The Lasting Impact of Fleeting Orders *

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ABSTRACT

We analyze the contribution of flickering quotes to price discovery. A flicker is a quote that is canceled shortly after entry. The price impact of flickers persists beyond their lifetime. The impact of the flicker depends on where it is placed in the limit order book. Flickers placed at the best quotes or improve the best quotes have a positive price impact, while flickers placed behind the best quotes have a negative price impact. Flickers account for around TBD of the total price discovery of limit orders. Flickers are highly concentrated among trading firms, and [TBD: contributes/does not contribute] towards firm profitability.

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Modern stock exchanges and financial markets have largely evolved into limit order books, where limit orders represent the bulk of the activity in the market. Limit orders are commitments to buy or to sell an asset at the limit price, and they face the risk of adverse selection. However, in the large-cap stocks of Euronext Amsterdam, an average of 19.42% of limit orders are canceled within a blink of an eye, while 7.93% of limit orders are canceled before a human can realize an order was entered.[1] Clearly, modern electronic trading relies on algorithmic and high-frequency trading (HFT), but why are there so many flickering quotes? How do these flickers affect the market?

The traditional view of price discovery is that informed traders reveal their private information with their trades, while the quotes of dealers reflect public information (see, e.g., Glosten and Milgrom, 1985; Kyle, 1985). In limit order books, limit orders are often thought to be functionally equivalent to a dealer's quote, and are generally seen as a passive supply of liquidity.[2] However, the empirical literature shows that limit orders contribute towards 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 towards price discovery (see, e.g., Kaniel and Liu, 2006; Goettler et al., 2005, 2009; Hoffmann, 2014).

For an informed trader, the primary tradeoff between limit orders and market orders is that limit orders earn the bid-ask spread, but face the risk of non-execution; while market orders pay the bid-ask spread, but execution is guaranteed. Limit orders can impound information into prices when traders revise their belief about the fundamental value of the asset to account for the possibility that the limit order was sent by an informed trader (see, e.g., Bhattacharya and Saar, 2021). However, if the potentially informed limit order is canceled, then, all else being equal, there should be a revision in beliefs that removes the

[1] A blink of an eye typically lasts between 100 and 400 milliseconds, while 8.3 milliseconds is the limit of subliminal perception (see Schräder et al., 2023).

[2] A number of papers examine the role of limit orders in a limit order book. Cohen et al. (1981) studies 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 dynamic equilibrium models of Parlour (1998), Foucault (1999), Foucault et al. (2005), and Roşu (2009) study a range of tradeoffs such as non-execution risk, adverse selection, and waiting costs.

initial effect of the limit order. Therefore, how can a limit order that turns out to be a flicker contribute towards price discovery?

Indeed, theoretical models show that flickering quotes do not contribute towards price discovery. Baruch and Glosten (2013) show that quotes flicker because players use mixed strategies to win price priority, and Yueshen (2021) shows that flickers arise when liquidity (book depth) overshoots due to queuing uncertainty. Bhattacharya and Saar (2021) show that quotes flicker when uninformed traders revise their belief about the fundamental value of the asset, and this revision occurs whenever there is a possibility that a limit order or market order was sent by an informed trader. However, in their model, flickering quotes do not impound information into prices; rather, flickers are reactions by uninformed traders to potential information.[3]

In contrast to the understanding of price discovery through limit orders and the theoretical predictions of flickering quotes, this paper shows that flickering quotes move markets and contribute toward price discovery.

Our analysis focuses on the large-cap stocks (AEX constituents) traded on Euronext Amsterdam. For these stocks, a substantial portion of limit orders is canceled shortly after entry: 36.11% within 1 second, 19.42% within 100 milliseconds, 7.93% within 10 milliseconds, 3.18% within 1 millisecond, and 1.46% within 100 microseconds. In this paper, we focus on limit orders that are canceled within 10 milliseconds as our primary definition of a flickering quote.

Although flickering quotes are common in modern electronic markets, we find that flickers are highly concentrated among a small subset of trading firms. By flicker count, the top firm accounts for 21.58% of all flickering quotes, while the top three and top five trading firms account for 62.26% and 86.03% of the flickers, respectively. Our analysis also shows that limit orders are more likely to flicker when prices move before the limit order arrives.

[3]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.

To understand if flickering quotes move the market and contribute towards price discovery, we use a signed price impact regression and a Structural Vector Autoregression (SVAR) of Fleming et al. (2018) and Brogaard et al. (2019) to study the impact of flickers posted at various price levels in the book. Regardless of where the flicker is placed, our results show that the price impact of flickering quotes persists after the cancelation leg of the flicker. Furthermore, the price impact of flickering quotes posted at the best quotes or that improve the best quotes is positive, where the price impact of flickers that improve the best quotes is higher than that of flickers placed at the best quotes. In contrast, the price impact of flickering quotes placed deeper in the limit order book is negative.

TBD: Contribution of flicker towards price discovery.

Our results are at odds with theoretical predictions of flickering quotes. The models of Baruch and Glosten (2013) and Yueshen (2021) do not predict any price movements associated with flickering quotes, because flickers are part of a quoting strategy to gain price and queue priority, respectively. On the other hand, although the model of Bhattacharya and Saar (2021) predicts price movements associated with flickering quotes, their model does not predict the direction of price changes associated with a flicker, or that the impact of flickers depend on where an order is placed.[4] Our results show that there is more to flickering quotes than what current theory predicts.

Hasbrouck and Saar (2009) study and document the emergence of flickering quotes. They provide evidence to support their chasing, cost-of-immediacy, and search hypothesis, which suggest that flickering quotes are components of strategies that demand liquidity, as opposed to the usual economic perspective where limit orders are viewed as patient suppliers of liquidity. Our result further highlights the role and contribution of these short-lived orders on price discovery.

Other empirical papers provide explanations for flickering quotes. Degryse et al. (2021)

[4]In their model, when uninformed traders update their beliefs and flicker their quotes in response to the potential arrival of an informed trader, all the outstanding limit orders in the book flicker. Thus, it does not predict a directional movement in the price associated with a flicker, or that the impact depends on where a flicker is placed.

argues that flickers can result from ghost liquidity, where firms duplicate their limit orders in other venues and upon execution of one of their orders, the remaining duplicates are canceled. Ulze et al. (2021) find evidence that flickering quotes lead to an improved price for liquidity demanding traders, which is likely a result of HFTs trying to clear their inventory. Hasbrouck (2018) studies whether flickering quotes explain the high volatility of bids and offers. However, he finds that Edgeworth cycles provide a better explanation than flickering quotes for the high volatility.

Flickers are largely tied to the behavior of HFTs because low-latency technology is a prerequisite for a firm to cancel a limit order shortly after entry. Indeed, the top five trading firms that account for 86.03% of flickers in our sample are all HFTs. Our result parallels those of Brogaard et al. (2019), but instead of analyzing HFT and non-HFT orders, we show that short-lived flickers have a meaningful role in price discovery.[5]

1. Flickering Quotes: Data and Summary Statistics

The dataset was provided by the Dutch Authority for the Financial Markets and contains all order entries, amendments, and cancellations on Euronext Amsterdam during the period from 2 January to 6 January 2023.[6] For each security, the data include fields such as the trading date, microsecond-level timestamps, order type, order volume, buy/sell indicator, and trading firm's identity.

Our sample covers all equities listed in the Dutch large-cap AEX index, the mid-cap AMX index, and the small-cap ASCX index at the time of writing of this paper. Each

[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) find that prices incorporate information more efficiently when HFT participation is high, while Conrad et al. (2015) find that high-frequency trading and 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.

[6]An amendment is a change to the price and/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 canceled. We exclude amendments from our analysis, since the deletions ultimately apply to the original order ID.

index comprises 25 stocks. The final dataset includes 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.

We exclude all order entries, amendments, and cancellations posted by members classified as "retail liquidity providers" (retail LPs). The orders, amendments, and cancellations (including the resulting transactions and volumes in the limit order book) of retail LPs are visible only to "retail" members.[7] Retail clients can trade with both retail LPs and the rest of the limit order book. In effect, this creates two limit order books, one for retail members and one for all other members. We exclude these messages so that we have the quoted spreads and depth available to non-retail participants. We also exclude cancellations of immediate-or-cancel orders because the resting time of these 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 analyses and from our computation of best bid/ask prices and quote volumes. Finally, we exclude the first and last five minutes of the trading day, restricting the analysis to the continuous trading session between 09:05 and 17:25.

The remainder of this section provides statistics of the main characteristics of flickering quotes: arrival frequency for various time horizons, distribution of bid and ask flickers, intraday patterns, and number of trading firms that use flickering quotes.

Quantity and time intervals of flickers A flickering quote is an order that is canceled shortly after entry. The lifetime of the order is the time interval between entry and its cancellation. Table 1 reports statistics on order activity and cancellations for large-, mid-, and small-cap stocks traded on Euronext Amsterdam during 2–6 January 2023. The table shows the number of orders, number of cancellations, and the proportion of cancellations for various time intervals: 1 second, 100 milliseconds, 10 milliseconds, 1 millisecond, and 100

[7] Retail Liquidity Provision is a contractual arrangement between the trading venue and the trading member, specifying the trading behavior allowed by the member when acting in that capacity. This classification is determined by the trading venue, not the regulator.

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

microseconds.

For large-cap stocks (AEX constituents), the average daily number of orders per stock is 180,898, of which 96.5% are canceled. A substantial portion of these cancellations occurs quickly after entry: 36.11% within 1 second, 19.42% within 100 milliseconds, 7.93% within 10 milliseconds, 3.18% within 1 millisecond, and 1.46% within 100 microseconds. These figures highlight the prevalence of short-lived orders in liquid stocks.

On average, flickering activity in mid-cap (AMX) and small-cap (ASCX) stocks is lower than that in large-cap stocks for the time intervals we consider. For mid-caps, 24.12% of orders are canceled within 1 second, and 5.80% within 10 milliseconds. Also, while there are fewer orders in small-cap stocks (average of 7,992 per day), the proportion of cancellations within 1 second is 17.59% and within 10 milliseconds is 6.62%, so there is also flickering in less liquid stocks.

The choice of a flickering time interval varies in the literature, where the intervals range from microseconds to seconds. We adopt a 10-millisecond interval because it captures a substantial share of fast cancellations while maintaining economic relevance comparable to shorter intervals (e.g., 1 millisecond), see Section 3 below.

INSERT TABLE 1 ABOUT HERE

Imbalance in the number of buy and sell flickering quotes Figure 1 (left panel) shows the clustering of flickering quotes, measured as the number of flickers per second. There is at least one flickering quote in 16.22% of the one-second intervals in our sample. Within these one-second intervals with at least one flickering quote, the average number of flickers is 3.41 per second, and in 25% of these one-second intervals there are four or more flickering quotes. Finally, 88% of the flickers are in seconds with at least one other flicker.

The right panel of Figure 1 shows the difference between the number of buy-side and sell-side flickers per second. The data show that almost 90% of seconds with at least one flicker is imbalanced. Furthermore, the imbalance in more than 25% of seconds is -1, i.e.,

one more sell-side flicker than buy-side flicker, and the imbalance in another 25% of seconds is +1, i.e., one more buy-side flicker than sell-side flicker.

INSERT FIGURE 1 ABOUT HERE

Time of day and number of firms Table 2 presents statistics of flickering quotes for different times of the trading day (top panel) and across firms (bottom panel) for the 25 large-cap (AEX) stocks. Flicker activity is most pronounced during the first hour of trading (14.12%), followed by the last hour (13.32%), with a relative decline in between (11.16% 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.

The firm-level breakdown indicates a high concentration of flickers among a small subset of members that trade in the exchange. By flicker count, the top firm accounts for 21.58% of all flickering quotes, while 62.26% and 86.03% of the flickers are by the top three and top five trading firms, respectively. The concentration of flickering behavior likely reflects their superior technological capabilities, which are not uniformly distributed across market participants, so there is concentration of flickering behavior among those with the most sophisticated and fastest systems.

INSERT TABLE 2 ABOUT HERE

2. Market Conditions and Flickering Quotes

We estimate a logistic regression model to study flickering quotes in large-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, deletions, and resting orders. Here, we focus on the binary outcome of whether a passive limit order is canceled within 10 milliseconds (i.e., is a flickering quote) or not.

We restrict our analysis to passive limit orders, i.e., orders that do not immediately result in a transaction upon entry. For each stock-day, we randomly sample 10% of all passive orders to construct our estimation sample.

The dummy variable $\text{Flicker}_{i,t}$ is equal to 1 if an order that entered at time t in stock i is canceled within 10 milliseconds after entry, and 0 otherwise. We estimate the model

$$\text{logit}(\text{Flicker}_{i,t}) = \beta_0 + \beta_1 \cdot |R_{i,t-h}| + \beta_2 \cdot \text{Spread}_{i,t} + \beta_3 \cdot D_{\text{FirstHour}} + \beta_4 \cdot D_{\text{MidDay}}.$$

Here, $|R_{i,t-h}|$ is the absolute return of the midpoint price in basis points over the window $h \in \{10\text{ms}, 100\text{ms}, 1\text{s}, 5\text{s}, 10\text{s}\}$ prior to order entry. $\text{Spread}_{i,t}$ is the relative bid-ask spread standardized per stock.[9] The dummy $D_{\text{FirstHour}}$ is equal to 1 if the order is submitted between 9:00 and 10:00, and the dummy D_{MidDay} is equal to 1 if the order is submitted between 10:30 and 16:30. Both $|\text{R}_{i,t-h}|$ and $\text{Spread}_{i,t}$ are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. The data include all 25 stocks of the Dutch large-cap (AEX) index for the five-day period 2-6 January 2023. Standard errors are double clustered by stock-day, see Thompson (2011).

INSERT TABLE 3 ABOUT HERE

Table 3 reports the results of the five logistic regressions (one for each time window) which estimate the likelihood that a passive limit order is a flickering quote. In all specifications, the intercept is negative and highly significant, indicating a low baseline probability of flickering quotes.

The results show a statistically significant relationship between recent price movements and the likelihood of flickering quotes. Specifically, a one basis point increase in the absolute midpoint return over the 10 milliseconds prior to order entry increases the log-odds of a flickering entry by 0.569, corresponding to an odds ratio of approximately 1.76. The table

[9]The relative bid-ask spread minus the stock's mean relative bid-ask spread, then divided by the stock's standard deviation.

shows that price changes over the 100 millisecond interval prior to order entry significantly increase the odds (coefficient = 0.363), corresponding to an odds ratio of approximately 1.44. For a longer time window, a one basis point increase in the absolute midpoint return over the 1 second prior to order entry increases the log-odds of an incoming flickering entry by 0.172. The effects of price changes over 5 and 10 seconds prior to order entry on the likelihood of an incoming passive order to flicker are statistically significant (coefficients are 0.060 and 0.041, respectively) but economically modest, suggesting that flickering is most responsive to very short-term price dynamics.

To illustrate the effect of price movement on the likelihood of an incoming passive order, consider the mean probability of a flickering order in large-cap stocks of $p = 0.0793$. In this case, the odds are $\frac{0.0793}{1-0.0793} \approx 0.0862$, which increase by a factor of 1.76 if there is a basis point increase in the absolute midpoint return over the 10 milliseconds prior to order entry. The new odds become $0.0862 \times 1.76 \approx 0.1517$, so the probability of an incoming order to flicker increases from approximately 7.93% to 13.17% ($\frac{0.1517}{1+0.1517}$).

The relative bid-ask spread is positively associated with flickering orders for the five time windows, though its effect is only significant in the 10 millisecond window and not statistically significant for the other windows we consider.

Time-of-day effects are robust across specifications. Orders submitted during the first hour of trading (9:00–10:00) are significantly less likely to flicker than orders entered in the last hour of trading, with coefficients ranging from –0.190 to –0.071. Similarly, orders entered during 10:30–16:30 are less likely to flicker than orders entered in the last hour of trading, with coefficients between –0.142 and –0.107, all significant at the 1% level.

Overall, these results suggest that flickering orders are sensitive to price movements prior to entry of the order, and especially to price movements in the 10 and 100 milliseconds prior to entry of the order.

To further explore the effect of large price movements, we use indicator variables for

medium and large price changes to estimate the logistic regression model

$$\text{logit}(\text{Flicker}_{i,t}) = \beta_0 + \beta_1 \cdot D\text{MediumPriceMove}_{i,t-h} + \beta_2 \cdot D\text{LargePriceMove}_{i,t-h} + \beta_3 \cdot \text{Spread}_{i,t} + \beta_4 \cdot D_{\text{FirstHour}} + \beta_5 \cdot D_{\text{MidDay}}.$$

The dummy $D\text{MediumPriceMove}_{i,t-h}$ is equal to 1 if the standardized $|\text{R}_{i,t-h}|$ is between one and two standard deviations, and it is 0 otherwise. The dummy $D\text{LargePriceMove}_{i,t-h}$ is equal to 1 if the standardized price change exceeds two standard deviations. All other variables are defined as above.

INSERT TABLE 4 ABOUT HERE

Table 4 presents the results of the logistic regressions. The effects of price movements over the 10 millisecond window prior to order entry are the strongest, where medium and large price changes increase the log-odds of an order to flicker by 0.908 and 1.159, respectively—corresponding to odds ratios of approximately 2.47 and 3.15. So the likelihood of orders to flicker more than triples when there are large short-term price movements prior to order entry. The effect of price changes over 100 milliseconds prior to order entry on the likelihood of an incoming limit order to flicker is substantial, with odds ratios of 2.22 (for medium price moves) and 2.13 (for large price moves). For the one-second window prior to order entry, the effect of medium and large price movements remain statistically significant but are more moderate (odds ratios of 1.49 and 1.31, respectively).

Over longer windows (5 and 10 seconds) prior to order entry, the impact of price changes on the likelihood of flickers diminishes but remains statistically significant. For instance, large price changes over the 10 seconds prior to order entry increase the odds of flickering by approximately 11%, suggesting that while price movement in the 10-second window prior to order entry matters, its economic relevance is limited.

Wider relative bid-ask spreads are weakly positively associated with flickering, while orders placed during the first hour or between 10:00-16:30 are less likely to flicker. Overall,

these patterns align with previous findings predicting flickering behavior (Hasbrouck and Saar, 2009).

3. Price Impact of Flickering quotes

3.1. Regression

In this section, we estimate the model

$$R^{\theta}_{i,t+h} = \beta_0 + \beta_1 \cdot D_{\text{Flicker}_{i,t}} + \beta_2 \cdot \text{FlickerVolumeImbalance}_{i,t-n} + \beta_3 \cdot \text{OrderbookImbalance}_{i,t} + \beta_4 \cdot \text{Spread}_{i,t}.$$

to quantify the price impact of flickering orders. Here, $R^{\theta}_{i,t+h}$ is the return in the mid-point price of stock i at time t in basis points over the next $h \in \{1, 5, 10\}$s-second window. The parameter $\theta \in \{\text{Pre-Entry}, \text{Post-Entry}, \text{Post-Cancel}\}$ indicates whether the price change is measured relative to the moment immediately before the entry of the flickering quote, immediately after the entry, or immediately after its cancellation. The variable $D_{\text{Flicker}_{i,t}}$ is equal to $+1$ for a flickering buy order and is equal to -1 for a flickering sell order. $\text{FlickerVolumeImbalance}_{i,t-n}$ is the difference between the volume of flickering buy orders and the volume of flickering sell orders over the previous n seconds, divided by their sum. $\text{Orderbook Imbalance}_{i,t}$ is the difference between the volume at the best bid and the volume at best ask, divided by their sum. $\text{Spread}_{i,t}$ is the relative bid-ask spread standardized per stock.

As before, the data include all 25 stocks of the Dutch large-cap (AEX) index, during 2-6 January 2023. We winsorize $\text{Spread}_{i,t}$ at the 1st and 99th percentiles to mitigate the influence of outliers. The data include flickering quotes that do not result in immediate transactions at the moment of entry, ensuring that the estimate of price impact is not caused by trade execution. Standard errors are double clustered by stock-day.

Pre-entry Table 5 shows the regression coefficients of the signed price impact of flickering orders measured starting the moment before the flickering order is placed.[10] The three panels of the table correspond to a different type of flickering order: (i) spread-improving, (ii) best-quote, and (iii) deeper-in-book.

The top panel shows that the price impact of the entry of spread-improving flickers is strong and positive for all time windows. The coefficient on $D_{\text{Flicker}_{i,t}}$ is approximately 0.36 at $h = 1s$ and 0.34 at $h = 10s$. This suggests that even though the orders are canceled within 10 milliseconds, their entry at improved prices influences expectations and trading behavior. The flicker imbalance coefficients are significantly negative for longer windows, showing that a prolonged period of flickering in one direction anticipates price movements in the opposite direction.

The price impact of flickering orders entered at the best bid/ask is positive and significant, though the magnitude of the coefficient is smaller than that of the price impact of spread-improving orders. The coefficient on $D_{\text{Flicker}_{i,t}}$ ranges from 0.026 to 0.037 for various windows, suggesting that while these flicker orders are less aggressive, they do anticipate future price movements. Most flickering imbalance coefficients are consistently positive and significant, reinforcing the finding that recent flickering activity anticipates short-term price movements. The order book imbalance remains a strong predictor, while the effect of the spread variable shows mixed effects.

In contrast, the bottom panel shows that the price impact of flickering orders placed deeper in the book is negative and statistically significant. The coefficient on $D_{\text{Flicker}_{i,t}}$ is approximately -0.06 for all windows, suggesting that such orders may anticipate adverse selection. The effect of flickering imbalance variables is small, and the effect of order book imbalance is positive and statistically significant. The coefficient of the relative bid-ask spread is negative and statistically significant at shorter windows.

The positive price impact of improving orders and orders entered at the best bid/ask is

[10] We use the terms price impact and signed price impact interchangeably, unless stated otherwise.

consistent with the results in Brogaard et al. (2019), whose price impact, all else being equal, is negative (positive).

Post-entry The top panel of Table 6 presents regression coefficients of the signed price impact of spread-improving flickering orders measured from the moment immediately *after* the flickering order is entered at time t. So any mechanical price movement caused by the order entry is already incorporated at time t. The coefficients for the order at best and deeper in the book are the same as those for the pre-entry regression because these orders have no mechnical effect on the midpoint price of this stock.

The price impact for the spread-improving orders $D_{\text{Flicker}_{i,t}}$ is strongly negative and statistically significant for all windows, with values around -0.60 basis points. This indicates that these flickering orders are followed by price movements in the opposite direction of the flicker. We expect these results because the buy (sell) flickering order will be canceled within the next 10 milliseconds, which will have negative (positive) price impact absent any new orders joining the book.

The coefficients of the flickering imbalance variables ($\text{FlickerVolumeImbalance}_{i,t-1}$ and $\text{FlickerVolumeImbalance}_{i,t-5}$) are negative and increasing in magnitude and statistical significance as the length of the window increases. The price impact of order book imbalance is positive, consistent with its role in capturing directional liquidity pressure. The relative bid-ask spread variable shows insignificant effects on midpoint returns.

Post-cancel Lastly, Table 7 presents the price impact following the cancel of flickering orders, measured over windows of 1, 5, and 10 seconds. The analysis shows the signed price impact of cancellations of orders that improved the spread (top panel), cancellations of orders entered at the best quote (middle panel), and cancellations of orders entered deeper in the book (bottom panel).

In the three panels and for all time windows, the coefficient on $D_{\text{Flicker}_{i,t}}$ is negative and statistically significant. This indicates that the cancellation of a buy (sell) order within

10 milliseconds of entry tends to be followed by a downward (upward) movement in the midpoint price. The effect is strongest in the cancellations at the best bid/ask. This finding is consistent with the negative signed price impact of cancellations of spread-improving orders or orders at the best bid/ask reported in Brogaard et al. (2019).

The price impact of a flickering volume imbalance (i.e., a larger volume of buy flickering than sell flickering in the 1 or 5 seconds prior to the moment of cancellation) is negative and statistically significant in all panels and for all windows. This suggests that traders react negatively (positive) to large buy (sell) cancellations. The price impact of orderbook imbalance is positive and statistically significant in all panels and for all windows. This confirms its role as a predictor of short-term price dynamics, consistent with Brogaard et al. (2014). The effect of spread is mixed. The price impact of a wider relative bid-ask spread is negative for short windows.

Overall, the results suggest that the price impact of spread-improving flickering orders is statistically significant and large, and persists after the cancellation of the flicker order. The signed price impact of orders at the best bid/ask is also positive and statistically significant, and the price impact of flickering orders deeper in the book is negative and statistically significant.

INSERT TABLES 5, 6, 7 ABOUT HERE

3.2. Vector Autoregression

To investigate how flickering quotes affect price discovery, we estimate a Structural Vector Autoregression (SVAR) model, see Brogaard et al. (2019) and Fleming et al. (2018). The SVAR model estimates movements in the efficient price using past price movements and the arrivals and cancellations of flickering and non-flickering orders. More specifically, the model dynamically estimates the relation between order submissions and cancellations and future movements in the efficient price. 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) constitutes one observation. In Section 3.1, we measure the price impact of flickering orders in calendar-time, which is less sensitive to the timing between events.

The SVAR incorporates trades and limit order activity, both submissions 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

$$r_t = \sum_{i=1}^{5} \alpha_i^1 \, r_{t-i} + \sum_{j=1}^{13} \sum_{i=0}^{5} \beta_i^{1,j} \, X_{t-i}^j + \mu_t^1,$$

$$X_t^1 = \sum_{i=1}^{5} \alpha_i^2 \, r_{t-i} + \sum_{j=1}^{13} \sum_{i=1}^{5} \beta_i^{2,j} \, X_{t-i}^j + \mu_t^2,$$

$$X_t^2 = \sum_{i=1}^{5} \alpha_i^3 \, r_{t-i} + \sum_{j=1}^{13} \sum_{i=1}^{5} \beta_i^{3,j} \, X_{t-i}^j + \mu_t^3,$$

$$X_t^{13} = \sum_{i=1}^{5} \alpha_i^{14} \, r_{t-i} + \sum_{j=1}^{13} \sum_{i=1}^{5} \beta_i^{14,j} \, X_{t-i}^j + \mu_t^{14}.$$

Here, α is the coefficient on the midpoint return series, r, lagged one to five periods, and β is the coefficient on the thirteen limit order and trade variables, X^1 through X^{13}. Note that 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 defined as follows: *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. The SVAR is estimated for each stock-day. The averages of the stock-day IRFs impact is reported in basispoints.

We invert the SVAR model into its vector moving average (VMA) to derive the IRFs. 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.

The SVAR framework captures the linear dynamics between variables and returns. IRFs then quantify the impact of the innovation on subsequent orders and price movements. This dynamic modeling is essential for accurately tracking the sequence of market events. For instance, consider the arrival of a *Flicker Improving order* order at the bid-side: other traders swiftly react by sending *Non-Flicker Order at best* orders at the bid-side. Other traders react by sending *Non-Flickering 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*.

Note that the interpretation of IRFs is subtle; 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 order is followed by the cancellation of the order, so the negative price impact of the cancellation is already incorporated in the effect of the flickering entry.

Table 8 reports the estimates of the return IRFs from the SVAR can be interpreted as the average permanent price impact of flickering and non-flickering events. The SVAR is estimated on 25 Dutch large-cap (AEX) shares during 2-6 January 2023, and standard errors are clustered by stock-day. Firstly, the results are consistent with the regressions estimates from Section 3.1. Like Section 3.1, the price impact of entering flickering improving orders is larger than the price impact of flicker orders entered at best. Specifically, the cumulative price impact of entering a spread-improving flickering order is 0.14 basis points and statistically significant, and the price impact of a flicker order entered at best is 0.04 basis points and statistically significant. In contrast, the price impact of a flickering order entered deeper in the book is negative and statistically significant (–0.05 basis points), again consistent with the negative coefficient in the pre-entry regressions of price impact.

Overall, we obtain the same sign and relative magnitude of price impacts for flickering quotes in the regressions as in the SVAR. Also, the direction and relative magnitude of the signed price impact of flickering quote messages in our SVAR is the same as those reported in the SVAR of Brogaard et al. (2019).

INSERT TABLE 8 ABOUT HERE

Message frequency Table 9 shows the frequency of flickering and non-flickering activity. Flickering is 9.22% of all activity. Most flickering activity is concentrated at the best bid/ask. *Flicker Order at best* and *Flicker Cancellation at best* account for respectively (2.84%) and (2.93%) of all messages. Flickering deeper in the book is about half as likely as flickering at the best, with *Flicker Order deeper in book* (1.28%) and *Flicker Cancel deeper in book* (1.30%). *Flicker Improving order* (0.48%) and *Flicker Worsening cancel* (0.39%) are less frequent. Non-flickering messages often occur deeper in the book —*Order Deeper in book* (23.24%) and *Cancel Deeper in book* (23.76%)— and at the bid/ask - *Order at best* (20.24%) and *Cancel at best* (18.78%). So 63% of flickering messages are at the best bid/ask, while only 44% of non-flickering messages are at the best bid/ask, flickering messages occur at the

best bid/ask relatively often.

INSERT TABLE 9 ABOUT HERE

Transition matrix The price of an order stays the same between entry of a flicker and cancellation of a flicker if there are no amendments to the order, but the order's distance to the best bid/ask may change. For example, orders entered at the best bid/ask may have moved deeper in the limit order book at the moment of cancellation. The SVAR corrects for these dynamics. Table 10 reports the frequency of flickering orders by entry and cancellation types. Most orders are canceled at the same distance to the best bid/ask as when they were entered. An exception is the *Improving order* entry, where 44.27% of orders are *Cancel at best* cancellations rather than *Worsening cancel* cancellations. This suggests other orders have joined the best price levels during the lifetime of the spread-improving flicker order, consistent with the positive pre-entry price impact of flickering spread-improving orders in Section 3.1 and our SVAR.

Most flickering orders are entered *Order at best* and canceled *Worsening cancel*, which accounts for 55.19% of all flickering events. This percentage is consistent with the findings in Table 9, where most flickering orders are placed at the best prices. Another frequent combination is the entry *Order deeper in book* combined with cancellation *Cancel deeper in book* (24.20%). In contrast, combinations involving *Improving order* account for only 10.48%, reflecting the limited number of aggressive order submissions.

INSERT TABLE 10 ABOUT HERE

Variance decomposition TBD.

4. Transactions after Flickering Quotes

Sections 3.1 and 3.2 show that the price impact of flickering buy (sell) order entries that improve the spread or are placed at the best bid/ask is positive (negative). Conversely,

the price impact of flickering buy (sell) orders submitted deeper in the order book is negative (positive). These findings suggest that deeper flickering orders anticipate adverse price movements, consistent with the hypothesis that cancellations deeper in the book mitigate the risk of adverse selection. Alternatively, the cancellation might invite other traders to adversely select remaining orders in the book.

If flickering orders deeper in the book anticipate adverse price movements, then we would expect a net number of buy (sell) liquidity taking transactions following the cancellation leg of a sell (buy) flickering order deeper in the book. In contrast, we would expect a net number of buy (sell) liquidity taking transactions following the cancellation leg of a buy (sell) flickering spread-improving orders or orders at best.

We estimate the linear regression

$$\text{NetLiquidityTakingImbalance}^{\theta}_{i,t+1\text{sec}} = \beta_0 + \beta_1 \cdot D_{\text{Flicker}_{i,t}}$$

to quantify the net number of buyer-initiated and seller-initiated trades following the entry of a flickering order. Here, $\text{NetLiquidityTakingImbalance}^{\theta}_{i,t+1\text{sec}}$ is the net number of buyer-initiated minus seller-initiated liquidity-taking transactions in the one-second window following the flickering entry for stock i at time t. The parameter $\theta \in \{\text{Spread-improving}, \text{At best}, \text{Deeper in book}\}$ describes the flickering order type. The dummy variable $D_{\text{Flicker}_{i,t}}$ is equal to $+1$ for entry of a flickering buy order and is equal to -1 for entry of a flickering sell order. The regression is estimated using data from 25 Dutch large-cap (AEX) stocks, with standard errors double-clustered by stock-day.

Table 12 reports a statistically significant and positive coefficient β_1 for both spread-improving and at-best flickering orders. This indicates that, on average, buy (sell) flickering orders are followed by buyer- (seller-) initiated trades, corroborating the positive price impact observed in Section 3.1. Interestingly, the coefficient associated with flickering orders placed

deeper in the book is statistically significant and negative. This implies that buy (sell) flickering orders deeper in the book are typically followed by seller- (buyer-) initiated trades, reinforcing the hypothesis that such orders are canceled to avoid adverse selection or invite other trades to adversely select remaining orders.

INSERT TABLE 12 ABOUT HERE

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				% Canceled within				
		orders	cancellations	1sec	100ms	10ms	1ms	100us
Large cap	Mean	180,898	174,619	36.11	19.42	7.93	3.18	1.46
	Min	29,416	27,978	23.08	12.90	5.20	1.99	0.98
	25th percentile	77,313	75,694	28.31	15.62	6.23	2.69	1.18
	50th percentile	130,521	124,995	34.84	18.31	7.50	3.05	1.47
	75th percentile	263,257	250,039	42.68	22.91	8.42	3.38	1.60
	Max	458,203	439,148	51.96	29.17	12.60	4.89	2.21
Mid cap	Mean	30,963	30,011	24.12	15.83	5.80	1.61	0.72
	Min	1,958	1,766	10.68	8.38	3.22	0.41	0.04
	25th percentile	5,731	5,151	21.10	14.32	4.46	0.69	0.17
	50th percentile	8,921	8,510	23.52	15.28	5.17	1.33	0.56
	75th percentile	41,191	39,986	27.60	16.61	6.06	2.19	1.11
	Max	176,014	171,107	42.33	35.33	19.17	4.72	2.69
Small cap	Mean	7,992	7,628	17.59	12.32	6.62	2.94	0.64
	Min	81	40	3.96	0.66	0.22	0.00	0.00
	25th percentile	996	891	7.58	5.49	2.53	0.49	0.11
	50th percentile	1,582	1,330	13.24	9.67	3.94	0.93	0.36
	75th percentile	4,782	4,395	24.28	14.36	5.62	2.74	0.72
	Max	46,122	45,052	48.71	41.74	35.90	17.24	3.12

Table 1: Order activity and cancellations: number of orders, number of cancellations, and the percentage of cancellations occurring within specific time intervals after order submission (1 second, 100 milliseconds, 10 milliseconds, 1 millisecond, and 100 microseconds). Data are reported per share per day for 25 AEX-index (large-cap), 21 AMX-index (mid-cap), and 21 ASCX-index (small-cap) stocks traded on Euronext Amsterdam during 2–6 January 2023.

Time of day	% of flickering quotes
First hour	14.12
Mid day (per hour)	11.16
Last hour	13.32
Firm	
Top 1	21.58
Top 3	62.26
Top 5	86.03

Table 2: Flickering quotes by time of day averaged per hour (top panel) and by firm (bottom panel). A flickering quote is an order canceled within 10 milliseconds after entry. Data include 25 stocks from the Dutch large-cap index (AEX) during 2-6 January 2023.

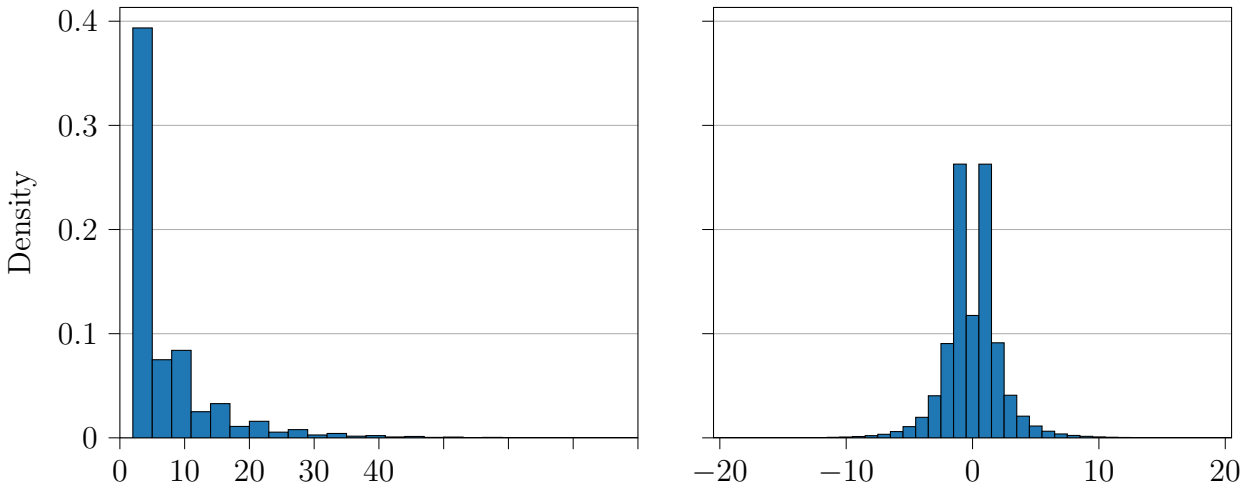


Fig. 1: Proportion of flickering quotes per second (left panel) and imbalance of the bid and ask flickers (right panel). A flickering quote is an order canceled within 10 milliseconds after entry. Seconds without any flickering activity are excluded. Data include 25 stocks from the Dutch large-cap index (AEX) during 2-6 January 2023.

	(1)	(2)	(3)	(4)	(5)
Intercept	-2.538***	-2.510***	-2.432***	-2.353***	-2.341***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$\lvert R_{i,t-10ms}\rvert$	0.569***				
	(0.002)				
$\lvert R_{i,t-100ms}\rvert$		0.363***			
		(0.002)			
$\lvert R_{i,t-1sec}\rvert$			0.172***		
			(0.002)		
$\lvert R_{i,t-5sec}\rvert$				0.060***	
				(0.001)	
$\lvert R_{i,t-10sec}\rvert$					0.041***
					(0.001)
$\text{Spread}_{i,t}$	0.036***	0.021***	0.001	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$D_{\text{FirstHour}}$	-0.190***	-0.168***	-0.110***	-0.077***	-0.071***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
D_{MidDay}	-0.142***	-0.141***	-0.122***	-0.110***	-0.107***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	2087748	2087748	2087748	2087748	2087748
Pseudo R^2	0.037	0.023	0.008	0.002	0.002

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3: This table report estimates of the logistic regression

$$\text{logit}(\text{Flicker}_{i,t}) = \beta_0 + \beta_1 \cdot |R_{i,t-h}| + \beta_2 \cdot \text{Spread}_{i,t} + \beta_3 \cdot D_{\text{FirstHour}} + \beta_4 \cdot D_{\text{MidDay}}.$$

The dummy variable $\text{Flicker}_{i,t}$ is equal to 1 if an order that entered at time t in stock i is cancelled within 10 milliseconds after entry, and 0 otherwise. $|R_{i,t-h}|$ is the absolute return in the midpoint price in basis points over the $0.01, 0.1, 1, 5, 10$ seconds prior to order entry. $\text{Spread}_{i,t}$ is the relative bid-ask spread standardized per stock. $D_{\text{FirstHour}}$ is equal to 1 for orders placed between 09:00 and 10:00 and 0 otherwise, and D_{MidDay} equals 1 for orders placed between 10:30 and 16:30 and 0 otherwise. The dataset consists of a 10% random sample of passive order entries per stock-day, covering 25 Dutch large-cap (AEX) stocks on Euronext Amsterdam during 2-6 January 2023. The standard errors are double clustered at the stock-day level.

	(1)	(2)	(3)	(4)	(5)
Intercept	-2.437***	-2.370***	-2.299***	-2.256***	-2.253***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
DMediumPriceMove$_{i,t-10ms}$	0.908***				
	(0.007)				
DLargePriceMove$_{i,t-10ms}$	1.159***				
	(0.007)				
DMediumPriceMove$_{i,t-100ms}$		0.798***			
		(0.006)			
DLargePriceMove$_{i,t-100ms}$		0.755***			
		(0.009)			
DMediumPriceMove$_{i,t-1sec}$			0.399***		
			(0.007)		
DLargePriceMove$_{i,t-1sec}$			0.273***		
			(0.011)		
DMediumPriceMove$_{i,t-5sec}$				0.111***	
				(0.007)	
DLargePriceMove$_{i,t-5sec}$				0.107***	
				(0.011)	
DMediumPriceMove$_{i,t-10sec}$					0.088***
					(0.008)
DLargePriceMove$_{i,t-10sec}$					0.104***
					(0.011)
Spread$_{i,t}$	0.038***	0.033***	0.006**	0.003	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$D_{\text{FirstHour}}$	-0.160***	-0.140***	-0.081***	-0.055***	-0.054***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
D_{MidDay}	-0.131***	-0.130***	-0.110***	-0.103***	-0.102***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	2087748	2087748	2087748	2087748	2087748
Pseudo R^2	0.027	0.014	0.003	0.000	0.000
Note:		*p<0.1; **p<0.05; ***p<0.01			

Table 4: This table report estimates of the logistic regression

$$\text{logit}(\text{Flicker}_{i,t}) = \beta_0 + \beta_1 \cdot D\text{MediumPriceMove}_{i,t-h} + \beta_2 \cdot D\text{LargePriceMove}_{i,t-h}\beta_3 \cdot \text{Spread}_{i,t} + \beta_4 \cdot D_{\text{FirstHour}} + \beta_5 \cdot D_{\text{MidDay}}$$

The dummy variable DMediumPriceMove$_{i,t-h}$ is equal to 1 if the standardized $|\text{R}_{i,t-h}|$ is between one and two standard deviations, and 0 otherwise. DLargePriceMove$_{i,t-h}$ is equal to 1 if the standardized $|\text{R}_{i,t-h}|$ exceeds two standard deviations, and 0 otherwise. All other variables are as in Table 3. The dataset consists of a 10% random sample of passive order entries per stock-day, covering 25 Dutch large-cap (AEX) stocks on Euronext Amsterdam during 2-6 January 2023. The standard errors are double clustered at the stock-day level.

	Variable	$h = 1s$	$h = 1s$	$h = 5s$	$h = 5s$	$h = 10s$	$h = 10s$
Improving	β_0	0.006	0.006	-0.021*	-0.021*	-0.043***	-0.043***
	$D_{\text{Flicker}_{i,t}}$	0.362***	0.362***	0.365***	0.365***	0.349***	0.349***
	Flickering Imbalance$_{i,t-1}$	-0.005		-0.016		-0.049***	
	Flickering Imbalance$_{i,t-5}$		-0.011		-0.009		-0.046***
	Orderbook Imbalance$_{i,t}$	0.294***	0.295***	0.356***	0.356***	0.374***	0.374***
	Spread$_{i,t}$	-0.008	-0.008	0.009	0.009	0.017	0.017
Best	β_0	0.001	0.001	-0.008***	-0.008***	-0.024***	-0.024***
	$D_{\text{Flicker}_{i,t}}$	0.026***	0.027***	0.036***	0.037***	0.035***	0.037***
	Flickering Imbalance$_{i,t-1}$	0.023***		0.026***		0.013**	
	Flickering Imbalance$_{i,t-5}$		0.010***		0.016***		-0.008
	Orderbook Imbalance$_{i,t}$	0.686***	0.686***	0.764***	0.764***	0.776***	0.776***
	Spread$_{i,t}$	-0.003**	-0.003**	0.008***	0.008***	0.005	0.005
Deep	β_0	0.009***	0.009***	0.007*	0.007*	-0.012**	-0.012**
	$D_{\text{Flicker}_{i,t}}$	-0.063***	-0.061***	-0.060***	-0.058***	-0.060***	-0.057***
	Flickering Imbalance$_{i,t-1}$	0.018***		0.006		0.002	
	Flickering Imbalance$_{i,t-5}$		-0.001		-0.011		-0.034***
	Orderbook Imbalance$_{i,t}$	0.873***	0.873***	0.935***	0.935***	0.959***	0.959***
	Spread$_{i,t}$	-0.011***	-0.011***	-0.001	-0.001	-0.011*	-0.011*

Table 5: This table reports estimates from the linear regression

$$R_{i,t+h}^{Pre-entry} = \beta_0 + \beta_1 D_{\text{Flicker}_{i,t}} + \beta_2 \text{FlickerVolumeImbalance}_{i,t-n} + \beta_3 \text{OrderbookImbalance}_{i,t} + \beta_4 \text{Spread}_{i,t}$$

The variable $R_{i,t+h}^{\text{Pre-entry}}$ is the return in midpoint price in basis points in the $h \in \{1, 5, 10\}$ seconds measured starting immediately before entry of the flickering order. The variable $D_{\text{Flicker}_{i,t}}$ equals $+1$ for a flickering buy order and -1 for a flickering sell order. FlickerVolumeImbalance$_{i,t-n}$ is the difference between volume of flickering buy orders and the volume of flickering sell orders over the previous n 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, divided by their sum. Spread$_{i,t}$ is the relative bid-ask spread standardized per stock. The table is structured into three panels: spread-improving flickering orders (top), flickering orders at the best quote (middle), and flickering orders deeper in the book (bottom). The data covers 25 large-cap Dutch stocks listed on Euronext Amsterdam, observed from January 2 to January 6, 2023. Standard errors are double-clustered by stock and day.

	Variable	$h = 1s$	$h = 1s$	$h = 5s$	$h = 5s$	$h = 10s$	$h = 10s$
Improving	β_0	0.012*	0.012*	-0.015	-0.015	-0.037**	-0.037**
	$D_{\text{Flicker}_{i,t}}$	-0.597***	-0.596***	-0.593***	-0.593***	-0.609***	-0.609***
	Flickering Imbalance$_{i,t-1}$	-0.004		-0.015		-0.048***	
	Flickering Imbalance$_{i,t-5}$		-0.018**		-0.016		-0.053***
	Orderbook Imbalance$_{i,t}$	0.327***	0.328***	0.390***	0.390***	0.407***	0.408***
	Spread$_{i,t}$	-0.006	-0.006	0.011	0.011	0.019	0.019
Best	β_0	0.001	0.001	-0.008***	-0.008***	-0.024***	-0.024***
	$D_{\text{Flicker}_{i,t}}$	0.026***	0.027***	0.036***	0.037***	0.035***	0.037***
	Flickering Imbalance$_{i,t-1}$	0.023***		0.027***		0.013**	
	Flickering Imbalance$_{i,t-5}$		0.010***		0.016***		-0.008
	Orderbook Imbalance$_{i,t}$	0.686***	0.686***	0.764***	0.764***	0.775***	0.776***
	Spread$_{i,t}$	-0.003**	-0.003**	0.008***	0.008***	0.005	0.005
Deep	β_0	0.009***	0.009***	0.007*	0.007*	-0.012**	-0.012**
	$D_{\text{Flicker}_{i,t}}$	-0.063***	-0.061***	-0.060***	-0.058***	-0.060***	-0.057***
	Flickering Imbalance$_{i,t-1}$	0.019***		0.006		0.003	
	Flickering Imbalance$_{i,t-5}$		-0.001		-0.011		-0.034***
	Orderbook Imbalance$_{i,t}$	0.873***	0.873***	0.935***	0.935***	0.959***	0.959***
	Spread$_{i,t}$	-0.011***	-0.011***	-0.001	-0.001	-0.011*	-0.011**

Table 6: This table reports estimates from the linear regression

$$R_{i,t+h}^{Post-entry} = \beta_0 + \beta_1 D_{\text{Flicker}_{i,t}} + \beta_2 \text{FlickerVolumeImbalance}_{i,t-n} + \beta_3 \text{OrderbookImbalance}_{i,t} + \beta_4 \text{Spread}_{i,t}$$

The variable $R_{i,t+h}^{\text{Post-entry}}$ is the return in midpoint price in basis points in the $h \in \{1, 5, 10\}$ seconds measured starting immediatelyafter entry of the flickering order. The variable $D_{\text{Flicker}_{i,t}}$ equals $+1$ for a flickering buy order and -1 for a flickering sell order. FlickerVolumeImbalance$_{i,t-n}$ is the difference between volume of flickering buy orders and the volume of flickering sell orders over the previous n 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, divided by their sum. Spread$_{i,t}$ is the relative bid-ask spread standardized per stock. The table is structured into three panels: spread-improving flickering orders (top), flickering orders at the best quote (middle), and flickering orders deeper in the book (bottom). The data covers 25 large-cap Dutch stocks listed on Euronext Amsterdam, observed from January 2 to January 6, 2023. Standard errors are double-clustered by stock and day.

	Variable	$h = 1s$	$h = 1s$	$h = 5s$	$h = 5s$	$h = 10s$	$h = 10s$
Improving	β_0	-0.006	-0.006	-0.003	-0.003	-0.022*	-0.021*
	$D_{\text{Flicker}_{i,t}}$	-0.028***	-0.038***	-0.013	-0.023**	-0.031**	-0.043***
	Flickering Imbalance$_{i,t-1}$	-0.055***		-0.064***		-0.095***	
	Flickering Imbalance$_{i,t-5}$		-0.056***		-0.068***		-0.112***
	Orderbook Imbalance$_{i,t}$	0.103***	0.102***	0.094***	0.093***	0.051**	0.050**
	Spread$_{i,t}$	-0.014***	-0.014***	0.006	0.006	0.000	0.000
Best	β_0	0.000	0.000	-0.010***	-0.009***	-0.027***	-0.026***
	$D_{\text{Flicker}_{i,t}}$	-0.055***	-0.045***	-0.056***	-0.043***	-0.051***	-0.038***
	Flickering Imbalance$_{i,t-1}$	0.009***		0.012**		-0.005	
	Flickering Imbalance$_{i,t-5}$		-0.023***		-0.025***		-0.056***
	Orderbook Imbalance$_{i,t}$	0.610***	0.610***	0.722***	0.722***	0.738***	0.738***
	Spread$_{i,t}$	-0.005***	-0.005***	0.004	0.004	-0.001	-0.001
Deep	β_0	0.011***	0.011***	0.004	0.005	-0.011**	-0.010**
	$D_{\text{Flicker}_{i,t}}$	-0.025***	-0.023***	-0.022***	-0.024***	-0.016**	-0.015**
	Flickering Imbalance$_{i,t-1}$	-0.001		-0.019**		-0.036***	
	Flickering Imbalance$_{i,t-5}$		-0.009*		-0.025***		-0.061***
	Orderbook Imbalance$_{i,t}$	0.601***	0.602***	0.703***	0.703***	0.727***	0.728***
	Spread$_{i,t}$	-0.003	-0.003	-0.001	-0.001	-0.004	-0.004

Table 7: This table reports estimates from the linear regression

$$R^{Post-cancel}_{i,t+h} = \beta_0 + \beta_1 D_{\text{Flicker}_{i,t}} + \beta_2 \text{FlickerVolumeImbalance}_{i,t-n} + \beta_3 \text{OrderbookImbalance}_{i,t} + \beta_4 \text{Spread}_{i,t}$$

The variable $R^{\text{Post-cancel}}_{i,t+h}$ is the return in midpoint price in basis points in the $h \in \{1, 5, 10\}$ seconds measured starting immediately after cancellation of the flickering order. The variable $D_{\text{Flicker}_{i,t}}$ equals $+1$ for a flickering buy order and -1 for a flickering sell order. FlickerVolumeImbalance$_{i,t-n}$ is the difference between volume of flickering buy orders and the volume of flickering sell orders over the previous n 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, divided by their sum. Spread$_{i,t}$ is the relative bid-ask spread standardized per stock. The table is structured into three panels: spread-improving flickering orders (top), flickering orders at the best quote (middle), and flickering orders deeper in the book (bottom). The data covers 25 large-cap Dutch stocks listed on Euronext Amsterdam, observed from January 2 to January 6, 2023. Standard errors are double-clustered by stock and day.

	Flicker	**Non-Flicker**
Improving order	0.14***	0.39***
Order at best	0.04***	0.16***
Order deeper in book	-0.05***	0.00***
Worsening cancel	0.24***	0.37***
Cancellation at best	0.07***	0.13***
Cancellation deeper in book	0.05***	0.04***
Trade	1.01	

Table 8: The table reports 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 flickering and non-flickering 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) shares on Euronext Amsterdam, during January 2–6, 2023. The *Trade* variables take the value of +1 for buyer-initiated trades, −1 for seller-initiated trades, and 0 otherwise. Asterisks (***), indicate significance at the 1% level, based on standard errors clustered by stock and by day.

	Flicker	Non-Flicker
Improving order	0.48%	2.05%
Order at best	2.84%	20.24%
Order deeper in book	1.28%	23.24%
Worsening cancel	0.39%	1.50%
Cancel at best	2.93%	18.78%
Cancel deeper in book	1.30%	23.76%
Trade	1.19%	

Table 9: 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 nook* to those placed further from the best price, with analogous definitions for cancels; *Trade* includes all executed trades; the dataset covers 25 large-cap (AEX) stocks traded on Euronext Amsterdam during January 2–6, 2023.

	Worsening cancel	Cancel at best	Cancel deeper in book
Improving order	5.61	4.64	0.23
Order at best	2.63	55.19	3.84
Order deeper in book	0.09	3.57	24.20

Table 10: Frequency of flickering orders by type of entry and cancellation. The analysis includes only flickering order entries that do not result in immediate transactions. Data are based on 25 large-cap Dutch stocks listed in the AEX index on Euronext Amsterdam during January 2–6, 2023.

	Flicker	Non-Flicker
Improving order	1.070%	2.300%
Order at best	0.110%	0.260%
Order deeper in book	0.069%	0.002%
Worsening cancel	1.560%	2.460%
Cancel at best	0.250%	0.240%
Cancel deeper in book	0.059%	0.024%
Trade	17.28%	

Table 11: The table reports the stock-day average variance decomposition from the strutural vector autoregression (SVAR) used in table 8 for the 25 Dutch large-cap (AEX) stocks in Euronext Amsterdam during January 2–6, 2023.

	(1)	(2)	(3)
	Spread-improving	At best	Deeper in book
Intercept	-0.023***	-0.023***	-0.018***
	(0.007)	(0.002)	(0.004)
$D_{\text{Flicker}_{i,t}}$	0.046***	0.035***	-0.049***
	(0.007)	(0.002)	(0.004)
Observations	76803	553964	205095
R^2	0.001	0.001	0.001
Adjusted R^2	0.001	0.001	0.001
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 12: This table reports estimates from a linear regression model

$$\text{NetLiquidityTakingImbalance}^{\theta}_{i,t+1\text{sec}} = \beta_0 + \beta_1 \cdot D_{\text{Flicker}_{i,t}}$$

$\text{NetLiquidityTakingImbalance}^{\theta}_{i,t+1\text{sec}}$ is the difference between the number of buyer-initiated and seller-initiated liquidity-taking transactions in the one-second interval following the entry of a flickering order, where $\theta \in \{\text{Spread-improving}, \text{At best}, \text{Deeper in book}\}$ is the type of flickering order. $D_{\text{Flicker}_{i,t}}$ equals $+1$ for entry of a flickering buy order and -1 for entry of a flickering sell order. The sample includes 25 Dutch large-cap (AEX) stocks. Standard errors are double-clustered by stock and trading day.