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Feedback Trading: The Intraday Case of Retail Derivatives

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ABSTRACT

We analyze retail order flow in terms of intraday feedback trading patterns. Using a unique data set of exchange trades and high-frequency quotes, we first provide evidence that retail investors actively and consciously respond to short-term intraday returns in a negative feedback, contrarian fashion. Second, we show that some retail investors also feedback trade on tick-by-tick returns. Third, we find that on average this behavior leads to significant losses on the day they open a position. These losses are primarily due to the bid-ask spread and to investors' timing inability, but not to market makers taking advantage of investors.

JEL Classification: C32, G11, G24, G41

1 | Introduction

The empirical literature shows that (misguided) beliefs in contrarianism or momentum are important drivers that make 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 do the reverse (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 tend to follow negative feedback trading strategies, while professional investors tend to follow positive feedback trading strategies based on recent returns (e.g., Sias 2007; Ng and Wu 2007; Barber, Odean, and Zhu 2009b; Kelley and Tetlock 2013; Barrot, Kaniel, and Sraer 2016).

The vast majority of the feedback trading literature focuses on responses to past returns for horizons from 1 day up to 1 year. In contrast, little is known about the feedback trading behavior of retail investors with respect to past intraday returns. Hindering factors include the reluctance of brokers to provide data on individual investors' trading accounts and the difficulty in disentangling order flow with regard to its origin. Often, small trades or broad exchange classifications are used as proxies for retail trades (e.g., Barber, Odean, and Zhu 2009a; Lemmon and Ni 2014). However, these proxies become increasingly unsuitable to identify retail trading activity, as the number of algorithmic traders who slice and dice orders into smaller pieces increases (O'Hara, Yao, and Ye 2014).

To circumvent these problems, we focus on the order flow in a unique market that is exclusively designed for retail investors—the European market for retail derivatives. This market has one major advantage over traditional equity markets with regard to analyzing retail trading activity: There is no need for a proxy to identify retail investors. As the derivatives are listed on the European Warrant Exchange (EUWAX), transactions and quotes are available and provide an accurate view on retail trading activity. Furthermore, retail derivatives are very popular among retail investors. According to the German Derivatives

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Association, the traded volume of leveraged retail derivatives amounted to 44 billion euros in 2022. A total of 63% of this volume is attributable to equity index derivatives. The German market index (Deutscher Aktienindex, DAX) is the most important underlying among these equity index derivatives, according to EUWAX.

We extend the literature by analyzing the trading patterns of investors in retail derivatives on an intraday basis. In particular, we analyze the trading activity in bank-issued warrants, which are securitized options specifically tailored to meet the needs of small investors. Their contract size is much smaller than that of regular options and they are traded like stocks (Schmitz and Weber 2012). Due to their embedded leverage, they are attractive to investors who want to speculate on small intraday price movements. They are therefore an ideal instrument to analyze intraday feedback trading of retail investors.

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, causing them to buy calls and sell puts. Following positive returns, they tend to buy puts and sell calls. Our first research question is whether this pattern also holds for short-term intraday returns of the underlying.

To answer this question, we aggregate trading activity within 15-min intervals during a trading day at the EUWAX, the world's largest exchange for bank-issued warrants. We analyze the trading activity in call and put warrants on the German DAX, EUWAX's most important underlying. Our data set reveals that the pattern of negative feedback trading is also present for short-term intraday returns. Investors respond to past return intervals of up to 2 h.

Furthermore, we consider tick-by-tick returns in the warrants themselves. Issuers act as market makers for their warrants and quote prices throughout the trading hours. On average, they quote two to three price updates (*ticks*) per minute for a warrant. Analyzing the trading response to such ticks, we find some evidence for a reversal of the feedback trading direction on very high frequencies: While the majority of retail investors do not care about past returns in the subminute segment, some traders react positively to tick-by-tick returns of the warrant (not the underlying). That is, they tend to buy calls and puts after a positive price tick of the respective warrant. We interpret this finding as an indication of a small subgroup of retail investors that speculates on momentum in the tick-by-tick returns of warrants.

The second part of the paper deals with the returns related to the observed intraday feedback trading behavior. On average, retail investors experience a negative return on the day they open a position, which is consistent with the literature on stock trading (e.g., Barrot, Kaniel, and Sraer 2016). Using a decomposition, we show that losses are primarily due to the bid-ask spread. Moreover, by comparing actual trades to a randomized control sample, we reveal that some investors use limit orders to enter trades skillfully but that, on average, they are also incapable of earning the bid-ask spread. The timing returns of investors who use market orders are indistinguishable at best and sometimes worse than those achieved by randomizing. Moreover, investors who positive feedback-trade in the direction of the last tick cannot enhance their intraday returns. We thus conclude that retail investors' feedback trading in warrants is noise trading.

Investors' returns are determined by the bid and ask prices quoted by issuers in their role as market makers. These prices do not necessarily reflect the fair value but rather the issuers' price-setting policy, which usually includes a dynamic mark-up (e.g., Stoimenov and Wilkens 2005; Baule 2011; Henderson and Pearson 2011). There is evidence that market makers anticipate and exploit specific order flow patterns by increasing their prices when they expect an excess in net investor demand and decreasing them when they expect an excess in net investor supply (Baule 2011; Baule, Frijns, and Tieves 2018). Despite the intensive trading activity in the overall market, trade in a single warrant occurs rarely. This is because investors can choose from a large variety of warrants from different issuers on the same underlying and a fine grid of strike prices and maturities. Consequently, market makers could employ a strategic intraday quotation policy, responding to a trade event by adjusting the traded warrant's quoted price to position themselves for future intraday order flow in that particular warrant. There are two competing hypotheses: (i) An investor buy could indicate great attractiveness and lead to further buys by other investors; and (ii) an investor buy could be followed by a resale by the same investor if they are speculating on short-term (intraday) gains. According to (i), market makers should increase the warrant's mark-up, according to (ii), they should decrease it.

We analyze whether market makers affect investor returns by strategically adjusting their quoted prices in response to a trade. To this end, we analyze differences-in-differences between prices of traded and nontraded 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, neither of the two hypotheses dominates the other, meaning that timing returns are a reflection of investors' (in)ability and not market-making strategies.

Our paper adds to the literature in several ways. First, we extend the literature on feedback trading with the first analysis on the intraday behavior of retail investors. We identify intraday price movements as distinct trade-motivating factors to which investors react with negative feedback trading for intervals covering the last 2 h. A small subset of retail investors also consider price movements in time intervals of less than 1 min and exhibit positive feedback trading on this time scale. On average, the intraday trading behavior leads to significant losses during the day on which a position is opened.

Second, this paper contributes to the literature on market-making strategies for exchange-traded structured products with the first analysis of strategic quotations in response to order flow. We demonstrate that investors' losses are primarily due to the bid-ask spread and not to strategic market-making in response to order flow. This is noteworthy, as existing studies show that issuers do exploit order flow patterns in other

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situations (Baule 2011; Baule, Frijns, and Tieves 2018; Pelster and Schertler 2019).

The remainder of this paper is organized as follows. Section 2 relates the paper to the existing literature on feedback trading, intraday trading, and market-making strategies. Section 3 introduces the data. Section 4 is dedicated to the analysis of feedback trading and Section 5 to investor returns. 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.[2] While there is extensive evidence for positive feedback trading by professional investors, the majority of findings for individual investors points towards negative feedback trading.[3] For recent returns, covering intervals up to 6 months in the past, this behavior is documented for the United States (Goetzmann and Massa 2002; Griffin, Harris, and Topaloglu 2003; Kaniel, Saar, and Titman 2008; Barber, Odean, and Zhu 2009b; Kaniel et al. 2012; Kelley and Tetlock 2013), Finland (Grinblatt and Keloharju 2000, 2001), France (Barrot, Kaniel, and Sraer 2016), Australia (Jackson 2003; Colwell, Henker, and Walter 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, Odean, and Zhu 2009b). However, there are also studies where the findings are more nuanced. In China, Feng and Seasholes (2004) find no evidence of feedback trading, while Ng and Wu (2007) show that less wealthy individuals are negative feedback traders. In Germany, executed limit (market) orders are associated with negative (positive) feedback trading (Dorn, Huberman, and Sengmueller 2008). In Japan, the results seem to depend on the time period (Kamesaka, Nofsinger, and Kawakita 2003; Kim and Nofsinger 2007; Hood et al. 2013). Finally, in Thailand, there is no evidence of feedback trading (Phansatan et al. 2012).

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, Cosemans, and Eichholtz 2009).[4] In the United States, aggregate daily and monthly trading activity in purchased and written options on individual stocks relates positively to past returns of the underlying for most horizons from 1 week up to 2 years (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 US index options is unrelated to the trailing 3-month return of the market index (Johnson, Liang, and Liu 2018).

Very few papers analyze feedback trading in bank-issued retail derivatives. 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. 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 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 intraday case, covering the response to short-term and tick-by-tick returns.

2.2 | Intraday Trading

The second strand of literature related to our paper covers intraday trading behavior. This literature focuses on day traders,[5] while the relation to past intraday returns is only sparse. For institutional day traders, there is consistent evidence for positive feedback trading with respect to recent intraday returns in stocks from the United States (Griffin, Harris, and Topaloglu 2003; Garvey and Murphy 2005) and futures from Korea (Chou, Wang, and Wang 2015). In contrast, the majority of studies on the behavior of individual investors points towards negative feedback trading. There is corresponding evidence for stocks from the United States (Griffin, Harris, and Topaloglu 2003), China (Seasholes and Wu 2007) and Korea (Chung, Choe, and Kho 2009) as well as for futures from Korea (Eom 2020) and Taiwan (Chou, Wang, and Wang 2015). However, some studies provide evidence that is inconsistent with this view. For futures in Taiwan, Cheng et al. (2016) find that most individual day traders follow positive feedback trading strategies. 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 day traders, our study is related since we focus on intraday behavior and suspect that warrants, due to their high leverage, are also traded by day traders.

2.3 | Market-Making Strategies

As bank-issued warrants belong to the retail market for exchange-traded structured products, our paper also relates to the literature on respective market-making 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 only tradable with its market maker, and short-selling by investors is impossible. Consequently, market makers have almost exclusive price-setting power over their products.[6] In the empirical literature, several stylized characteristics of prices in this market have been documented.[7] Many researchers find structured retail products 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, Frijns, and Tieves 2018), the Netherlands (ter Horst and Veld 2008), Spain

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(Abad and Nieto 2011) and Hong Kong (Li and Zhang 2011). Examining the degree of overpricing more closely, the order flow hypothesis postulates that market makers anticipate systematic patterns in the order flow and adjust their quotes accordingly (Wilkens, Erner, and Röder 2003; Baule 2011). While many studies find support for this hypothesis over longer time horizons, only very few test it in an intraday setting. For leverage certificates, Entrop, Schober, and Wilkens (2013) and Baller et al. (2016) find increased mark-ups towards the end of the day, though net investor supply dominates. They attribute this conflicting finding to an overnight jump risk of the underlying which dominates possible mark-downs from the order flow imbalance. In the case of warrants, which face no overnight jump risk, Baule, Frijns, and Tieves (2018) find decreasing mark-ups during the course of the day. They assume that issuers try to exploit an intraday order flow imbalance pattern. This paper provides evidence for its existence. Apart from strategies that anticipate order flow patterns, Pelster and Schertler (2019) analyze strategies that respond to past 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 intraday analysis on quotation strategies that respond to order flow on a trade-by-trade basis in the product to be priced.

3 | Data and Descriptive Statistics

Bank-issued warrants are securitized options specifically tailored to meet the needs of retail investors. Their contract size is much smaller than that of regular options, with a typical cover ratio of 0.01 for DAX warrants (i.e., one warrant refers to 1% of the DAX level) and a lot size of one. Retail investors can only take long positions (although they can take a short exposure to the underlying through put warrants). As securities, warrants are traded like stocks. Since the maximum loss is limited to the investment amount, no margin account is required. Typically, the tick size is one cent.

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 as the underlying.[8] These issuers are: BNP Paribas, Citigroup, Commerzbank, Deutsche Bank, DZ Bank, Goldman Sachs, HSBC, UniCredit, and Vontobel. The intraday tick price quotations of the warrants as well as the DAX were obtained from LSEG Tick History. Warrant features were provided by Solvians IT Solutions GmbH. Data on the VDAX NEW were obtained from LSEG Datastream.

Table 1 provides an overview of our trade and quote data. The original data set includes tick prices for approximately 41,000 warrants during our sample period. On average, there are 1.93 (1.64) price updates per minute for calls (puts). Of the 41,000 warrants, only about 16,000 were actually traded on the exchange.[9] The trading activity amounts to 107,003 trades with a total volume of almost 600 million euros. The order data provided by EUWAX directly classify trades into investor purchases (issuer sales) and investor sales (issuer repurchases). The number of investor purchases exceeds the number of investor sales by 32%, although the trading volume in euros is only slightly higher. As a possible explanation, some investors might 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.

Table 2 provides an overview of the order characteristics. It shows that the median volume per trade is below 2000 euros, although the volume is highly skewed. Investors prefer short-dated warrants, with 50% of the demanded warrants having a time to maturity of fewer than 34 days when they are bought. The median time to maturity is about 9 days shorter when a warrant is sold; this difference can, however, deviate from the average holding period due to the reasons discussed above. 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. This behavior reflects a preference for leverage. Moreover, we report the time between an order entry or the last modification and its execution. Generally,

TABLE 1 | Data overview.

	# 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	12,405	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	17,911	12,753	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	60,889	46,114	302.55	293.1	1.93	1.64

Note: The first two columns list the number of warrants which were traded on the exchange. The third and fourth columns list the number of exchange trades. 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.

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TABLE 2 | Order statistics.

Variable	Direction	Mean	5%	25%	50%	75%	95%
Volume	Buy	4969	140	525	1350	3700	20,400
	Sell	6356	116	636	1771	4806	24,768
Days to maturity	Buy	124	4	12	34	134	538
	Sell	102	3	10	25	104	453
Moneyness	Buy	−4.06	−19.18	−5.13	−1.67	−0.26	3.77
	Sell	−2.56	−15.67	−4.10	−1.03	0.43	5.26
Minutes to fill	Buy	176	0.01	0.01	0.08	1.80	212
	Sell	312	0.01	0.02	0.15	7.02	689
Variable	Direction	Limit	Market	Stop loss	Stop buy	Event-driven	
Order types	Buy	73.84	24.33	–	1.61	0.22	
	Sell	59.33	23.14	14.72	–	2.81	

Note: The table shows means and quantiles for the volume in euros, the days to maturity, the moneyness, measured for warrant i at time t as $\frac{S_t - K_i}{S_t}$ for calls and $\frac{K_i - S_t}{S_t}$ for puts, where S_t is the level of the DAX at time t and K_i is the strike price, and the minutes to fill for the transactions in our data set. Furthermore, the percentage proportion of order types is shown. The data are grouped by the trade direction (buy and sell).

orders are executed quickly regardless of their type, as 75% of the buys (sells) are filled within 2 min (7 min). As investors predominantly use limit orders,[10] the quick execution must be due to limits close to or at the market price. Overall, the behavior and preferences described above are similar for calls and puts.

4 | Feedback Trading

In this section, we examine whether and how retail investors respond to short-term intraday returns of the underlying and tick-by-tick returns of warrants themselves. The section is organized as follows: First, we examine the investors' response, as defined by different measures of intraday retail order flow, to returns of the underlying within the last 2 h (Section 4.1). Second, we analyze the response to tick-by-tick returns of warrants,[11] with a usual reaction time of less than 1 min (Section 4.2).

4.1 | Short-Term Returns

4.1.1 | Order Flow Measures and Descriptive Statistics

For the feedback trading analysis on short-term returns of the underlying, we aggregate information over 15-min 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 that are too small.[12] We measure order flow based on the number of orders executed. Weighting each order equally, regardless of its size, makes it robust against large-volume trades. We have also used other weighting schemes, in particular volume-weighted order flow measures, coming to very similar results.

As a first measure, we consider the number of orders executed within each 15-min interval in a trading day (see Venezia and Shapira 2007, for a similar measure).[13] While EUWAX allows trading from 9:00 a.m. to 8:00 p.m. CET during 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 intraday returns of the DAX, we restrict our order flow sample to 15-min intervals between 9:00 a.m. and 5:45 p.m. CET per day.[14] This gives us 35 intervals per 252 trading days in 2014 and a total of 8820 observations. We define the buy and sell intensities in call and put warrants on day $t \in \{1, ..., 252\}$ within interval $i \in \{1, ..., 35\}$, $CALLBUY_{t,i}$, $CALLSELL_{t,i}$, $PUTBUY_{t,i}$, and $PUTSELL_{t,i}$, as the number of respective trades.

As a second measure, 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, Kaniel, and Sraer 2016, for a similar measure). For each 15-min interval, we divide the difference between sell and buy trades by the total number of trades:

$$IMB_{t,i}^{CALL} = \frac{CALLBUY_{t,i} - CALLSELL_{t,i}}{CALLBUY_{t,i} + CALLSELL_{t,i}}; \quad (1)$$

$$IMB_{t,i}^{PUT} = \frac{PUTBUY_{t,i} - PUTSELL_{t,i}}{PUTBUY_{t,i} + PUTSELL_{t,i}}. \quad (2)$$

If there is no trading within an interval, we set the imbalance measure equal to zero.

In addition, we calculate the overall and the purchase-based order flow imbalance in warrants as

$$IMB_{t,i} = \frac{(CALLBUY_{t,i} - CALLSELL_{t,i}) - (PUTBUY_{t,i} - PUTSELL_{t,i})}{CALLBUY_{t,i} + CALLSELL_{t,i} + PUTBUY_{t,i} + PUTSELL_{t,i}}; \quad (3)$$

$$IMB_{t,i}^{BUY} = \frac{CALLBUY_{t,i} - PUTBUY_{t,i}}{CALLBUY_{t,i} + PUTBUY_{t,i}}. \quad (4)$$

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TABLE 3 | Descriptive statistics of order flow intensity and imbalance.

	$CALLBUY_{t,i}$	$CALLSELL_{t,i}$	$PUTBUY_{t,i}$	$PUTSELL_{t,i}$	$IMB_{t,i}^{CALL}$	$IMB_{t,i}^{PUT}$	$IMB_{t,i}$	$IMB_{t,i}^{BUY}$
Mean	2.85	2.15	3.25	2.38	0.13	0.20	−0.04	−0,09
Median	2.00	1.00	2.00	1.00	0.00	0.14	0.00	0.00
Std.	4.21	3.45	4.14	3.74	0.63	0.60	0.54	0.62
Skew	3.91	4.5	3.44	3.49	−0.22	−0.29	0.05	0.12
Min.	0	0	0	0	−1	−1	−1	−1
Max.	51	68	53	42	1	1	1	1
Q_{10}	12,511	8991	9656	9768	1520	1552	2931	2143

Note: The table shows descriptive statistics of the order flow per 15-min interval. The Ljung-Box statistic Q_{10} assesses the null hypothesis that a series exhibits no autocorrelation for 10 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 $T = 8820$.

Table 3 provides descriptive statistics and Figure 1 shows histograms of the variables. The intensities are low nonnegative 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.[15]

The order flow exhibits a diurnal pattern. As shown in Figure 2a, the order flow intensities of buys and sells in calls and puts are highest in the morning, with the first 15-min interval accounting for roughly 10% of the total number of daily trades. From then on, the intensity per 15-min 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 the day. This L-shape is similar for all four intensity measures. Such an activity peak in the morning is also reported for retail-oriented mini options in the United States and may be due to individual investors with full-time jobs who have little time to spare during working hours and place their orders before the market opens (Li, Zhao, and Zhong 2021). This order flow thus looks different from the distinct U-shape of trading activity in stocks (Admati and Pfleiderer 1988).

With regard to the diurnal order flow imbalance, Figure 2b 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 (Baule, Frijns, and Tieves 2018).

4.1.2 | Feedback of Order Flow Intensity

In the following, we examine the response of the order flow intensities to short-term intraday returns of the underlying. We consider the intraday return of the DAX on day t within the 15-min interval i, as defined above, denoted by $INTRA_{t,i}$. In our regression analysis for an order flow measure of interval i, we include up to eight lags of DAX returns, that is, 2 h.[16] We also include recent interday returns of the underlying (Baule and Blonski 2012; Schmitz and Weber 2012). In particular, 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 $NIGHT_t$. Furthermore, we include squared returns $INTRA_{t,i}^2, INTER_t^2$, and $NIGHT_t^2$, as controls for nonlinear responses.

Intraday trading activity has been found to increase near round numbers of the underlying (Niederhofer 1965; Bhattacharya, Holden, and Jacobsen 2012; Kuo, Lin, and Zhao 2015; Chen 2018). We introduce the binary variable $ROUND_{t,i}$, which is 1 if the DAX passes a multiple of 100 within interval i and 0 otherwise. We also control for the impact of general market conditions on trading activity. For this purpose, we use the 1-day lagged implied DAX volatility $VOLA_{t-1}$, measured by the VDAX-NEW. To control for diurnal and weekly seasonal effects as well as monthly variability in trading activity (Chordia, Roll, and Subrahmanyam 2001), we include a battery of respective dummy variables $\sum SEASONALS$.

For the regression model of the count data, we use a generalized linear autoregressive moving average model of order $p = 1$ and $q = 1$ (GLARMA(1,1)) with covariates, introduced by Davis, Dunsmuir, and Streett (2003) and Davis et al. (2005). This model is particularly suitable for time series of low, nonnegative count data. It considers the order flow intensities $y_{t,i}$ as realizations of a Poisson process and models the log of the conditional mean of this process as the dependent variable of a linear regression:

$$y_{t,i} | \mathcal{F}_{t,i} \sim Po(\mu_{t,i}); \tag{5}$$

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

Here, Po is the Poisson density. Furthermore, the model allows us to control for remaining serial correlation and persistence in order flow, which may result from positioning

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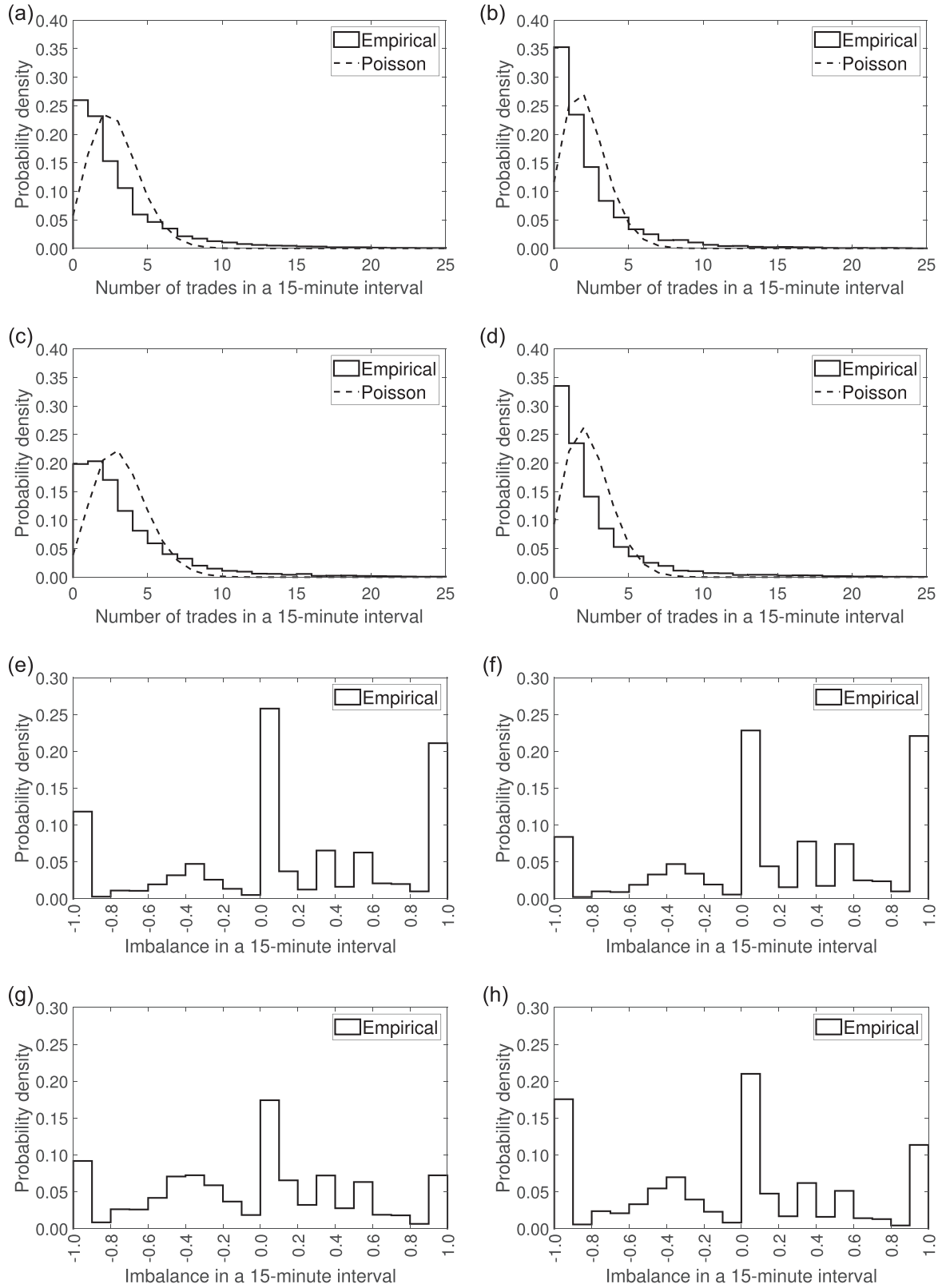

FIGURE 1 | Histograms of intensity and imbalance of order flows. Graphs (a)–(d) show the empirical and estimated unconditional Poisson density of the number of trades. Graphs (e)–(h) show the imbalance of the order flow.

around news events (Barber and Odean 2008; Riordan et al. 2013; Meyer, Schroff, and Weinhardt 2014), chart patterns (Grinblatt and Keloharju 2001; Kavajecz and Odders-White 2004; Bender, Osler, and Simon 2013) or herding in general (Dorn, Huberman, and Sengmueller 2008; Barber, Odean, and Zhu 2009a). These effects are captured by the error term $z_{t,i}$, which is modeled as an autoregressive moving average process:

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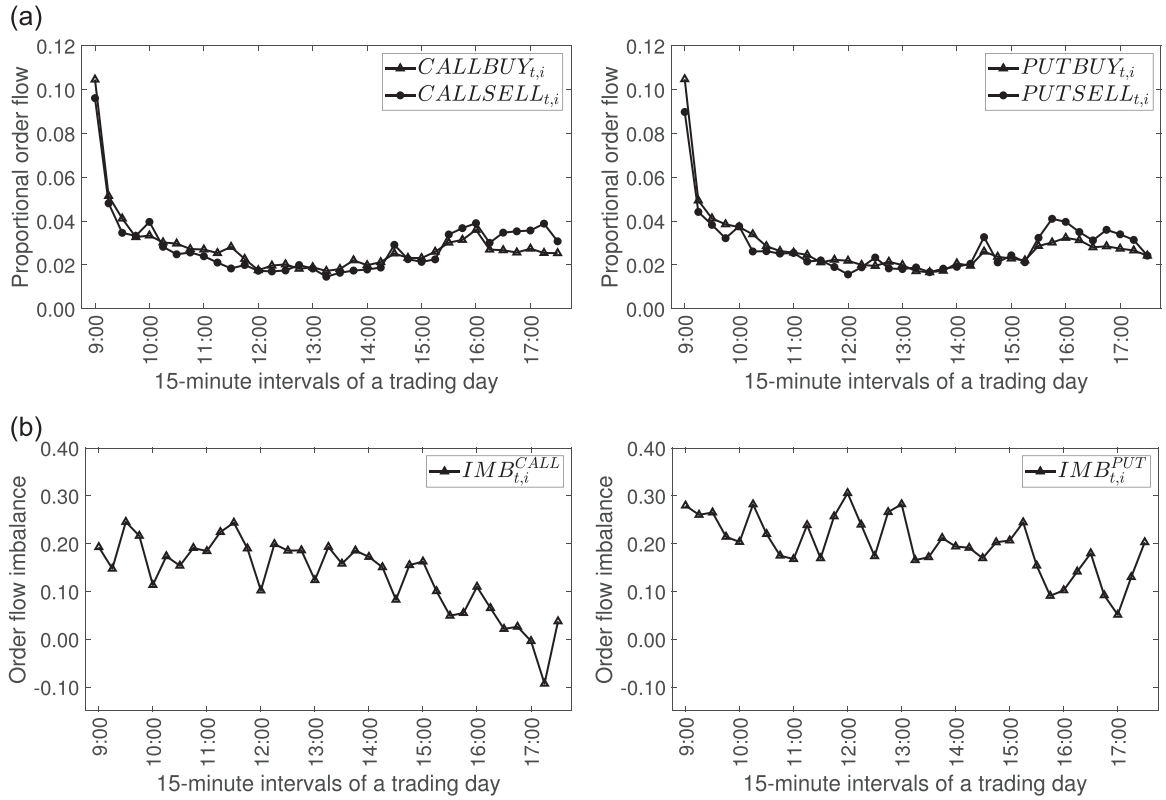

FIGURE 2 | Diurnal figures of proportional order flow intensity and order flow imbalance. Panel (a) shows the diurnal proportional number of trades, defined as the number of trades in a 15-min interval divided by the total daily number of trades. The results are separated by the warrant's type and the trade direction. Panel (b) shows the diurnal imbalance in the number of buy and sell trades, calculated analogously.

$$z_{t,i} = \phi_1 z_{t,i-1} + \theta_1 e_{t,i-1} \tag{7}$$

with

$$e_{t,i} = \frac{y_{t,i} - \mu_{t,i}}{\sqrt{\mu_{t,i}}}. \tag{8}$$

For $t \leq 0$, $e_{t,i} = z_{t,i} = 0$; and for $i - j \leq 0$, $e_{t,i-j} = e_{t-1,36-j}$ and $z_{t,i-j} = z_{t-1,36-j}$.

Fixed effects involve month, weekday, and 15-min interval-of-day dummies. 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. Since this dummy controls for all effects measured on the daily frequency, we omit all other daily variables, in particular interday returns. Estimation is carried out using a maximum likelihood approach (Davis et al. 2005).

Table 4 presents the results of the time series regressions for the order flow intensities $CALLBUY_{t,i}$, $CALLSELL_{t,i}$, $PUTBUY_{t,i}$, and $PUTSELL_{t,i}$. The signs of the coefficients of the intraday returns are negative for calls bought and positive for calls sold. This indicates that the buying (selling) intensity of calls increases following negative (positive) intraday 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. This is indeed the case. Thus we find consistent and significant negative feedback trading on intraday returns in all four categories. The investors' response tends to dwindle for more distant intraday returns and is strongest for buying calls and selling puts. In addition, for sales of calls and purchases of puts, the first two lags of squared intraday returns are significantly positive. For calls (puts), a one standard deviation shock of 0.14% to the intraday return translates via the coefficients of $INTRA_{t,i}$ and $INTRA^2_{t,i}$ to a decrease (increase) in the buying intensity of −8.7% (6.4%) and an increase (decrease) in the selling intensity of 7.4% (−9.7%) in the next interval. As illustrated in Figure 3a, the responses to this initial shock accumulate for calls (puts) to a decrease (increase) in the buying intensity of −36.3% (14.9%) and an increase (decrease) in the selling intensity of 30.4% (−55.3%) over 2 h. The results remain virtually unchanged when controlling for all effects on the daily frequency.

Investors also respond to past overnight returns (except for buying puts), showing the same negative feedback pattern. Furthermore, the significantly positive coefficients of squared overnight returns show that overnight price movements stimulate trading activity, regardless of the warrant type and trade direction. Surprisingly, the order flow intensities are almost unaffected by lagged inter-day returns. Only yesterday's return has a significant negative impact on the number of puts sold today.

It is possible that the results are influenced by the investors' preference for limit orders. Limit buy and sell orders that are not immediately marketable remain in the order book. These orders

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TABLE 4 | Order flow intensity and feedback trading.

	$CALLBUY_{t,i}$		$CALLSELL_{t,i}$		$PUTBUY_{t,i}$		$PUTSELL_{t,i}$	
$INTRA_{t,i-1}$	−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	0.102***	0.083***	0.093***	0.079***	0.090***	0.080***	0.121***	0.107***
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	25,135	25,135	18,966	18,966	28,659	28,659	20,964	20,964
R^2	0.652	0.612	0.508	0.499	0.567	0.548	0.574	0.560

Note: The table shows the estimation results for the GLARMA model (5). For each option type, the first column provides the results of the baseline regression, while the second replaces daily control variables with daily fixed effects. The final rows list the number of observations T, the number of trades n, and the adjusted R^2. Inference is based on robust standard errors. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***).

have buy (sell) limits below (above) the best ask (bid) quote. Therefore, declines (increases) in intraday prices could trigger these limit buy (sell) orders. Such trades would then be consistent with negative intraday feedback trading. The observed contrarian intraday order flow might thus be driven by limit orders instead of conscious responses to intraday returns.

To analyze the unbiased response to intraday returns observable at the time of order entry, we use the subsample of market orders only. Table 5 repeats the analysis of Table 4 for this subsample.[17] The results are fairly similar to the total sample, in particular, the strong evidence for negative feedback trading in the case of calls bought and puts sold. The effect for puts bought

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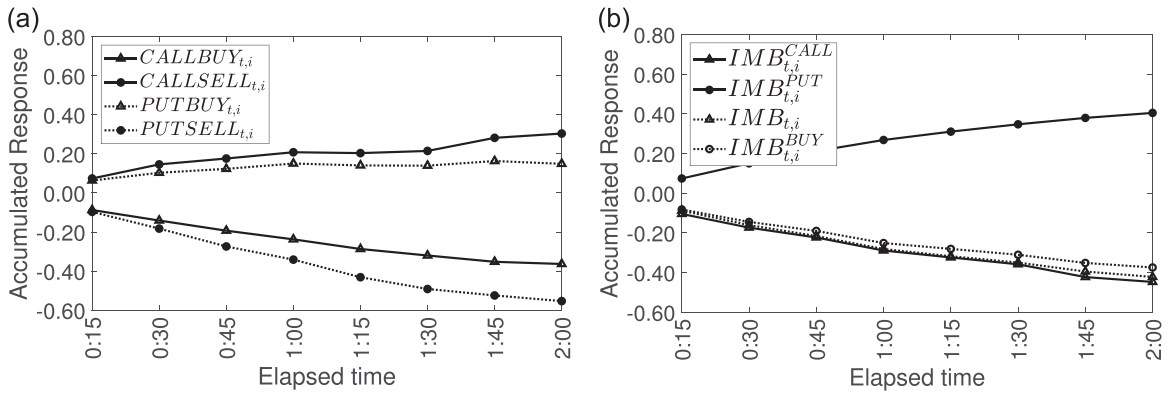

FIGURE 3 | Accumulated impulse response functions for an intraday return shock. The graphs show the accumulated responses of a one standard deviation impulse to the variable $INTRA_{t,i}$ (the 15-min underlying return) on the future order flow intensity in percentage terms (a) and imbalance in absolute terms (b).

becomes somewhat weaker (no significance for the first two intraday lags), but the negative response remains significant in the majority of cases. We conclude that the observed negative feedback trading is not mainly driven by limit orders. Instead, individual investors consciously respond to intraday returns in a contrarian fashion.

4.1.3 | Feedback of Order Flow Imbalance

Finding return-contrarian buy and sell intensities suggests a return-contrarian net positioning of individual investors. To analyze this net effect in more detail, we examine the response of order flow imbalances $IMB_{t,i}^{CALL}$, $IMB_{t,i}^{PUT}$, $IMB_{t,i}$, and $IMB_{t,i}^{BUY}$ to intraday returns. To this end, we use almost the same regression model as in (5), but regress directly on the imbalance as a metric variable instead of defining a Poisson process for the count data. As the imbalances respond to intraday returns in a way qualitatively similar to the intensities, we do not tabulate the results here.

However, we illustrate the accumulated impulse response function in Figure 3b. For calls (puts), a one standard deviation shock of 0.14% to the intraday return results, via the coefficients of $INTRA_{t,i}$ and $INTRA_{t,i}^2$, in a decrease (increase) in order flow imbalance of −0.104 (0.075) and a decrease in the overall (purchase-based) imbalance of −0.088 (−0.082). Over 2 h, the responses to the initial shock accumulate to a decrease (increase) in the order flow imbalance in calls (puts) by −0.447 (0.405) and the overall (purchase-based) imbalance by −0.422 (−0.374).

Overall, these results are consistent with those for order flow intensities but provide additional evidence that the net order flow is intraday return contrarian.

4.2 | Tick-By-Tick Returns

4.2.1 | Methodology

This section takes a closer look at the microstructure of trading activity. The sparse literature on traders who execute intraday strategies manually indicates that they closely monitor tick-by-tick returns to determine their entry and exit points (Harris and Schultz 1998; Garvey and Murphy 2005). Therefore, we examine whether and how individual investors respond to the last tick direction of the quoted warrant price when entering their orders.[18] In contrast to our analysis in the previous section, these incremental returns are not necessarily due to returns of the underlying (Bakshi, Cao, and Chen 2000). We focus on market orders since they reflect investors' unadulterated opinion at that moment about future prices (Dorn, Huberman, and Sengmueller 2008).

We restrict our sample to warrants that had at least two price changes within the 15 min before the order was placed. This ensures a lower bound of recent price fluctuations, which is attractive to active traders (Kyröläinen 2008; Chung, Choe, and Kho 2009). For each order i, we denote the quoted price of the respective warrant at time t as $PRICE_{i,t}$. In the 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 the time of the order entry, t_{-1}^i and t_{-2}^i the times of the two most recent ticks in the warrant price with $t_{-2}^i < t_{-1}^i < t_0^i$ and $t_0^i - t_{-2}^i \leq 15$ min. 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 trade directions and $UP_i = \mathbf{1}_{\{PRICE_{i,t_{-2}^i} < PRICE_{i,t_{-1}^i}\}}$ and $DOWN_i = \mathbf{1}_{\{PRICE_{i,t_{-2}^i} > PRICE_{i,t_{-1}^i}\}}$ to mark ticks with an increase or decrease in the warrant price from t_{-2}^i to t_{-1}^i, we determine the ratio of upticks to downticks before buy and sell orders, as

$$TICK^{\text{Buy}} = \frac{\sum_i UP_i \times \mathbf{1}_{\{BUY_i=1\}}}{\sum_i DOWN_i \times \mathbf{1}_{\{BUY_i=1\}}}, \tag{10}$$

$$TICK^{\text{Sell}} = \frac{\sum_i UP_i \times \mathbf{1}_{\{BUY_i=0\}}}{\sum_i DOWN_i \times \mathbf{1}_{\{BUY_i=0\}}}. \tag{11}$$

The methodology is summarized in Figure 4 using a timeline of possible and analyzed price paths along with relevant events.

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TABLE 5 | Order flow intensity and feedback trading (market orders only).

	$CALLBUY_{t,i}$		$CALLSELL_{t,i}$		$PUTBUY_{t,i}$		$PUTSELL_{t,i}$	
$INTRA_{t,i-1}$	−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***	13,529***	14,727***	9175***	9515***	6080*	5957*
$INTRA^2_{t,i-2}$	8006***	8610***	9652***	10,813***	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**		0.0730***		0.037	
AR	0.933***	0.385*	0.865***	0.440***	0.907***	0.498**	0.790***	0.451***
MA	0.095***	0.063***	0.114***	0.070***	0.085***	0.048***	0.150***	0.120***
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

Note: The table shows the estimation results for the GLARMA model (5) for market orders only. For each option type, the first column provides the results of the baseline regression, while the second replaces daily control variables with daily fixed effects. The final rows list the number of observations T, the number of trades n, and the adjusted R^2. Inference is based on robust standard errors. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***).

If investors do not react to previous ticks, we would expect the ratio of upticks to downticks before buy or sell orders to be equal to one.[19] Significant deviations from one would indicate conscious feedback trading on tick-by-tick returns.

4.2.2 | Results

Table 6 shows the ratio of upticks to downticks before the entry of a market order (Panel A). The results are presented in aggregate and separated by the warrants' type and the trade direction.

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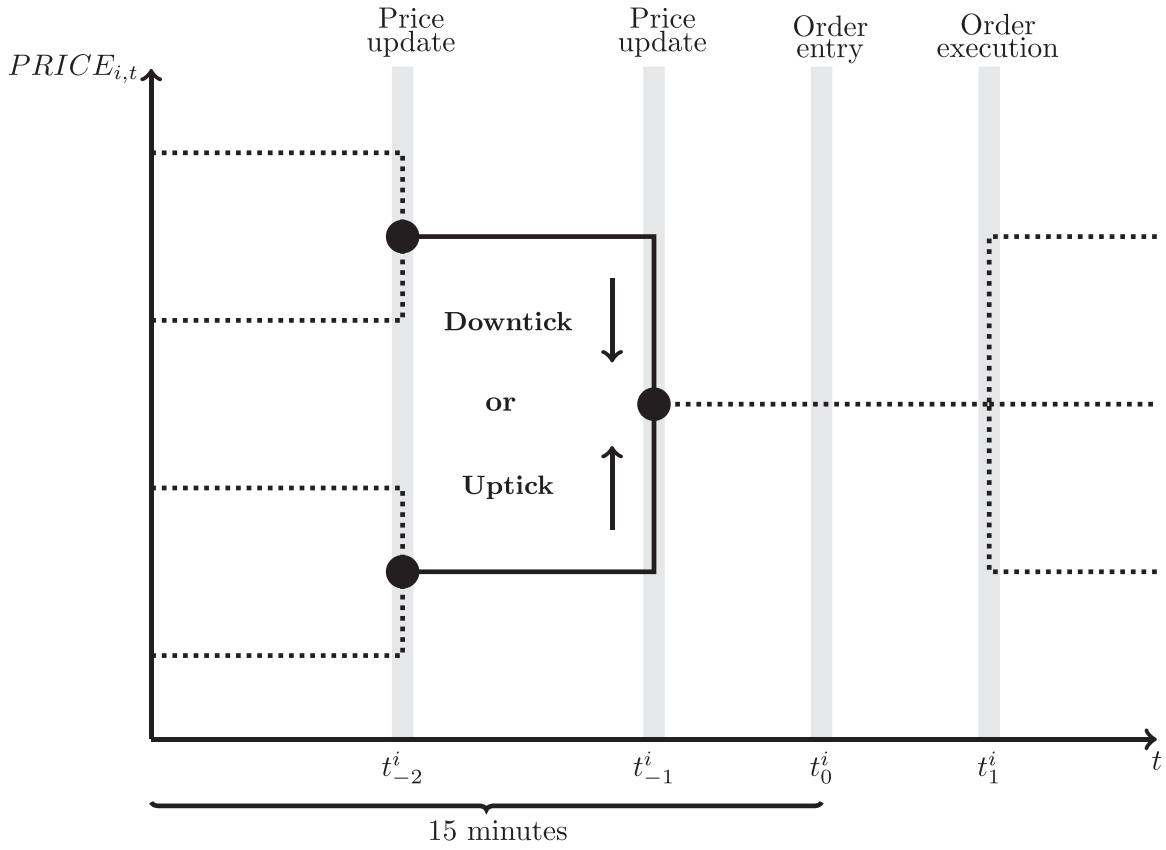

FIGURE 4 | Illustration of tick price and trade direction methodology. The figure shows, for an order i, the price $PRICE_{i,t}$ of the respective warrant at time t. In the case of a buy (sell) order, we use ask (bid) price quotes. Dotted lines represent possible price paths. Bold circles represent the two most recent price changes before the order entry. The solid lines are the two possible price paths containing the tick on which we base our analysis. The points in time of the analyzed price updates, order entry, and order execution are highlighted in gray.

We find slightly more buys after an uptick and more sells after a downtick, which is consistent with positive feedback trading. This pattern is consistent for calls and puts. The deviation from one is, however, small and amounts to only 6%–13%. For the total sample, it is nonetheless significant at the 1% level.

As the tilt is small, it could be the case that investors need some time to respond to a tick. We restrict the sample in Panel B to those orders where there is at least 1 min between the last tick and the order entry. While the behavior observed in Panel A is confirmed, statistical significance does not increase.

Since tick-by-tick returns are more meaningful in percentage terms for warrants with a low price than for expensive ones, we suspect that the effect is more pronounced for low-priced warrants. In Panel C, we only consider warrants with an ask price of less than 0.50 euros before the order entry. Indeed, the deviations from one increase to 14%–21% at a high significance level, despite the smaller number of observations.

Separating trades with a traded volume in the upper and lower 20% quantile in Panels D and E shows that especially small traders respond to tick price changes when executing sales, while larger traders do not. For large trades significance vanishes, while it increases at a high significance level for small sales.

In summary, we find that some retail investors use market orders to follow a momentum strategy (positive feedback trading) on tick-by-tick returns. This effect is more pronounced for low-priced warrants and small trades. According to these findings, there is a small subgroup of retail investors that act on the tick direction. Given negative feedback trading on lower frequencies (15 min to 2 h), this could be interpreted as an attempt to time a reversal.

5 | Investor Returns

In this section, we investigate how the observed feedback trading drives investment outcomes, that is, investor returns. The section is organized as follows: First, we separate components of investor returns and determine whether returns are attributable to timing and therefore associated with feedback trading. (Section 5.1). Second, we examine whether timing returns are only driven by investor behavior or whether they are influenced by market makers' strategic intraday quotation policies (Section 5.2).

5.1 | Intraday Return Attribution

5.1.1 | Methodology

As feedback trading is essentially a timing strategy, we are particularly interested in returns due to the ability to time entry

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TABLE 6 | Tick direction and feedback trading.

	Market orders					
	Call		Put		Total	
	Buy	Sell	Buy	Sell	Buy	Sell
Panel A: Full sample						
Up/Down	1.070	0.915	1.068	0.865***	1.069**	0.886***
# Obs.	2703	1856	3477	2482	6180	4338
Panel B: Time between tick and order entry ≥1-min						
Up/Down	1.042	0.817	1.153	0.753***	1.105	0.779**
# Obs.	531	298	717	419	1248	717
Panel C: Warrant price ≤0.5 euro						
Up/Down	1.173*	0.782**	1.147	0.830*	1.160**	0.808***
# Obs.	754	490	687	591	1441	1081
Panel D: Traded volume in the upper 20% quantile						
Up/Down	1.016	1.052	1.036	0.887	1.028	0.958
# Obs.	510	437	733	534	1243	971
Panel E: Traded volume in the lower 20% quantile						
Up/Down	1.044	0.625***	0.990	0.828*	1.013	0.739***
# Obs.	464	351	595	510	1059	861

Note: The table gives an overview of the ratio of upticks to downticks before 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 min before the order entry. Panel B shows the ratio for orders with at least 1 min between the last price update and the order entry. Panel C shows the ratio for orders where the warrants' ask price before the order entry was less or equal to 0.50 euros. Panel D (E) shows the ratio for orders with a traded volume in the upper (lower) 20% quantile. The number of observations is given in the second row of each Panel. Significant results of two-sided binomial tests for the null hypothesis, namely that up and down ticks are equally likely to occur before an order are indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***).

points. Therefore, we decompose the intraday returns of investors who buy warrants into returns from this timing ability, (negative) returns from the bid-ask spread, and—in the case of market orders—returns from the order execution.[20]

For a given intraday holding period of τ minutes, we calculate the return for an investor buy trade i as

$$RETURN_{i,\tau} = \frac{PRICE^{Bid}_{i,t_1^i+\tau} - TRADE_i}{TRADE_i}, \tag{12}$$

where $TRADE_i$ is the transaction price and $PRICE^{Bid}_{i,t_1^i+\tau}$ is the quoted bid price τ minutes after the trade. We then decompose this return into three components: spread, timing, and execution.

As investors can only sell to the market maker at the quoted bid price, they lose the bid-ask spread when they wish to close the trade. This loss at the end of the holding period is the *spread component* computed as

$$RETURN^{Spread}_{i,\tau} = \frac{PRICE^{Bid}_{i,t_1^i+\tau} - PRICE^{Ask}_{i,t_1^i+\tau}}{TRADE_i}, \tag{13}$$

where $PRICE^{Ask}_{i,t_1^i+\tau}$ is the quoted ask price τ minutes after the trade.

With market orders, investors place an order based on the observed indicative quote. Thus the *timing component* is defined as

$$RETURN^{Timimg}_{i,\tau} = \frac{PRICE^{Ask}_{i,t_1^i+\tau} - PRICE^{Ask}_{i,t_{-1}^i}}{TRADE_i}, \tag{14}$$

where $PRICE^{Ask}_{i,t_{-1}^i}$ is the quoted ask price immediately before the entry of a market order.

However, the actual transaction price of an executed order can differ from the price quoted immediately before the execution. As quoted prices are indicative only, market makers are requested to submit a binding bid or ask after the arrival of a market order.[21] Acquiring knowledge of the investor's trade direction and volume, market makers might adjust their binding order. As such, a market order can be executed at a price better or worse than the last visible indicative quote on the basis of which the investor placed his order. We therefore define the *execution component* of the intraday return as

$$RETURN^{Execution}_{i,\tau} = \frac{PRICE^{Ask}_{i,t_{-1}^i} - TRADE_i}{TRADE_i}. \tag{15}$$

It is obvious that

$$RETURN_{i,\tau} = RETURN^{Spread}_{i,\tau} + RETURN^{Timing}_{i,\tau} + RETURN^{Execution}_{i,\tau}. \tag{16}$$

In contrast, investors who use limit orders do not trade directly on the basis of the quote $PRICE^{Ask}_{i,t_{-1}^i}$—they know that their

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transaction price will be no more than the limit price. Therefore, we define the execution component as zero for these trades and calculate the timing component based on the transaction price:

$$RETURN_{i,\tau}^{Timing} = \frac{PRICE_{i,t_1^i+\tau}^{Ask} - TRADE_i}{TRADE_i}. \quad (17)$$

To determine whether feedback trading of retail investors reflects skill in intraday timing rather than noise trading, we compare the actual trading data with a randomized control sample. The control sample consists of trades in the same warrant and on the same trading day as in the original sample. Thus for each actual trade, we sample a randomized control trade for the same day.[22] For statistical inference, we resample the control data 10,000 times to get a bootstrapped distribution. In this way, we can reject the null hypothesis of no timing ability at level α if the actual average return lies beyond the respective quantile of the bootstrapped distribution.

5.1.2 | Results

Table 7 shows weighted average returns (12) and their components (13), (14), (15), and (17) for holding periods of 1, 15, and 60 min. As weights, we use traded volume in euros. We indicate returns that are significantly different from zero with asterisks, and timing returns that deviate significantly on the lower (upper) side from bootstrapped resamples with minus (plus) signs.

Most of the returns are significantly negative. On average, investors who buy warrants lose money on the day they enter a trade. These losses tend to be larger for trades that are smaller (Panel A), where the warrants have a low price (Panel A), and where they are entered via market orders (Panel C). Furthermore, untabulated results show that returns remain negative until the end of the trading day.

The return decomposition shows that returns are primarily driven by losses due to the bid-ask spread. These losses amount to slightly more than 1% of the invested amount, on average. They are significantly larger for smaller trades (up to 7%), and warrants with a low price (6%).

The timing of entry points is poor in the short run (Panel A). However, for holding periods of more than 15 min, investors tend to earn slightly positive timing returns (less than 1%, on average). These timing returns are higher for investors who use limit orders and those who trade small amounts and warrants with a low price (Panels A and B). In these cases, these timing returns are almost instantaneously larger than expected from a random strategy according to the bootstrapped distribution. However, on average, they are insufficient to cover losses from the bid-ask spread. Therefore, significant timing returns could originate from market makers who are happy to fill limit orders inside the spread, if the spread is so large that they are confident of profiting from the trade anyway.[23] An alternative interpretation is that investors manage to buy low-priced warrants, which are usually very volatile due to high leverage, with limit orders at lower prices.

Users of market orders perform worse on average (Panel C). Market order users generate timing returns that are indistinguishable from zero and perform even significantly worse than if they submitted their orders randomly throughout the day. The execution returns resulting from differences with respect to the tick direction in a warrant's price before the entry of a market order are only minor. As such, investors who do positive feedback-trades on the last tick direction seem to trade on noise. Finally, although not significantly, market orders lead to slightly adverse execution prices, particularly for large trades. This indicates that some market makers could use their knowledge of the trade direction and size to fill market orders at adverse prices.

Overall, we find that retail investors who do feedback-trading on short-term returns of the underlying and use tick-by-tick returns of warrants are noise traders without sufficient timing ability to generate positive returns. Among different investors, those that trade small amounts, low-priced warrants and use market orders perform worst. On average, they experience a negative return on the day of a trade. This finding is consistent with short-term returns in stocks (Barrot, Kaniel, and Sraer 2016) and longer term returns in retail derivatives (Entrop et al. 2016). Considering that retail investors may also pay commissions to their broker, their effective returns are likely to be even lower.

5.2 | Strategic Quotation

5.2.1 | Methodology

In the previous section, we showed that investor returns are determined by the bid and ask prices quoted by market makers. We now investigate whether market makers strategically alter these quotes in response to trades. If this is the case, then (poor) investor returns would not be due to investor behavior alone, but also to market makers exercising their price-setting power.

Usually the market maker for a warrant is the respective issuer and quotes prices with a mark-up on top of the fair value. There is evidence that market makers of retail derivatives increase their quoted prices when they expect an excess in net investor demand and decrease them when they expect an excess in net investor supply (Baule 2011; Baule, Frijns, and Tieves 2018). This is reflected in the order flow hypothesis (Wilkens, Erner, and Röder 2003). As outlined in the introduction, there are two competing hypotheses that would both affect investors' timing returns: (i) An investor buy could indicate great attractiveness and lead further buys by other investors; and (ii) an investor buy could be followed by a re-sale by the same investor if they are speculating on short-term (intraday) gains. According to (i), the market maker should increase the warrant's markup, according to (ii), the market maker should decrease it.

To study if and how market makers use these hypothetical quotation strategies, we use a difference-in-differences (DD)

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TABLE 7 | Return decomposition.

	Total			Spread			Timing			Execution
	$t+1$	$t+15$	$t+60$	$t+1$	$t+15$	$t+60$	$t+1$	$t+15$	$t+60$	
Panel A										
Full sample	−1.19***	−0.97***	−0.88**	−1.32***	−1.40***	−1.43***	0.13_{++}	0.43^{**}_{+}	0.54^{*}_{+}	–
Calls	−1.29***	−1.05***	−1.15***	−1.41***	−1.49***	−1.52***	0.13_{+++}	0.44_{+}	0.37_{+}	–
Puts	−1.10***	−0.89***	−0.64	−1.23***	−1.31***	−1.34***	0.14_{+}	0.42^{*}_{++}	0.70	–
Large volume	−0.85***	−0.62***	−0.58*	−0.91***	−0.97***	−0.99***	0.06	0.35^{*}_{+}	0.40	–
Small volume	−5.18***	−4.71***	−4.37***	−6.51***	−6.68***	−6.90***	1.33^{*}_{+++}	1.97^{**}_{+++}	2.53^{***}_{+++}	–
Low price	−4.98***	−4.30***	−3.84***	−5.64***	−6.09***	−6.32***	0.66_{+++}	1.79^{***}_{+}	2.48^{**}_{+}	–
Panel B										
Limit orders	−1.22***	−0.92***	−0.70*	−1.40***	−1.50***	−1.53***	0.18_{++}	0.59^{**}_{+}	0.83^{*}_{+}	–
Large volume	−0.85***	−0.52***	−0.33	−0.94***	−1.02***	−1.03***	0.09_{+}	0.50^{**}_{+}	0.70*	–
Small volume	−5.60***	−4.97***	−4.73***	−7.18***	−7.42***	−7.69***	1.58^{**}_{+++}	2.45^{***}_{+++}	2.96^{***}_{+++}	–
Panel C										
Market orders	−1.08***	−1.11***	−1.45***	−1.04***	−1.04***	−1.07***	0.05	0.01	-0.30_{-}	−0.08
Large volume	−0.87***	−0.93***	−1.42***	−0.79***	−0.79***	−0.82***	0.05	−0.01	-0.47_{-}	−0.13
Small volume	−4.02***	−4.03***	−3.37***	−4.65*	−4.63*	−4.71*	−0.08	−0.11	0.62	0.71
Down tick	−0.94***	−0.99***	−1.51**	−0.95***	−0.95***	−0.94***	0.07	0.02	-0.51_{-}	−0.06
Up tick	−1.14***	−1.18***	−1.35*	−1.04***	−1.04***	−1.11***	0.03	−0.01	−0.11	−0.13

Note: The table shows volume-weighted averages of the returns (12) as well as the components of the returns (13), (14), (15), and (17) of investor buy trades for holding periods τ of 1, 15, and 60 min. The average returns are calculated for samples formed according to the warrants' type, the order size, the trade price, the order type, and the tick direction in the quoted price before the entry of a market order. Trades with a transaction volume in the upper (lower) 20% quantile are termed large (small). Trades with a transaction price of 0.50 euros or less are termed low-priced. The terms up and down indicate the tick direction before the entry of a market order. The returns are shown in percentage points. Mean returns that are significantly different from zero are indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***). Mean timing returns that significantly deviate on the lower/upper side from bootstrapped resamples are indicated at the 5% level (−/+), the 1% level (++), and the 0.1% level (+++).

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approach. 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.[24]

We define an investor's trade as a "treatment" and use a matching procedure to create the control group. For each trade in a warrant, we look for an identical warrant (in terms of underlying, strike, and time to maturity) from a different issuer that was not traded within the investigation period (2014) and for which we observe at least one tick within 60 min before and after the treatment. If there is more than one match, we only add to our control group the warrant whose price is closest to the treated warrant.[25] If there is no match, we discard the trade from the treatment group.[26] This matching procedure ensures that common valuation effects, such as movements in the underlying, cancel out.

For each trade i, we compute time-weighted average prices of treated warrants and control warrants before and after the treatment. Averaging accounts for the effect that issuers do not update their quotes simultaneously. This leaves us with a total of four observations per trade i. To be more precise, for $g \in \{treat, control\}$ and $p \in \{before, after\}$, the price $\overline{PRICE}_{i,g,p}$ is the time-weighted average price within 60 min before and after the trade. The methodology is summarized in Figure 5.

For ease of notation, we introduce the binary variables $TREAT_{i,g} = \mathbf{1}_{\{g=treat\}}$ and $POST_{i,p} = \mathbf{1}_{\{p=after\}}$ to indicate to which group a specific price $\overline{PRICE}_{i,g,p}$ belongs. The baseline DD regression reads as follows:

$$\overline{PRICE}_{i,g,p} = \alpha_i + \beta_1 TREAT_{i,g} + \beta_2 POST_{i,p} + \beta_3 POST_{i,p} \times TREAT_{i,g} + \epsilon_{i,g,p}, \quad (18)$$

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 treatment and control warrants. The coefficient of the variable $POST_{i,p}$ captures the mean change on average prices after a treatment. Since these variables cover all pricing-specific aspects, no further control variables are needed. The

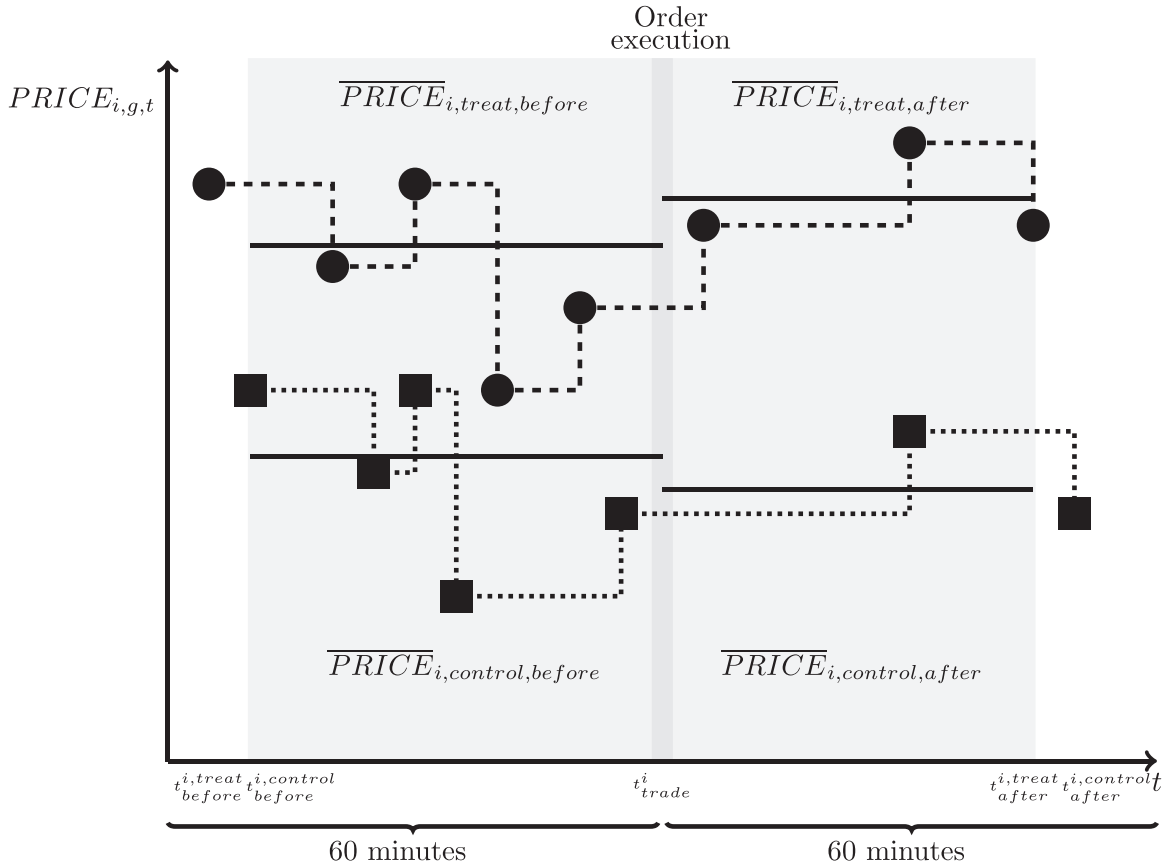

FIGURE 5 | Illustration of difference-in-differences methodology. The figure summarizes the calculation of the time-weighted average prices $\overline{PRICE}_{i,g,p}$, represented by solid lines, used in the difference-in-differences analysis. For each trade i the averages are calculated as $\overline{PRICE}_{i,g,before} = \sum_{t=\underline{t}^i}^{t^i_{trade}} PRICE_{i,g,t} / \left(t^i_{trade} - \underline{t}^i\right)$ and $\overline{PRICE}_{i,g,after} = \sum_{t=t^i_{trade}}^{\bar{t}^i} PRICE_{i,g,t} / \left(\bar{t}^i - t^i_{trade}\right)$, where time t is measured in millisecond increments, and $\underline{t}^i = \max\left\{t^{i,treat}_{before}, t^{i,control}_{before}\right\}$, $\bar{t}^i = \min\left\{t^{i,treat}_{after}, t^{i,control}_{after}\right\}$. The timestamp $t^{i,g}_{before}$ is the time of the first tick within 60 min before the trade and the timestamp $t^{i,g}_{after}$ is the time of the last tick within 60 min after the trade. The point in time of the order execution t_{trade} is highlighted in the dark gray. The time window considered for calculating the time-weighted averages is shaded in light gray. For buy (sell) orders we use quoted ask (bid) prices. 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 min before and after the trade. The time and price scales are for illustration only.

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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 effects of strategic quotation.

Pelster and Schertler (2019) have shown that issuers engage in cross-pricing when they have sold supplementary products. In particular, the magnitude of this effect depends on the trading volume. To analyze whether the degree of price adjustment in response to a trade similarly differs with trading volume, we indicate high-volume trades with the binary variable

$$HIGH_i = \begin{cases} 1, & \text{if the volume of trade } i \text{ is in the upper 20\% quantile,} \\ 0, & \text{if the volume of trade } i \text{ is not in the upper 20\% quantile,} \end{cases} \tag{19}$$

and include interaction terms with this variable in the DD regression.[27]

Above, we argued that there are two competing hypothetical quotation strategies. However, regardless of the strategy employed, it is unlikely that a market maker would react to a second trade in a particular warrant in the same way as to the first. The response to the first trade of the day in a warrant may therefore give a clearer picture of strategic quotation, while the responses to later trades of the day might be damped. To capture effects exclusive to the first trade per warrant and trading day, we introduce a further binary variable

$$FIRST_i = \begin{cases} 1, & \text{if the warrant is treated for the first time on the treatment day,} \\ 0, & \text{if the warrant was treated on the treatment day before.} \end{cases} \tag{20}$$

5.2.2 | Results

Table 8 presents the results for the DD regression models. To capture nuances of strategic quotation, we run the regressions

TABLE 8 | Strategic quotation.

	$\overline{PRICE}_{i,g,p}$ (cents)					
	(1)		(2)		(3)	
	Buy	Sell	Buy	Sell	Buy	Sell
$TREAT_{i,g}$	−5.83***	−6.29***	−5.74***	−6.37***	−7.44***	−8.07***
	(0.15)	(0.18)	(0.17)	(0.21)	(0.26)	(0.27)
$TREAT_{i,g} \times HIGH_i$			−0.47	0.32		
			(0.38)	(0.40)		
$TREAT_{i,g} \times FIRST_i$					2.6***	3.4***
					(0.32)	(0.35)
$POST_{i,p}$	−2.33***	3.2***	−2.47***	2.63***	−3.01***	3.9***
	(0.17)	(0.25)	(0.18)	(0.28)	(0.30)	(0.34)
$POST_{i,p} \times HIGH_i$			0.73	2.27***		
			(0.50)	(0.65)		
$POST_{i,p} \times FIRST_i$					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)
$POST_{i,p} \times TREAT_{i,g} \times HIGH_i$			−0.05	−0.08		
			(0.05)	(0.06)		
$POST_{i,p} \times TREAT_{i,g} \times FIRST_i$					−0.07	0.12*
					(0.04)	(0.05)
FE per Trade	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	22,584	17,200	22,584	17,200	22,584	17,200
# Trades	5646	4300	5646	4300	5646	4300

Note: The table shows the estimation results for the difference-in-differences regressions of the time-weighted average prices, separated by buy and call trades. 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 is based on cluster-robust standard errors with clusters formed at the trade level. Significance is indicated at the 5% level (*), the 1% level (**), and the 0.1% level (***).

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separately for purchases and sales. For the baseline regression (18) 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, with a size of only 0.03 to 0.06 cents (where 1 cent is the minimum tick size). This observation still holds after separating high and low volume trades. Also the exclusive look at warrants that have been treated for the first time a day yields no considerably different results.

A reason for our lack of evidence on strategic quotation 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 strategic quotation in the aggregate across all issuers. To address this cross-sectional issue, we re-run our regressions separately for each issuer. The results are similar to those shown for the aggregate and are therefore not tabulated here. As there is no evidence of economically significant strategic quotation, the returns according to (14) can be attributed solely to the investors' behavior.

The remaining variables in the regressions provide additional insights. The significantly negative coefficient of the variable $TREAT_{i,g}$ indicates, in all regressions, 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 another issuer that was on average more expensive. This is consistent with the finding that retail investors' demand for warrants is price-sensitive (Baule and Blonski 2015).[28] Finally, we find a statistically and economically significant pattern for the effect of the variable $POST_{i,p}^{i}$. For all regressions, the coefficient of this variable is negative for purchases and positive for sales. This indicates that, on average, the direction of retail investors' trades is contrary to the change in warrants' prices. As such, this pattern is consistent with negative feedback trading. However, as trades do not occur on average prices, no conclusions can be drawn about intraday timing ability.

Overall, our analysis in this section shows that retail investors who use warrants for feedback trading on recent intraday returns are noise traders who earn negative returns. These losses are primarily caused by the bid-ask spread, but are not due to market makers trying to take advantage of investors by responding to trades by strategically changing their quotes.

6 | Conclusion

Although feedback trading is prevalent among professional and retail investors and across multiple time horizons, the existing literature documents little about its existence with regard to the intraday time scale. Using a unique data set of exchange trades and quotes for bank-issued warrants on the DAX, we provide new evidence on the intraday feedback trading behavior of retail investors.

We find that retail investors consciously respond to intraday returns of the underlying for up to 2 h, showing a strong pattern of negative feedback trading. This behavior suggests that retail investors expect recent intraday returns to reverse. This is in line with the lower-frequency feedback trading literature. Moreover, there is a subgroup of investors who speculate on high-frequency momentum in the tick-by-tick returns of warrants. Although these investors appear more attentive, their returns are indistinguishable from returns of random order submissions.

Retail investors who use warrants to feedback trading on intraday returns are noise traders who earn, on average, negative returns. This is also consistent with the literature. We find that these losses are primarily caused by the bid-ask spread, but are not due to market makers trying to take advantage of investors by responding to trades by strategically changing their quotes. It is investors' behavior that determines returns. Among different investors, those that trade small amounts, low-priced warrants and market orders perform worst. Timing returns of investors who use market orders are at best indistinguishable and sometimes worse than those of random timing. Although some investors use limit orders skillfully to enter trades, on average they also fail to earn the bid-ask spread.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from EUWAX, LSEG Tick History, Solvians IT Solutions GmbH, and LSEG Datastream. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of EUWAX, LSEG Tick History, Solvians IT Solutions GmbH, and LSEG Datastream.

Endnotes

[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.

[2] Feedback trading is also documented extensively from market prices (see, e.g., Tayeh and Kallinterakis 2022, for a recent overview), and from experiments (Bloomfield, O'Hara, and Saar 2009).

[3] Positive feedback trading is documented for institutional investors in general (e.g., Nofsinger and Sias 1999; Sias 2007; Choi and Skiba 2015), and in particular for mutual fund managers (e.g., Boyer and Zheng 2009) and foreign investors (e.g., Choe, Kho, and Stulz 1999; Richards 2005; Phansatan et al. 2012). However, there is also some contradictory evidence (e.g., Phansatan et al. 2012; Kremer and Nautz 2013).

[4] To the best of our knowledge, Bauer, Cosemans, and Eichholtz (2009) provide the only study on the relationship between trading

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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 thereafter (Lemmon and Ni 2014). For this reason, the origin of option trades cannot be determined with certainty.

[5]Day traders follow an active trading strategy in which they attempt to make intraday profits 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, Choe, and Kho 2009). We refer to an institutional (proprietary) day trader as an employee who day trades on behalf of a firm (Garvey and Murphy 2005).

[6]In reality, limits to the price-setting power might arise from prices set by competing issuers for similar or identical products in combination with the investor's price sensitivity (Baule and Blonski 2015).

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

[8]We had to merge data from different sources, including academic research data offerings from EUWAX and Solvians IT Solutions. Unfortunately, both providers have since discontinued these special offers for academics, preventing us from using more recent data. However, since the market structure of EUWAX in 2014 remains unchanged until today, there is good reason to believe that the main conclusions are still valid.

[9]To satisfy different investor preferences for warrant features, banks typically issue a large number of warrants. Although all of these warrants are subsequently listed, not all of them are traded by investors.

[10]Similar relations are reported by Baller et al. (2016) for transactions in leverage certificates. In contrast, a database of retail trades in US 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.

[11]We refer to a *tick* as a price update in the issuer's quote (not a volume update).

[12]Methodologically related studies on stock trades by Heinen and Rengifo (2007), Quoreshi (2008) and Jung, Liesenfeld, and Richard (2011) use 5-min intervals. Since warrants are traded less frequently than stocks, our interval length of 15 min is slightly larger. However, our results are not driven by the particular choice of interval length. We rerun our analysis, outlined below, for 30-min intervals and draw similar conclusions.

[13]In line with the literature, we allocate orders to an interval based on their time of execution. However, our results are almost unchanged when using the order entry time. This is because, for most orders, the time between entry and execution is well below 15 min (see, Table 2).

[14]To rule out any opening-effects on our results, we drop the first interval of each trading day and repeat our analysis. The results are very similar and do not alter our conclusions.

[15]The count-based measures are highly correlated with their volume-based counterparts, which we have also calculated for robustness. The correlations are 0.87, 0.84, 0.80, and 0.83 for volume- and count-based order flow imbalances in calls, puts, overall, and purchase based respectively. Therefore, results are similar.

[16]During the first 2 h of trading, we set $INTRA_{t,i-j} = 0$ if $i - j \leq 0$.

[17]As an alternative, we repeat the analysis of Table 4 for the entire sample, but use the time of the order entry to allocate trades to an interval. This procedure is also robust against the choice of order type. The untabulated results are almost unchanged.

[18]We do not consider the last tick before the execution of an order. 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.

[19]To be more precise, we would expect the ratio to equal the unconditional empirical ratio of upticks to downticks, which is 0.9989 in our entire sample, covering 4.1 billion ticks.

[20]We focus on buy trades, as our exchange data do not identify traders, making it difficult to match buys and sells and track inventory.

[21]The principle that the transaction price for a market order is determined after an investor has entered into a buy or sell commitment is not unique to EUWAX. It is also applied on other exchanges in Germany that rely on indicative quotes, and when buying or redeeming mutual funds (see, e.g., Capponi, Glasserman, and Weber 2020).

[22]Resampling returns from the same warrants as in the original data ensures that we generate returns that vary only due to timing and not to warrant features like moneyness or maturity.

[23]Limit orders can receive price improvements compared to the current quote. When there is a limit order that could be matched with an indicative quote or lies within the bid-ask spread, market makers are requested to submit a binding bid or ask. By adjusting their binding order, they can (opportunistically) fill investors' orders that were previously inside the spread.

[24]Recent examples of applying DD in a similar context are Arnold, Pelster, and Subrahmanyam (2022), Pelster and Schertler (2019), and Pelster and Hofmann (2018).

[25]For robustness, we have alternatively used the warrant with the highest number of ticks and rerun our analysis. The results are robust to this change in the matching procedure. If there are multiple treatments of a warrant on the same day, the same control warrant is matched throughout that day.

[26]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.

[27]The upper 20% quantile corresponds to a value of 5400 euros. Since the variable itself is a linear combination of fixed effects, it is only included in interaction terms.

[28]An alternative interpretation is that investors prefer an issuer whose warrants are cheaper, although they do not compare prices.

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