Feedback trading and feedback pricing: The intra-day case of retail derivatives

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January 11, 2022

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Abstract

We analyze intra-day feedback effects in retail order flow and the pricing of bank-issued warrants. Using a unique data set of exchange trades and high-frequency quotes, we first provide evidence that retail investors actively and consciously respond to recent intra-day returns in the warrants' underlying in a negative feedback, contrarian fashion. This pattern cannot be explained by order type preferences alone and persists after controlling for other trade-motivating factors. Second, we show that some retail investors also feedback trade on the direction of the last tick in the warrant price itself. Third, we document that issuers do not take advantage of investors by adjusting the mark-up of single products in response to a trade. However, we find evidence that all issuers in our sample substantially increase the number of quote updates per minute after a warrant is traded to safeguard against latency arbitrage.

JEL Classification

C32 *Multiple or Simultaneous Equation Models, Multiple Variables: Time-Series Models, Dynamic Quantile Regressions, Dynamic Treatment Effect Models, Diffusion Processes, State Space Models*,

D40 *Market Structure, Pricing, and Design: General*,

G11 *General Financial Markets: Portfolio Choice, Investment Decisions*,

G12 *General Financial Markets: Asset Pricing, Trading Volume, Bond Interest Rates*,

G13 *General Financial Markets: Contingent Pricing, Futures Pricing*,

G24 *Financial Institutions and Services: Investment Banking, Venture Capital, Brokerage, Ratings and Ratings Agencies*,

G41 *Behavioral Finance: Role and Effects of Psychological, Emotional, Social, and Cognitive Factors on Decision Making in Financial Markets*

Keywords

Feedback trading, feedback pricing, retail investors, retail derivatives, warrants, order flow, issuer pricing strategies, intra-day

1 Introduction

In the sense of Black (1986), noise traders are those whose trading activity does not process new information about fundamentals. Although noise is vital to the functioning of markets, the puzzle of what exactly motivates noise trades remains an active field of research. The empirical literature shows that (misguided) believes in contrarianism or momentum are one driver that makes investors trade (Grinblatt and Keloharju, 2001).[1] This dynamic relation between trading activity and past returns is referred to as feedback trading. Negative feedback traders buy securities after prices have fallen and sell them after prices have risen, while positive feedback traders act vice versa (De Long et al., 1990). However, equilibrium constraints imply that not all investors can follow the same feedback trading strategy. Empirical studies show that the group of individual (retail) investors tends to negative feedback trade, while professional investors tend to positive feedback trade with respect to recent returns (see, e.g., Sias, 2007; Ng and Wu, 2007; Barber et al., 2009b; Kelley and Tetlock, 2013; Barrot et al., 2016).

The vast majority of the literature on feedback trading focuses on responses to past returns for horizons from one day up to one year. In contrast, very little is known about the feedback trading behavior of retail investors with respect to past intra-day returns. Hindering factors include the reluctance of brokers to provide individual investors' trading histories and the difficulty to disentangle exchange order flow with respect to its origin. In the latter case, small trades or broad exchange classifications are common as proxies for retail trades (see, e.g., Barber et al. (2009a); Lemmon and Ni (2014)). In addition, intra-day studies usually focus exclusively on day traders (see, e.g., Harris and Schultz, 1998; Seasholes and Wu, 2007; Chou et al., 2015). We avoid these shortfalls, as our unique data set consists of unconditioned order flow in a market which is exclusively designed for retail investors — the market for retail derivatives.

We extent results from the literature by analyzing trading patterns of investors in retail derivatives on an intra-day basis. In particular, we analyze the trading activity in bank-issued warrants, which are leverage products and thus predestinated for intra-day

[1] In addition to other motives for noise trades that are rooted in behavioral biases, there are also rational motives such as portfolio rebalancing or tax-loss selling.

speculative trading. Bank-issued warrants are securitized options specifically tailored to the needs of small investors, as their contract size is much small than that of regular options and they are tradable like stocks without the need for a margin account (Schmitz and Weber, 2012). Their leverage properties make them attractive to investors who want to profit from small intra-day price movements. Therefore, they are an ideal instrument to analyze intra-day feedback trading of retail investors. Furthermore, as they are exchange-listed, transactions and quotes are available from the respective exchange.

We hypothesize that retail investors use bank-issued warrants to speculate on price movements in the underlying. Schmitz and Weber (2012) document a consistent picture of negative feedback trading with respect to returns of the underlying over the last days: Following negative returns, retail investors expect future positive returns, which makes them buy calls and sell puts. Following positive returns, they tend to buy puts and sell calls. Our first research question is whether this patterns also holds for short-term intra-day returns of the underlying.

To answer this question, we aggregate trading activity within 15-minute intervals through the course of a trading day at the world's largest exchange for bank-issued warrants: The European Warrant Exchange (EUWAX). We analyze the trading activity in call and put warrants on the German DAX, which is EUWAX's most important underlying. Our data set reveals that the pattern of negative feedback trading is also present for short-termed intra-day returns. Investors respond to past return intervals of up to two hours. We show that this response is conscious and, at best, can be explained to a small extent by preferences for certain types of orders.

Furthermore, we consider extremely short-termed returns in the warrants themselves. On average, each bank-issued warrant experiences 2–3 price updates (*ticks*) per minute. Analyzing the trading response to such ticks, we find some hints for a reversal of the feedback trading direction at very high frequencies: While the majority of retail investors does not care about past returns in the sub-minute segment, there are some traders who react positively to price ticks in the warrant (not the underlying). That is, they tend to buy calls as well as puts after a positive price tick of the respective warrant. We interpret this finding as indicating that there is a small subgroup of retail investors that behaves more like professional investors than their peers. This subgroup continuously monitors the prices of warrants and anticipates high-frequency momentum in the prices of both calls and puts.

Figure 1 summarizes this paper's part on feedback trading, as outlined above, in terms of the examined time horizons, sources of return impulses and relation to the literature.

[INSERT FIGURE 1 ABOUT HERE]

The second part of the paper deals with the reaction of issuers on trades. Issuers offer a large variety of warrants on the same underlying, spanning a fine grid of strike prices and maturities. Moreover, similar and often identical warrants are offered by different issuers. Therefore, investors can choose from a large set of warrants, which means that despite intensive trading activity in the overall market, the activity in a single warrant is rather low. Given that issuers act as sole market makers for their own warrants and continuously quote binding bid and ask prices, observed prices on the exchange do not necessarily reflect the fair value, but rather the issuers' price-setting policy which usually includes a dynamic mark-up (see, e.g., Stoimenov and Wilkens, 2005; Baule, 2011; Henderson and Pearson, 2011). There is evidence that issuers anticipate and exploit longer-term (Baule, 2011) and diurnal order flow patterns (Baule et al., 2018) in a way that they increase their prices when they expect an excess in net investor demand and decrease them when they expect an excess in net investor supply.

Since the trade in a single warrant is a relatively rare event[2], an issuer could engage in *feedback pricing*, responding to a trade event by adjusting the traded warrant's price level in order to position for future intra-day order flow in that particular warrant. However, there are two competing hypotheses: (i) An investor buy could indicate a high attractiveness and lead further buys of other investors. (ii) An investor buy could be followed by a re-sale of the same investor in case she is speculating on short-term (intra-day) gains. According to (i), the issuer should increase the warrant's mark-up, according to (ii), she should decrease it.

[2]In our sample, there are on average 425 trades per day, spread over the warrants offered by nine issuers.

We make use of the market fragmentation and analyze differences in price differences between traded and non traded warrants with identical features before and after a trade. We find no evidence that issuers adjust their mark-ups in response to single trades. Thus, none of the two hypotheses dominates the other.

However, our analysis of the intra-day price-setting behavior reveals another feedback pricing pattern: We find evidence that all issuers in our sample substantially increase the number of quote updates per minute after a warrant is traded. This elevated pricing intensity tends to persist for the rest of the day. A possible explanation for this behavior is that issuers are exposed to latency arbitrage (Wah and Wellman, 2016; Wah, 2016), if they do not update their prices fast enough. Since there are retail traders who monitor tick prices, we suspect that issuers adjust the pricing intensity in order to guard themselves against latency arbitrage. As the number of structured products offered per issuer is huge and pricing all of them at the highest intensity possible comes at a computational cost, we hypothesize that issuers prioritize the pricing intensity of warrants that are currently in the focus of investors and that they use trades in order to do so.

Our paper adds to the literature in several ways. First, we extend the literature on feedback trading with the first analysis on the aggregate intra-day behavior of retail investors. However, contrary to most studies on the intra-day case, we do not restrict our analysis to day traders only. We identify the intra-day returns as distinct trade-motivating factors on which investors react in a contrarian fashion for intervals covering the last two hours and in a momentum fashion on intervals covering the sub-minute segment.

Second, this paper also contributes to the literature on market makers' pricing strategies for exchange-traded structured products with the first analysis on feedback effects of the order flow on the price-setting behavior. While existing studies show that issuers exploit anticipated order flow patterns (Baule, 2011; Baule et al., 2018) and engage in cross-pricing of supplementary products (Pelster and Schertler, 2019), the response to order flow has to date not been analyzed. We provide the first intra-day analysis on feedback pricing strategies that respond to order flow on a trade by trade basis in the product to be priced.

The remainder of this paper is organized as follows. Section 2 relates the paper to the existing literature on feedback trading, intra-day trading and pricing strategies of structured retail products. Section 3 introduces the data used in this paper. Section 4 is dedicated to the analysis of feedback trading and section 5 to the analysis of feedback pricing. Section 6 concludes.

2 Relation to the literature

2.1 Feedback trading

The first strand of literature related to our paper provides empirical evidence for feedback trading from order flow and ownership data.[3] While there is extensive evidence for positive feedback trading by professional investors, the majority of findings for individual investors points towards negative feedback trading.[4] For recent returns, covering intervals up to six months in the past, this behavior is documented for the U.S. (Goetzmann and Massa, 2002; Griffin et al., 2003; Kaniel et al., 2008; Barber et al., 2009b; Kaniel et al., 2012; Kelley and Tetlock, 2013), Finland (Grinblatt and Keloharju, 2000, 2001), France (Barrot et al., 2016), Australia (Jackson, 2003; Colwell et al., 2008) and several emerging markets (Richards, 2005). For more distant returns, covering quarters $t-4$ through $t-10$, the feedback trading behavior tends to turn positive (Barber et al., 2009b). However, there are also studies where the findings are more nuanced. In China, there is no evidence of feedback trading in the aggregate (Feng and Seasholes, 2004), but there is positive and negative feedback trading after controlling for wealth (Ng and Wu, 2007). In Germany, the directional feedback differs with regard to the order type used (Dorn et al., 2008). In

[3]Feedback trading is also documented extensively from market prices (see, e.g. Tayeh and Kallinterakis (2022) for a recent overview), and from experiments (Bloomfield et al., 2009).

[4]Positive feedback trading is documented for institutional investors in general (Nofsinger and Sias, 1999; Grinblatt and Keloharju, 2000, 2001; Froot et al., 2001; Griffin et al., 2003; Sias, 2007; Ng and Wu, 2007; Griffin et al., 2011; Cohen and Shin, 2013; Choi and Skiba, 2015), and in particular for mutual fund managers (Grinblatt et al., 1995; Walter and Weber, 2006; Boyer and Zheng, 2009) and foreign investors (Choe et al., 1999; Lin and Swanson, 2003; Richards, 2005; Boyer and Zheng, 2009; Jeon and Moffett, 2010; Tayde and Rao, 2011; Phansatan et al., 2012). However, there is also some contradictory evidence (Kamesaka et al., 2003; Phansatan et al., 2012; Kremer and Nautz, 2013; Hood et al., 2013; Bing and Ma, 2021).

Japan, the results seem to depend on the market regime (Kamesaka et al., 2003; Kim and Nofsinger, 2007; Hood et al., 2013). Finally, in Thailand, there is no evidence of feedback trading (Phansatan et al., 2012).

Moreover, the disposition effect (Shefrin and Statman, 1985), which describes the tendency to hold on to losing stocks and sell winning stocks, is also consistent with negative feedback trading. This effect is documented for individual investors by, e.g., Odean (1998, 1999).

With regard to trading in options, there is evidence from the Netherlands, that retail investors tend to extrapolate the previous month's return into the next month (Bauer et al., 2009).[5] In the U.S. aggregate nonmarket makers' daily and monthly trading activity in purchased and written calls on individual stocks relates positively to past returns of the underlying for horizons from one week up to two years (Lakonishok et al., 2007; Chen and Sabherwal, 2019). While for put positions, with the exception of purchased calls to open, the relation is negative for returns up to one month in the past (Lakonishok et al., 2007), but, in all cases, positive for more distant returns of up to two years in the past (Lakonishok et al., 2007; Chen and Sabherwal, 2019). These effects are similar for public customers of discount brokers, including retail investors. Noteworthy are differences in terms of the underlying. Monthly demand for positive exposure to the underlying via options is positively related to past market returns only if the underlying is a stock and unrelated to past returns if the underlying is an index (Lemmon and Ni, 2014). Similarly, the daily aggregate open interest in U.S. index options is unrelated to the trailing three-month return of the market index (Johnson et al., 2018).

Very few papers analyze feedback trading in bank-issued structured retail products. For option-like warrants (Schmitz and Weber, 2012; Baule and Blonski, 2012) and knock-out warrants (Farkas and Váradi, 2021), there is evidence that individual investors follow negative feedback trading strategies with respect to recent inter-day returns of the underlyings.

[5] To the best of our knowledge, Bauer et al. (2009) provide the only study on the relation between trading activity in options and past returns, that uses trades that can be clearly sourced to retail customers of a broker. Most of the remaining studies cited, use open interest and trading volume of options listed on the Chicago Board Options Exchange (CBOE). Although the CBOE subdivided public customer orders into categories of origin until 2001, they switched to a volume based classification scheme there after (Lemmon and Ni, 2014). As such, the origin of option trades cannot be determined with certainty.

Consistent with stock trading behavior, the feedback turns positive for more distant returns and large trades (Schmitz and Weber, 2012; Baule and Blonski, 2012). Differences in terms of whether the underlying is a stock or an index are minor (Schmitz and Weber, 2012). This paper extends the analysis of feedback trading towards the intra-day case of structured retail products, while covering the response to price changes in the underlying as well as the warrant itself.

2.2 Intra-day trading

The second strand of literature related to our paper covers studies on intra-day trading behavior. Most of the studies in this strand focus exclusively on day traders[6], but only few investigate the response to past intra-day returns. For institutional day traders, there is consistent evidence for positive feedback trading with respect to recent intra-day returns in stocks from the U.S. (Griffin et al., 2003; Garvey and Murphy, 2005) and futures from Korea (Chou et al., 2015). In contrast to that, the majority of studies on the behavior of individual investors points towards negative feedback trading. There is corresponding evidence for stocks from the U.S. (Griffin et al., 2003), China (Seasholes and Wu, 2007) and Korea (Chung et al., 2009) as well as futures from Korea (Eom, 2020) and Taiwan (Chou et al., 2015). However, some studies provide evidence that is inconsistent with that view. For futures in Taiwan, Cheng et al. (2016) find that most of the individual day traders, except for the highest performing quintile, follow a positive feedback trading strategy. In addition, Harris and Schultz (1998) demonstrate that individual day traders, who use the small order execution system of the Nasdaq, tend to follow a momentum strategy. Although we do not focus exclusively on order flow from day traders, our study is related to that of day traders since we focus on intra-day behavior and suspect that warrants, due to the high leverage, are also traded by day traders. Furthermore, non-day traders could act as day traders with regard to their trade timing.

[6]Day traders follow an active trading strategy in which they attempt to make profits intra-day on small price changes (Barber and Odean, 2001). Typically, they close positions by the end of each trading day to avoid the risk associated with overnight price changes (Chung et al., 2009). We refer to an institutional (proprietary) day trader as an employee who day trades on behalf of a firm (Garvey and Murphy, 2005).

2.3 Market makers' pricing strategies

As bank-issued warrants belong to the retail market for exchange-traded structured products, our paper also relates to the literature on the respective market makers' pricing strategies. The environment in this market is unique, as inventory costs and the presence of informed traders are insignificant (Baller et al., 2016). In addition, a product is tradeable solely with its issuer and short-selling by investors is not possible. Consequently, a market maker has almost exclusive price-setting power over his products.[7] In the empirical literature, several stylized characteristics of prices in this market have been documented.[8] Many researchers find structured retail products to be overpriced relative to their components or a pricing model. In the case of bank-issued warrants, there is evidence of overpricing from Germany (Ruf, 2011; Baule et al., 2018), the Netherlands (ter Horst and Veld, 2008), Spain (Abad and Nieto, 2011) and Hong Kong (Li and Zhang, 2011).[9] Examining the degree of overpricing more closely, the order flow hypothesis postulates that issuers anticipate systematic patterns in the order flow and adjust their quotes accordingly (Wilkens et al., 2003; Baule, 2011). While many studies find support for this hypothesis over longer time horizons, only very few papers focus on intra-day patterns in the order flow and quotes. In the case of leverage certificates, Baller et al. (2016) show that net investor supply dominates toward the late trading hours. Though, Entrop et al. (2013) and Baller et al. (2016) find increased mark-ups towards the end of the day. This conflicting pricing-strategies can be resolved by the fact that leverage certificates are subject

[7] In reality, limits in the price-setting power might arise from prices set by competing issuers for similar or identical products in combination with the investors price sensitivity (Baule, 2011; Baule and Blonski, 2015).

[8] A theoretical model of a profit maximizing pricing strategy in the market environment of structured retail products is developed by Baller et al. (2016).

[9] Evidence of overpricing for other kinds of products has been reported for Germany by Wilkens et al. (2003); Stoimenov and Wilkens (2005); Muck (2006); Wilkens and Stoimenov (2007); Baule et al. (2008); Baule (2011); Baule and Tallau (2011); Pelster and Schertler (2019); Baule and Shkel (2021), for the U.S. by Chen and Kensinger (1990); Chen and Sears (1990); Baubonis et al. (1993); Benet et al. (2006); Henderson and Pearson (2011), for Switzerland by Wasserfallen and Schenk (1996); Burth et al. (2001); Grünbichler and Wohlwend (2005); Wallmeier and Diethelm (2009) and for the Netherlands by Szymanowska et al. (2009); Hernández et al. (2013).

to an overnight jump risk of the underlying. Since this risk increases throughout the day, it seems to dominate possible mark-downs from the order flow imbalance. In the case of warrants, Baule et al. (2018) find an opposing intra-day pricing-strategy: On average, the mark-ups decrease during the course of day. Since warrants do not face an overnight jump risk, they assume that issuers try to exploit an intra-day order flow imbalance pattern. However, this assumed pattern is, to the best of our knowledge, not yet documented in the literature. This paper provides evidence for its existence. Apart from pricing strategies that anticipate order flow patterns, only Pelster and Schertler (2019) analyze pricing strategies that respond to realized order flow. They find evidence that issuers engage in cross-pricing when supplementary products are sold to investors. We extend this path and provide the first intra-day analysis on *feedback pricing* strategies that respond to order flow on a trade by trade basis in the product to be priced.

3 Data and descriptive statistics

We consider quoted prices and executed orders at the EUWAX in the year 2014 in call and put warrants from nine issuers with the DAX performance index (DAX) as the underlying. Namely, these issuers are: BNP Paribas, Citigroup, Commerzbank, Deutsche Bank, DZ Bank, Goldman Sachs, HSBC, UniCredit, and Vontobel.[10] The intra-day tick price quotations of the warrants as well as the DAX were obtained from Thomson Reuters Tick History. Warrant features were provided by the financial services provider Solvians IT Solutions GmbH. Data on the VDAX NEW were obtained from Refinitiv Datastream.

Table 1 provides an overview of our price and trade data. The data set includes tick prices for approximately 41,000 warrants during our sample period of 2014. On average, there are 1.93 (1.64) price updates (*ticks*) per minute for calls (puts). In total, about 16,000 different warrants were actually traded on the exchange, while most of these were issued by Deutsche Bank (19%) and Commerzbank (17%). The trading activity amounts to 107,003 trades with a total volume of almost 600 million euros. The number of investor purchases exceeds the number of investor sales by 32%, although the trading volume in euros is only

[10]Due to a lack of price data, we eliminated UBS from our sample.

slightly higher. This may be due to some investors who hold warrants to maturity, buy warrants over time with several trades and sell them with a single trade, or execute sales over the counter via the issuers' trading platforms.

[INSERT TABLE 1 ABOUT HERE]

Figure 2 provides an overview of the order characteristics. Panel (a) shows that the median volume per trade is below 2,000 euros, although the volume is highly skewed. This clearly indicates a high degree of retail trading activity. Furthermore, investors prefer short-dated warrants, as 50% of the warrants in demand have a time to maturity of less than 34 days (Panel (b)). Although the median time to maturity is about 9 days shorter when selling a warrant, this difference cannot be interpreted as the average holding period due to reasons discussed above. Moreover, most of the trading activity is concentrated in warrants that are slightly out of the money, with a median moneyness of −1.7% for buys and −1.0% for sells (Panel (c)). Here, we measure the moneyness of warrant i at time t as

$$MONEY_{i,t} = \begin{cases} \frac{S_t - K_i}{S_t} & \text{for call warrants,} \\ \frac{K_i - S_t}{S_t} & \text{for put warrants,} \end{cases} \tag{1}$$

where S_t is the level of the DAX at time t and K_i is the warrant's strike price. This behavior reflects a preference for leverage. Finally, in Panel (d) we report the time between the entry of an order or the last modification and its execution. Generally, orders are executed quickly regardless of their type, as 75% of the buys (sells) are filled within two minutes (seven minutes). This is surprising, as Figure 3 shows that investors predominantly use limit orders.[11] However, the quick execution suggests that many orders are marketable or have limits close to the market price. Overall, the behavior and preferences described above are similar for calls and puts.

[INSERT FIGURE 2 ABOUT HERE]

[INSERT FIGURE 3 ABOUT HERE]

[11] Similar relations are reported by Baller et al. (2016) for transactions in leverage certificates. In contrast, a database of retail trades in U.S. common stocks, covering an estimated one-third of the retail market, used by Kelley and Tetlock (2013) contains significantly more market orders than limit orders.

4 Feedback trading

4.1 Impulses from the underlying's price

4.1.1 Order flow measures and descriptive statistics

In this section, we examine whether and how retail investors respond to intra-day price changes in the underlying's price and the warrant price itself. The section is organized as follows: First, we examine the response of different measures of intra-day order flow on impulses from the underlying's price within the last two hours. Second, we analyze the response of the trade direction on impulses from the warrants' tick prices.

For our feedback trading analysis on impulses from the underlying's price, we aggregate information over 15-minute intervals in a trading day. This interval length is a compromise between keeping the information loss on the dynamics of the trading process low and avoiding too many zeros for intervals which are too small.[12] We base this analysis on two kinds of intra-day order flow measures.

First, we measure the order flow intensity as the number of orders executed within each 15-minute interval in a trading day (see, e.g., Venezia and Shapira (2007) for a similar measure). This measure weights each order equally, regardless of its size. Consequently, it is robust against large volume trades and allows us to analyze the trading behavior of retail investors in a broad sense.[13] While EUWAX allows trading from 9:00 a.m. to 8:00 p.m. CET in our sample period, the DAX is only calculated from 9:00 a.m. to 5:30 p.m. CET during trading on XETRA. Since our feedback analysis requires lagged intra-day returns of the DAX, we restrict our order flow sample to 15-minute intervals between 9:00 a.m. and 5:45 p.m. CET per day. This gives us 35 intervals on 252 trading days from January 2nd to December 30th in 2014 and a total of 8,820 observations. Following this methodology, we

[12]Related studies on stock trades by Heinen and Rengifo (2007), Quoreshi (2008) and Jung et al. (2011) use 5-minute intervals. Since warrants are traded less frequently than stocks our interval length of 15 minutes is slightly larger.

[13]Our results are robust to various changes in the order flow measures. We obtain similar results when we break down the order flow intensities in terms of volume per trade and moneyness per trade, and especially, when we use a volume-based measure of order flow instead.

define the buy and sell intensities in call and put warrants on day $t \in \{1, \ldots, 252\}$ within interval $i \in \{1, \ldots, 35\}$ as $CALLBUY_{t,i}, CALLSELL_{t,i}, PUTBUY_{t,i}$ and $PUTSELL_{t,i}$.

Second, we compute the interval-wise order flow imbalance as the normalized difference in the buying and selling intensity (see, e.g., Venezia and Shapira (2007), Kelley and Tetlock (2013) and Barrot et al. (2016) for a similar measure). For each 15-minute interval, we subtract the number of sell trades from the number of buy trades and then divide by the total number of trades.[14] If there is no trading within an interval, we set the imbalance measure equal to zero. For calls and puts, we define the order flow imbalance as

$$IMB_{t,i}^{CALL} = \frac{CALLBUY_{t,i} - CALLSELL_{t,i}}{CALLBUY_{t,i} + CALLSELL_{t,i}}, \tag{2}$$

$$IMB_{t,i}^{PUT} = \frac{PUTBUY_{t,i} - PUTSELL_{t,i}}{PUTBUY_{t,i} + PUTSELL_{t,i}}, \tag{3}$$

respectively. In addition, we calculate the overall order flow imbalance in warrants as

$$IMB_{t,i} = \frac{(CALLBUY_{t,i} - CALLSELL_{t,i}) - (PUTBUY_{t,i} - PUTSELL_{t,i})}{CALLBUY_{t,i} + CALLSELL_{t,i} + PUTBUY_{t,i} + PUTSELL_{t,i}}.^{15} \tag{4}$$

Table 2 provides descriptive statistics and Figure 4 shows histograms of the variables. In summary, the intensities are low non-negative integers and highly autocorrelated. The imbalances in calls and puts are slightly positive on average, but close to zero in aggregate. They are also significantly autocorrelated.

[INSERT TABLE 2 ABOUT HERE]

[INSERT FIGURE 4 ABOUT HERE]

The order flow exhibits diurnal patterns. To determine the diurnal proportional order flow intensity, we divide the number of trades per interval by the total daily number of trades. As shown in Panel (a) of Figure 5, the order flow intensities of buys and sell in calls and puts are highest in the morning, as the first 15-minute interval accounts for roughly 10%

[14] Our count-based measures are highly correlated with their volume-based counterparts. The correlations are 0.87, 0.84 and 0.80 for volume- and count-based order flow imbalances in calls, puts, and overall, respectively. Therefore, results are similar.

[15] This measure is similar to the Euwax Sentiment published by Börse Stuttgart.

of the total number of daily trades. From then on, the intensity per 15-minute interval ranges between 2% and 5% of the total number of daily trades. After a low around midday, the intensity tends to increase again until the end of day. This L-shape is similar for all four intensity measures. However, it differs sharply from the distinct U-shape of trading activity in stocks (Admati and Pfleiderer, 1988; Foster and S., 1993; Jung et al., 2011; Heinen and Rengifo, 2007). The activity peak in the morning is also reported for retail oriented mini options in the US and may be due to individual investors with full time jobs who have limited attention during working hours and place their orders before the market opens (Li et al., 2021).

[INSERT FIGURE 5 ABOUT HERE]

With regard to the diurnal order flow imbalance, Panel (b) of Figure 5 shows that the number of calls bought on average exceeds the number of calls sold in most intervals of the day. Towards the end of the trading day, however, the imbalance decreases and turns negative for the interval 17:15-17:30. Although a gradual diurnal decrease in the order flow imbalance is also observed for puts, there is no interval with a negative imbalance. This pattern is likely caused by day traders closing their positions towards the end of the day. Issuers are aware of these traders and tend to charge higher mark-ups in the morning (Baule et al., 2018).

4.1.2 Response of the order flow intensity

We begin by examining the response of the order flow intensities to recent intra-day returns of the DAX. Therefore, we denote the intra-day return of the DAX on day t within the 15-minute interval i, as defined above, as $INTRA_{t,i}$. We denote the lags $j = 1,\ldots,8$ of this variable as $INTRA_{t,i-j}$. Since we are only interested in responses to intra-day returns, we set $INTRA_{t,i-j} = 0$ if $i - j \leq 0$. This way, we can analyze the investors' response to a moving window of intra-day returns of up to two hours.

To assess whether intra-day returns are distinct trade-motivating factors, we control for other potential factors. First, we control for the response to recent inter-day returns of the underlying (Baule and Blonski, 2012; Schmitz and Weber, 2012). Here, we consider three lags of daily returns, measured from close to close and denoted as $INTER_{t-k}$ for $k = 1,2,3$, as well as the overnight return $NIGHT_t$. Second, we consider squared returns, defined as $INTRA^2_{t,i}$, $INTER^2_t$ and $NIGHT^2_t$, respectively, to control for non-linear responses. Third, we introduce the binary variable

$$ROUND_{t,i} = \begin{cases} 1 \text{ if DAX passes a multiple of 100 within interval } i, \\ 0 \text{ if DAX passes no multiple of 100 within interval } i, \end{cases} \tag{5}$$

to control for intra-day trading activity clusters at round numbers (Niederhofer, 1965; Bhattacharya et al., 2012; Kuo et al., 2015; Chen, 2018). Fourth, we control for the impact of general market conditions on the trading activity. For this purpose, we use the one-day lagged implied DAX volatility $VOLA_{t-1}$, measured by the VDAX-NEW. Fifth, we control for diurnal and weekly seasonal effects as well as monthly variability in the trading activity (Chordia et al., 2001). Finally, the choice of regression model allows us to control for remaining serial correlation and persistence in the order flow. This may result from positioning around news events (Barber and Odean, 2008; Riordan et al., 2013; Meyer et al., 2014), chart patterns (Grinblatt and Keloharju, 2001; Kavajecz and Odders-White, 2004; Bender et al., 2013) or herding in general (Dorn et al., 2008; Barber et al., 2009a).

We employ a generalized linear autoregressive moving average model of order $p = 1$ and $q = 1$ with covariates, introduced by Davis et al. (1999, 2003, 2005). The model accounts for the principal features of our data by specifying the log of the conditional mean Poisson process as a function of previous counts and covariates. We choose the most parsimonious model order still able to capture persistence. We define our baseline GLARMA(1,1) model for a general count of trades $y_{t,i}$ as follows:

$$y_{t,i} | \mathcal{F}_{t,i} \sim Po(\mu_{t,i}) \tag{6}$$

where Po is the Poisson density,

$$\begin{aligned} \log \mu_{t,i} = & \sum_{j=1}^{8} \beta_{1,j} INTRA_{t,i-j} + \beta_2 NIGHT_t + \sum_{k=1}^{3} \beta_{3,k} INTER_{t-k} \\ & + \sum_{j=1}^{8} \beta_{4,j} INTRA^2_{t,i-j} + \beta_5 NIGHT^2_t + \sum_{k=1}^{3} \beta_{6,k} INTER^2_{t-k} \\ & + \beta_7 ROUND_{t,i} + \beta_8 VOLA_{t-1} + \sum DUMMIES + z_{t,i} \end{aligned} \tag{7}$$

and $z_{t,i} = \phi_1(z_{t,i-1} + e_{t,i-1}) + \theta_1 e_{t,i-1}$, with $e_{t,i} = (y_{t,i} - \mu_{t,i})/\mu_{t,i}^{0.5}$, $e_{t,i} = z_{t,i} = 0$ for $t \leq 0$, and $e_{t,i-j} = e_{t-1,36-j}$, $z_{t,i-j} = z_{t-1,36-j}$ for $i - j \leq 0$. The variable $\mu_{t,i}$ denotes the mean or intensity of the process conditioned on its own history and covariates. The variable $e_{t,i}$ is a martingale difference and $z_{t,i}$ is an autoregressive moving average recursion with parameters ϕ_1 and θ_1 that capture the serial dependence. Following Jung and Tremayne (2011), we set the parameter termed λ by Davis et al. (2005) equal to 0.5. Fixed effects involve month dummies, weekday dummies and 15-min interval-of-day dummies. Where necessary, we exclude one effect to prevent linear combinations. To address concerns about the impact of missing variables, we additionally consider a modified regression, where the fixed effects for weekdays and months are substituted with a dummy variable for each day of the year. This dummy controls for all effects measured on the daily frequency. Accordingly, we drop all other daily variables. Estimation is carried out using a maximum likelihood approach along the lines of Davis et al. (2005).

Table 3 presents the results of the time series regressions, where we replace $y_{t,i}$ with our order flow measures $CALLBUY_{t,i}$, $CALLSELL_{t,i}$, $PUTBUY_{t,i}$ and $PUTSELL_{t,i}$, respectively. Here, the entire sample of orders is considered regardless of the order type. The signs of the coefficients of the intra-day returns are negative for calls bought and positive for calls sold. This indicates that the buying (selling) intensity of calls increases following negative (positive) intra-day returns. Since the sensitivity of put prices towards price changes in the underlying is opposite to that of calls, we would expect opposite signs for the coefficients of puts. That is indeed the case. Therefore, we find consistent and significant negative feedback trading on intra-day returns in all four categories. The investors' response tends to dampen for more distant intra-day returns and is strongest when buying calls and selling puts. In addition, for sales of calls and purchases of puts, the first two lags of squared intra-day return are significantly positive. For calls (puts), a one standard deviation shock to the intra-day return (0.14%) translates via the corresponding coefficients to a decrease (increase) in the buying intensity of -8.71% (6.39%) and an increase (decrease) in the selling intensity of 7.41% (-9.66%). However, for trending intra-day returns, investors' memory of more distant return lags amplifies these effects tremendously. The respective impulse response functions are shown in Figure 6. Overall, the negative feedback, contrarian behavior of individual investors is reflected in the way they buy and sell calls and puts within a day.

Investors also respond to the some of the potentially trade-motivating control variables. In particular, they adjust their buying and selling intensity of calls in a fashion that is contrarian to the overnight return. However, for puts, the overnight return only significantly affects the selling intensity. Since the coefficients of squared overnight returns are positive and significant in all cases, investors tend to trade more after large overnight returns. Surprisingly, the intra-day order flow intensities are almost unaffected by the lagged inter-day returns. Only yesterday's return has a significant negative impact on the number of puts sold today. Moreover, we find that investors trade significantly more when the underlying crosses a multiple of 100 during the trading day. The corresponding coefficients translate to an increase in trading activity between 20% (puts bought) and 35% (puts sold). This emphasizes that individual investors monitor the underlying's price. In addition, investors tend to sell significantly more calls and buy more puts in response to increases in the implied volatility.

The autoregressive (AR) and moving average (MA) coefficients capture significant positive serial correlation, remaining after controlling for our set of trade-motivating factors. This correlation pattern is consistent for both types of warrants and trading directions. Panel (a) in Figure 7 shows the respective impulse response functions for the ARMA part. An one standard deviation impulse to the order flow intensity tends to fade slowly over several hours. Finally, we find no weekday effects in the order flow, but significant diurnal seasonal effects as already shown in Panel (a) of Figure 5.

[INSERT TABLE 3 ABOUT HERE]

[INSERT FIGURE 7 ABOUT HERE]

It is possible that our results above are influenced by the investors' preference for limit orders. Limit buy and sell orders that are not immediately marketable remain in the order book until they become marketable, are matched with an other market order or get canceled. These orders have buy (sell) limits below (above) the best ask (bid) quote.

Therefore, intra-day price declines (increases) could cause the execution of these limit buy (sell) orders. Such trades would then be consistent with negative intra-day feedback trading. However, depending on the timing of the order entry, investors would not be able to observe the intra-day returns prior to execution in the future and therefore would not be able to respond to them. Moreover, an investor entering a non marketable limit buy order would probably not mind if his order is filled following an overnight or an intra-day price decline. Consequently, we must assume that part of the contrarian intra-day order flow is not due to conscious responses to intra-day returns.

To analyze the unbiased response to intra-day returns observable at the time of order entry, we use the subsample of market orders. Table 4 reports the results of Table 3 for this subsample. Although the response of the put buying intensity towards the first two intra-day return lags vanishes, the negative response to intra-day returns remains significant in the majority of cases. Thus, we conclude that the aggregate of individual investors consciously responds to intra-day returns in a contrarian fashion.

[INSERT TABLE 4 ABOUT HERE]

In addition to the market order analysis, there are two arguments against a meaningful impact of limit orders that are not immediately marketable on our analysis. First, 75 % (80 %) of the limit buy (sell) orders are filled within six minutes (15 minutes). Since we analyze 15-minute intervals, the majority of limit orders cannot contribute coincidentally to the significance of most intra-day return lags. Second, stop loss orders, although of minor importance in our data set, cause an opposing effect which should offset at least part of the effect of non-marketable limit orders.

4.1.3 Response of the order flow imbalance

Finding return-contrarian buy and sell intensities, we investigate whether they amount to a return-contrarian net positioning of individual investors. To do so, we examine the response of order flow imbalances to intra-day returns of the DAX. In order to evaluate whether intra-day returns are distinct determinants of the net trade direction, we use the same set of control variables as above. We base the analysis on a regression model where the errors are modeled as an autoregressive moving average process of order $p = 1$ and $q = 1$. Thus, we have a parsimonious model that adequately captures the dependence structure of the order flow imbalance. We define the baseline regression model as follows:

$$\begin{aligned} y_{t,i} =& \sum_{j=1}^{8} \beta_{1,j} INTRA_{t,i-j} + \beta_2 NIGHT_t + \sum_{k=1}^{3} \beta_{3,k} INTER_{t-k} \\ &+ \sum_{j=1}^{8} \beta_{4,j} INTRA^2_{t,i-j} + \beta_5 NIGHT^2_t + \sum_{k=1}^{3} \beta_{6,k} INTER^2_{t-k} \\ &+ \beta_7 ROUND_{t,i} + \beta_8 VOLA_{t-1} + \sum DUMMIES + z_{t,i} \end{aligned} \tag{8}$$

and $z_{t,i} = \phi_1 z_{t,i-1} + \theta_1 e_{t,i-1} + e_{t,i}$, $e_{t,i} = z_{t,i} = 0$ for $t \leq 0$, and $e_{t,i-j} = e_{t-1,36-j}$, $z_{t,i-j} = z_{t-1,36-j}$ for $i - j \leq 0$. The variable $e_{t,i} \sim N(0,\sigma^2)$ is an error term. Again, fixed effects involve month dummies, weekday dummies and 15-min interval-of-day dummies to cover seasonalities. Where necessary, we exclude one effect to prevent linear combinations. Additionally, we consider a modified regression, where the fixed effects for weekdays and months are substituted with a dummy variable for each day of the year. This dummy controls for all effects measured on the daily frequency. Accordingly, we drop all other daily variables. Estimation is carried out using maximum likelihood.

Table 5 presents the results of the time series regressions, where we replace $y_{t,i}$ with our measures of order flow imbalance $IMB^{CALL}_{t,i}, IMB^{PUT}_{t,i}$ and $IMB_{t,i}$, respectively. For all categories, we find significant negative feedback trading on the intra-day time scale. Although the effect weakens for higher order lags, it remains highly significant for all lags considered. In contrast, squared intra-day returns have barely no effect. For calls (puts), a one standard deviation shock to the intra-day return (0.14%) translates via the corresponding coefficients to a decrease (increase) in the order flow imbalance of −0.104 (0.075) and a decrease in the overall imbalance of −0.088. Again, trending intra-day returns amplify these effects. The respective impulse response functions are shown in Figure 6. Overall, the results are consistent with those for order flow intensities, but provide additional evidence that the net order flow is intra-day return contrarian.

With regard to the control variables, we find that the order flow imbalances are also contrarian to the overnight return and lagged inter-day returns. While the response to yesterday's return is always significant, order flow imbalances for puts and overall are also affected by the the second and third as well as the second lag, respectively. Although investors trade significantly more when the underlying crosses a multiple of 100, the crossing has no systematic effect on the order imbalance. Moreover, an increase in the implied volatility negatively affects the order flow imbalance in calls but has no effect for puts.

The AR and MA coefficients capture significant positive serial correlation remaining after controlling for our set of trade-motivating factors. Panel (b) in Figure 7 shows the respective impulse response functions for the ARMA part. An one standard deviation impulse to the order flow imbalance tends to die out over several 15-min intervals. Finally, there are barely significant day of week effects in puts on Tuesdays and Wednesdays. The diurnal seasonal effects in calls and puts as shown in Panel (b) of Figure 5 are significant, but cancel out in the aggregate imbalance.

[INSERT TABLE 5 ABOUT HERE]

4.2 Impulses from the warrants' prices

4.2.1 Tick price directions

This subsection takes a closer look at the microstructure of trading activity. The sparse literature on the strategies of day traders indicates that they closely monitor tick price changes to determine entry and exit points (Harris and Schultz, 1998; Garvey and Murphy, 2005). Therefore, we examine whether and how individual investors use market orders to respond to the last tick direction of the warrant price when entering their orders.[16] We focus on market orders, since they reflect investors' unadulterated opinion about future prices in a timely manner (Dorn et al., 2008). In contrast to our analysis in the previous section, these incremental price changes are not necessarily due to price changes in the underlying (Bakshi et al., 2000) and they happen on short time intervals aggregated above.

Since day traders prefer stocks with higher intra-day volatility (Kyröläinen, 2008; Chung et al., 2009), we restrict our sample to warrants that had at least two price changes within

[16]We do not consider the last tick prior to the execution of an order since this measure may be biased. This is because the time between entry and execution could introduce a look-ahead bias since the investor cannot react to a tick in the future.

the 15 minutes before the order was placed. This ensures a lower bound of recent price fluctuations. For each order i, we denote the price of the respective warrant at time t as $PRICE_{i,t}$. In case of a buy (sell) order, we use ask (bid) prices. Let t_1^i be the time of the order execution, t_0^i be the time of the order entry or its last modification, t_{-1}^i and t_{-2}^i be the times of the two most recent ticks in the warrant price with $t_{-2}^i < t_{-1}^i < t_0^i$ and $t_0^i - t_{-2}^i \leq 15$ minutes. Using the binary variables

$$BUY_i = \begin{cases} 1 & \text{if the order } i \text{ is an investor's buy order,} \\ 0 & \text{if the order } i \text{ is an investor's sell order,} \end{cases} \tag{9}$$

to distinguish the trade direction and $UPTICK_i = \mathbf{1}_{\{PRICE_{i,t_{-2}^i} < PRICE_{i,t_{-1}^i}\}}$ to mark up ticks, we determine the percentage proportion of up ticks prior to buy and sell orders, as

$$Up^{\text{Buy}} = \frac{1}{\sum_i^N \mathbf{1}_{\{BUY_i=1\}}} \times \sum_i^N UPTICK_i \times \mathbf{1}_{\{BUY_i=1\}}, \tag{10}$$

$$Up^{\text{Sell}} = \frac{1}{\sum_i^N \mathbf{1}_{\{BUY_i=0\}}} \times \sum_i^N UPTICK_i \times \mathbf{1}_{\{BUY_i=0\}}, \tag{11}$$

where the indicator function $\mathbf{1}_{\{\text{Criterion}\}}$ equals 1 when the criterion is met and is zero otherwise. The methodology is summarized in Figure 8 using a timeline of possible and analyzed price paths along with relevant events.

[INSERT FIGURE 8 ABOUT HERE]

Since the tick direction is binomially distributed, we can test whether there are significant deviations from the uniform distribution before the order entry.[17]

4.2.2 Response of the trade direction

Panel A in Table 6 shows the percentage proportion of up ticks prior to the entry of a market order. The results are presented in aggregate and separated by the warrants' type and the trade direction.

[17]The empirical percentage proportion of intra-day up ticks in our entire sample, covering 4.1 billion ticks, is 0.4997.

[INSERT TABLE 6 ABOUT HERE]

We find slightly more buying after an up tick and more selling after a down tick, which is consistent with positive feedback trading. This pattern is consistent for calls and puts and deviates in aggregate significantly from the uniform distribution.

Since the tilt is small, it could be the case that investors need some time to respond to a tick. Therefore, we restrict the sample in Panel B to those orders where there is at least one minute between the last price update and the order entry. Overall, the behavior observed in Panel A is confirmed, as most proportions are shifted even more.

According to Chung et al. (2009), day traders favor lower-priced stocks. If this preference also holds for warrants, we expect the tilts to be stronger for warrants with a low price. In Panel C, we only consider warrants with an ask price of half an euro or less prior to the order entry. We find further evidence of positive feedback trading on the tick level. The results are significant in the majority of cases.

In summary, we find that some retail investors use market orders to positive feedback trading on the tick level. This effect is more pronounced for trades in low-priced warrants with at least one minute response time to the last tick. We interpret this finding as indicating that there is a small subgroup of retail investors that behaves more like professional investors than their peers. This subgroup continuously monitors the prices of warrants and anticipates high-frequency momentum in the prices of both calls and puts.

[INSERT FIGURE 8 ABOUT HERE]

5 Feedback pricing

5.1 Response of the price level

5.1.1 Methodology

In this section, we examine whether issuers systematically adjust price level and pricing intensity after an investor buys or sells a warrant. While the first subsection examines the intra-day response of warrant price levels on trade events, the second subsection focuses on the response of the pricing intensities.

There is evidence that issuers anticipate and exploit longer-term (Baule, 2011) and diurnal order flow patterns (Baule et al., 2018) in a way that they increase their prices when they expect a net investor demand overhang and decrease them when they expect a net investor supply overhang. This is subject of the order flow hypothesis (Wilkens et al., 2003).

We investigate whether and how issuers use single trades to anticipate future order flow. Since a trade in a single warrant is a relatively rare event[18], an issuer could engage in feedback pricing, responding to a trade event by adjusting the traded warrant's price level in order to position for future order flow in that particular warrant. However, there are two competing hypotheses: (i) An investor buy (sell) could indicate a high (low) attractiveness and lead further buys (sells) of other investors. (ii) An investor buy (sell) could be followed by a re-sale (re-buy) of the same investor in case she is speculating on short-term (intra-day) gains. According to (i), the issuer should increase (decrease) the warrant's mark-up after a buy (sell), according to (ii), she should decrease (increase) it after a buy (sell).

To study these feedback effects, we use Differences-in-Differences (DD). The DD approach is a popular method for estimating causal relationships and allows us to eliminate the effects of other factors, such as price changes in the warrants' underlying.[19]

We define the investors' trades as the treatment. Then, for each trade $i = 1, \ldots, N$, we denote the average price of the treated warrant before the treatment as $\overline{PRICE}_{i,0,1}$ as well as the average price after the treatment as $\overline{PRICE}_{i,1,1}$. Thus, our initial treatment group consists of all traded warrants.[20] We use a matching procedure to create the control group. For each trade in a warrant, we look for an identical warrant from a different issuer that was not traded within the investigation period (2014) and for which we observe at least one tick within 60 minutes before and after the treatment.[21] If there is more than

[18]In our sample, there are on average 425 trades per day, spread over nine issuers.

[19]Recent examples, among others, of the usage of DD in a similar context are Arnold et al. (2021), Pelster and Schertler (2019) and Pelster and Hofmann (2018).

[20]Note that we consider a warrant multiple times if it has been treated multiple times.

[21]The warrants are identical in terms underlying, strike and time to maturity.

one match, we only add the warrant to our control group whose price is closest to the treated warrant .[22] If there are multiple treatments of a warrant on the same day, the same warrant is matched on that day. If there is no match, we discard the trade from the treatment group.[23] We denote the pre-treatment price of the respective control warrant as $\overline{PRICE}_{i,0,0}$, and the post-treatment price as $\overline{PRICE}_{i,1,0}$. This matching procedure ensures that common valuation effects, such as movements in the underlying, cancel out.[24] By introducing the group membership variable $g \in \{0,1\}$ and the time variable $p \in \{0,1\}$, we define the average price in general terms as $\overline{PRICE}_{i,g,p}$ and $\overline{TICK}_{i,g,p}$. This leaves us with a total of four observations per trade i.

The price $\overline{PRICE}_{i,g,p}$ is the time-weighted average price within the overlapping period of observed tick prices of the treatment and control warrant within 60 minutes before and after the trade. Formally, we caluculate

$$\overline{PRICE}_{i,g,0} = \sum_{t=\underline{t}^i}^{t_0^i} PRICE_{i,g,t}/(t_0^i - \underline{t}^i), \tag{12}$$

$$\overline{PRICE}_{i,g,1} = \sum_{t=t_0^i}^{\overline{t}^i} PRICE_{i,g,t}/(\overline{t}^i - t_0^i), \tag{13}$$

where time t is measured in millisecond increments, t_0^i is the time of the trade, $t_{-1}^{i,g}$ is the time of the first tick within 60 minutes before the trade, $t_1^{i,g}$ is the time of the last tick within 60 minutes after the trade, $\underline{t}^i = \max\{t_{-1}^{i,1}, t_{-1}^{i,0}\}$, $\overline{t}^i = \min\{t_1^{i,1}, t_1^{i,0}\}$. The methodology is summarized in Figure 9. Note that it accounts for asynchronous pricing.

[INSERT FIGURE 9 ABOUT HERE]

[22] As an alternative, we add the warrant with the highest number of ticks and rerun our analysis. The results are robust to this change in the matching procedure.

[23] Finally, we remove pairs from the top 10% quantiles of absolute and relative price differences between treatment and control warrant to eliminate possible mismatches and data errors.

[24] Only a possible effect from differences in changes in the issuers' credit risk remains. Since our focus is on intra-day effects, we consider this effect neglectable. Anyway, we account for its possibility with a fixed effect.

For each trade i, the respective group membership g of the observation $\overline{PRICE}_{i,g,p}$ is given by the binary variable

$$TREAT_{i,g} = \begin{cases} 1 \text{ if } g = 1 \text{ in } \overline{PRICE}_{i,g,p}, \\ 0 \text{ if } g = 0 \text{ in } \overline{PRICE}_{i,g,p}. \end{cases} \tag{14}$$

Furthermore, the binary variable

$$POST_{i,p} = \begin{cases} 1 \text{ if } p = 1 \text{ in } \overline{PRICE}_{i,g,p}, \\ 0 \text{ if } p = 0 \text{ in } \overline{PRICE}_{i,g,p}, \end{cases} \tag{15}$$

indicates whether the observation $\overline{PRICE}_{i,g,p}$ concerns the period before or after the treatment.

With the variables above, we set up our baseline DD regression as follows:

$$\overline{PRICE}_{i,g,p} = \alpha_i + \beta_1 TREAT_{i,g} + \beta_2 POST_{i,p} + \beta_3 POST_{i,p} \times TREAT_{i,g} + \epsilon_{i,g,p}, \tag{16}$$

where α_i is a fixed effect for each trade covering all common pricing-specifics of each warrant pair at the time of trade. The coefficient of the variable $TREAT_{i,g}$ accounts for the mean difference in the average prices of the treatment and control warrants. The coefficient of the variable $POST_{i,p}$ captures the mean change in the average prices after a treatment. Since these variables cover all pricing-specific aspects, no further control variables are needed. The coefficient of the interaction term between $TREAT_{i,g}$ and $POST_{i,p}$ captures the additional mean change in the average prices of treated warrants after a treatment and thus represents possible feedback pricing effects.

Using daily data, Pelster and Schertler (2019) show that issuers engage in cross-pricing when supplementary products are sold by the issuer. In particular, they show that the magnitude of this effect depends on the trading volume. To analyze whether the degree of feedback pricing similarly differs with respect trading volume, we indicate high-volume trades with the binary variable

$$HIGH_i = \begin{cases} 1 \text{ if the volume of trade } i \text{ exceeds 10,000 euros}, \\ 0 \text{ if the volume of trade } i \text{ does not exceed 10,000 euros}. \end{cases} \tag{17}$$

With the variable $HIGH_i$ we modify the baseline DD regression (16) as follows:

$$\begin{aligned}\overline{PRICE}_{i,g,p} =& \alpha_i + \beta_1 TREAT_{i,g} + \beta_2 TREAT_{i,g} \times HIGH_i \\ &+ \beta_3 POST_{i,p} + \beta_4 POST_{i,p} \times HIGH_i + \beta_5 POST_{i,p} \times TREAT_{i,g} \\ &+ \beta_6 POST_{i,p} \times TREAT_{i,g} \times HIGH_i + \epsilon_{i,g,p}.\end{aligned} \tag{18}$$

The variable $HIGH_i$ is only included as part of interaction terms, as the variable itself is a linear combination of fixed effects. The coefficient of the interaction term $POST_{i,p} \times TREAT_{i,g} \times HIGH_i$ captures the additional mean change in the average prices of treated warrants after a high volume treatment. Similarly, the other two interaction terms with the variable $HIGH_i$ capture additional differences, that are exclusive to high-volume treatments.

Above, we argued that there are two competing hypothetical feedback pricing strategies. However, regardless of the strategy employed, it is unlikely that an issuer would react on a homogeneous sequence of buys or sells in the same fashion ad infinitum. This is because upper bounds for the margins might arise from prices set by competing issuers for similar or identical products in combination with the investors price sensitivity (Baule, 2011; Baule and Blonski, 2015), and lower bounds might arise from the prices of duplicating options. Therefore, we assume that the response to the first trade of the day in a warrant could give a clearer picture of feedback pricing, while the responses to latter trades of the day might be clouded by these bounding issues. To capture feedback effects exclusive to the first trade per warrant and trading day, we introduce with the binary variable

$$FIRST_i = \begin{cases} 1 \text{ if the warrant is treated for the first time on the treatment day,} \\ 0 \text{ if the warrant was treated on the treatment day before.} \end{cases} \tag{19}$$

With the variable $FIRST_i$, we modify the baseline DD regression (16) analogous to (18):

$$\begin{aligned}\overline{PRICE}_{i,g,p} =& \alpha_i + \beta_1 TREAT_{i,g} + \beta_2 TREAT_{i,g} \times FIRST_i \\ &+ \beta_3 POST_{i,p} + \beta_4 POST_{i,p} \times FIRST_i + \beta_5 POST_{i,p} \times TREAT_{i,g} \\ &+ \beta_6 POST_{i,p} \times TREAT_{i,g} \times FIRST_i + \epsilon_{i,g,p},\end{aligned} \tag{20}$$

Again, that the variable $FIRST_i$ is only included as part of interaction terms, as the variable itself is a linear combination of fixed effects. The coefficients of the interaction term

$POST_{i,p} \times TREAT_{i,g} \times FIRST_i$ captures the additional mean change in the average prices of treated warrants after the first treatment of the day. Similarly, the other two interaction terms with the variable $FIRST_i$ capture additional differences that are exclusive to the first treatment of the day.

5.1.2 Results

Table 7 presents the results for the DD regression models given by (16) in columns one and two, (18) in columns three and four, and (20) in columns five and six. To capture nuances in the issuer pricing strategies, we run the regressions separately for purchases and sales. For the baseline regression (16) of buys and sells, we find that the coefficients of the interaction term are slightly positive and significantly different from zero. However, the size of the effect is economically insignificant. A possible reason for this could be that the price level feedback differs with respect to volume and time. Therefore, we run the regression (18) and analyze differences in terms of trading volume. Although the additional mean price changes that are exclusive to treated warrants after the treatment are slightly significant in a statistical sense, they remain economically insignificant for high and low volume trades. Besides the volume differentiation, it is plausible that the feedback could differ with respect to the timely order of trades in a warrant. These differences are analyzed by the regression (20). Again, we find some statistically significant but economically insignificant effects of the coefficients that capture the additional mean price changes exclusive to treated warrants after the first daily treatment. Overall, the observed mean feedback pricing effects are at most roughly a tenth of a cent. Even after considering the fact that we analyze differences in differences of time-weighted average prices, we conclude that the effect is too low in order to be considered evidence of economically significant feedback pricing by issuers as a group.

A reason for our lack of evidence on feedback pricing could be that not all issuers employ such strategies and that those who do might use opposing strategies. Consequently, it would be difficult to detect feedback pricing in the aggregate across all issuers. To address this cross-sectional issue, we rerun our regressions separately for each issuer. The results are not tabulated here, but are similar to those shown for the aggregate. There is no evidence of economically significant feedback pricing in terms of the price-level.

The remaining variables in the regressions provide additional insights. First, the coefficient of the variable $TREAT_{i,g}$ is significantly negative in all regressions. This indicates that treated warrants are on average cheaper than control warrants before the treatment. Put differently, at the time of trade there was at least one identical warrant offered by an other issuer that was on average more expensive. This is consistent with the finding that individual investors' demand for warrants is margin sensitive and that they tend to buy the cheaper product (Baule and Blonski, 2015). Furthermore, the coefficient of the interaction term $TREAT_{i,g} \times FIRST_i$ in the regression (20) is significantly positive for both buys and sells. This indicates that the price difference between treated and control warrants is higher for subsequent trades of a day than for the first trade of a day. In light of Baule et al. (2018), we attribute this to a systematic decrease of mark-ups through out the day to exploit the diurnal imbalance in order flow. This pricing strategy seems to effect particularly treated warrants. Second, we find a statistically and economically significant pattern for the effect of the variable $POST_{i,p}$. For all regressions considered, the coefficient of this variable is negative for purchases and positive for sales. This indicates that intra-day timing of trades is poor on average. On average, investors could have bought lower and sold higher within an hour after a trade. The effect remains, even after controlling for the timely order of the trades. This finding is consistent with Barrot et al. (2016), who document that individual investors experience a negative return on average on the day of a trade.

[INSERT TABLE 7 ABOUT HERE]

Although, we find no evidence of feedback pricing in terms of the price level, we add to the evidence that issuers adjust mark-ups to exploit the diurnal order flow imbalance. In addition, we document that investors prefer to trade cheaper warrants when identical warrants are available by multiple issuers. Finally, we document poor intra-day timing ability.

5.2 Response of the pricing intensity

5.2.1 Methodology

While the motivation for studying price levels is clear, as they obviously affect issuers' and investors' profit and loss, the motivation for studying pricing intensities may not be. However, the pricing intensity, measured as the number of quote updates per minute, is also highly relevant to the success of both parties. This is because the opportunity for latency arbitrage from the investor's perspective and the risk from the issuer's perspective both depend on the pricing intensity.

In the context of trading, Wah and Wellman (2016) define latency as the time needed to receive, process, and act upon new information. Consequently, a latency arbitrage opportunity arises, when an advantage in access and response time enables a trader to book a certain profit. While this strategy is usually associated with algorithmic high-frequency traders (Wah and Wellman, 2016; Wah, 2016), it is possible that there are some retail investors who exploit latency arbitrage opportunities in the market for warrants, though on a much lower frequency. In this market, such an opportunity arises, when an issuer's pricing policy would require a price increase at time t, that is only quoted at time $t+1$. Then, an investor who buys at the price at time t gets the warrant, at the expense of the issuer, too cheap. Contrary, when an issuer's pricing policy would require a price decrease at time t, that is only quoted at time $t+1$. Then, an investor who owns the warrant and sells at time t, receives a price, at the expense of the issuer, too high. Even if the size of the price difference between t and $t+1$ would not guarantee a certain profit to the investor, this trading behavior is certainly detrimental to the issuer's success.

As there are often similar and identical warrants from different issuers as well as regular options, investors can compare prices and ticks in order to spot a lagging quote. Despite of this, there are two reasons why issuers might not quote all of their warrants all the time at the highest intensity possible: (i) As the majority of retail investors is relatively uninformed and algorithmic trading is prohibited on the EUWAX, the risk of large scale latency arbitrage may be rather low for issuers. (ii) The number of structured products offered per issuer is huge and pricing all of them at a high intensity comes at a computational cost.

Due of the trade-off in (ii), we hypothesize that issuers prioritize the pricing intensity of warrants that are currently in the focus of investors and that they use trades in order to do so. This hypothesis stems from a repeatably observable pricing pattern, that is illustrated in Figure 10 by an empirical example. It shows the intra-day pricing behavior of two different issuers for warrants with identical features within 60 minutes before and after the warrant in Panel (a) is traded. Before the trade, both issuers updated prices similarly. While the issuer in Panel (a) responds to the purchase of the warrant with an increase of the pricing intensity, the issuer of the nontraded warrant in Panel (b) does not change his pricing intensity.

[INSERT FIGURE 10 ABOUT HERE]

To analyze this feedback pricing strategy more formally, we follow the same methodology as used for the price level. We define the number of ticks per minute within the overlapping time window of observed tick prices of the treatment and control warrant within 60 minutes before and after the trade as

$$\overline{TICK}_{i,g,1} = \sum_{t=\underline{t}^i}^{t_0^i} \mathbf{1}_{\{PRICE_{i,g,t} \neq PRICE_{i,g,t-1}\}} / (t_0^i - \underline{t}^i), \tag{21}$$

$$\overline{TICK}_{i,g,0} = \sum_{t=t_0^i}^{\bar{t}^i} \mathbf{1}_{\{PRICE_{i,g,t} \neq PRICE_{i,g,t-1}\}} / (\bar{t}^i - t_0^i), \tag{22}$$

where time t is now measured in minutes. Thus, our baseline DD regression is

$$\overline{TICK}_{i,g,p} = \alpha_i + \beta_1 TREAT_{i,g} + \beta_2 POST_{i,p} + \beta_3 POST_{i,p} \times TREAT_{i,g} + \epsilon_{i,g,p}, \tag{23}$$

where α_i is a fixed effect for each trade covering all common pricing-specifics of each warrant pair at the time of trade. The coefficient of the variable $TREAT_{i,g}$ accounts for the mean difference in the average pricing intensity of the treatment and control warrants. The coefficient of the variable $POST_{i,p}$ captures the mean change in the average pricing intensity after a treatment. Since these variables cover all pricing-specific aspects, no further control variables are needed. The coefficient of the interaction term between

$TREAT_{i,g}$ and $POST_{i,p}$ captures the additional mean change in the average pricing intensity of treated warrants after a treatment and thus represents possible feedback pricing effects.

Following the argumentation above, we expect issuers to increase the pricing intensity in response to a trade. However, if a warrant is traded multiple times in a day, we hypothesize that issuers increase the pricing intensity after the first trade and do not increased it further with each new trade on the same day. To test whether this is the case, we modify the baseline DD regressions (23) with the variable $FIRST_i$ as follows:

$$\begin{aligned} \overline{TICK}_{i,g,p} = &\alpha_i + \beta_1 TREAT_{i,g} + \beta_2 TREAT_{i,g} \times FIRST_i \\ &+ \beta_3 POST_{i,p} + \beta_4 POST_{i,p} \times FIRST_i + \beta_5 POST_{i,p} \times TREAT_{i,g} \\ &+ \beta_6 POST_{i,p} \times TREAT_{i,g} \times FIRST_i + \epsilon_{i,g,p}. \end{aligned} \tag{24}$$

The variable $FIRST_i$ is only included as part of interaction terms, since the variable itself is a linear combination of fixed effects. The coefficients of the interaction term $POST_{i,p} \times TREAT_{i,g} \times FIRST_i$ captures the additional mean change in the average prices or respectively the pricing intensity of treated warrants after the first treatment of the day. Similarly, the other two interaction terms with the variable $FIRST_i$ capture additional differences that are exclusive to the first treatment of the day.

5.2.2 Results

Table 8 presents the results for the DD regression models given by (23) in columns one and two and (24) in columns three and four. To capture nuances in the pricing strategies, we run the regressions separately for purchases and sales. For the baseline regressions of buys and sells, we find that the coefficients of the interaction term are significantly positive. This suggests that issuers update their quotes more frequently after a trade, regardless of its direction.

To examine the pricing intensity in more detail, we account for the timely order of trades per warrant in the regression (24). Although the additional mean change in the pricing intensity exclusive to treated warrants after the treatment remains significantly positive, this change is significantly higher for those treated for the first time on a day. Compared to the unconditional mean pricing intensity in Table 1, these feedback effects correspond to economically significant increases of more than 100%.

In addition, the coefficients of the variables $TREAT_{i,g}$ and $TREAT_{i,g} \times FIRST_i$ show that treated warrants are quoted only slightly more frequently than their control warrants before the first treatment on a given day. However, after the first trade but before subsequent trades on the same day, the pricing intensity is already elevated. This suggests that issuers increase the pricing intensity for a warrant after it is traded for the first time on a given day. The elevated intensity then persists for the rest of the day. Finally, there are no common changes in the pricing intensity between treated and control warrants that are economically significant. This strengths the case that changes in the pricing intensity are due to a deliberate issuer pricing policy.

[INSERT TABLE 8 ABOUT HERE]

To visualize the treatment effect on the pricing intensity, we follow Dawson and Richter (2006) and rewrite equation (24) as

$$\begin{aligned}\overline{TICK}_{i,g,p} =& \alpha_i + (\beta_3 POST_{i,p} + \beta_4 POST_{i,p} \times FIRST_i) \\ & + (\beta_1 + \beta_2 FIRST_i + \beta_5 POST_{i,p} \\ & + \beta_6 POST_{i,p} \times FIRST_i) \times TREAT_{i,g} + \epsilon_{i,g,p}.\end{aligned} \tag{25}$$

Since we are only interested in differences in the pricing intensity due to the binary variables, we can neglect α_i. The first set of parentheses in the equation then represents the intercept on a graph of $\overline{TICK}_{i,g,p}$ against $TREAT_{i,g}$. The part in the second set of parentheses represents the slope of the line. Conditioning on the binary variables, there are four lines with different slopes and intercepts visualizing the overall treatment effect in all cases. These lines are shown in Figure 11. They underline the interpretation given above.

[INSERT FIGURE 11 ABOUT HERE]

To examine the behavior in the cross-section of issuers, we rerun the regressions based on (24) for each issuer separately but jointly for buys and sells. The results are presented in

Table 9 and show that all issuers adjust the pricing intensity similarly in response to a trade.

[INSERT TABLE 9 ABOUT HERE]

Finally, there might be an alternative explanation for the observed feedback pricing: Increasing the pricing intensity after a trade might encourage the investor to trade more, as it increases the number of price impulses to react on. This could than be understood as an attempt to exploit individual investors' preferences for gambling (Kumar, 2009), entertainment (Dorn and Sengmueller, 2009) and attention-grabbing investments as well as sensation-seeking in general (Barber and Odean, 2008; Grinblatt and Keloharju, 2009). However, we believe the first explanation to be more convincing.

Overall, we provide evidence that issuers in our sample increase the pricing intensity on a daily basis after the first trade. This elevated pricing intensity then tends to persist for the rest of the day.

6 Conclusion

The existing literature documents little about the factors that motivate retail investors to trade on the intra-day time scale. Using a unique data set of exchange trades and issuer quotes for bank-issued warrants on the DAX, we analyze the intra-day feedback trading behavior of retail investors and the feedback pricing behavior of issuers.

First, we analyze the investors' response to intra-day price changes in the underlying of the warrants for intervals of the last two hours. We find that retail investors' order flow intensity and imbalance respond in a negative feedback, contrarian fashion to past intra-day returns. Moreover, we show that this pattern cannot be explained by order type preferences alone and that intra-day returns are distinct from other trade-motivating factors. We therefore conclude that the aggregate of individual investors actively and consciously responds to intra-day returns. In addition, we find that they respond negatively to the overnight return as well as to low lags of inter-day returns. They are also prone to round number effects, trade more at market opens, execute gradually fewer buy trades in excess of sell trades throughout the day and form clusters of high and low order flow.

Second, we examine whether retail investors respond to short-term price changes in the warrant itself. From the proportion of up ticks before order entries, we find that some investors tend to use market orders to positive feedback trade on the direction of the last tick.

Third, we analyze whether issuers exploit the high level of product fragmentation and their pricing power to take advantage of investors by adjusting the mark-up of single products in response to trades. Although we find no evidence that issuers employ such a feedback pricing strategy, our analysis reveals a common feedback pricing strategy in terms of the pricing intensity. We find evidence that all issuers in our sample significantly increase the number of price updates per minute after the first trade of a warrant on a daily basis. Given the large number of products issued combined with limited computing power, we suspect that this strategy is a protection against latency arbitrage.

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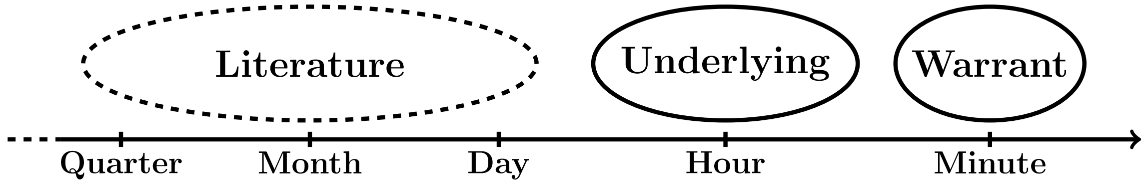
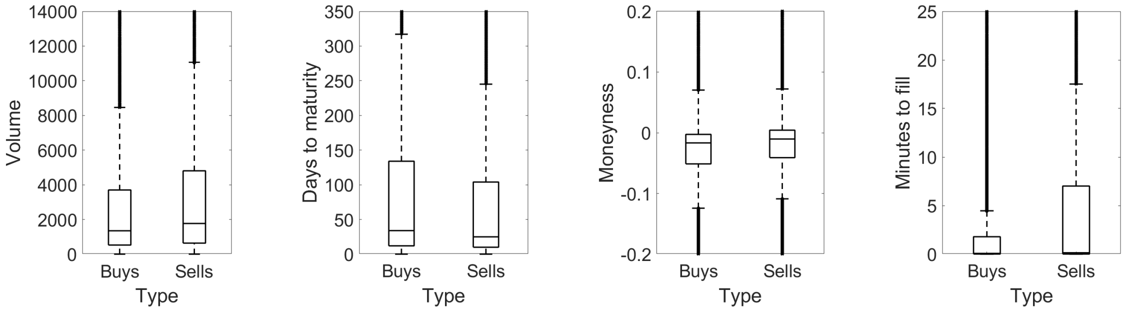


Figure 1. ***Timeline.*** *The figure outlines the analysis on feedback trading in this paper in terms of the examined time horizons and sources of return impulses as well as the state of the literature.*



(a) *Volume in euros.* **(b)** *Days to maturity.* **(c)** *Moneyness.* **(d)** *Minutes to fill.*

Figure 2. ***Order statistics.*** *The figure shows box plots for the volume in euros (a), the days to maturity (b), the moneyness (c) and the minutes to fill (d) for the transactions in our data set. The data are grouped by the trade direction (buys ans sells). On each box, the central mark indicates the median, and the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively. The whiskers extend to data points that cover approximately 99 percent of the data under the normality assumption. Data points that do not fall into this range are marked as crosses.*

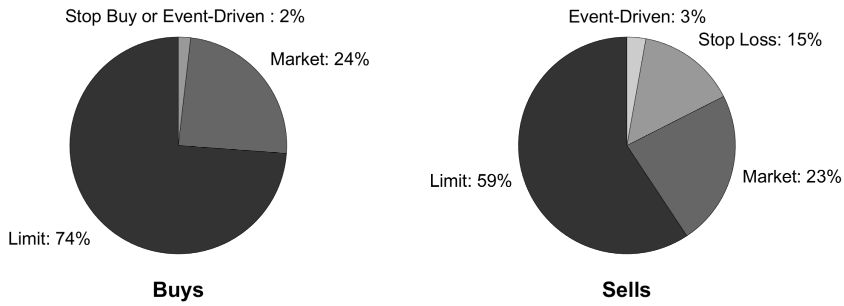
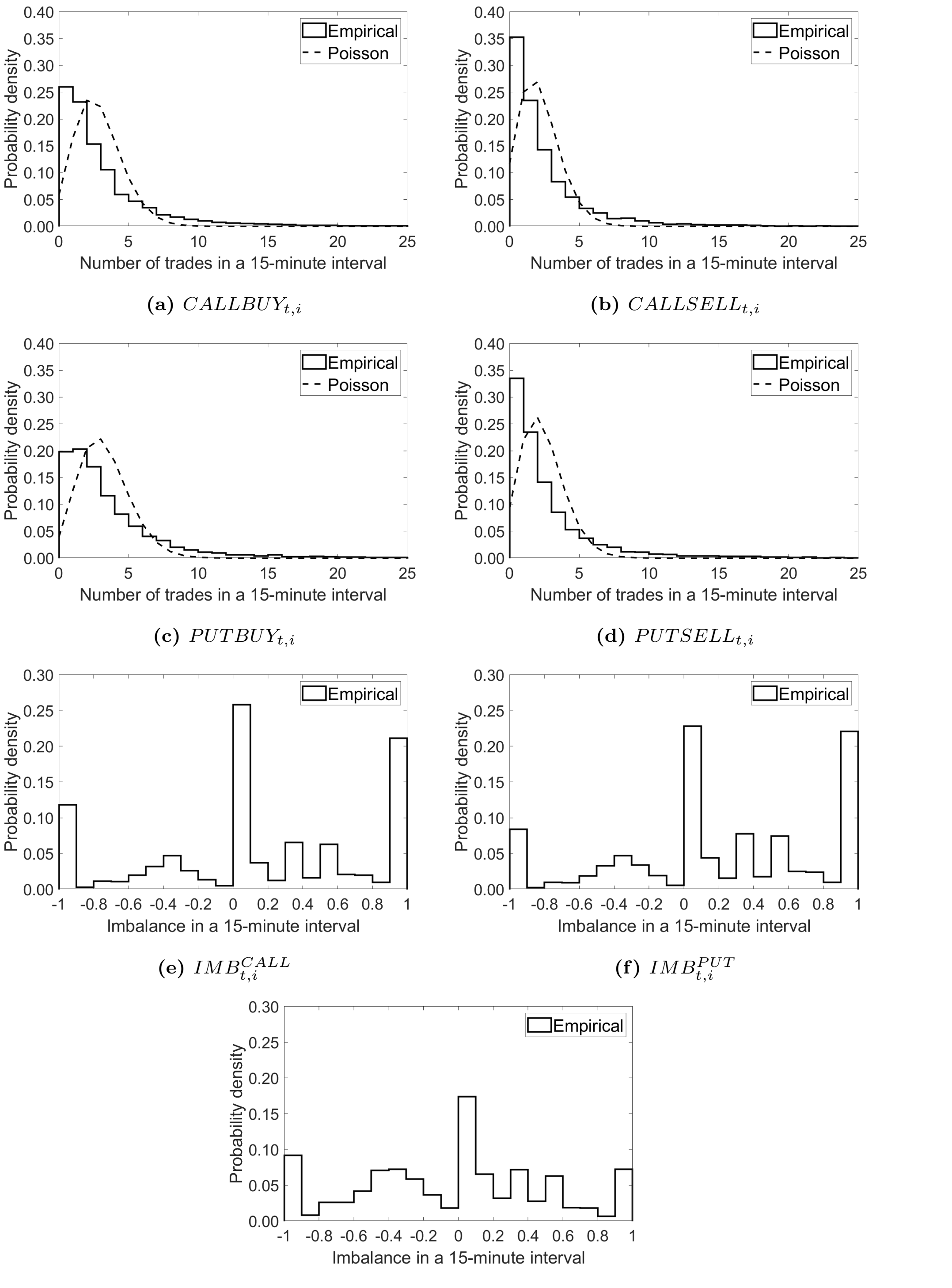
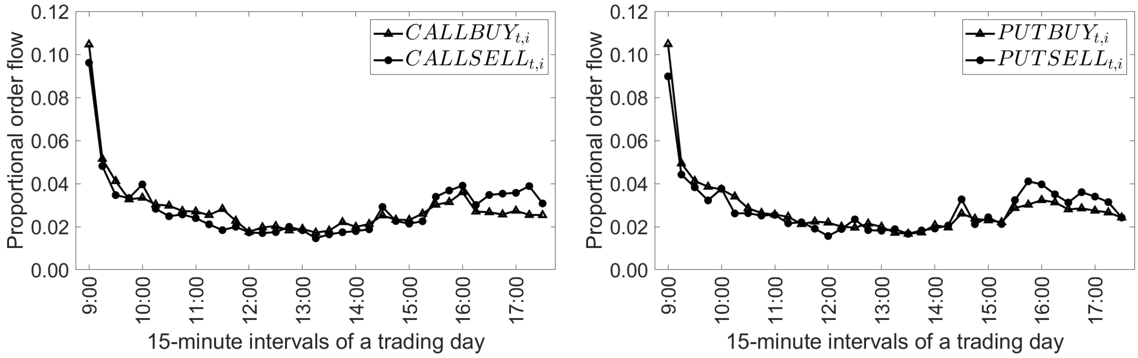


Figure 3. ***Order types.*** *The pie charts give an overview of the order types used for buy and sell orders, respectively. The category Event-Driven contains the order types Trailing Stop and One Cancels Other.*

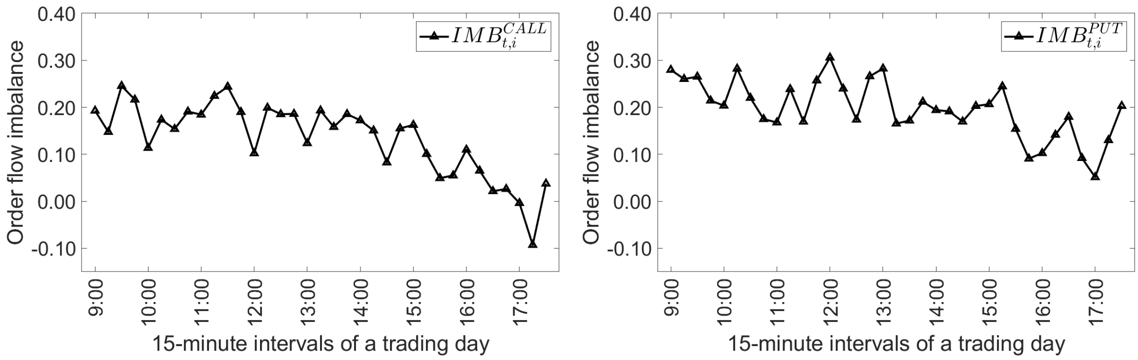


(a) $CALLBUY_{t,i}$ **(b)** $CALLSELL_{t,i}$ **(c)** $PUTBUY_{t,i}$ **(d)** $PUTSELL_{t,i}$ **(e)** $IMB^{CALL}_{t,i}$ **(f)** $IMB^{PUT}_{t,i}$ **(g)** $IMB_{t,i}$

Figure 4. ***Histograms of order flow intensity and imbalance.*** *For each variable we group the data into bins. Panels (a) to (d) show the empirical and unconditional Poisson densitiy of the number of trades grouped into bins with a width of 1. Panels (e) to (g) show the imbalance of the order flow grouped into bins with a width of 0.1.*

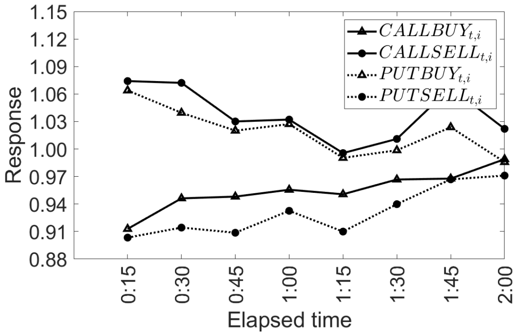


(a) *Diurnal proportional order flow intensity.*

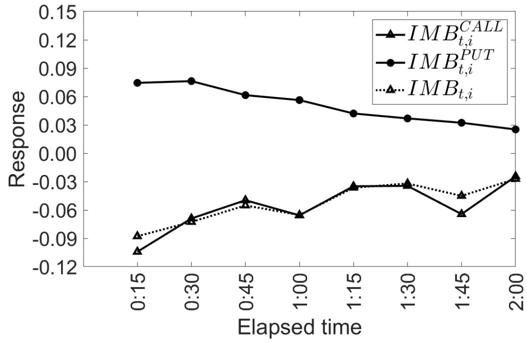


(b) *Diurnal order flow imbalance.*

Figure 5. ***Diurnal figures of proportional order flow intensity and order flow imbalance.*** *Each trading day between 9:00 a.m. and 17:45 p.m. CET is divided into 15-minute intervals. Panel (a) shows the diurnal proportional number of trades. For each 15-minute interval in a trading day, we calculate the number of trades and then divide it by the total daily number of trades. The results are separated by the warrant's type and the trade direction. Panel (b) shows the diurnal imbalance in the number of buy and sell trades. For each 15-minute interval in a trading day, we subtract the number of sell trades from the number of buy trades and then divide it by the total number of trades. The results are separated by the warrants' type. The sample period is the year 2014.*

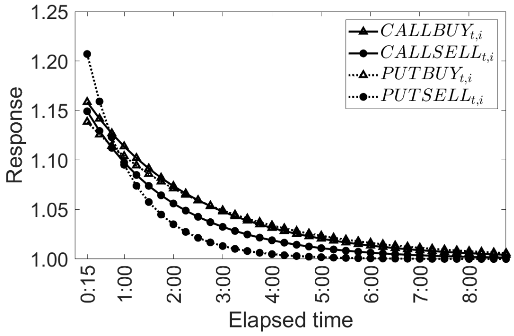


(a) *Order flow intensity.*

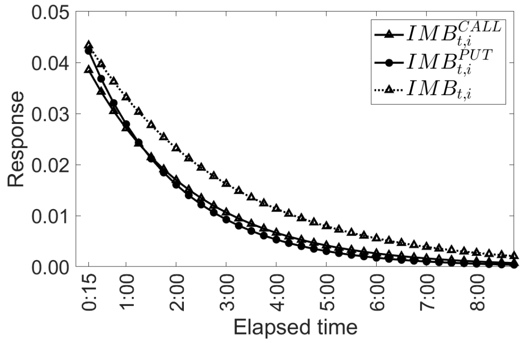


(b) *Order flow imbalance.*

Figure 6. ***Impulse response functions for an intra-day return shock.*** *Panel (a) shows the responses of an one standard deviation impulse to the variable $INTRA_{t,i}$ in estimated the baseline models in Table 3. The response is the multiplicative impact on the future order flow intensity with no further impulses in the future. Panel (b) shows the responses of an one standard deviation impulse to the variable $INTRA_{t,i}$ in the estimated baseline models in Table 5. The response is the additive impact on the future order flow imbalance with no further impulses in the future.*



(a) *Order flow intensity.*



(b) *Order flow imbalance.*

Figure 7. ***Impulse response functions for an intensity or imbalance shock.*** *Panel (a) shows the responses of an one standard deviation impulse to the order flow intensity via the ARMA part of the estimated baseline models in Table 3. The response is the multiplicative impact on the future order flow intensity with no further impulses in the future. Panel (b) shows the responses of an one standard deviation impulse to the order flow imbalance via the ARMA part of the estimated baseline models in Table 5. The response is the additive impact on the future order flow imbalance with no further impulses in the future.*

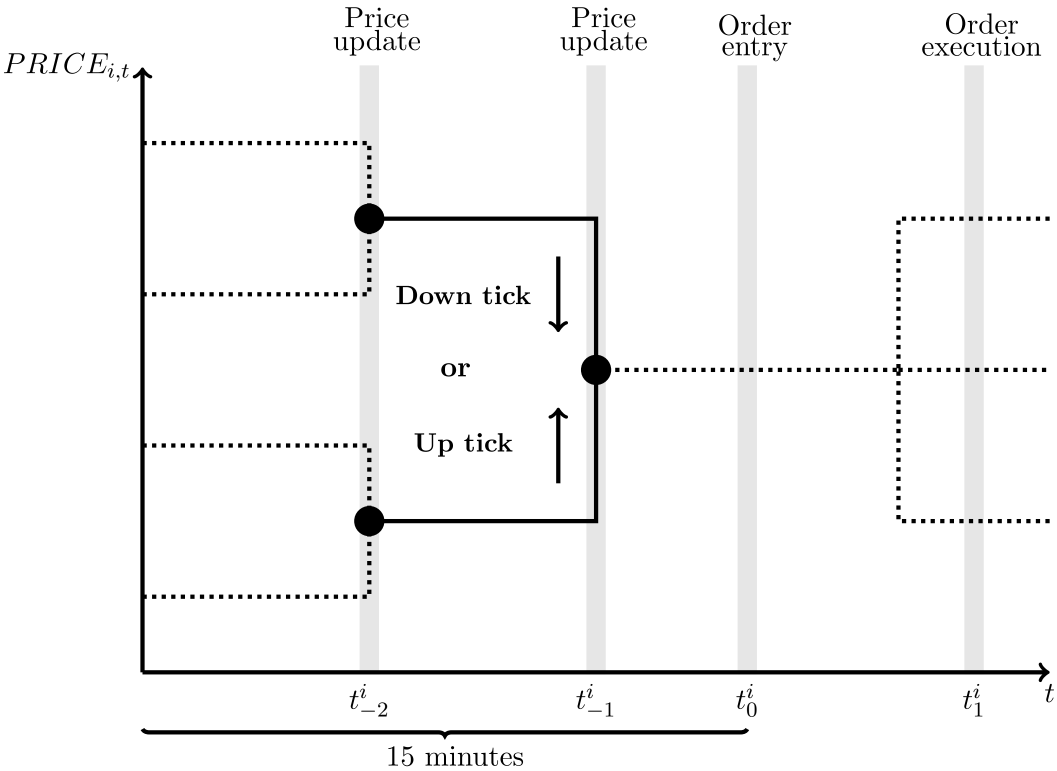


Figure 8. ***Illustration of tick price and trade direction methodology.*** *The figure shows, for an order i, the price $PRICE_{i,t}$ of the respective warrant at time t. In case of a buy (sell) order, we use ask (bid) prices. Dotted lines represent possible price paths, that are not considered in the analysis. Bold circles represent the two most recent price changes within 15 minutes prior to the order entry. The solid lines are the two possible price paths containing the tick on which we base our analysis. Empirically, we observe either the up tick or the down tick. The points in time of the analyzed price updates, the order entry, and the order execution are highlighted in gray. The time and price scales are for illustration only.*

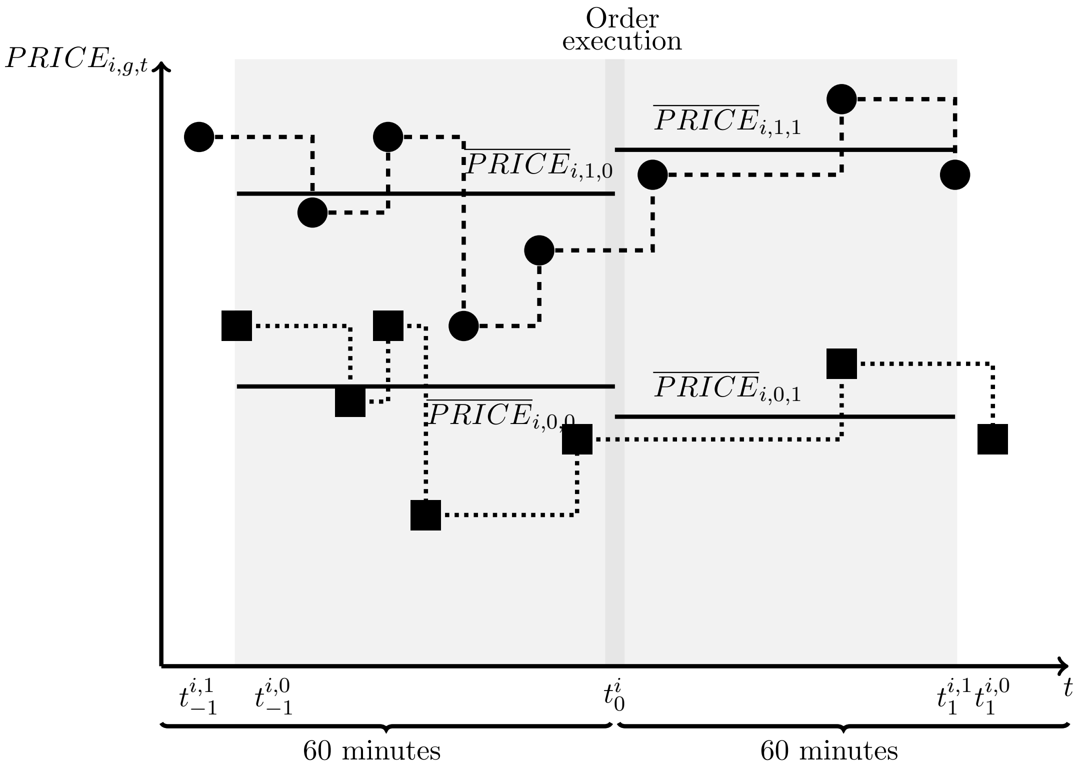
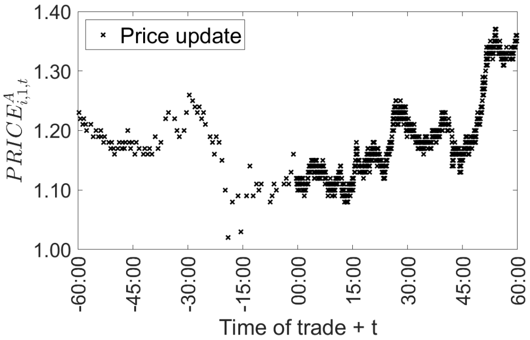
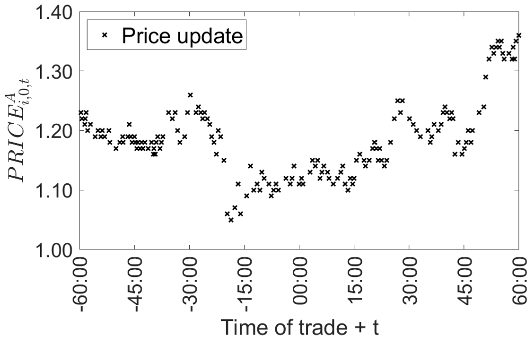


Figure 9. ***Illustration of differences-in-differences methodology.*** *The figure summarizes the calculation of the average prices $\overline{PRICE}_{i,g,t}$ used in the difference-in-differences analysis. They are represented by solid lines. For each trade i the averages are calculated from the price $PRICE_{i,g,t}$ of the respective warrant at time t. The point in time of the order execution t_0 is highlighted in dark gray. The time stamp $t^{i,g}_{-1}$ is the time of the first tick within 60 minutes before the trade and the time stamp $t^{i,g}_{1}$ is the time of the last tick within 60 minutes after the trade. The time window considered for calculating the averages is shaded in light gray. For a buy order we define $PRICE_{i,g,t} = PRICE^{A}_{i,g,t}$ and for a sell order we define $PRICE_{i,g,t} = PRICE^{B}_{i,g,t}$. Dashed lines represent a possible price path of the treated warrant. Dotted lines represent a possible price path of the respective control warrant. Bold circles and rectangles represent observed price changes within 60 minutes before and after the trade. The time and price scales are for illustration only.*



(a) *Treated warrant (GT7SWD).*



(b) *Control warrant (DE8EXF).*

Figure 10. ***Example of feedback pricing.*** *The figures show quoted ask prices for a treated call warrant from Goldman Sachs which was bought at 15:06:15 on 2014-03-12 for the first time (a), and a nontreated control warrant from Deutsche Bank (b) within 60 minutes before and after the treatment. Both warrants have identical features.*

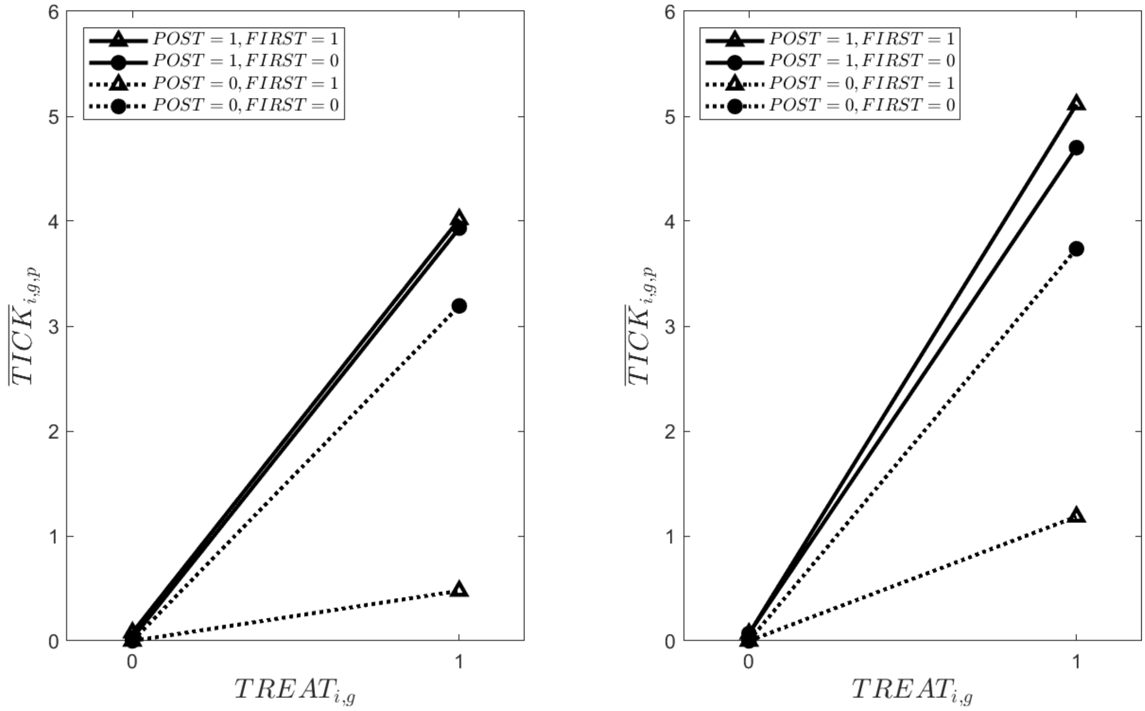


Figure 11. ***Pricing intensity and feedback pricing.*** *Three-way interaction plots illustrating slopes of* $\overline{TICK}_{i,g,t}$ *on different values of* $POST_{i,t}$ *and* $FIRST_{i,g}$*. Slope differences illustrate the treatment effect. The left (right) graph shows the model (2) for buy (sell) trades from Table 8, written in the form of equation (25) where* α_i *is dropped.*

Table 1. ***Data overview.*** *The first two columns list the number of warrants which were traded on the exchange. The third and fourth column list the number of exchange trades. The columns five to six list the total euro trading volume. The last two columns list the average number of ticks per minute within the investigation period. The data are separated by the issuer as well as the warrants' type or the investors' trade direction. The sample period covers the year 2014.*

	# Warrants traded		# Trades		Volume [Mio. euro]		# Ticks per minute	
Issuer	Call	Put	Buy	Sell	Buy	Sell	Call	Put
BNP Paribas	940	1003	6116	4558	36.67	30.25	2.21	1.31
Citigroup	897	972	7187	5329	25.32	26.31	2.02	1.62
Commerzbank	1324	1509	12405	9958	45.17	47.00	2.67	1.99
DZ BANK	494	676	3240	2341	15.88	13.91	2.51	1.53
Deutsche Bank	1366	1777	17911	12753	104.42	95.41	1.76	1.57
Goldman Sachs	809	938	3882	3346	31.68	35.81	2.50	1.72
HSBC Trinkaus	113	138	710	445	2.62	2.38	1.86	1.29
UniCredit	572	646	2656	2280	9.92	9.67	2.03	1.82
Vontobel	948	1158	6782	5104	30.86	32.36	1.93	1.61
Total	7463	8817	60889	46114	302.55	293.1	1.93	1.64

Table 2. ***Descriptive statistics of order flow intensity and imbalance.*** *The table shows descriptive statistics of the order flow per 15-minute interval. The Ljung–Box statistic Q_{10} assesses the null hypothesis that a series exhibits no autocorrelation for ten lags. For all measures, the null hypothesis is rejected as the critical value for $\alpha = 0.01$ is 23.21. The number of observations is T = 8820.*

	$CALLBUY_{t,i}$	$CALLSELL_{t,i}$	$PUTBUY_{t,i}$	$PUTSELL_{t,i}$	$IMB_{t,i}^{CALL}$	$IMB_{t,i}^{PUT}$	$IMB_{t,i}$
Mean	2.85	2.15	3.25	2.38	0.13	0.20	−0.04
Median	2.00	1.00	2.00	1.00	0.00	0.14	0.00
Std.	4.21	3.45	4.14	3.74	0.63	0.60	0.54
Skew	3.91	4.5	3.44	3.49	−0.22	−0.29	0.05
Min.	0	0	0	0	−1	−1	−1
Max.	51	68	53	42	1	1	1
Q_{10}	12511	8991	9656	9768	1520	1552	2931

Table 3. ***Order flow intensity and feedback trading.*** *The table shows the estimation results for the model given by (6) and (7). All trades are considered, regardless of their order type. The columns separate the results by the warrants' type (Call or Put) and trade direction (Buy or Sell):* $CALLBUY_{t,i}, CALLSELL_{t,i}, PUTBUY_{t,i}$ *and* $PUTSELL_{t,i}$. *Fixed effects are included, as indicated below the regression results, for each month, weekday, day and 15-minute interval of the day. Where necessary, we exclude one effect per group to prevent linear combinations. The final rows list the number of observations* T*, the number of trades* n *and the adjusted* R^2 *per regression. Inference is based on robust standard errors computed from a sandwich estimator of the covariance matrix (see, e.g., Davidson and MacKinnon, 2003, ch. 10, eq. 10.45).*

	$CALLBUY_{t,i}$		$CALLSELL_{t,i}$		$PUTBUY_{t,i}$		$PUTSELL_{t,i}$	
$INTRA_{t,i-1}$	−64.1***	−66.3***	48.7***	42.7***	30.6***	26.9***	−82.7***	−84.7***
$INTRA_{t,i-2}$	−43.4***	−51.1***	43.2***	40.9***	20.2***	19.5***	−68.7***	−76.4***
$INTRA_{t,i-3}$	−39.0***	−48.9***	18.5*	21.0*	11.4	13.7*	−68.7***	−75.2***
$INTRA_{t,i-4}$	−35.1***	−43.5***	18.3*	22.3**	16.6**	19.7**	−50.4***	−56.1***
$INTRA_{t,i-5}$	−33.8***	−41.4***	−1.8	2.4	−0.1	3.4	−58.8***	−64.4***
$INTRA_{t,i-6}$	−24.0**	−29.1***	7.0	9.4	0.1	2.1	−41.9***	−46.6***
$INTRA_{t,i-7}$	−23.1**	−26.5***	44.6***	43.0***	17.3**	18.2**	−22.3*	−28.0**
$INTRA_{t,i-8}$	−13.7	−14.4	9.1	8.5	−7.2	−5.4	−17.6	−19.5*
$NIGHT_t$	−11.50*		16.48***		−0.87		−27.39***	
$INTER_{t-1}$	0.73		3.35		1.80		−8.72***	
$INTER_{t-2}$	−0.33		1.82		1.49		−1.89	
$INTER_{t-3}$	−0.44		1.85		0.64		−0.57	
$INTRA^2_{t,i-1}$	616	441	6213***	6192***	8524***	8347***	649	−53
$INTRA^2_{t,i-2}$	3529*	3116*	5246***	6518***	4598***	5384***	-235	−710
$INTRA^2_{t,i-3}$	1420	1020	−969	448	1609	2281	-613	−983
$INTRA^2_{t,i-4}$	2519	2784	851	2282	1410	2164*	1599	1108
$INTRA^2_{t,i-5}$	-910	−1053	2166	3501**	−4610***	−3407*	152	−1114
$INTRA^2_{t,i-6}$	395	56	−4870*	−3708	−748	176	2632	1146
$INTRA^2_{t,i-7}$	250	−195	−1006	−400	−677	146	1652	558
$INTRA^2_{t,i-8}$	4166**	4030**	−5008*	−4678*	−1900	−1224	1023	445
$NIGHT^2_t$	1479**		2548***		2388***		1410**	
$INTER^2_{t-1}$	191		−138		−122		152	
$INTER^2_{t-2}$	−120		−146		−132		17	
$INTER^2_{t-3}$	−57		-242		−277**		57	
$ROUND_{t,i}$	0.224***	0.198***	0.273***	0.277***	0.182***	0.18***	0.297***	0.275***
$VOLA_{t-1}$	−0.006		0.089***		0.086***		0.019	
AR	0.901***	0.633***	0.875***	0.535***	0.914***	0.638***	0.785***	0.480***
MA	−0.799***	−0.550***	−0.782***	−0.456***	−0.823***	−0.559***	−0.664***	−0.373***
Interval	yes	yes	yes	yes	yes	yes	yes	yes
Day	no	yes	no	yes	no	yes	no	yes
Weekday	yes	no	yes	no	yes	no	yes	no
Month	yes	no	yes	no	yes	no	yes	no
T	8820	8820	8820	8820	8820	8820	8820	8820
n	25135	25135	18966	18966	28659	28659	20964	20964
R^2	0.652	0.612	0.508	0.499	0.567	0.548	0.574	0.560

* Significance at the 5% level.

** Significance at the 1% level.

*** Significance at the 0.1% level.

Table 4. ***Market order flow intensity and feedback trading.*** *The table shows the estimation results for the model given by (6) and (7) for market orders only. The columns separate the results by the warrants' type (Call or Put) and trade direction (Buy or Sell):* $CALLBUY_{t,i}, CALLSELL_{t,i}, PUTBUY_{t,i}$ *and* $PUTSELL_{t,i}$. *Fixed effects are included, as indicated below the regression results, for each month, weekday, day and 15-minute interval of the day. Where necessary, we exclude one effect per group to prevent linear combinations. The final rows list the number of observations* T, *the number of trades* n *and the adjusted* R^2 *per regression. Inference is based on robust standard errors computed from a sandwich estimator of the covariance matrix (see, e.g., Davidson and MacKinnon, 2003, ch. 10, eq. 10.45).*

	$CALLBUY_{t,i}$		$CALLSELL_{t,i}$		$PUTBUY_{t,i}$		$PUTSELL_{t,i}$	
$INTRA_{t,i-1}$	−43.3***	−40.1***	31.5**	23.1	1.9	−1.2	−75.3***	−72.4***
$INTRA_{t,i-2}$	−34.4***	−31.5**	48.7***	41.4***	3.2	−1.7	−74.2***	−71.8***
$INTRA_{t,i-3}$	−44.2***	−41.5***	21.8	13.3	22.0**	17.7*	−56.1***	−52.5***
$INTRA_{t,i-4}$	−38.7***	−34.7***	27.3*	24.5*	23.3**	19.4*	−45.1***	−41.7***
$INTRA_{t,i-5}$	−50.7***	−44.7***	23.5	18.6	11.9	7.7	−75.8***	−73.2***
$INTRA_{t,i-6}$	−58.7***	−51.3***	41.0**	34.1*	9.2	6.6	−65.7***	−62.8***
$INTRA_{t,i-7}$	−48.8***	−43.9***	62.0***	57.2***	15.3	13.1	−28.8*	−27.3
$INTRA_{t,i-8}$	−24.4*	−15.8	22.6	22.6	−6.5	−6.0	−26.1	−23.6
$NIGHT_t$	5.29		13.47*		−9.40*		−24.72***	
$INTER_{t-1}$	2.68		8.59**		0.56		−8.04**	
$INTER_{t-2}$	−1.46		4.92		0.09		−5.42*	
$INTER_{t-3}$	-3.32		1.91		2.41		-2.06	
$INTRA^2_{t,i-1}$	8009**	8982***	13529***	14727***	9175***	9515***	6080*	5957*
$INTRA^2_{t,i-2}$	8006***	8610***	9652***	10813***	7691***	8023***	1825	1460
$INTRA^2_{t,i-3}$	2620	2685	2820	3584	5063***	5436***	1552	1566
$INTRA^2_{t,i-4}$	2777	3277	3129	4323	6748***	6997***	4922***	4674**
$INTRA^2_{t,i-5}$	1750	2263	846	2579	−7958**	−7735**	−721	−1262
$INTRA^2_{t,i-6}$	−5989	−6654	509	2536	733	1100	−1418	−2593
$INTRA^2_{t,i-7}$	1410	1332	−2251	−528	155	402	3951	3884
$INTRA^2_{t,i-8}$	3706	4137	−2583	−1537	−407	−480	1675	498
$NIGHT^2_t$	1807**		2937***		2239***		1412*	
$INTER^2_{t-1}$	106		−187		106		178	
$INTER^2_{t-2}$	−119		−238		−205		81	
$INTER^2_{t-3}$	−3		−268		−109		192	
$ROUND_{t,i}$	0.093*	0.048	0.089	0.09	0.092*	0.078*	0.141**	0.082
$VOLA_{t-1}$	0.038		0.069**		0.073***		0.037	
AR	0.933***	0.385*	0.865***	0.44***	0.907***	0.498**	0.79***	0.451***
MA	−0.838***	−0.323	−0.751***	−0.371***	−0.822***	−0.451**	−0.639***	−0.331***
Interval	yes	yes	yes	yes	yes	yes	yes	yes
Day	no	yes	no	yes	no	yes	no	yes
Weekday	yes	no	yes	no	yes	no	yes	no
Month	yes	no	yes	no	yes	no	yes	no
T	8820	8820	8820	8820	8820	8820	8820	8820
n	5539	5539	3721	3721	7417	7417	5226	5226
R^2	0.417	0.417	0.267	0.327	0.351	0.366	0.402	0.421

* Significance at the 5% level.

** Significance at the 1% level.

*** Significance at the 0.1% level.

Table 5. ***Order flow imbalance and feedback trading.*** *The table shows the estimation results for the model given by (8). All trades are considered, regardless of their order type. The columns separate the results by the order flow imbalance in call and put warrants as well as the overall order flow imbalance:* $IMB^{CALL}_{t,i}$, $IMB^{PUT}_{t,i}$ *and* $IMB_{t,i}$. *Fixed effects are included, as indicated below the regression results, for each month, weekday, day and 15-minute interval of the day, with one exception per group in order to prevent multicollinearity, where necessary. The final rows list the number of observations* T, *the number of trades* n *and the adjusted* R^2 *per regression. Inference is based on robust standard errors computed from a sandwich estimator of the covariance matrix (see, e.g., Davidson and MacKinnon, 2003, ch. 10, eq. 10.45).*

	$IMB^{CALL}_{t,i}$		$IMB^{PUT}_{t,i}$		$IMB_{t,i}$	
$INTRA_{t,i-1}$	−68.3***	−62.8***	51.2***	47.0***	−58.9***	−55.0***
$INTRA_{t,i-2}$	−46.7***	−41.5***	52.6***	48.7***	−49.1***	−45.3***
$INTRA_{t,i-3}$	−35.7***	−30.4***	41.0***	37.2***	−37.7***	−34.1***
$INTRA_{t,i-4}$	−43.1***	−37.6***	39.4***	35.4***	−44.1***	−40.8***
$INTRA_{t,i-5}$	−22.4***	−17.0***	32.4***	28.4***	−26.1***	−23.6***
$INTRA_{t,i-6}$	−24.4***	−18.8***	26.1***	22.2***	−22.5***	−19.9***
$INTRA_{t,i-7}$	−44.2***	−38.5***	23.6***	20.2***	−31.2***	−28.8***
$INTRA_{t,i-8}$	−21.4***	−15.4**	17.6***	14.3**	−21.2***	−18.4***
$NIGHT_t$	−15.54***		11.92***		−13.25***	
$INTER_{t-1}$	−2.89**		4.67**		−2.57*	
$INTER_{t-2}$	−1.21		2.54*		−2.12*	
$INTER_{t-3}$	−0.99		2.20		−1.71*	
$INTRA^2_{t,i-1}$	−2696**	−2302*	290	376	−1325	−1147
$INTRA^2_{t,i-2}$	−791	−512	198	323	−831	−750
$INTRA^2_{t,i-3}$	878	1130	1145	1257	−411	−307
$INTRA^2_{t,i-4}$	−1686	−1438	−284	−264	−821	−673
$INTRA^2_{t,i-5}$	−1253	−1214	−2240*	−1988*	549	426
$INTRA^2_{t,i-6}$	321	275	−379	28	248	3
$INTRA^2_{t,i-7}$	−296	−381	−876	−491	−7	−232
$INTRA^2_{t,i-8}$	3075**	2781**	−71	533	1641	1173
$NIGHT^2_t$	−107		436*		−326	
$INTER^2_{t-1}$	228***		1		128**	
$INTER^2_{t-2}$	60		−8		23	
$INTER^2_{t-3}$	87		−157*		122*	
$ROUND_{t,i}$	−0.007	−0.019	−0.025	−0.017	0.007	−0.003
$VOLA_{t-1}$	−0.023**		0.013		−0.019*	
AR	0.889***	0.193	0.871***	0.465***	0.914***	0.448***
MA	−0.824***	−0.17	−0.795***	−0.44***	−0.826***	−0.41***
σ^2	0.344***	0.325***	0.314***	0.297***	0.238***	0.223***
Interval	yes	yes	yes	yes	yes	yes
Day	no	yes	no	yes	no	yes
Weekday	yes	no	yes	no	yes	no
Month	yes	no	yes	no	yes	no
T	8820	8820	8820	8820	8820	8820
n	44101	44101	49623	49623	93724	93724
R^2	0.138	0.164	0.135	0.158	0.185	0.214

* Significance at the 5% level.

** Significance at the 1% level.

*** Significance at the 0.1% level.

Table 6. ***Tick direction and feedback trading.*** *The table gives an overview of the percentage proportion of up ticks prior to the entry of a market order, separated by the warrants' type, the order type and the trade direction. Panel A considers all trades with at least two price updates within the last 15 minutes prior to the order entry. Panel B shows the percentage proportion for orders with at least 1 minute time between the last price update and the order entry. Panel C shows the percentage proportion for orders where the warrants' ask price prior to the order entry was at most half a euro. The relevant number ob observations is given in the last row of each Panel. Signifigant results of two-sided binomial tests for the null hypothesis that up and down ticks are equally likely to occur before an order are indicated by asteriks.*

	Market orders					
	Call		Put		Total	
	Buy	Sell	Buy	Sell	Buy	Sell
Panel A: Full sample						
Up [%]	51.68	47.79	51.65	46.37***	51.67**	46.98***
# Obs.	2703	1856	3477	2482	6180	4338
Panel B: Time between tick and order entry $\geq$ 1-minute						
Up [%]	51.04	44.97	53.56	42.96***	52.48	43.79**
# Obs.	531	298	717	419	1248	717
Panel C: Warrant's price $\leq$ 0.5 euro						
Up [%]	53.98*	43.88**	53.42	45.35*	53.71**	44.68***
# Obs.	754	490	687	591	1441	1081

* Significance at the 5% level.

** Significance at the 1% level.

*** Significance at the 0.1% level.

Table 7. ***Price level and feedback pricing.*** *The table shows the estimation results for the Differences-in-Differences regression models given by (16), (18) and (20). The twelve columns separate the results by the trade direction (Buy or Sell). Fixed effects are included for each trade. The results are shown in euro cents. The final rows list the number of observations and the number of trades per regression. Inference ist based on clustered-robust standard errors computed from a sandwich estimator of the covariance matrix, see, e.g. Arellano (1987). The clusters are formed on the trade level.*

	$\overline{PRICE}_{i,g,p}$ [cents]					
	(1)		(2)		(3)	
	Buy	Sell	Buy	Sell	Buy	Sell
$TREAT_{i,g}$	−5.83***	−6.29***	−5.82***	−6.33***	−7.44***	−8.07***
	(0.15)	(0.18)	(0.16)	(0.19)	(0.26)	(0.27)
$TREAT_{i,g} \times HIGH_i$			−0.06	0.24		
			(0.5)	(0.48)		
$TREAT_{i,g} \times FIRST_i$					2.6***	3.4***
					(0.32)	(0.35)
$POST_{i,p}$	−2.33***	3.2***	−2.39***	2.96***	−3.01***	3.9***
	(0.17)	(0.25)	(0.18)	(0.26)	(0.3)	(0.34)
$POST_{i,p} \times HIGH_i$			0.58	1.6°		
			(0.69)	(0.83)		
$POST_{i,p} \times FIRST_i$					1.09**	−1.34**
					(0.37)	(0.5)
$POST_{i,p} \times TREAT_{i,g}$	0.03°	0.06*	0.04°	0.08**	0.08*	0.00
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
$POST_{i,p} \times TREAT_{i,g} \times HIGH_i$			−0.02	−0.12°		
			(0.07)	(0.07)		
$POST_{i,p} \times TREAT_{i,g} \times FIRST_i$					−0.07°	0.12*
					(0.04)	(0.05)
FE per Trade	yes	yes	yes	yes	yes	yes
# Observations	22584	17200	22584	17200	22584	17200
# Trades	5646	4300	5646	4300	5646	4300

° Significance at the 10% level.

* Significance at the 5% level.

** Significance at the 1% level.

*** Significance at the 0.1% level.

Table 8. ***Pricing intensity and feedback pricing.*** *The table shows the estimation results for the Differences-in-Differences regression models given by (23) and (24). The eight columns separate the results by the trade direction (Buy or Sell). Fixed effects are included for each trade. The final rows list the number of observations and the number of trades per regression. Inference ist based on clustered-robust standard errors computed from a sandwich estimator of the covariance matrix, see, e.g. Arellano (1987). The clusters are formed on the trade level.*

	$\overline{TICK}_{i,g,p}$			
	(1)		(2)	
	Buy	Sell	Buy	Sell
$TREAT_{i,g}$	1.51***	2.41***	3.19***	3.74***
	(0.05)	(0.08)	(0.1)	(0.12)
$TREAT_{i,g} \times FIRST_i$			-2.72***	-2.55***
			(0.12)	(0.15)
$POST_{i,p}$	0.06**	0.07**	0.03	0.07*
	(0.02)	(0.02)	(0.03)	(0.03)
$POST_{i,p} \times FIRST_i$			0.05	0.00
			(0.04)	(0.05)
$POST_{i,p} \times TREAT_{i,g}$	2.42***	2.44***	0.72***	0.89***
	(0.06)	(0.07)	(0.07)	(0.08)
$POST_{i,p} \times TREAT_{i,g} \times FIRST_i$			2.75***	2.97***
			(0.1)	(0.13)
FE per Trade	yes	yes	yes	yes
# Observations	21700	16664	21700	16664
# Trades	5425	4166	5425	4166

* Significance at the 5% level.

** Significance at the 1% level.

*** Significance at the 0.1% level.

Table 9. ***Pricing intensity and feedback pricing in the cross-section.*** *The table shows the estimation results for the Differences-in-Differences regression model given by (24). The nine columns separate the results by the issuer. Fixed effects are included for each trade. The final rows list the number of observations and the number of trades per regression. Inference is based on clustered-robust standard errors computed from a sandwich estimator of the covariance matrix, see, e.g. Arellano (1987). The clusters are formed on the trade level.*

	$\overline{TICK}_{i,g,p}$								
	BNP Paribas	Citigroup	Commerzbank	DZ Bank	Deutsche Bank	Goldman Sachs	HSBC Trinkaus	UniCredit	Vontobel
$TREAT_{i,g}$	3.78***	4.12***	2.55***	1.47***	3.4***	7.74***	10.21***	1.59	4.09***
	(0.31)	(0.21)	(0.11)	(0.24)	(0.16)	(0.42)	(2.12)	(1.4)	(0.28)
$TREAT_{i,g} \times FIRST_i$	−3.01***	−3.06***	−2.04***	−1.3***	−2.62***	−5.58***	−9.01***	−0.58	−3.71***
	(0.35)	(0.26)	(0.14)	(0.26)	(0.18)	(0.51)	(2.13)	(2.06)	(0.32)
$POST_{i,p}$	0.05	-0.06	0.02	0.05	0.14**	0.1	−0.08	0.37	0.03
	(0.09)	(0.06)	(0.04)	(0.07)	(0.05)	(0.07)	(0.15)	(0.98)	(0.05)
$POST_{i,p} \times FIRST_i$	0.13	0.05	0.07	0.05	−0.11°	0.01	0.26	−0.12	−0.01
	(0.12)	(0.08)	(0.05)	(0.09)	(0.06)	(0.11)	(0.20)	(1.03)	(0.08)
$POST_{i,p} \times TREAT_{i,g}$	0.85***	1.37***	0.62***	0.46***	0.63***	1.72***	−1.13	−1.83***	0.85***
	(0.21)	(0.18)	(0.08)	(0.14)	(0.10)	(0.33)	(0.71)	(0.19)	(0.15)
$POST_{i,p} \times TREAT_{i,g} \times FIRST_i$	3.02***	2.47***	2.59***	2.18***	3.06***	4.02***	5.01***	2.63*	2.41***
	(0.30)	(0.28)	(0.13)	(0.19)	(0.15)	(0.47)	(0.89)	(1.04)	(0.24)
FE per Trade	yes	yes	yes	yes	yes	yes	yes	yes	yes
# Observations	3756	3268	11900	3400	9352	3120	352	32	3184
# Trades	939	817	2975	850	2338	780	88	8	796

° Significance at the 10% level.

* Significance at the 5% level.

** Significance at the 1% level.

*** Significance at the 0.1% level.