper in the book is negative and statistically significant. On average, in the baseline specification a flicker buy order entered deeper in the book is followed by 0.051 more seller-initiated than buyer-initiated transactions in the 10-second window after its entry. This implies that buy (sell) flicker orders deeper in the book are typically followed by seller- (buyer-) initiated trades.

This directional asymmetry confirms that the opposite sign of price impact for deep flickers is not noise, but rather reflects a genuinely different mechanism such as to avoid adverse selection or induce other trades to trade with remaining liquidity in the order book.

INSERT TABLE 11 ABOUT HERE

4.3. Who Flickers and Who Trades?

In this section, we study how much HFT and non-HFT trade in the interval following a flickering quote, how much of their trading is liquidity taking and liquidity providing, and how much is in the direction of the flicker and opposite to it. We also study how many more transactions occur in time intervals with a flicker than in time intervals without flickering.

Subfigure B of Figure 3 reports that HFTs account for the vast majority of flickers. Specifically, HFTs account for 90.89% of all flickers. Furthermore, flicker activity is highly concentrated within the HFT group: the largest HFT accounts for 26.36% of all flickers, the top three HFTs for 56.79%, and the top five together represent 77.76% of all flickers.

Section 4.2 shows that buy flickers entered inside the spread or at the best quote are, on average, followed by more buyer-initiated than seller-initiated trades, while the opposite holds for sell flickers. We refer to these trades as being initiated in the direction of the flicker; the other trades are initiated in the opposite direction of the flicker. Similarly, liquidity-providing (passive) buy transactions following a flicker buy order are in the direction of the flicker, and passive sell transactions are in the direction opposite to the flicker.

We estimate a linear regression $\text{TradeCount}_{i,g,\ell,d} = \alpha_{g,\ell,d} + \epsilon_{i,g,\ell,d}$ for each trader group g, liquidity type ℓ, and direction d. Here, $\text{TradeCount}_{i,g,\ell,d}$ denotes the number of trades executed by group g of liquidity type ℓ in direction d during the 10-second interval following flicker i.[15] The tradings groups are $g \in \{\text{Flickerer}, \text{HFT}, \text{non-HFT}, \text{All}\}$, where Flickerer is the firm entering the flicker; the liquidity types are $\ell \in \{\text{Liquidity Taking}, \text{Liquidity providing}\}$; the directions are $d \in \{\text{Same direction}, \text{Opposite direction}\}$.

The OLS estimator $\alpha_{g,\ell,d}$ is mechanically equal to the sample mean of $\text{TradeCount}_{i,g,\ell,d}$, because the regression includes only a constant. So the reported coefficients can be interpreted directly as the average number of liquidity taking and providing trades submitted by each trading group in the specified direction following a flicker.

We include only flickers entered inside the spread and at the best quote because these flickers contribute the most to price discovery. Standard errors are clustered by stock-day, and statistical significance is reported with respect to the baseline trading activity without flickering.

Trading activity in 10-second window after flicker Table 12 reports the results of the regression. After the entry of a flicker, HFTs do on average of 0.813 liquidity-taking trades in the same direction and an average of 0.706 liquidity-taking trades in the opposite direction within 10 seconds. The difference between the two (0.107) suggests that HFTs condition their liquidity taking on the flicker, and are more likely to take liquidity in the direction of the flicker than in the opposite direction. On the other hand, HFTs supply liquidity for 0.864 trades in both the same and opposite directions, which is a highly symmetric response. Thus, the most notable directional tilt in HFT activity is in liquidity taking rather than liquidity provision.

Non-HFTs have a similar level of liquidity taking as HFTs, with an average of 0.833 trades in the same direction and 0.734 in the opposite direction. The directional difference

[15] If a liquidity taking order executes against multiple liquidity providing orders, we count these as multiple trades.

in liquidity taking (0.099) is close to that of HFTs, which indicates that both groups react similarly to flickers when taking liquidity. However, the main difference between HFTs and non-HFTs is how they provide liquidity. Non-HFTs provide substantially less liquidity in the same direction (0.576) than HFTs (0.864), a difference of 0.288, whereas the gap is much smaller in the opposite direction (0.782 versus 0.864, a difference of 0.082). This asymmetry suggests that HFTs play a more dominant role in replenishing liquidity on the same side as the flicker, while non-HFT liquidity provision is more concentrated on the opposite side. Thus, the primary behavioral difference between HFTs and non-HFTs following a flicker is how they provide liquidity rather than how they take liquidity.

Flickerers have a lower trading activity following their flicker. They do on average 0.148 same-direction and 0.122 opposite-direction liquidity-taking trades, and 0.181 same-direction versus 0.157 opposite-direction liquidity-providing trades. In both taking and providing liquidity, their activity is modest compared to HFTs and non-HFTs. Specifically, 91% of the liquidity-taking transactions in the direction of the flickers are by firms other than the Flickerer. This affirms that most activity after the flicker is not by the Flickerer itself, but the flicker actually induces other traders to trade.[16]

A comparison with the 10-second baseline of average trading activity highlights how strongly flickers accelerate trading activity. For HFTs, the total number of liquidity-taking trades increases from an average of 0.879 to 1.519 (a 73% increase) in the 10 seconds after a flicker. Their liquidity provision rises even more sharply, from 0.909 to 1.728 trades (a 89% increase). These jumps show that HFTs substantially increase both their aggressive and passive trading following a flicker, compared to their average activity.

Non-HFTs have an even stronger response to flickers: their liquidity taking grows from 0.684 to 1.567 trades (a 129% increase), while their liquidity provision rises from 0.654 to 1.358 trades (a 108% increase). So flickers are associated with more than a doubling of normal trading activity for non-HFT, which means that flickers coincide with a sharp intensification

[16]For computation efficiency we include only the top six firms who flicker. These six firms alone account for 95.46% of all flickers posted at the best quote or within the spread.

of non-HFT trading that far exceeds baseline market conditions.

INSERT TABLE 12 ABOUT HERE

Trading activity in 1-second window after flicker We also apply the linear regression $\text{TradeCount}_{i,g,\ell,d} = \alpha_{g,\ell,d} + \epsilon_{i,g,\ell,d}$ to the 1-second interval after the flicker, to study how much of the trading occurs very rapidly after the flicker. Table 13 reports the results. The magnitudes are naturally smaller than for the 10 seconds interval, but disproportionally high. For example, the number of liquidity-taking trades in the 1 second interval following a flicker is 0.966, which is more than 30% of the number of liquidity-taking trades in the 10 second interval.

The directional patterns are clearer for the 1 second interval than for the 10 second interval. The liquidity provision asymmetry for non-HFT is more pronounced, with nearly twice as many trades on the opposite side (0.327) than on the flicker side (0.164). Also, the relative difference in liquidity taking between same side trades (0.313) and opposite side trades (0.231) increases. The change for HFT is less pronounced. This implies that when the interval after the flicker gets shorter, the difference between HFT and non-HFT trading activity increases.

Within 1 second (i.e., while the flicker is still alive or just cancelled), trading activity spikes dramatically relative to the baseline. The baseline of 0.009 trades in seconds without flickers compared to the 0.966 trades in seconds with flickers underscores how much activity flickers induce. Specifically, HFTs execute 0.422 liquidity-taking trades in the second after a flicker, which is more than 100 times the rate in non-flicker seconds. Non-HFTs show an even stronger reaction, rising from a baseline of 0.006 to 0.544 trades. A similar pattern holds for liquidity provision.

INSERT TABLE 13 ABOUT HERE

Overall, our results show that HFT and non-HFT firms take more liquidity in the direction of the flicker than in the opposite direction. Their contributions to directional liquidity

taking are remarkably similar in magnitude, with each group accounting for roughly half of the total liquidity-taking trades in the direction of the flicker in the 10-second interval following a flicker. The most pronounced difference between HFT and non-HFT firms is on the liquidity-providing side. HFTs supply liquidity in a largely symmetric manner, being equally active in the direction of the flicker and in the opposite direction. In contrast, non-HFT firms predominantly provide liquidity in the direction opposite to the flicker. Our results show that the vast majority of liquidity-taking transactions following a flicker are by firms other than the Flickerer itself. Finally, flickers dramatically increase the number of trades in the interval following their entry, which is consistent with the notion that flickers induce other trades to trade.

5. Conclusion

HFTs have reshaped trading activity via the introduction of short-lived limit orders, also known as flickering quotes. We find that around 40% of all limit orders are cancelled within a second. The common denominator among theoretical models of flickering quotes is that flickers are uninformed byproducts of quoting strategies in a limit order book, and that flickering quotes do not contribute to price discovery. Bayesian learning implies that if a limit order is cancelled, then there should be a revision in traders' beliefs that removes the initial effect of the limit order. Therefore, flickers should have a net price impact of zero.

Our results show that flickers have price impact that persists beyond their lifetime, contradicting existing theory. Moreover, flickers contribute substantially to price discovery and account for around 20% of the total price discovery of limit orders, even though they account for less than 0.3% of the total lifetime of all limit orders that get cancelled. We use proprietary data that identifies each trading firm to understand the mechanism by which flickers contribute to price discovery. The analyses show that flickers have a permanent price impact because they induce other traders to trade, the effect of which persists beyond the

lifetime of the flicker. Specifically, flickers induces both non-HFTs and other HFTs to take more liquidity in the direction of the flicker than against it. Furthermore, following a flicker, most market orders are by firms other than the flickerer.

The fact that flickers contribute to price discovery is consistent with their potential use for strategic purposes. Indeed, it is precisely because flickers, on average, both convey information and trigger responses from other market participants that they can be used strategically to induce responses. This dual role of flickers underscores the importance to understand not only the informational content in flickers but also the incentives behind their use.

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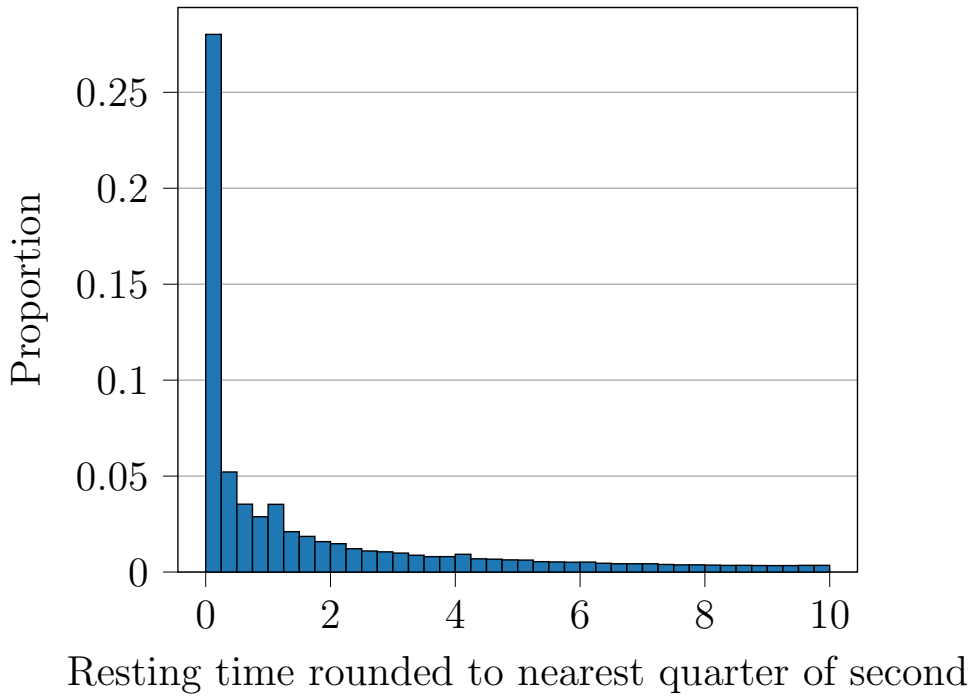
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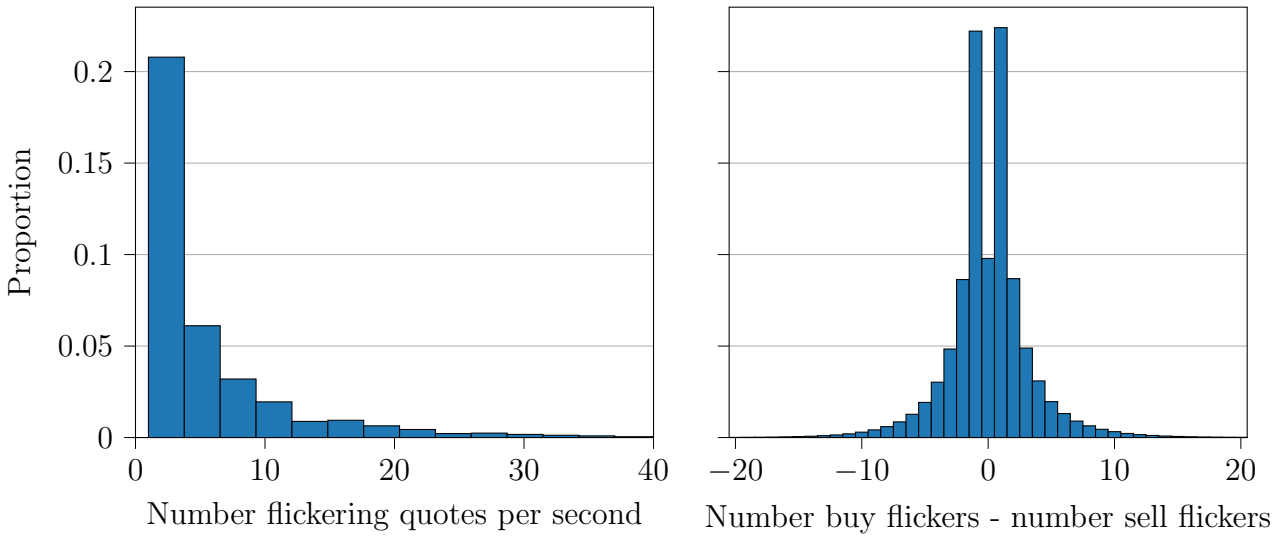
Resting Time of Orders

Fig. 1: Distribution of resting times for cancelled orders, rounded to nearest quarter of a second. Proportions are calculated over all cancelled orders, but only cancellations within the first 10 seconds after order entry are shown. The sample covers 25 large cap stocks (AEX-index), 21 mid-cap stocks (AMX-index), and 21 small-cap stocks (ASCX-index) traded on Euronext Amsterdam during January 2023.



Number of Flickers per Second and Imbalance

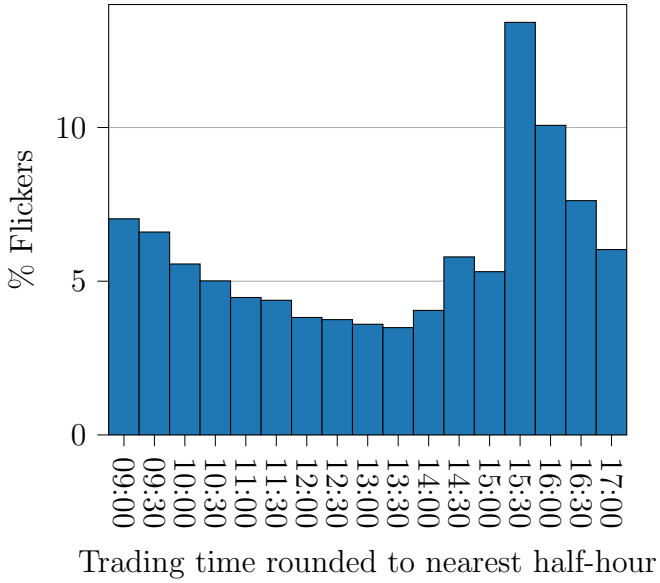
Fig. 2: Number of flicker orders per second (left panel) and imbalance of the bid and ask flickers (right panel). Seconds without any flicker activity are excluded. The sample covers 25 large cap stocks (AEX-index), and 21 mid-cap stocks (AMX-index) traded on Euronext Amsterdam during January 2023.



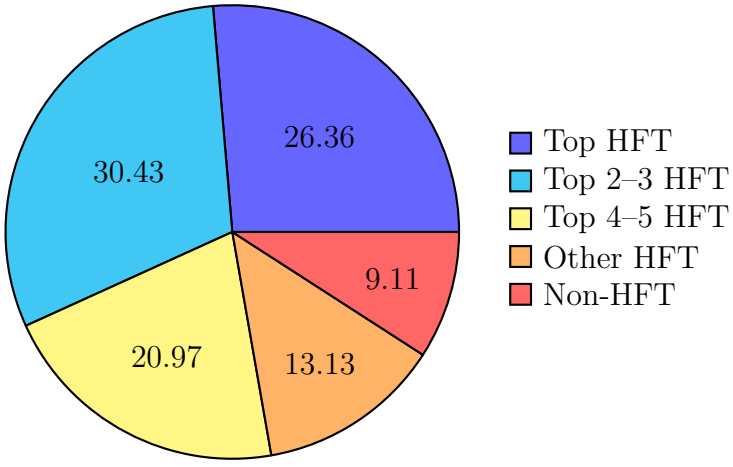
Flickers by Time of Day and Trader Type

Fig. 3: Flickering quotes by time of day and trader type. A flickering quote is an order cancelled within 1 second after entry. The sample covers 25 large-cap (AEX) stocks and 21 mid-cap (AMX) stocks traded on Euronext Amsterdam during January 2023. Subfigure A shows the percentage of flickering quotes per half-hour interval. Subfigure B shows the percentage of flickering quotes by HFT and Non-HFT.

Subfigure A: Flickers by Time of Day



Subfigure B: Flickers by HFT and Non-HFT



Variable Definitions

Table 1: This table defines the dependent and independent variables used throughout the paper, listed in the order in which they are first defined in the text.

Variable	Role	Definition
$\text{Flicker}_{i,t}$	Dep. var.	Indicator equal to 1 if an order in stock i entered at time t is cancelled within 1 second after entry, and 0 otherwise.
$\text{Return}_{i,t-h}$	Indep. var.	Midpoint-price return of stock i over the $h \in \{0.1, 1, 5, 10\}$ seconds prior to order entry, standardized to have zero mean and unit variance per stock-day.
$\text{Spread}_{i,t}$	Indep. var.	Relative bid–ask spread standardized to have zero mean and unit variance per stock-day.
$\mathbb{1}_{\text{FirstHour}}$	Indep. var.	Indicator equal to 1 if the order is entered between 09:15 and 10:00, and 0 otherwise.
$\mathbb{1}_{\text{MidDay}}$	Indep. var.	Indicator equal to 1 if the order is entered between 10:30 and 16:30, and 0 otherwise.
$\mathbb{1}_{\text{LargePriceMoveUp}_{i,t-h}}$	Indep. var.	Indicator equal to 1 if the standardized midpoint return in the h seconds prior to order entry exceeds 2 standard deviations, and 0 otherwise.
$\mathbb{1}_{\text{MediumPriceMoveUp}_{i,t-h}}$	Indep. var.	Indicator equal to 1 if the standardized midpoint return in the h seconds prior to order entry is between 1 and 2 standard deviations, and 0 otherwise.
$\mathbb{1}_{\text{MediumPriceMoveDown}_{i,t-h}}$	Indep. var.	Indicator equal to 1 if the standardized midpoint return in the h seconds prior to order entry is between -1 and -2 standard deviations, and 0 otherwise.
$\mathbb{1}_{\text{LargePriceMoveDown}_{i,t-h}}$	Indep. var.	Indicator equal to 1 if the standardized midpoint return in the h seconds prior to order entry is below -2 standard deviations, and 0 otherwise.

Continued on next page

Table 1 (continued)

Variable	Role	Definition
$\text{PriceImpact}_{i,t}$	Dep. var.	Midpoint-price return of stock i at time t, measured in basis points over the next 10 seconds starting the moment immediately before entry of the flickering quote.
$\text{SignedFlicker}_{i,t}$	Indep. var.	Signed indicator equal to $+1$ for entry of a flicker buy order and -1 for entry of a flicker sell order.
$\text{FlickerVolumeImbalance}_{i,t}$	Indep. var.	Difference between the volume of flicker buy orders cancelled at the best bid and the volume of flicker sell orders cancelled at the best ask over the previous 5 seconds, divided by their sum.
$\text{OrderbookImbalance}_{i,t}$	Indep. var.	Difference between the volume at the best bid and the volume at the best ask at time t, divided by their sum.
r_t	Dep./Indep. var.	Midpoint-return series in the SVAR. It is the dependent variable in the return equation and enters the system through lagged values.
X_t^1 (Trade)	Dep./Indep. var.	Trade-message variable in the SVAR: $+1$ for buyer-initiated trades, -1 for seller-initiated trades, and 0 otherwise.
X_t^2 (Flicker Improving order)	Dep./Indep. var.	Flicker order entry that improves the best quote: $+1$ for bids placed, -1 for offers placed, and 0 otherwise.
X_t^3 (Flicker Order at best)	Dep./Indep. var.	Flicker order entry at the best quote: $+1$ for bids placed, -1 for offers placed, and 0 otherwise.
X_t^4 (Flicker Order deeper in book)	Dep./Indep. var.	Flicker order entry deeper in the book: $+1$ for bids placed, -1 for offers placed, and 0 otherwise.
X_t^5 (Non-Flicker Improving order)	Dep./Indep. var.	Non-flicker order entry that improves the best quote: $+1$ for bids placed, -1 for offers placed, and 0 otherwise.
X_t^6 (Non-Flicker Order at best)	Dep./Indep. var.	Non-flicker order entry at the best quote: $+1$ for bids placed, -1 for offers placed, and 0 otherwise.

Continued on next page

Table 1 (continued)

Variable	Role	Definition
X_t^7 (Non-Flicker Order deeper in book)	Dep./Indep. var.	Non-flicker order entry deeper in the book: $+1$ for bids placed, -1 for offers placed, and 0 otherwise.
X_t^8 (Flicker Worsening cancel)	Dep./Indep. var.	Flicker cancellation that worsens the quote: -1 for bid-side cancellations, $+1$ for ask-side cancellations, and 0 otherwise.
X_t^9 (Flicker Cancellation at best)	Dep./Indep. var.	Flicker cancellation at the best quote: -1 for bid-side cancellations, $+1$ for ask-side cancellations, and 0 otherwise.
X_t^{10} (Flicker Cancellation deeper in book)	Dep./Indep. var.	Flicker cancellation deeper in the book: -1 for bid-side cancellations, $+1$ for ask-side cancellations, and 0 otherwise.
X_t^{11} (Non-Flicker Worsening cancel)	Dep./Indep. var.	Non-flicker cancellation that worsens the quote: -1 for bid-side cancellations, $+1$ for ask-side cancellations, and 0 otherwise.
X_t^{12} (Non-Flicker Cancellation at best)	Dep./Indep. var.	Non-flicker cancellation at the best quote: -1 for bid-side cancellations, $+1$ for ask-side cancellations, and 0 otherwise.
X_t^{13} (Non-Flicker Cancellation deeper in book)	Dep./Indep. var.	Non-flicker cancellation deeper in the book: -1 for bid-side cancellations, $+1$ for ask-side cancellations, and 0 otherwise.
$\text{NetLiquidityTakingDirection}_{i,t}$	Dep. var.	Net number of buyer-initiated minus seller-initiated liquidity-taking transactions in the 10-second window following the entry of a flicker order for stock i at time t.
$\text{TradeCount}_{i,g,\ell,d}$	Dep. var.	Number of trades executed during the post-flicker interval, for trader group $g \in \{\text{Flickerer}, \text{HFT}, \text{non-HFT}, \text{All}\}$, liquidity type $\ell \in \{\text{Liquidity Taking}, \text{Liquidity Providing}\}$, and direction $d \in \{\text{Same direction}, \text{Opposite direction}\}$.

Flicker Frequency

Table 2: Order activity and cancellations: number of orders, number of cancellations, and the percentage of cancellations occurring within specific time intervals after order entry (1 second, 100 milliseconds, 10 milliseconds, 1 millisecond, and 100 microseconds). Data are reported per stock-day for 25 large cap stocks (AEX-index), 21 mid-cap stocks (AMX-index), and 21 small-cap stocks (ASCX-index) traded on Euronext Amsterdam during January 2023.

				% Cancelled within				
		orders	cancellations	1sec	100ms	10ms	1ms	100μs
Large cap	Mean	166,075	159,539	33.44	18.25	7.36	2.89	1.24
	Min	22,038	21,369	15.60	9.33	3.36	1.43	0.60
	25th percentile	70,009	67,483	25.55	14.63	5.86	2.25	0.93
	50th percentile	112,820	109,065	30.87	17.34	7.06	2.77	1.14
	75th percentile	257,231	247,991	42.30	21.62	8.48	3.43	1.46
	Max	600,779	567,202	55.00	31.70	13.70	6.82	4.67
Mid cap	Mean	30,162	29,106	23.07	15.18	5.01	1.37	0.57
	Min	1,176	1,055	4.07	3.11	0.99	0.03	0.00
	25th percentile	4,870	4,454	19.76	12.82	3.01	0.49	0.13
	50th percentile	9,475	8,857	23.03	14.74	4.72	0.96	0.32
	75th percentile	39,293	38,207	26.52	17.32	6.05	1.96	0.94
	Max	284,237	276,378	47.77	40.76	24.54	10.29	8.74
Small cap	Mean	7,957	7,545	16.01	11.08	5.71	2.49	0.58
	Min	7	3	0.00	0.00	0.00	0.00	0.00
	25th percentile	674	577	6.30	4.15	1.52	0.39	0.00
	50th percentile	1,389	1,234	12.70	9.10	3.28	0.92	0.23
	75th percentile	7,031	6,205	23.57	14.15	5.38	2.16	0.76
	Max	63,061	61,251	63.72	54.81	48.75	31.36	7.83

Message Frequency

Table 3: Frequency of message types by flickering and non-flickering. *Improving order* refers to orders that improve the best price, *Order at best* to those placed at the best price, and *Order deeper in book* to those placed further from the best price, with analogous definitions for cancels; *Trade* refers to orders that are executed immediately upon entry; the dataset covers 25 large-cap (AEX) stocks and 21 mid-cap (AMX) stocks traded on Euronext Amsterdam during January 2023.

	Flicker	**Non-Flicker**
Improving order	1.35%	1.21%
Order at best	10.82%	9.95%
Order deeper in book	7.21%	19.63%
Worsening cancel	1.10%	0.72%
Cancel at best	10.85%	8.48%
Cancel deeper in book	7.47%	19.88%
Trade	1.32%	

Flicker Entries and Cancellations

Table 4: Frequency of flicker orders by type of entry and cancellation. The analysis includes only flicker order entries that do not execute immediately upon entry. Data are based on 25 Dutch large-cap (AEX) and 21 mid-cap (AMX) stocks on Euronext Amsterdam during January 2023.

	Worsening cancel	**Cancel at best**	**Cancel deeper in book**
Improving order	3.30%	3.33%	0.33%
Order at best	2.16%	49.23%	4.43%
Order deeper in book	0.16%	3.28%	33.78%

Likelihood of Flickers for Recent Returns

Table 5: Averages of the coefficients of logistic regressions estimating the likelihood (in log-odds) that an order is cancelled within 1 second after entry for each stock-day in 25 large-cap (AEX-index) stocks, and 21 mid-cap (AMX-index) stocks. The sample period is January 2023. We fit separate models on buy orders (columns (1)-(4)) and sell orders (columns (5)-(8)). $\text{Return}_{i,t-h}$ is the return in the midpoint price over the $0.1, 1, 5, 10$ seconds prior to order entry, standardized to have zero mean and unit variance. $\text{Spread}_{i,t}$ is the relative bid-ask spread, standardized to have zero mean and unit variance. $\mathbb{1}_{\text{FirstHour}}$ is equal to 1 for orders placed between 09:15 and 10:00 and 0 otherwise, and $\mathbb{1}_{\text{MidDay}}$ equals 1 for orders placed between 10:30 and 16:30 and 0 otherwise. The asterisk(s) * (**) next to the coefficient indicates that the coefficient is statistically different from zero at the 5% (1%) significance level using standard errors clustered by stock and by day. Standard errors are in parentheses.

	BUY				**SELL**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-0.949^{**}	-0.945^{**}	-0.942^{**}	-0.941^{**}	-0.939^{**}	-0.935^{**}	-0.931^{**}	-0.930^{**}
	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)
$\text{Return}_{i,t-100\text{ms}}$	0.090^{**}				-0.097^{**}			
	(0.003)				(0.003)			
$\text{Return}_{i,t-1\text{sec}}$		0.075^{**}				-0.085^{**}		
		(0.003)				(0.003)		
$\text{Return}_{i,t-5\text{sec}}$			0.064^{**}				-0.071^{**}	
			(0.003)				(0.003)	
$\text{Return}_{i,t-10\text{sec}}$				0.058^{**}				-0.064^{**}
				(0.002)				(0.003)
$\text{Spread}_{i,t}$	-0.006	-0.007^{*}	-0.008^{*}	-0.009^{*}	-0.004	-0.005	-0.006	-0.006
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
$\mathbb{1}_{\text{MidDay}}$	-0.047^{**}	-0.046^{**}	-0.045^{**}	-0.045^{**}	-0.058^{**}	-0.058^{**}	-0.057^{**}	-0.057^{**}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$\mathbb{1}_{\text{FirstHour}}$	-0.097^{**}	-0.092^{**}	-0.090^{**}	-0.089^{**}	-0.098^{**}	-0.095^{**}	-0.092^{**}	-0.091^{**}
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)

Likelihood of Flickers for Discrete Price Movements

Table 6: Averages of the coefficients of logistic regressions estimating the likelihood (in log-odds) that an order is cancelled within 1 second after entry for each stock-day in 25 large-cap (AEX-index) stocks, and 21 mid-cap (AMX-index) stocks. The sample period is January 2023. We fit separate models on buy orders (columns (1)-(2)) and sell orders (columns (3)-(4)). $\mathbb{1}_{\text{LargePriceMoveUp}_{i,t-h}}$ is equal to 1 if the standardized return in midpoint in the h seconds prior to order entry is larger than 2 standard deviations, and 0 otherwise; $\mathbb{1}_{\text{MediumPriceMoveUp}_{i,t-h}}$ is equal to 1 if this value is between 1 and 2 standard deviations, and 0 otherwise; $\mathbb{1}_{\text{MediumPriceMoveDown}_{i,t-h}}$ is equal to 1 if this value is between -1 and -2 standard deviations, and 0 otherwise; $\mathbb{1}_{\text{LargePriceMoveDown}_{i,t-h}}$ is equal to 1 if this value is less than -2 standard deviations, and 0 otherwise. All other variables are as in Table 5. The asterisk(s) * (**) next to the coefficient indicates that the coefficient is statistically different from zero at the 5% (1%) significance level using standard errors clustered by stock and by day. Standard errors are in parentheses.

	BUY		**SELL**	
	(1)	(2)	(3)	(4)
Intercept	-0.995^{**}	-0.962^{**}	-0.984^{**}	-0.950^{**}
	(0.022)	(0.021)	(0.021)	(0.020)
$\mathbb{1}_{\text{LargePriceMoveUp}_{i,t-1sec}}$	0.414^{**}		0.130^{**}	
	(0.013)		(0.013)	
$\mathbb{1}_{\text{MediumPriceMoveUp}_{i,t-1sec}}$	0.325^{**}		0.161^{**}	
	(0.013)		(0.012)	
$\mathbb{1}_{\text{MediumPriceMoveDown}_{i,t-1sec}}$	0.176^{**}		0.339^{**}	
	(0.012)		(0.012)	
$\mathbb{1}_{\text{LargePriceMoveDown}_{i,t-1sec}}$	0.162^{**}		0.435^{**}	
	(0.014)		(0.013)	
$\mathbb{1}_{\text{LargePriceMoveUp}_{i,t-10sec}}$		0.239^{**}		0.055^{**}
		(0.011)		(0.010)
$\mathbb{1}_{\text{MediumPriceMoveUp}_{i,t-10sec}}$		0.197^{**}		0.033^{**}
		(0.009)		(0.008)
$\mathbb{1}_{\text{MediumPriceMoveDown}_{i,t-10sec}}$		0.035^{**}		0.199^{**}
		(0.008)		(0.009)
$\mathbb{1}_{\text{LargePriceMoveDown}_{i,t-10sec}}$		0.059^{**}		0.262^{**}
		(0.013)		(0.012)
$\text{Spread}_{i,t}$	-0.014^{**}	-0.015^{**}	-0.011^{**}	-0.013^{**}
	(0.003)	(0.003)	(0.003)	(0.003)
$\mathbb{1}_{\text{MidDay}}$	-0.050^{**}	-0.048^{**}	-0.059^{**}	-0.058^{**}
	(0.007)	(0.007)	(0.007)	(0.007)
$\mathbb{1}_{\text{FirstHour}}$	-0.108^{**}	-0.100^{**}	-0.108^{**}	-0.100^{**}
	(0.010)	(0.010)	(0.010)	(0.010)

Price Impact of Flickers

Table 7: Averages of the coefficients of OLS regressions on the signed price impact (in basis points) of flicker orders in the 10 second-window measured from the instant *before* entry of the flicker order for each stock-day in all 25 stocks part of the Dutch large-cap index, and 21 stocks part of the Dutch mid-cap index. The sample period is January 2023. $\text{SignedFlicker}_{i,t}$ equals +1 for a flicker buy order and −1 for a flicker sell order. $\text{FlickerVolumeImbalance}_{i,t}$ is the difference between volume of flicker buy orders cancelled at the best bid and the volume of flicker sell orders cancelled at the best ask over the previous 5 seconds, divided by their sum. $\text{Orderbook Imbalance}_{i,t}$ is the difference between the volume at the best bid and the volume at the best ask, divided by their sum. $\text{Spread}_{i,t}$ is the relative bid-ask spread standardized per stock. (1) and (2) are estimated on spread-improving flicker orders, (3) and (4) on flicker orders entered at the best quote, and (5) and (6) on flicker orders deeper in the book. The asterisk(s) * (**) next to the coefficient indicates that the coefficient is statistically different from zero at the 5% (1%) significance level using standard errors clustered by stock and by day. Standard errors are in parentheses.

	IMPROVING		BEST		DEEP	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.118^{**}	-1.831^{**}	0.140^{**}	0.145^{**}	0.137^{**}	0.148^{**}
	(0.021)	(0.276)	(0.020)	(0.021)	(0.017)	(0.020)
$\text{SignedFlicker}_{i,t}$	1.211^{**}	1.090^{**}	0.174^{**}	0.230^{**}	-0.269^{**}	-0.184^{**}
	(0.032)	(0.031)	(0.016)	(0.017)	(0.015)	(0.011)
$\text{FlickerVolumeImbalance}_{i,t}$		0.072^{*}		0.114^{**}		0.119^{**}
		(0.031)		(0.022)		(0.023)
$\text{Orderbook Imbalance}_{i,t}$		0.565^{**}		1.100^{**}		1.152^{**}
		(0.037)		(0.033)		(0.030)
$\text{Spread}_{i,t}$		1.271^{**}		-0.017		-0.021
		(0.176)		(0.014)		(0.012)

Return Impulse Response Function

Table 8: Stock-day average return impulse response functions (IRFs) from a structural vector autoregression (SVAR). The IRF is cumulative over 20 events. There is one equation for each of the variables listed in the table, for flicker and non-flicker messages, as well as for the midpoint return and trade variable. The SVAR is estimated in event time, where each message is treated as one observation. *Order* variables take the value of +1 for bids placed, −1 for offers placed, and 0 otherwise. For *Cancels*, analogous definitions apply, with signs such that cancels at the bid take the value −1 and cancels at the offer take the value +1. The analysis includes 25 large-cap (AEX) stocks and 21 mid-cap (AMX) stocks on Euronext Amsterdam, during January 2023. The *Trade* variables take the value of +1 for buyer-initiated trades, −1 for seller-initiated trades, and 0 otherwise. The asterisks **, indicate significance at the 1% level, based on standard errors clustered by stock and by day.

	Flicker	**Non-Flicker**
Improving order	0.38^{**}	0.79^{**}
Order at best	0.24^{**}	0.38^{**}
Order deeper in book	-0.13^{**}	0.02^{**}
Worsening cancel	0.29^{**}	0.66^{**}
Cancellation at best	0.18^{**}	0.27^{**}
Cancellation deeper in book	0.04^{**}	0.06^{**}
Trade	1.73	

Variance Decomposition

Table 9: Stock-day average variance decomposition from the structural vector autoregression (SVAR) used in Table 8 for 25 Dutch large-cap (AEX) stocks and 21 Dutch (AMX) mid-cap stocks. The sample period is January 2023.

	Flicker	**Non-Flicker**
Improving order	1.16%	4.47%
Order at best	0.93%	7.09%
Order deeper in book	0.24%	0.14%
Worsening cancel	0.77%	1.73%
Cancel at best	0.97%	2.68%
Cancel deeper in book	0.18%	0.56%
Trade	21.55%	

Message Impulse Response Function

Table 10: Stock-day average message impulse response functions (IRFs) from the structural vector autoregressions (SVARs) in Table 8 for 25 Dutch large-cap (AEX) stocks and 21 Dutch mid-cap (AMX) stocks. The sample period is January 2023. The SVAR is in event time, where every message is an observation. The rows correspond to the variable being shocked by one unit. The columns represent the variable being affected. The IRF is cumulative over 20 events. *ImpOrd*, *BestOrd* and *DeepOrd* take the value of +1 for respectively bids placed inside the spread, bids placed at the best quote and bids placed deeper in the book, −1 for offers placed, and 0 otherwise. *WrsCan*, *BestCan* and *DeepCan* take the value of −1 for respectively bids cancelled that widen the spread, bids cancelled at the best quote and bids cancelled deeper in the book, +1 for offers cancelled, and 0 otherwise. Messages are grouped by flicker or non-flicker events. The analysis includes 25 large-cap (AEX) stocks and 21 mid-cap (AMX) stocks on Euronext Amsterdam, during January 2023. *Trade* takes the value of +1 for buyer-initiated trades, −1 for seller-initiated trades, and 0 otherwise. Observations include all displayed messages between 9:15 and 17:15 CEST . The asterisk(s) * (**) next to the coefficient indicates that the coefficient is statistically different from zero at the 5% (1%) significance level using standard errors clustered by stock and by day.

		Flickers						Non-flickers						
		Imp Ord	Best Ord	Deep Ord	Wrs Can	Best Can	Deep Can	Imp Ord	Best Ord	Deep Ord	Wrs Can	Best Can	Deep Can	Trade
Flicker	ImpOrd	0.03**	0.45**	0.07**	-0.17**	0.04**	-0.15**	0.01**	0.19**	0.36**	0.04**	0.29**	-0.30**	0.34**
	BestOrd	0.04**	0.18**	0.02**	-0.00**	-0.46**	-0.08**	0.01**	0.08**	0.12**	0.02**	0.14**	-0.07**	0.03**
	DeepOrd	-0.00	0.02**	0.08**	-0.02**	-0.02**	-0.56**	-0.00**	0.03**	0.06**	-0.00**	0.02**	-0.04**	-0.02**
	WrsCan	-0.10**	0.16**	-0.11**	0.05**	0.14**	0.05**	-0.05**	0.04**	-0.19**	0.00**	-0.11**	0.04**	0.32**
	BestCan	-0.00	-0.08**	-0.04**	0.06**	0.15**	0.02**	0.01**	-0.03**	-0.13**	0.01**	0.04**	0.05**	-0.01**
	DeepCan	0.00	0.01**	-0.12**	0.02**	0.01**	-0.02**	0.00**	-0.01**	-0.13**	0.00*	-0.00*	0.03**	0.00**
Non-flickers	ImpOrd	-0.00	0.33**	-0.04**	0.05**	0.12**	-0.08**	0.02**	0.66**	0.50**	0.05**	0.40**	-0.29**	0.30**
	BestOrd	0.03**	0.10**	-0.01**	0.02**	0.03**	-0.02**	0.05**	0.38**	0.16**	0.04**	0.21**	-0.02**	0.04**
	DeepOrd	0.00	0.01**	0.00**	-0.00**	-0.01**	-0.01**	0.01**	0.06**	0.09**	0.00**	0.02**	-0.08**	0.00**
	WrsCan	0.00**	0.22**	-0.10**	0.03**	-0.05**	0.06**	-0.01**	0.08**	-0.37**	0.02**	0.25**	0.45**	0.32**
	BestCan	0.03**	0.08**	-0.01**	-0.01**	-0.03**	-0.01**	0.03**	0.16**	-0.11**	0.06**	0.40**	0.07**	0.01**
	DeepCan	0.01**	0.02**	-0.03**	0.01**	0.01**	0.02**	0.00**	-0.00**	-0.25**	0.01**	0.02**	0.05**	0.01**
	Trade	0.21**	0.38**	0.05**	0.04**	0.05**	-0.01**	0.18**	0.41**	0.03**	0.07**	0.48**	0.29**	0.48**

Trade Direction after Flicker

Table 11: This table presents average coefficients from OLS regressions estimating the number of buyer-initiated minus seller-initiated transactions in the 10 seconds following entry of a flicker order. The dataset covers 25 large-cap (AEX) stocks and 21 mid-cap (AMX) stocks traded on Euronext Amsterdam during January 2023. $\text{SignedFlicker}_{i,t}$ equals $+1$ for entry of a flicker buy order and -1 for entry of a flicker sell order. $\text{Return10sec}_{i,t}$ is the return in the midpoint price over the 10 seconds prior to order entry, standardized to have zero mean and unit variance. The other variables are as defined in Table 7. (1) and (2) are estimated on spread-improving flicker orders, (3) and (4) on flicker orders entered at the best quote, and (5) and (6) on flicker orders deeper in the book. The asterisk(s) * (**) denote statistical significance at the 5% (1%) level, based on standard errors clustered by stock and by day. Standard errors are in parentheses.

	IMPROVING		BEST		DEEP	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.005	-0.485^{**}	0.015^{*}	0.013	0.013	0.012
	(0.008)	(0.176)	(0.007)	(0.007)	(0.007)	(0.007)
$\text{SignedFlicker}_{i,t}$	0.042^{**}	0.062^{**}	0.065^{**}	0.062^{**}	-0.051^{**}	-0.042^{**}
	(0.005)	(0.006)	(0.003)	(0.003)	(0.002)	(0.002)
$\text{FlickerVolumeImbalance}_{i,t}$		0.010		0.029^{**}		0.044^{**}
		(0.006)		(0.005)		(0.006)
$\text{Orderbook Imbalance}_{i,t}$		-0.092^{**}		0.038^{**}		0.075^{**}
		(0.011)		(0.006)		(0.007)
$\text{Spread}_{i,t}$		0.317^{**}		-0.006		-0.006
		(0.113)		(0.004)		(0.003)
$\text{Return}_{i,t-10\text{sec}}$		-0.047^{**}		-0.027^{**}		-0.046^{**}
		(0.007)		(0.006)		(0.007)

Liquidity Taking and Liquidity Providing Trades in 10 Seconds after Flicker by HFT and NON-HFT

Table 12: This table reports the average coefficients from OLS regressions estimating the number of liquidity-taking and liquidity-providing trades by group $g \in \{\text{Flickerer}, \text{HFT}, \text{non-HFT}, \text{All}\}$ in the direction of the flicker and in the direction opposite to the flicker in the 10 second interval following the entry of a flicker. The table also report the average baseline number of liquidity-taking and liquidity-providing transactions per 10-second time window per stock-day. The sample covers 25 large-cap (AEX) stocks and 21 mid-cap (AMX) stocks traded on Euronext Amsterdam in January 2023. We include only flickers entered inside the bid–ask spread or at the best quote. Asterisks * (**) indicate that the totals are statistically different from their respective baseline at the 5% (1%) level based on standard errors clustered by stock and trading day. Standard errors are in parentheses.

		All	HFT	non-HFT	Flickerer
Liquidity taking	Same direction flicker	1.646	0.813	0.833	0.148
		(0.047)	(0.025)	(0.026)	(0.005)
	Opposite direction flicker	1.440	0.706	0.734	0.122
		(0.046)	(0.024)	(0.025)	(0.004)
	Total for Liquidity taking	3.086**	1.519**	1.567**	0.270
	Baseline (mean 10 seconds)	1.563	0.879	0.684	
Liquidity providing	Same direction flicker	1.440	0.864	0.576	0.181
		(0.046)	(0.033)	(0.017)	(0.006)
	Opposite direction flicker	1.646	0.864	0.782	0.157
		(0.047)	(0.034)	(0.019)	(0.006)
	Total for Liquidity providing	3.086**	1.728**	1.358**	0.338
	Baseline (mean 10 seconds)	1.563	0.909	0.654	

Liquidity Taking and Liquidity Providing Trades in 1 Second after Flicker by HFT and NON-HFT

Table 13: This table reports the average coefficients from OLS regressions estimating the number of liquidity-taking and liquidity-providing trades by group $g \in \{\text{Flickerer}, \text{HFT}, \text{non-HFT}, \text{All}\}$ in the direction of the flicker and in the direction opposite to the flicker in the 1 second interval following the entry of a flicker. The table also report the average baseline number of liquidity-taking and liquidity-providing transactions in seconds without flickering. The dataset includes 25 large-cap (AEX) stocks and 21 mid-cap (AMX) stocks traded on Euronext Amsterdam in January 2023. We include only flickers entered inside the bid–ask spread or at the best quote. Asterisks * (**) indicate that the totals are statistically different from their respective baseline at the 5% (1%) level based on standard errors clustered by stock and trading day. Standard errors are in parentheses.

		All	HFT	non-HFT	Flickerer
Liquidity taking	Same direction flicker	0.569	0.256	0.313	0.052
		(0.011)	(0.005)	(0.010)	(0.003)
	Opposite direction flicker	0.397	0.166	0.231	0.037
		(0.009)	(0.004)	(0.008)	(0.002)
	Total for Liquidity taking	0.966**	0.422**	0.544**	0.089
	Baseline (no flickers)	0.009	0.003	0.006	
Liquidity providing	Same direction flicker	0.397	0.232	0.164	0.068
		(0.009)	(0.006)	(0.007)	(0.004)
	Opposite direction flicker	0.569	0.242	0.327	0.059
		(0.011)	(0.007)	(0.010)	(0.004)
	Total for Liquidity providing	0.966**	0.474**	0.491**	0.127
	Baseline (no flickers)	0.009	0.003	0.006	