The Role of Technical Analysis in Retail Investor Trading[*]

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Abstract

Technical Analysis (TA) is a security analysis methodology based on the study of past market data. Although it has been criticized by academics and the profitability of many related strategies has been statistically rejected, TA remains highly popular among practitioners and retail investors, in particular. We analyze the role of TA for retail investors trading structured products on Stuttgart Stock Exchange. We find a 35% increase in trading activity on days of chart pattern trading signals and an 11% increase for moving average signals. The increase in activity typically reverses on the following trading days. Furthermore, we identify trading characteristics of round-trip trades and find that trades associated with TA trading signals differ. First, we find significantly higher raw returns in TA-related trades while leverage levels at purchase as well as holding duration appear to be lower. Second, the shape of the realized return distribution of trades in accordance to TA signals is distinct from their peer groups. Specifically, realized returns are significantly less left-skewed (more right-skewed). In this regard, retail investors using TA methods might be less prone to the disposition effect due to the system-based trading approach. If we assume a general gambling intention with respect to the considered products, then TA-related trades tend to reach this goal more effectively.

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1 Introduction

Technical Analysis (TA) has a long history in security analysis and its roots date back to the invention of the Dow Theory in the late 19th century which is often considered as the foundation of TA. The main idea of most TA methodologies is to analyze historical price and volume data regarding regularities and other 'typical' developments that can be used to infer signals about future prices. Many TA concepts base on the idea that markets and prices behave cyclically or move in trends. In fact, the set of TA methodologies is vast and ranges from simple moving price averages to complex chart patterns or transformations of price and volume data. Although TA has been highly criticized by academics and the profitability of many related strategies has been statistically rejected[1], it remains highly popular among practitioners and retail investors. While in the pre-computer era TA was mostly applied by professionals who had the resources to systematically access and process data and draw charts by hand, the introduction of computer-based trading as well as brokerage accounts and information providers gave retail investors (RI) full-scale access to basically any historical market data at almost no cost. On the other hand, professional investment advice, for instance from bank advisers or wealth managers, is quite costly - especially for small accounts. From this point of view, trading recommendations from TA seem cheap and easy to use for any investor, while being complex enough to suggest a potential validity of the considered investment, compared to a purely random approach, for example. In addition, TA is also popular among professional investors like fund managers as the survey by Menkhoff and Taylor (2007) confirms.

To imitate (allegedly) successful investors seems to be a natural way to solve the "investment problem" of RIs. Furthermore, the ongoing development in the broker and financial (online) media industry is likely to amplify the relevance of TA related methods for RI. Almost any brokerage trading tool and financial website excessively promotes their visualization and charts as well as the availability of (historical) market data. Many of those sites and tools also offer complex charting tools or even automatic systems like pattern recognition to generate trading signals which is promoted as valuable investment research.

Based on the above considerations, the question arises how RI trading and TA is related. In particular, we want to access how two most popular TA methods, i.e. moving averages and chart patterns, and RI trading activity is related and whether trades which can be related to TA show different characteristics. Therefore, we analyze trading at Stuttgart Stock Exchange which is a German stock exchange predominately addressing

[1] Cf. Bajgrowicz and Scaillet (2012),Neuhierl and Schlusche (2011), as well as citations in Park and Irwin (2007)

the trading needs of RIs. Major business segments for Stuttgart Stock Exchange are listing of and trading services for structured products (so-called 'investment certificates'). These products are issued by banks and legally are bearer bonds with option-like or other payoff schemes. There exists a huge universe of structured products of which we focus on two popular types: knock-outs and warrants[2] having the German DAX index or its constituents as underlying. Our approach algorithmically identifies trading signals from TA and relates trades in the considered instruments to these signals. Our first main finding is that trading activity highly increases on days of TA signals. On average, a pattern signal can be associated with a 35% increase in excess turnover whereas MA signals lead to an increase of 11%. Applying regression models, we confirm and refine this finding and show that Head-and-Shoulders pattern and Double Tops & Bottoms have a particularly large impact. The second main finding is that trades in accordance to TA signal tend to have quite different trade characteristics than trades on non-signal days. We show that these trades usually have higher returns and are less left-skewed than their peers. This suggests that TA traders could be less prone to the disposition effect due to a systematic trading approach and (or) effectively use TA to realize return distributions with stronger gambling characteristics, i.e. more right-skewed returns.

Our study is closely related to a series of papers. Bender et al. (2013) find evidence in US stocks that a typical Head-and-Shoulders chart pattern is associated with increased trading and decreased spreads. Hoffmann and Shefrin (2014) combine brokerage data from retail clients and a corresponding survey about the usage of TA. They find that TA users tend to trade more frequently, earn lower returns, and choose higher non-systematic risk. Moreover, current working papers by Etheber (2014) and Etheber et al. (2014) address aspects of TA-based trading. The former relates MA trading signals to trading activity on Xetra[3] and finds increased trading turnover of up to 55% while the latter relates MAs and trading activity in client accounts of a German discount broker. They document a 30% increase in trading turnover and show that about 10% of the accounts can be classified as MA users whose trading activities can be explained to a large extent by MA signals.

Our paper contributes to the literature on TA-related trading by showing that TA is also highly related to trading activity on a RI-dedicated market in speculative structured products. The advantage of our sample is that the vast majority of orders is submitted by

[2]Basically, knock-outs are securitized barrier options (down-and-out calls and up-and-out puts) and warrants are securitized plain vanilla options which due to the legal implementation contain a counterparty risk for the investor since no CCP exists.

[3]Xetra is the largest German trading platform hosted by Deutsche Börse which predominantly is addressing institutional investors, for instance by offering customized high-performance accesses and co-locations.

RIs. Due to the properties of the structured products market, we are able to reconstruct round-trip trades for many orders and thus can evaluate how trades of market participants perform and which characteristics these trades have. Furthermore, we consider and compare a broader range of TA methods - namely three[4] typical chart patterns and different types of moving averages. By showing that RI trading activity is likely to be driven by TA signals, we provide evidence that unprofitable (noise) trading systems like TA can alter the trading behavior and results of those investors.

The remainder of the paper is organized as follows. In Section 2 we present previous results on RI trading and the role of TA. Based on the literature, we formulate our research hypotheses in Section 3. Section 4 describes the employed data sets and Section 5 our methodological approach. The results on trading activity is presented in Section 6. In Section 7 we consider the performance of trades and their characteristics in relation to TA. Eventually, Section 8 concludes.

2 Literature

2.1 Retail Investor Trading Behavior

The fact that despite the overwhelming empirical evidence of systematic under-performance over many decades the irrational trading behavior among retail investors still persists, is a long-standing puzzle. Numerous empirical studies document that investment accounts of retail investors exhibit bad performance, are under-diversified, tend to pick bad stocks and suffer from high trading costs. The reasons for irrational trading or investing typically mentioned are behavioral or psychological shortcomings like limited attention, overconfidence, bounded-rationality, greed, or a lack of education. The sensation seeking and gambling aspect of trading might compensate retail investors for the realized under-performance. Extensive overviews on retail investor trading and behavioral finance are provided by Subrahmanyam (2008) and Barber and Odean (2011), among others.

Empirical studies have found various patterns in RIs' trading and corresponding realized returns. Although different trading behavior of RI between socio-demographic groups (Goetzmann and Kumar, 2008) and personal capabilities (Grinblatt et al., 2012) has been documented, the population of retail investors tends to herd, i.e. they act similarly and simultaneously (Kumar and Lee, 2006). Similar information, e.g. media (Engelberg et al. (2011),Barber and Odean (2007)) or other attention grabbing events (Seasholes and Wu, 2007), (stock) familiarity biases (Keloharju et al., 2012), investor sentiment (Kumar and Lee, 2006) or related trading techniques like a focus on dividend

[4]Each having a long and a short version which generate buy and sell signals, respectively.

stocks (Graham and Kumar, 2006) are common explanations. The high turnover in RI portfolios is often linked to overconfidence (Daniel et al. (1998),Grinblatt and Keloharju (2009)) which has also been confirmed for German retail investors by (Glaser and Weber, 2004). Overconfidence causes RIs to misinterpret signals as information (Odean, 1998b), to overestimate the precision of their return forecasts (Glaser et al., 2007), or, in general, to believe being able to beat the market. This trait could also promote the use of TA if traders are overconfident regarding the profitability of TA related trading techniques. As a result of excessive and correlated turnover, RI trading can have an impact on the overall market which means excess turnover and momentum. RI trading imbalances have also been found to predict long-run returns (Barber et al., 2008). However, results on the actual positioning of retail investors are mixed. Both, contrarian behavior (Barber and Odean, 2000) and trend-following behavior (Dhar and Kumar, 2001), i.e. momentum trading, has been attributed to retail investors. This contradiction might be caused by opposed trading behaviors over different time horizons.

Another characteristic of retail investors is the so-called disposition effect, i.e. the tendency to ride loosing trades long and to sell winning positions early (Shefrin and Statman, 1985), which has been documented in several empirical studies (Odean (1998a), Grinblatt and Keloharju (2000), Dhar and Zhu (2006)) and is also a driver of correlated trading of RI (Barber et al. (2009). Entertainment and gambling as a motivation for many RI to trade has been documented in several studies (Dorn and Sengmueller (2009),among others) and implies a preference for assets providing right-skewed payoffs (Han and Kumar, 2013). Hence, TA could be an appealing method for sensation seeking traders to place their bets. Since most studies mentioned above use broker data from the 90's and early 2000's, the role of computer trading tools has been proliferated in recent years. In fact, Benamar (2013) shows that an alternative (updated) trading user interface can alter trading behavior, e.g. increasing trade frequency or changing the usage of different order types. Considering that today almost every finance website and broker account provides price charts and many also (automated) TA functionality like trend-lines or chart pattern recognition, it is likely that these tools also influence the decision making process of RI in some way.

Several studies have empirically analyzed German RIs and particularly trading in structured products[5] in Germany. Structured products contain substantial inner costs (premia) which depending on product type, issuing bank, and valuation model were found to be about 1% to 6% p.a. of the invested capital (see Wilkens et al. (2003), Stoimenov

[5]There exists a large universe of bank-issued structured product types, e.g. discount certificates, bonus certificates, knock-out warrants, (standard) warrants, and index certificates to name some of the most popular ones. For each type there are several sub-types having alternated pay-off schemes and other product characteristics.

and Wilkens (2005), Fritz and Meyer (2012), among others). Due to these costs (inter alia), RI trading structured products typically are found to realize bad returns on their investments. Entrop et al. (2014) find that, on average, RIs lose almost 2% in (standard) warrants and more than 5% in knock-out warrants per round-trip trade. Nevertheless, a relevant share of trading activity in RI portfolios at German discount brokers is in bank-issued structured products and Bauer et al. (2009) (among others) show that investors engaged in trading derivatives or other option-like instruments trade more frequently. Thus the pay-off structure of these products might be particularly appealing to RI to compensate for the drawbacks of structured products compared to a direct investment in the underlying, for example. Gambling and lottery aspects of (option-like) structured products have been put forward as an explanation (Dorn and Sengmueller, 2009). In fact, many types of structured products feature lottery-like payoffs with large leverage while (portfolio) hedging seems to play no central role for the excessive use of structured products (Schmitz and Weber, 2012). Analyses of trading patterns in structured products find typical characteristics of RI trading behavior, too. Schmitz and Weber (2012) find that RI exhibit contrarian trading behavior, i.e. buying calls (selling put) after price drops in the underlying and vice versa. Furthermore, the disposition effect has been verified for investors in structured products by several papers. Attention-grabbing events like news (Meyer et al., 2014) or earnings announcements (Schroff et al., 2013) can be associated with excess turnover in structured products while both studies indicate that RIs as a population have no superior private information, on average. However, Bauer et al. (2009) show on a subject level that a small group of traders is able to earn persistent excess returns[6]. This fact might motivate others to trade in hope of earning excess returns or, at least, to figure out if they are able to beat the market.

2.2 Technical Analysis

Financial economists have studied technical analysis over many decades. As a direct contradiction to Fama's efficient market theory, TA related strategies have been used to test the efficiency of financial markets. In the 1960's and 1970's a number of papers analyzed different strategies with mixed results (e.g. James (1968), Jensen and Benington (1970), among others). In 1990's, Brock et al. (1992) applied sampling methodologies to verify the profitability of moving average trading rules and found consistent excess returns in the considered strategies. Blume et al. (1994) develop a theoretical model to analyze the role of volume for TA and show that traders using market data information can do better

[6] Correspondingly, Barber et al. (2014) find that a small group (less than 1%) of Taiwanese traders earn persistent excess returns on their portfolios.

than others. Lo et al. (2000) find that chart patterns like head-and-shoulders contain information about the future return distribution. Savin et al. (2006) use an adapted definition of head-and-shoulder patterns and provide evidence for risk-adjusted excess returns for strategies based on these patterns. The literature review on the profitability of TA by Park and Irwin (2007) provides a detailed discussion of the topic and emphasizes the often contradictory results while questioning the robustness of these findings. By using a refined data snooping detection measure, Bajgrowicz and Scaillet (2012) present further evidence that TA rules are not able to earn consistent excess returns after transaction costs.

For our study it does not play a crucial role whether TA is actually profitable or not. It seems unlikely that the average retail investor really determines the best performing rules and calibration, but might use TA because she believes it is useful for her trading activities or because she thinks other successful investor use it. In this respect, behaviouristically motivated papers on the usage of TA find a high popularity of TA-related methods among professional investors. For example Flanegin and Rudd (2005), Menkhoff and Taylor (2007), and Menkhoff (2010) show that fund managers and professional traders believe that TA has some relevance in financial markets. The survey replies from fund managers in Menkhoff (2010) show that for 87% TA plays a role in their investment process and for 18% it is the preferred way of information processing. Using a large sample of Dutch discount brokerage clients and a corresponding survey, Hoffmann and Shefrin (2014) find that 32% use TA to some extent while for 9% it is the exclusive trading strategy. By matching the survey responses to the investor's accounts, they show that TA is highly detrimental to investors' wealth causing a marginal cost of about 50 basis point per month. Furthermore investors using TA trade more frequently and hold more concentrated portfolios with higher non-systematic risk exposure. Interestingly, the share of TA users is even higher than reported by Lease et al. (1974) in the 1970's which might be due to increased availability of TA tools typically provided by financial websites and online brokerages today. Hoffmann and Shefrin (2014) also show that TA investors trade lottery-like instruments with right-skewed return distributions, but negative risk-adjusted returns. Ebert and Hilpert (2013) sample return distributions of moving-average strategies and argue that the increasing right-skewness compared to a buy-and-hold strategy might be particularly appealing to investors having prospect theory preferences. The triggering of TA trading signals might just generate attention in a particular stock and thereby addresses the search problem of RI (Barber et al., 2008) resulting in increased turnover due to an attention effect.

In fact, previous research has shown that TA-based trading also affects trading on a market-wide level. Osler (2000) and Osler (2003) finds that currency exchange rates tend to stop moving (or reverse) more often at support and resistance levels announced by professional TA trading firms. Kavajecz and Odders-White (2004) analyze order flow at the NYSE around moving average crossovers. These technical levels coincide with increased depth on the limit order book and thus seem to be able to detect liquidity. Similar, Bender et al. (2013) find liquidity effects when head-and-shoulder patterns are triggered. They argue that the increased uninformed technical trading leads to decreased bid-ask spread, probably due to smaller adverse-selection risks for liquidity suppliers during periods of increased noise trading.

3 Hypotheses

Previous research indicates that technical analysis plays a role in security markets. Ongoing developments in the broker industry and financial media promote the use of IT tools for RIs. Most trading accounts and financial websites provide massive chart tools and automatic TA signal detection which presumably influence RI trading decisions. However, the actual effects on trading are opaque. In this paper we want to develop a methodology to access TA related strategies algorithmically to identify "TA events" in the German DAX index and its constituents. Having identified those events which potentially might be used by retail investors, we want to access two main research questions. The first research question considers the aggregated market-level, namely

RQ1: *How do TA-based strategies and the corresponding trading signals influence trading activity in structured products on an RI-dedicated market?*

Based on previous literature presented above, we assume that retail investors rely on TA-driven trading strategies which results in the following hypotheses regarding RQ1 which we will address in section 6.

H1a: Trading activity in speculative (structured) products is abnormally high on TA event days, i.e. on days of a TA buy or sell signal.
H1b: TA buy (sell) signals lead to a positive (negative) net positioning of RI.

The second question considers TA and trading on a trade-based level, i.e. round-trip trades completed at the Stuttgart stock exchange.

RQ2: *Which are the characteristics of trades that have been initiated in accordance to TA trading signals and how do these trades differ from others?*

The previous section has shown that RI, in general, and particularly when trading structured products (or other derivatives) consistently under-perform, probably due to informational and cognitive shortcomings. Since TA trading techniques can be considered as an algorithmic modification of the realized return distribution (cf. Ebert and Hilpert (2013)) - if followed strictly and if transaction costs are ignored - the sample of TA-related trades has different characteristics than typical RI trades. Potentially alternated characteristics might be trade (under-)performance due to (bias-induced) unfavorable market timing, disposition effect (i.e. left-skewed realized return distributions), or leverage and realized volatility of a trade. The leads to following hypotheses regarding **RQ2**:

H2a: Trades in accordance with TA trading signals earn higher raw returns and risk-adjusted returns.
H2b: The realized return distributions of trades which are in accordance to TA trading signals are less left-skewed than the realized return distributions of comparable trades.

In particular, hypothesis H2b can be interpreted as a weaker propensity of TA-based traders to the disposition effect. In this sense, TA could be an effective tool for RI to realize a return distribution which is (more) in accordance with their actual (pre-trade) preferences.

4 Data

In this paper, we focus on TA signals in the German blue chip index DAX and its 30 constituents based on the index composition[7] at end of 2013 (henceforth DAX30 stocks). Minutely and end-of-day price data as well as corporate action data ranging from 01/01/2009 to 12/31/2013 are obtained from Thomson Reuters Tick History through the Securities Industry Research Center of Asia Pacific[8] (SIRCA). To detect TA signals, daily closing prices are adjusted for dividend payments and stock splits which chartists consider as not meaningful for chart patterns (Kirkpatrick II and Dahlquist, 2012, p.367). In Section 7 minutely (closing) prices are used to calculate returns in the underlying which are used as benchmark for the trade performance of retail investors trading structured products on these underlyings.

To analyze retail investor trading behavior, we focus on leveraged (structured) products. In particular, we use warrants and knock-out products with limited time to ma-

[7]There were four changes of the index composition in 2009 and two in 2012. However, all new stocks have been Xetra listed before the DAX entry and complete trading data is available.
[8]We thank SIRCA for providing access to the data.

turity[9]. Boerse Stuttgart[10] provides us master and transaction data from 04/01/2009 to 12/31/2013. Master data contain information about product name, underlying, option type, first and last trading day, expiration date, knockout barrier, strike level, and subscription ratio. We only use instruments for which complete master data information is available. Transaction data observations contain a timestamp, product identifier, trade direction, trade price, trade size, and routing information. We delete trades below EUR 0.1 as these prices usually imply extremely high leverage. Furthermore we delete all trades in the upper 1 percent turnover and volume quantiles (based on each underlying and product class) since these trades are unlikely to be on behalf of retail investors. The sample contains 266,783 traded instruments, about 3.7 million trades, and a total turnover of EUR 15.2bn. Table 1 shows a detailed compilation of each product and option type. For the analyses in the later sections, we use April 2009 as pre-period and December 2013 as post-period which both are not considered for the statistical evaluation in section 6 & 7. The post-period is also necessary with respect to the matched sample since towards the end of the sample matching orders is often not possible anymore.

Insert Table 1 here.

Based on the transaction data sample we construct a matched sample which includes completed round-trip trades. We believe that retail investors who are buying structured products at Stuttgart Stock Exchange are also likely to sell there as well. Therefore we use a matching algorithm which was also used by Meyer et al. (2014) to analyze the trading skill of retail investors. The algorithm matches buys in an instrument with subsequent sells having the same size and routing information given a first-in, first-out principle. Due to the huge number of instruments there are usually only few trades in each instrument making the trade characteristics quite unambiguous. Thus the chance of mismatches is relatively low. If no matching sell order is found, we check whether there are sells in the instrument having the same routing information. If this is the case we leave the buy order unmatched; if not, we check whether the product has been knock-out or has expired and assume that the corresponding final value of the instrument has been realized[11]. Note that we use the unfiltered transaction data, i.e. all potentially matchable sell orders are considered. In section 6 we show that most trades typically are completed within one month. Overall, we are able to match 72.0% of knock-out buys and 48.6% of warrant buys, respectively. Again, we delete round-trip trades with buy prices below EUR 0.1,

[9]There are also many open-end knock-out products which therefore have a rolling knock-out barrier. However, we have no historical data of the daily strike updates and thus we delete these instruments from the sample.

[10]We thank Boerse Stuttgart for providing the data for this research paper.

[11]Knocked-out or expired instruments do not have to be sold by the investor as they are automatically cleared from the trading account by the broker and the issuing bank, respectively.

delete trades in the upper 1% volume and turnover quantile, and trades completed in less than two minutes or more than one year. The final matched sample contains 1,085,349 round-trip trades.

5 Methodology

The foundation for the analysis of technical analysis based trading is to define corresponding trading techniques, i.e. to generate trading signals. This involves three tasks: First, methods to (algorithmically) identify chart structures in price series. Second, the selection and explicit definition of the technical analysis techniques. Third, we must calibrate these techniques as they usually include several parameters which describe the visual appearance of a pattern, for example. For this study we focus on two different classes of TA techniques - chart patterns and moving averages. We keep the set of pattern types and moving averages small and specific in their calibration in order to obtain a relatively small number of trading signals. Due to the great fuzziness of the recognition and definition of technical analysis techniques, we try to use popular techniques to capture as many traders as possible. In the following, we describe the employed algorithms to detect trading signals from technical analysis.

Chart pattern recognition. The main idea of our pattern recognition is based on the seminal paper by Lo et al. (2000) who use smoothing techniques to identify chart patterns. Chart patterns are defined by a sequence of highs and lows and a trigger price condition. The smoothing tries to capture the eye-balling identification of 'significant' local highs and lows (also called peaks and troughs) in the price chart. Analogously to Lo et al. (2000) and Savin et al. (2006), we use kernel regressions to reduce the noise in some price series $P_t, t = 1, ..., n$, i.e. we apply the Nadaraya-Watson estimator to obtain the smoothed series

$$(1) \quad m_t = \frac{\sum_{j=1}^{n} P_j \times K_h(j-t)}{\sum_{j=1}^{n} K_h(j-t)},$$

where $K_h(\cdot)$ is the Gaussian Kernel

$$K_h(x) = \frac{1}{h\sqrt{2\pi}} \exp^{-x^2/2h^2},$$

with bandwidth parameter h. Then, we search for local extrema in the smoothed series $m_t, t = 1, ..., n$, i.e. all $k \in \{2, ..., n-1\}$, satisfying $m_{k-1} < m_k$ and $m_k > m_{k+1}$ as a precondition for a local high and vice versa for a local low. The actual local extremum is defined at the maximum (minimum) of the actual prices P_{k-1}, P_k, P_{k+1} around k which results in a sequence of extrema E_i. Note that the procedure ensures that the sequence $E_i, i = 1, 2, ...$ always consists of alternating highs and lows.

The above procedure is not carried out on the complete time series of (closing) prices from our sample, but on (moving) windows of fixed length. To some extent, the window length restricts the duration over which patterns can evolve. The length is only of subordinated importance for the number of patterns found. We use windows of 84 (trading) days which represents about 4 months. This seems to be sufficient since we assume traders using daily price observations usually are not looking for patterns of much longer duration. Furthermore the types of instruments we consider for this study are typically used for short-term trading. Note that it is not necessary to use a window length which a trader would use (and which would probably be longer in case of daily data) since it is only relevant for the maximum possible length of a single pattern, i.e. the distance between the first and last price involved in the pattern. We require that within a window the last extremum of a pattern is the 75th observation[12] which ensures that each occurrence of a pattern is only found once.

The most influencing factor in the above procedure is the bandwidth h, i.e. the degree of smoothing. A large value of h results in fewer detected extrema and thus fewer patterns found. It also influences the duration of patterns since more extrema in a fixed time window allow patterns to evolve over a shorter period of time. Lo et al. (2000) and related papers use cross-validation[13] to determine the value of h. However, our tests applying cross-validation seem sto produce undesirable calibrations for the purpose of detecting chart patterns. First, h becomes relatively small which is why other studies (Savin et al., 2006) use multiples of h to increase the degree of smoothing[14]. Secondly, the value of h varies quite much from window to window which we believe is not practical as we do not expect that traders change their (visual or algorithmic) recognition calibration when a new observation updates the price chart. Furthermore, strongly varying h can lead to the situation where a detected pattern is not detected in the next window which we believe would be inconsistent to some extent (although we exclude repeating patterns). Nevertheless, we assume that traders might change the 'cognitive' degree of smoothing

[12]This leaves 9 observations subsequent to the trigger point which ensures that there are enough observations for the kernel regression in order to avoid boundary effects on smoothed prices in the range of the pattern.

[13]Cross-validation determines h by minimizing the (overall) squared error when using the model to (sequentially) predict an observation by all others (n predictions) which is the so-called leave-one-out method.

[14]That the procedure results in small h values seems not surprising since if we assume the price series to be close to random walks, the best place to look for the left-out price observation for the cross-validation would be between the adjacent observations. Therefore, most of the weight is given to these observations, i.e. the bandwidth h becomes very small.

they apply to a chart, for example when prices are more volatile. Thus, for each window i we define $h_i = 1 + 8\sigma_i$, where σ_i denotes the standard deviation of the price differences in window i. This definition results in similar average h as in the cross-validation case with multiplier 3.0, but with much less and smoother variation between windows.

Chart pattern definitions. We consider three types of chart patterns each including a long (buy signal) and a short (sell signal) version: (inverse) head-and-shoulders, double top & bottom, and rectangle top & bottom. The pattern definitions are similar to those in previous literature and all include 'neckline-conditions' which Kirkpatrick II and Dahlquist (2012) describe as an important aspect for the pattern validity.

The head-and-shoulders pattern requires a sequence of extrema $E_1, ..., E_6$ such that

- E_1 is a maximum
- $E_3 > E_1$ and $E_3 > E_5$ (head above shoulders)
- $|E_i - \bar{E}| \leq 0.015 \times \bar{E}$, for $i = 1, 5$, where $\bar{E} = (E_1 + E_5)/2$ (shoulders have similar height)
- $|E_i - \bar{E}| \leq 0.015 \times \bar{E}$, for $i = 2, 4$, where $\bar{E} = (E_1 + E_5)/2$ (points are in similar range)

If the above conditions are satisfied, we check if the price crosses the so-called neckline, which is defined as a line through E_2 and E_4. The sell signal (if any) is generated at the first price between $E5$ and $E6$ below the neckline.

Analogously, the inverse head-and-shoulder pattern is defined as

- E_1 is a minimum
- $E_3 < E_1$ and $E_3 < E_5$ (head below shoulders)
- $|E_i - \bar{E}| \leq 0.015 \times \bar{E}$, for $i = 1, 5$, where $\bar{E} = (E_1 + E_5)/2$ (shoulders have similar height)
- $|E_i - \bar{E}| \leq 0.015 \times \bar{E}$, for $i = 2, 4$, where $\bar{E} = (E_1 + E_5)/2$ (neck points are in similar range)

If the above conditions are satisfied, we check if the price crosses the neckline, which here is defined as the line through E_2 and E_4. The buy signal (if any) is generated at the first price between $E5$ and $E6$ above the neckline.

Let the function $d(\cdot)$return the position of a observation within the window. Double tops are characterized by (not necessarily consecutive) extrema E_1, E_2, E_3 satisfying

- E_3, E_1 are maxima
- $d(E_3) - d(E_1) \geq 10$,
- $|E_i - \bar{E}| \leq 0.015 \times \bar{E}$, for $i = 1, 3$, where $\bar{E} = (E_1 + E_3)/2$
- $E_2 = \min_i(E_i : d(E_1) < d(E_i) < d(E_3))$
- $E_j > \max_i(E_i : d(E_1) < d(E_i) < d(E_3)), j = 1, 3$

If the above conditions are satisfied, we check if the price crosses the neckline which here is defined as the line through E_2 and E_4. The sell signal (if any) is generated at the first price after $E3$ below the neckline. Double Bottoms are defined as inverted Double Tops and generate a buy signal.

Rectangle Tops consist of five consecutive extrema $E_1, ..., E_5$ satisfying the following conditions:

- E_1 is maximum
- $1/1.01 < E_i/\bar{E} < 1.01$, for $i = 1, 3, 5$, where $\bar{E} = (E_1 + E_3 + E_5)/3$
- $1/1.01 < E_j/\bar{E} < 1.01$, for $j = 2, 4$, where $\bar{E} = (E_2 + E_4)/2$
- $E_j < E_i$, for $i = 1, 3, 5$, $j = 2, 4$

If the above conditions are satisfied, we check if the price crosses the neckline, which is defined as the line through E_2 and E_4. The sell signal (if any) is generated at the first price between $E5$ and $E6$ below the neckline.

Rectangle Bottoms are defined as inverted Rectangle Tops and generate a buy signal. Note that in technical analysis handbooks (e.g. Bulkowski (2011) and Kirkpatrick II and Dahlquist (2012)) Rectangle Tops and Bottoms are often defined as both, reversal and continuation patterns, depending on the direction of the breakout (i.e. upwards for buy signals and downwards for sell signals). We only use the reversal types to restrict the patterns to generate either buy or sell signals.

Insert Table 2 here.

For our final sample of 31 instruments and the parameter calibration specified above, we find 529 patterns of which 52.17% are buy signals. Table 2 shows detailed numbers on each type of pattern. To assess the consistency of the smoothing parameter h, Table 3 presents pattern detection results based on different ways of calibrating h. We consider $h = 1$ constant, $h = 1.5$ constant, and h determined by cross-validation multiplied by 3. Larger h-values lead to fewer detected signals, but the set of signals remains relatively consistent, i.e. the signals detected under stronger smoothing are a subset of the signals detected under less smoothing. In the presented alternative calibrations the share of signals in accordance to our final calibration used for the remainder of this study is between 49% and 95%.

Insert Table 3 here.

Moving Averages. Another popular technical analysis technique are moving averages. Although their implementation is very simple compared to chart patterns, the fuzziness regarding the selection of a moving average type (simple, exponentially-weighted, truncated, filtered, etc.) and calibration of parameters is of similar magnitude. We use three types of moving averages: 200-day simple moving average with 0.1% filter bands, 20-day/100-day dual (simple) moving average crossover, and 50-day/200-day dual (simple) moving average crossover.

The 200-day simple moving average with 0.1%−filter generates a buy signal on day t if $MA^{200}_{t-1} > P_{t-1}$ and $P_t > 1.001 \times MA^{200}_t$, and a sell signal if $MA^{200}_{t-1} < P_{t-1}$ and $1.001 \times P_t < MA^{200}_t$, where MA^{200}_t denotes the arithmetic mean of $P_t, ..., P_{t-199}$. The filter bands reduce the number of so-called 'whipsaw' signals when prices are moving closely around the moving average.

Dual moving average crossover generate buy (sell) signals when the shorter MA crosses the longer from below (above). That is, a buy signal of a 20-day/100-day dual MA occurs if $MA^{100}_{t-1} > MA^{20}_{t-1}$ and $MA^{20}_t > MA^{100}_t$, and a sell signal if $MA^{100}_{t-1} < MA^{20}_{t-1}$ and $MA^{20}_t < MA^{100}_t$.

Based on these three rules, we find 1709 trading signals in our sample. Table 2 shows details on each type of moving average under consideration.

Regarding the calibration of MA strategies basically the same considerations as for chart patterns apply. Shorter MAs and larger filter bands generate fewer signals. Furthermore, using a large number of different MAs (e.g. 5, 10, 20, 50 day SMA or DSMA combinations thereof) seems to be not helpful for the analyses because we might run into data snooping issues. For a large set of strategies producing trading signals, the chance is high that we find some result for some of the strategies just by chance, so we prefer to stick with those few we assume to be as most ambiguous and most popular in financial media as well as in academic literature - in particular the SMA200.

Excess trading turnover. To capture retail investor trading activity, we use two measures of trading intensity based on our (unmatched) transaction sample. Because of the large number of knock-out and warrants from distinct issuers that typically have different product characteristics, we adjust the actual trade turnover for subscription ratio and leverage of the traded product. Otherwise, our measure would not reflect the net position size of RIs, i.e. the capital (turnover) that would have been necessary to build a position in the underlying containing the same level of risk. From the actual turnover[15] TO_{act} of a transaction we derive the leverage-adjusted turnover

$$\text{(2)} \quad \text{TO} = \text{TO}_{act} \times \left(1 + \frac{R \times K}{P}\right), \text{ for calls, and}$$

$$\text{(3)} \quad \text{TO} = \text{TO}_{act} \times \left(\frac{R \times K}{P} - 1\right), \text{ for puts,}$$

where R and K denote subscription ratio and strike price of the traded instrument and P is the trade price.

The first measure of RI trading activity is based on the logarithm of aggregated (adjusted) turnover $\text{TO}_t^{(j)}$ of all transactions per day t and underlying j. To reduce the impact of extreme observations, we replace the 197 stock-day observations having zero turnover by the smallest observation in the respective stock during the sample period. We replace these observations, since in general even small trades have a numerically 'large' value. Thus zero-observation would introduce relatively much (meaningless) variation to the time series which we want to omit.

In general, a time series of (aggregated) turnover has specific (statistical) properties to consider. Turnover is always positive and typically has a right-skewed distribution. Furthermore, turnover time series are auto-correlated and related to stock and market volatility. To account for the above properties of the turnover series, we use a similar approach as Bender et al. (2013) who define excess turnover as the residual of an auto-regressive model. For each underlying j, we apply the following model and use the resulting residuals $\{\epsilon_t^{(j)}\}_{t=1,\ldots,T}$ as a measure of excess turnover, i.e.

$$\text{(4)} \quad \begin{aligned} \ln(\text{TO}_t^{(j)}) = \alpha + \sum_{k=1}^{20} \beta \ \ln(\text{TO}_{t-k}^{(j)}) + \sum_{i=0}^{5} \Big(\gamma_i \ \text{Range}_{t-i}^{(j)} + \delta_i \text{ret}_{t-i}^{(j)} + \zeta_i \ \text{VDAX}_{t-i}\Big) \\ + \eta \ \text{ret}_{t,t+10}^{(j)} + \theta t + \epsilon_t^{(j)}, \end{aligned}$$

where $\text{Range}_t^{(j)}$ is the (absolute) price range of underlying j on day t, $\text{ret}_t^{(j)}$, denote daily log-returns in the underlying, VDAX is the DAX (implied) volatility index, and $\text{ret}_{t,t+10}$ denotes the underlying log-return over the next 10 day period. In particular, we are able to remove the trend and the correlation to market and underlying volatility. The resulting measure can be interpreted as the surplus of turnover on a given day that we would not

[15]We also run trading activity analyses with the unadjusted (actual) turnover yielding very similar results.

have expected based on the model.

Since we want to analyze the positioning (long or short) of RIs in relation to the direction of TA trading signals, we define a second measure of directional trading activity. Therefore, we apply the same adjustment as in the first case, but we only aggregate purchases of calls as long turnover, and purchases of puts as short turnover, respectively. This means we exclude sell transactions for this consideration because of several reasons. First, due to the market structure of structured products always requires buying a product before it can be sold. Thus, the initialization of a long or short trade always requires the purchase of a call or a put. Second, selling a previously bought instrument can have several other reasons (e.g. liquidity needs). Even if traders use TA for their trading decision, they might have to close their position because the original TA signal does not work as anticipated, although there is no new opposed signal[16] Third, because it is also possible to sell an instrument on another exchange or directly to the issuer, missing sells could introduce some bias regarding long or short positioning, e.g. investors could prefer selling calls directly to the issuer. For the directional measure of excess turnover, we use an adopted vector auto-regression model as follows. Let $L_t^{(j)}$ the aggregated turnover of knock-out calls and call warrants on underlying j bought on day t and analogously $S_t^{(j)}$ put purchases. We define $X_t^{(j)} = (L_t^{(j)}, S_t^{(j)})^\intercal$ and the VAR equation

$$\begin{aligned} X_t^{(j)} = \alpha + \sum_{k=1}^{5} \beta \ \ln(\mathrm{X}_{t-k}^{(j)}) + \sum_{i=0}^{5} \Big(\gamma_i \ \mathrm{Range}_{t-i}^{(j)} + \delta_i \mathrm{ret}_{t-i}^{(j)} + \zeta_i \ \mathrm{VDAX}_{t-i}\Big) \\ + \eta \ \mathrm{ret}_{t,t+10}^{(j)} + \theta t + \epsilon_t^{(j)}, \end{aligned} \tag{5}$$

where the variables are in accordance to equation 4, but expanded to two-dimensional vectors with identical entries. We consider the resulting two-dimensional residuals $\epsilon_t^{(j)}$ as excess long and short turnover and the difference $\delta_t^j = (1, -1) \cdot \epsilon_t^{(j)}$ of its entries as excess turnover imbalance which will be used to analyze the positioning of retail investors.

6 Trading Activity

Overall trading activity. To test hypothesis H1a, we consider the overall trading activity in warrants and knock-outs at Stuttgart stock exchange. Therefore, we employ the excess turnover time series obtained as the residual of the turnover model (4). In

[16] For instance, we do not consider pattern confirmations or failures like so-called pull-backs in case of head-and-shoulders pattern. Furthermore, we do not check whether a triggered signal is negated which is usually the case when price break the trigger price levels (e.g. the neckline) in the opposite direction (cf. Bulkowski, 2011). In general, when trading on TA patterns it is not necessarily intended to close a position only when a signal in the opposite direction occurs, but after a given time or a given price target has been reached, for example.

a first step, we compare the average excess volume on TA signal days and non-signal days. Additionally we analyze the 3 trading days before and 5 trading days after a signal. Figure 1 and Table 4 show the differences of (lagged) signal days and non-signal days to which we apply a t-test (Sattertwaith). Panel A shows the results for pattern signals and Panel B for moving average signals, respectively. In both cases, we find large excess turnover on signal days which are significantly different from non-signal days. In case of pattern signals, this means that on signal days there is about 35% more turnover than we would have expected. For MA signals this value is about 11%. The smaller impact of MA signals could indicate a preference for patterns over a long-term MA or that the clientele for structured products prefers shorter MAs (considered patterns evolve mostly over less than two months) as their trading activities tend to have a shorter horizon.

Insert Figure 1 here.

Insert Table 4 here.

Considering the days before and after a signal, we find negative differences, i.e. negative excess turnover two days before a pattern signal. This could indicate that RI using TA wait for the triggering of a pattern after the last relevant extremum has emerged. Note that this difference is only significant on the 5% level due to the relatively large deviation. Similarly, MA signals exhibit a reversal in excess volume two days after a signal occurred as well as positive excess turnover 4 days after the signal which is of smaller magnitude than on the signal day, however. This might also be a result of the combination of MAs which often have slightly shifted trigger days or varying individual filter criteria applied in practice. Assuming that not all RIs are day traders or are trading each day, the lagged observation[17] of a TA signal could result in increased excess volume multiple days after an event.

In a second step, we apply a panel regression analysis to confirm the descriptive evidence. Therefore, we estimate the following regression for the excess turnover, i.e. the residuals $\epsilon_t^{(j)}$ obtained from model (4).

$$(6) \quad \epsilon_t^{(j)} = \alpha + \beta * Psig_t^{(j)} + \gamma * MAsig_t^{(j)} + \xi_t^{(j)},$$

where $Psig_t^{(j)}$and $MAsig_t^{(j)}$ equal 1 if a TA and MA signal occurred in underlying j on day t or are zero, else. Note that, we do not include firm dummies since the input excess turnover series was estimated per firm and the resulting residuals have zero mean. Consequently the intercept is not significant. However, the variance of those models

[17] Lo et al. (2000, p.1719) use a 3-day lag to "control for the fact that in practice we do not observe a realization [...] as soon as it has completed".

estimated per stock can differ in general. Thus we use Thompson (2011) clustered standard errors which cluster in time (day) and stock as well as in the intersection. Estimation results are shown in Table 5, column (1). Confirming the descriptive test, both signal types have a significant and positive effect on excess turnover at Stuttgart stock exchange. Naturally, R-squares are very low for these regressions as most of the explainable variation is already absorbed by the preceding models (4) or (5). Furthermore, signals are in general a quite rare event (about 6% of stock days) and can therefore not explain much of the overall variation. Despite that, the model confirms the large impact of a triggered trading signal on excess turnover. When we extend equation (4) by an additional interaction term of MA and pattern signal indicators, Column (2) shows that this effect is not significant. In general this is an extremely rare event[18] in our data.

Insert Table 5 here.

Alternatively to the two-step approach, we could also combine models (4) and (6) to estimate the normalization and TA signal effects simultaneously. Although the interpretation regarding the parameters used for the validation of hypothesis H1 remain unchanged, we prefer the two-step approach as the statistically more sound way to obtain this results. This is basically because we allow the impacts of variables used in model (4) to be stock specific and independent of potential effects from TA signals. Indeed, we do not account for cross-sectional effects or industry effects and only account for market volatility measured by VDAX index. The estimation results from the full model add no further insights[19] and are less consistent to analyze the hypothesized effect (H1a) since the two-step approach measures the effect with respect to the turnover that would have been expected from contemporaneous and lagged trading variables.

To differentiate between the considered pattern and moving average types, we adapt the regression model by including dummies for each considered pattern and MA type. Estimation results are reported in Table 5, column (3). Double Tops and Bottoms and (Inverse) Head and Shoulder patterns have the largest impact on excess turnover while both are statistically significant. The estimated effect of rectangle tops and bottoms is positive but not significant. This could indicate a more ambiguous definition of this pattern type or that the pattern is not as popular as the two previous ones. For moving average type signals similar results emerge. The SMA200 (with 0,1% filter) can be associated with a 20% increase in excess turnover which is highly significant on a 0.1% confidence level. However, both crossover MA types show values close to zero. This might be due to the more subjective implementation of double moving averages. While the 200-day SMA is quite unique, the shorter MA of the dual MA strategy could be applied with

[18] Only on 36 stock-days a pattern and MA signal is triggered simultaneously.

[19] Thus, results are not printed but can be made available on request.

basically any length. This could dilute the time of observation we consider and could also mean that the turnover based on these strategies is distributed over multiple days. We also tested DSMA10/100 and DSMA20/200 with very similar regression results. Hence, we drop the dual DSMA signals for the remainder of this paper.

Positioning. With respect to hypothesis H1b, we consider the excess turnover long-short imbalance obtained from regression (5). We apply two regression models similar to model (6). In the first model we use two dummy variables which equal one if any buy (sell) signal in an underlying occurred on day t. For the second model, we use all long and short signal of head and shoulder, double top and bottom, and rectangle top & bottom pattern, as well as the 200-day simple moving average, i.e. eight signal dummy variables in total. Results are reported in Table 6. Both models do not support hypothesis H1b. For the first model, reported in column (1), estimated coefficients of buy signal and sell signal dummies are not significant and close to zero but the signs are in the expected direction. The second model, reported in column (2), shows that the estimates for individual trading signals neither have a significant impact on turnover imbalances on a 10 % level. Note that, we only consider call buys and put buys, respectively, i.e. there are no direct reversal effects from selling positions which could be considered as long or short positioning and thus might affect the model results in any direction. A possible explanations for the results on excess turnover imbalances could be that only a subgroup of RI use TA while another group acts in the opposite direction. Since TA signals always appear after a price movement in the same direction[20] of the signal, contrarian trading usually is opposed to TA based trading. Overall, hypothesis H1b must be rejected in the sense that TA signals cannot reliably predict (net) positioning of RIs measured by daily (excess) trading imbalances.

Insert Table 6 here.

7 Trading Characteristics

In addition to the aggregated trading activity in structured products at Stuttgart Stock Exchange, we now focus on trade characteristics of round-trip trades. Therefore, we use the sample of matched trades described in Section 4. For each round-trip trade i we calculate three return measures, i.e. log-return r_i, risk-adjusted return r_i^{adj}, and risk-

[20]I.e. price increase for a buy signal and price decrease for a sell signal, respectively.

adjusted excess return r_i^{adjex} defined as

$$r_i = 100 * \log\left(\frac{P_{sell}}{P_{buy}}\right)$$

$$r_i^{adj} = 100 * \log\left(\frac{P_i^{sell}}{P_i^{buy}}\right) / (L * \sigma_i))$$

$$r_i^{adjex} = \begin{cases} 100 * \left(\log\left(\frac{P_i^{sell}}{P_i^{buy}}\right) - \log\left(\frac{U_i^{sell}}{U_i^{buy}}\right)\right) / (L_i * \sigma_i)\,, \text{for calls} \\ 100 * \left(\log\left(\frac{P_i^{sell}}{P_i^{buy}}\right) + \log\left(\frac{U_i^{sell}}{U_i^{buy}}\right)\right) / (L_i * \sigma_i)\,, \text{for puts} \end{cases}$$

where P^{buy} (P^{sell}) denotes the buying (selling[21]) price, $U_i^{buy}(U_i^{sell})$ the price of the underlying at purchase (sale), L_i is the leverage of the traded product at purchase as defined in equation (2), and σ_i denotes the annualized 20-day volatility of the underlying. We use the historical volatility to account for the risk involved since realized volatility calculated over the holding period often behaves erratically, in particular for very short trading horizons like a couple of hours.

Insert Figure 2 here.

Figure 2 depicts the empirical distributions of leverage, holding period, and log-returns of the whole sample. The high leverage ratio incorporated in the traded instruments highlights the highly speculative character of these trades. Since the population of RI are considered to be uninformed noise traders (cf. Meyer et al., 2014), gambling and entertainment seem to be a major incentive for trading KOs and warrants. The holding duration supports the consideration of this trades (and products) as short-term bets. The median holding period is less than two days, i.e. most trades are completed within one or two days[22]. The numbers regarding earned returns are quite devastating for RI trading KOs and warrants. On average, a trade loses about 4% of the invested capital. Interestingly, the median log-return is positive, i.e. the log-return distribution is highly skewed to the left. RI realize profits more often, but also realize extreme losses which in many cases means the total invested capital. Approximately 7.48% of the trades considered are knocked-out or expire worthless. These descriptive facts are an indication for the presence of the disposition effect for RI trading structured products which confirms several existing studies on RIs (see Section 2.1).

[21]As described in Section 5, we use a selling price of 1 cent if a product is knocked-out and the inner value of the product if it expires.

[22]Note that the histogram is cut off after 30 days, although the maximum trade duration considered is one year. Generally there are also long-term trades which the much larger mean (about 14 days) in comparison to the median indicates.

To assess research question RQ2, we analyze whether there are differences between trades that have been entered on days of a TA trading signal. To achieve this, we use trading signals generated by the three pattern types and the SMA200. We define the dummy variables $buysig_i$ and $sellsig_i$ which equal one if a buy signal and a sell signal, respectively, occurred on the day on which round-trip trade i was entered. To test whether there are significant drivers of round-trip trade returns, we estimate the following linear regression with double-clustered standard errors (Thompson (2011), Cameron et al. (2011)).

$$\begin{aligned} (7) \quad r_i =& \beta_1 * buysig_i * c_i + \beta_2 * buysig_i * p_i + \gamma_1 * sellsig_i * c_i + \gamma_2 * sellsig_i * p_i \\ &+ \delta_1 * holding_i * c_i + \delta_2 * holding_i * p_i + \eta * market_i + \zeta * ko_i + controls + \epsilon_i, \end{aligned}$$

where c_i and p_i are dummy variables for call and put, $holding_i$ denotes the duration of trade i in days, $market_i$ is a dummy for market buy order, and ko_i indicates trades in knock-out products. The term $controls$ is defined as $\sum_j \left(ul_i^{(j)} * c_i + ul_i^{(j)} * p_i \right)$, where dummy $ul_i^{(j)}$ equals 1 if the underlying of $trade_i$ is j. This means we have fixed effects for each underlying and trade direction (i.e. long or short trades) in terms of call or put products. Thus we evaluate whether trade performance varies within the peer group of products on the same underlying and of the same option type but assume that the effects regarding TA trading signals are related across all groups. This is necessary because puts and calls on the same underlying generally behave diametrically[23]. Since the expected effects of trading signals on performance are opposed for puts and calls, we use separate dummies for buy signals and sell signals, respectively.

Insert Table 7 here.

For the three return measures defined above we report the estimation results in Table 7. The model indicates that round-trip trades which are entered on days of TA buy signals and are in accordance to those signals, i.e. call products, earn higher (raw) log-returns, while put trades earn lower returns (see column 1) on these signal days. Parameter β_1 and β_2 show that these trades have 8.27% higher resp. 13.99% lower (log-) returns and both estimates are significant on a 1% level. Note that the abnormal returns estimated by the parameter coefficients are with respect to other trades on the same underlying and option type. This does not mean that these trades must have been profitable at all, but at least

[23]In case the underlying price does not change while the underlying volatility increases or time progresses, both, put and call prices could increase or decrease. However, due to the large number of trades and the long observation period such special cases can be neglected here. Alternatively, we could estimate the model for puts and calls separately but then it is not possible to distinguish whether all trades were profitable on buy (sell) signal days or just calls (puts).

have been less unprofitable than comparable trades. Analogously, trades entered on sell signal days tend to have better performance for puts and weaker performance for calls. The estimates indicate an impact on log-returns of 5.23% for puts and -3.23% for calls, thus the effect is of smaller magnitude than in the buy signal case, but still significant on a 1% level.

Considering risk-adjusted returns, we observe the same effect in case of buy signals. Naturally, the parameter estimates are smaller since dividing by leverage and volatility dampens the return values. If a call trade is entered on a buy signal, there is a positive effect on performance of 1.11% while puts earn 1.97% less. For sell signals the estimates differ from the non-adjusted case. While calls do not earn significantly differing risk-adjusted returns compared to the remaining trades, puts even show worse performance than puts on non-signal trades and on the same underlying. This could mean that puts on signal days buy the extra return from increased risk. So it might be the case that the results regarding raw returns of puts bought on sell signal days are driven by some very successful trades which use very high leverage. For risk-adjusted excess returns we basically get a similar result as for risk-adjusted returns. Here, estimates are very small as most variation is absorbed by the standardization. Since the return of a KO or warrant is (to a large extend) a function of the return of the underlying and the incorporated leverage, the standardized excess return mainly consists of time-dependent and non-linear components of the price and mispricing which includes product premia and other costs, for example. The estimates indicate that for this remaining part of the return, effects are close to the risk-adjusted case, i.e. a significant positive (negative) effect for calls (puts) on buy signal days, and no effect in case of sell signals.

Other trade characteristics affecting the performance of a round-trip trade turn out to be as expected. A longer holding duration has a negative impact on returns, likely due to the inner costs of structured products. Not surprisingly, market orders also imply lower returns since RI have to pay the spread[24] in this case. If we do not adjust for leverage, there is no significant difference between knock-outs and warrants. In case of risk-adjustment, knock-outs earn higher (risk-adjusted) returns since these trades show less leverage. On the other hand, price changes are more affected by leverage in case of knock-outs compared to warrants[25].

To check whether differences in realized returns can also be found in other trade characteristics, we consider the (log) leverage at purchase and the holding period of a

[24]Our return measures always include spread costs (if applicable) and do not consider exchange fees or other costs. Spreads are usually fixed by the market maker and issuing bank on a specific level (typically EUR 0.01) which can have a major impact on returns for low-price products.

[25]Since the option delta of warrants is smaller than one, prices do not change as much if the leverage of both products is equal.

trade. We run a regression model similar to (7) where we only use variables which are known at the time of the independent variable observation. Thus terms containing the holding period are not regressed on leverage (at purchase). We also add terms for the underlying's volatility (at purchase). In case of holding duration, we only control for underlying and use a single call product dummy instead of one for each underlying. The estimation results are reported in Table 8.

Insert Table 8 here.

General effects on the leverage of the product at purchase tend to be as expected. Higher underlying volatility leads to less leverage in the selected product as the underlying itself tends to be more risky. With respect to TA signals, the results confirm the interpretations regarding regression model (7) applied to risk-adjusted returns. Call round-trip trades on buy-signal days do not incorporate higher leverage which could explain the positive effect on performance, but even tend to involve less leverage. An analogous interpretation holds in case of puts. That is, in those trades which are in accordance to TA signals, RIs have chosen less leverage compared to trades on the same underlying and option type on non-signal days.

For the duration of round-trip trades we find that call trades initiated on buy signal days and put trades on sell signal days tend to be sold sooner compared to their benchmark group. Although a longer holding period is generally costly due to the inner costs of a structured product and therefore does influence the performance of a trade (for which we control in model (7)), the favorable (unfavorable) performance of trades probably influences the holding duration when RI are affected by the disposition effect. Since we have no subject-level information it is impossible to disentangle the inter-dependencies between (current) performance of the trade, holding duration (i.e. the decision to close a position), and the disposition effect of a RI.

Insert Figure 3 here.

In the above models, we considered the trading performance (and other characteristics) of round-trip trades, i.e. purchases of puts and calls on days of a TA buy and sell signal, respectively, and on days when no signal occurred. The regression models show that there are differences in the means of the considered groups of trades. Now we also want to investigate potential differences in the total return distribution. Figure 3 shows the (de-meaned) empirical distributions of round-trip trades in calls and puts on signal, and no-signal days, respectively. For the upper plot buy signals are considered and for the bottom plot sell signals, respectively. In case of buy signals, we see quite different shapes of the empirical distribution. Call trades, which would be in line with TA-based trading, show less extreme and more symmetric returns around the mean compared to call trades on non-signal days. In case of puts the difference is even more evident. Put trades entered on buy signal days have a very long left tail and generally more extreme returns compared to put trades on non-buy-signal days. To assess the differences in the shape and the higher moments of the return distributions we run two tests. First, we use a two-sample Kolmogorov-Smirnov test on the standardized[26] (by mean and standard-deviation) return distributions and compare call (put) trades on buy (sell) signal days compared to the other groups. The test results shown in column 3 of Table 9 confirm that the considered return distributions are significantly different on a 0.1% level. This means the return distributions have statistically significant differences in their higher moments. Since we are particularly interested in the skewness of the realized returns, we calculate the Bowley coefficient s^B and Groeneveld and Meeden (1984) skewness measure s^{GM}. For a random variable X with mean μ_X, median ν_X, and quartiles $Q_i, i = 1, 2, 3$, these measures are defined by

$$
\begin{aligned}
s^B &= \frac{Q_3 + Q_1 - 2Q_2}{Q_3 - Q_1} \\
s^{GM} &= \frac{\mu_X - \nu_X}{\mathrm{E}|X - \nu_X|}.
\end{aligned}
$$

We do not use the standard sample skewness since it is not robust to outliers and fat-tailed distributions which here is the case (cf. Groeneveld and Meeden, 1984). To test whether the skewness measures can be (statistically) distinguished between two sets of round-trip trades, we construct confidence levels from a resampling procedure. Therefore, we pool the observation from both samples and randomly draw two new sets having the same size as the original ones. For the sampled sets we calculate the absolute difference of the skewness measures. We run 100,000 repetitions to obtain the distribution of this difference from which we derive the 0.1% confidence levels. Panel A of Table 9 shows the results for buy signals while for Panel B presents results for sell signals. The corresponding confidence levels for the absolute difference of the skewness measures are reported in parentheses. For buy signals (Panel A), we find that the return distribution of calls bought on signal days is less left-skewed ($s^B = -0.1049$, $s^{GM} = 0.1993$) than the return distributions of other groups which is significant on a 0.1% level in all cases. Puts bought on buy signal days (i.e. opposed to trade direction of the TA signal) exhibit the most left-skewed return distribution ($s^B = -0.4482$, $s^{GM} = -0.3825$). A reason for this might be that signal triggers are associated with short-term momentum since the signals require a (preceding)

[26]We also run Kolmogorov-Smirnov tests on the original and centered distribution, both resulting in rejection of the null in all pairwise comparisons.

price movement in the direction of the signal. The opposite trade could then suffer from this short-term momentum, but the high leverage and the risk to be knocked-out can quickly lead to an undesirable situation for the investor where she must sell the position with a big loss. If we assume that traders prefer right-skewed returns, then traders who follow TA signals in our sample actually achieve this. The latter is in accordance to the simulation result of Ebert and Hilpert (2013). Furthermore the tendency to realize less left-skewed returns indicates that RI who use TA-based strategies are less prone to the disposition effect. Using a static rule or another systematic approach might reduce the risk to be influenced by behavioral biases as the decision of closing a trading position is given by the applied TA strategy or some other trading rule.

Insert Table 9 here.

For sell signals (Panel B) it turns out that call trades exhibit less left-skewed returns than trades in put products. A reason might be the generally worse performance of put round-trip trades which to a large extent is due to the strong market recovery during the observation period[27]. Thus, a randomly entered put trade was usually an unfavorable bet with a high chance that the investor's position falls below the purchase price. Consequently, these trades are more often faced with a big loss which traders who are prone to the disposition effect are reluctant to realize, but eventually the trade ended up even worse. Comparing put trades entered on sell signal and non-signal days, shows that the skewness measure are $s^B - 0.1092$ ($s^{GM} = -0.3035$) for the signal group and $s^B - 0.2739$ ($s^{GM} = -0.3628$) for the non-signal which is significantly different on 0.1% level. So for both, buy signals and sell signals, we can confirm hypothesis H2b, i.e. trades in accordance to the respective trading signals are less (left-)skewed than trades in the same direction on non-signal days. In this sense, TA traders could be more disciplined in their trading effort and realize losses sooner.

8 Conclusion

In this study, we have explored the relation between TA and trading on a RI-dedicated market. Based on a set of trading signals from typical TA techniques, chart patterns and moving averages, we have addressed two main research questions regarding the influence of TA on trading (cf. Section 3). How do TA-based strategies and the corresponding trading signals influence trading activity[...] (RQ1) and which are the characteristics of trades that have been initiated in accordance to TA trading signals[...] (RQ2). With respect to

[27]The DAX rose from 4075 on April 1, 2009 to 9552 at the end of 2013, that is an increase of about 134% in less than five years.

RQ1, we find that overall trading activity is substantially increased on TA signal days. A pattern signal from the three considered pattern types is associated with a 35% increase in excess turnover, on average. Regression results show that Head & Shoulders and Double Tops & Bottoms have a particularly strong impact on market activity. For MA signals an increase of 11% is observed. This means, trading activity in speculative structured products is related to TA signals. However, our analysis of (long-short) excess trading imbalances of RI reveals that there is no significant (positive or negative) relation between trading signal direction and the positioning of RI. This might be due to other attention effects which influence RIs and their trading behavior. For example, on an intraday level the increased turnover could initially induce attention and thereby attract more traders who tend to trade in a contrarian way, i.e. opposed to the TA signal. Then, we would find increased excess turnover on this day, but no reliable explanation for the exposure in the direction of the TA signal. Unfortunately, the sparsity of RI trading activity in products on a specific stock and the generally fuzzy observation of TA signals does not allow for a higher time granularity on a reasonable basis.

Regarding RQ2 we find that the trade characteristics of round-trip trades which were initiated in accordance to the direction of TA trading signals (i.e. long or short) do remarkably differ from round-trip trades on the same underlying and in the same direction. In terms of raw returns, these trades tend to perform significantly better than comparable trades on non-signal days. Based on our analyses it is hardly possible to infer the origin of the improved performance. We share the view of previous studies that TA as a systematic trading strategy is not able to earn consistent above-market returns (net of transaction costs). Yet, the exploitation of short-term momentum (maybe even induced by the increased attention itself) might play a role and could lead to increased returns for a limited period of time. Furthermore we find that the return distribution of trades in accordance to TA trading signals differ in the shape of their return distribution. Round-trip trades in calls on buy signal days, and puts on sell signal days, respectively, are less left-skewed than their peers. Using a resampling methodology, these differences turn out to be not by chance (on a 0.1% level). This can be interpreted as a reduced propensity to the disposition effect, i.e. realizing gains earlier than losses which would result in a left-skewed return distribution. Another interpretation of this result is that TA addresses the gambling and entertainment aspects of trading and is used by traders to place their bets. Indeed, the effect of TA strategies to skew the realized return distribution to the right has been found theoretically (Ebert and Hilpert, 2013) and is confirmed in our study empirically based on the distribution of realized returns of the considered trades on Stuttgart Stock Exchange. In addition to performance, other trade characteristics are found to differ for TA-related round-trip trades. They tend to be of shorter duration and contain less leverage at the time of purchase. Both findings confirm the view that TA changes typical trade characteristics of RIs.

Our results are limited with respect to the assumptions made. We apply a relatively narrow set of TA strategies which we assume to be relevant based on the literature and our view on practice, for example in financial media, TA handbooks or trading blogs. The calibration of the patterns and MAs is somewhat subjective, however the consideration of daily observations might offset some of the fuzziness regarding the exact triggering of a signal. It is also possible that the relative narrow set of MAs and the fixed pattern calibration do not include the most typical calibration of MA and patterns which RI trading structured products are using. Yet we believe that searching (fitting) the TA method yielding the "highest" result would not have been a sensible approach in our case. With respect to the trading data from Stuttgart Stock Exchange, we are limited by the fact that we can observe trading only on a population level, i.e. no individual trading information is available. Therefore, we cannot conclude that the observed effects are consistent in the sense that some trader who trades on a signal actually has traded on that signal and also will do so on a future signal of that (and only that) kind. A complementary survey[28] among trading participants could be an interesting extension to shed light on the trading incentives of RI trading at Stuttgart Stock Exchange.

If we conclude that RI use TA, like our study is indicating, the question arises why people actually use TA. Does the use of TA and the related trading just entertain investors - hence it had a value in itself - or does the lack of investment knowledge and the demand for a guiding system for making (profitable) investment decisions play a dominant role? If the latter is true, many offers by brokers and information providers excessively praising chart and TA tools should be considered critically. Therefore, the way TA, charts, and other related methods influence trading decisions of investors is an important question which we leave for future research.

[28] Similar to the approach of Hoffmann and Shefrin (2014) who use a survey to identify the investment style of broker clients.

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Tables and Figures

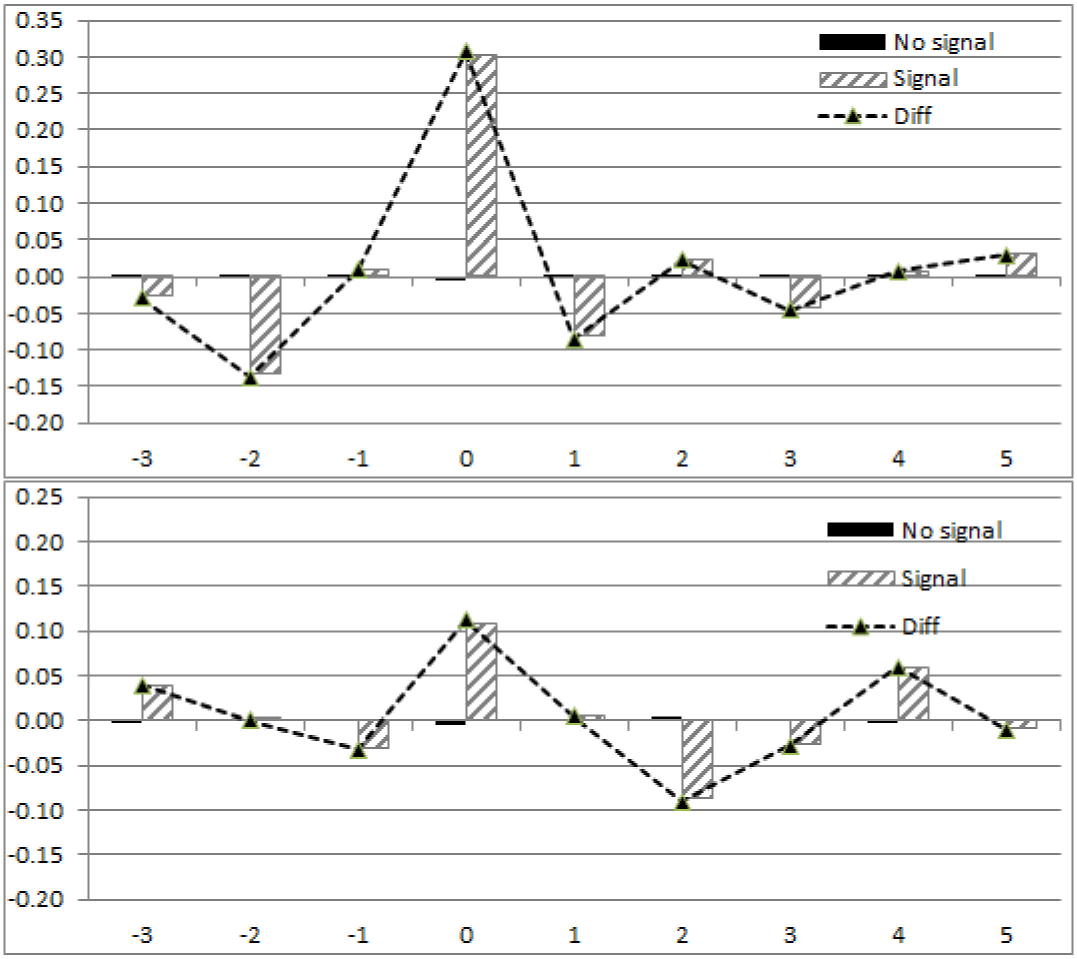

Figure 1: Excess trading on TA signal days.

The figures depict excess turnover in structured product at Stuttgart Stock Exchange from three days before to 5 days after a TA signal occurred in the respective underlying. The top and bottom plot are based on signals by chart patterns signals and moving average signals, respectively.

Table 1: Descriptive Statistics of Trading Data from Stuttgart Stock Exchange.

Key facts of trade data from Stuttgart Stock Exchange. The sample contains all trades in DAX and DAX30 warrants and knock-outs from 2009/04/01 to 2013/12/31. The matching rate refers to the share of buy transactions that can be matched by the algorithm described in section 5. From the resulting sample of round-trip trades, trades below EUR 0.1 or completed in less than two minutes are deleted.

	Overall	Knock-Outs		Warrants	
		Calls	Puts	Calls	Puts
# Instruments	266,783	62,408	47,466	96,827	60,082
# Trades (mn)	3.6950	0.7647	0.9292	1.2330	0.7680
# Buys (mn)	1.9761	0.3753	0.4611	0.6974	0.4424
# Sells (mn)	1.7189	0.3894	0.4681	0.5357	0.3256
Total Turnover (mnEUR)	15.2376	2.1885	2.5711	6.7007	3.7773
Buy Turnover (mnEUR)	7.6444	1.0264	1.2414	3.3844	1.9922
Sell Turnover (mnEUR)	7.5932	1.1621	1.3297	3.3163	1.7851
Avg. Trade Size (EUR)	3,995	2,862	2,767	5,434	4,918
Avg. Time to maturity (d), buys only	129	60	92	234	131
Matching rate	58.1%	72.1%	71.9%	47.8%	49.8%
Round-trip trades (mn)	1.0853				

Table 2: Technical analysis trading signals in DAX and DAX30 stocks.

Trading Signals in DAX and DAX30 stocks from May 2009 to November 2013 (1209 trading days) generated by the technical analysis algorithms introduced in section 5

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Event type	Overall signals	Signals per stock/day	Buy signals	Sell signals
(Inverse) Head-and-Shoulders	327	0.87%	172	155
Double Top & Bottom	100	0.27%	48	52
Rectangle Top & Bottom	102	0.27%	56	46
SMA 200 (0.1% filter)	979	2.61%	499	480
Dual SMA-20-100	522	1.39%	265	257
Dual SMA-50-200	208	0.55%	117	91
Overall	2238	5.97%	1157	1081

Table 3: Comparison of pattern recognition calibration.

This table compares TA signal generated from different calibrations of the smoothing factor h of the Kernel regression. The first block contains recognition results from h determined by cross-validation with multiplier 3. The second and third block show results from constant $h = 1.0$, and $h = 1.5$, respectively. Row (1), (2), and (3) show details on the recognition of (Inverse) Head-and-Shoulders, Double Top & Bottom, and Rectangle Top & Bottom, respectively. For each calibration the total number of signals found and the absolute and relative number of signals matching the signals of the main calibration ($h = 1 + 8\sigma_i$, where σ_i denotes the standard deviation of the price differences in window i) are reported.

	cross-validation, h-multiplier=3.0			constant h=1.0			constant h=1.5		
		matches			matches			matches	
	# signals	abs.	rel.	# signals	abs.	rel.	# signals	abs.	rel.
(1)	277	160	57.76%	361	281	85.93%	178	127	71.35%
(2)	89	58	65.17%	97	92	94.85%	116	77	77.00%
(3)	99	49	49.49%	128	96	94.12%	51	43	84.31%

Table 4: Excess trading turnover on TA signal days.

Trading Signals in DAX and DAX30 stocks from May 2009 to November 2013 (1209 trading days) generated by the technical analysis algorithms introduced in section 5

Panel A: Pattern signal

Lag	No signal	Signal	Diff	Ttstat	p-value
-3	0.0018	-0.0272	-0.0290	-0.63	0.5260
-2	0.0037	-0.1327	-0.1364	-2.50	0.0125
-1	0.0010	0.0098	0.0088	0.18	0.8569
0	-0.0050	0.3018	0.3068	7.19	0.0001
1	0.0031	-0.0816	-0.0847	0.65	0.5175
2	0.0006	0.0236	0.0230	0.15	0.8778
3	0.0019	-0.0435	-0.0454	-0.90	0.3679
4	0.0006	0.0080	0.0074	0.46	0.6430
5	0.0004	0.0307	0.0303	-1.66	0.0982

Panel B: Moving Average Signal

Lag	No signal	Signal	Diff	Ttstat	p-value
-3	-0.0011	0.0382	0.0393	1.21	0.2253
-2	0.0001	0.0003	0.0002	0.01	0.9946
-1	0.0016	-0.0300	-0.0316	-0.94	0.3499
0	-0.0039	0.1082	0.1121	3.91	0.0001
1	0.0009	0.0056	0.0047	-0.27	0.7883
2	0.0045	-0.0862	-0.0907	1.99	0.0463
3	0.0021	-0.0252	-0.0273	-0.86	0.3925
4	-0.0014	0.0580	0.0594	-2.61	0.0091
5	0.0009	-0.0085	-0.0093	0.14	0.8895

Table 5: Excess trading turnover regressed on TA signal indicators.

Column (1) presents estimation results from the regression $\epsilon_t^{(j)} = \alpha + \beta * Psig_t^{(j)} + \gamma * MAsig_t^{(j)} + \xi_t^{(j)}$, where $\epsilon_t^{(j)}$ is the excess turnover in stock j on day t, $Psig_t^{(j)}$and $MAsig_t^{(j)}$ equal 1 if a TA and MA signal occurred in underlying j on day t or are zero, else. We use Thompson (2011) (double) clustered standard errors. In column (2) the model contains an interaction term of pattern and MA-event indicators and for column (3) each pattern and MA-type is used as a separate dummy. *, **, and *** denote significance on the 5%, 1%, and 0.1% level, respectively.

	Excess Turnover					
	(1)		(2)		(3)	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Intercept	-0.0101	0.0070	-0.0103	0.0070	-0.007	0.0071
Pattern signal	0.3012***	0.0443	0.3106***	0.0466		
MA signal	0.1191***	0.0285	0.1232***	0.0286		
Pattern * MA signal			-0.1937	0.1575		
Double Top & Bottom					0.2607***	0.1291
(Inverse) Head & Shoulders					0.2164***	0.0623
Rectangle Top & Bottom					0.1824	0.1497
SMA200 signal					0.1774***	0.0336
DSMA20/100 signal					0.0329	0.0427
DSMA50/200 signal					0.008	0.0628
Number of Observations	36301		36301		36301	
R-Square	0.0015		0.0016		0.0010	

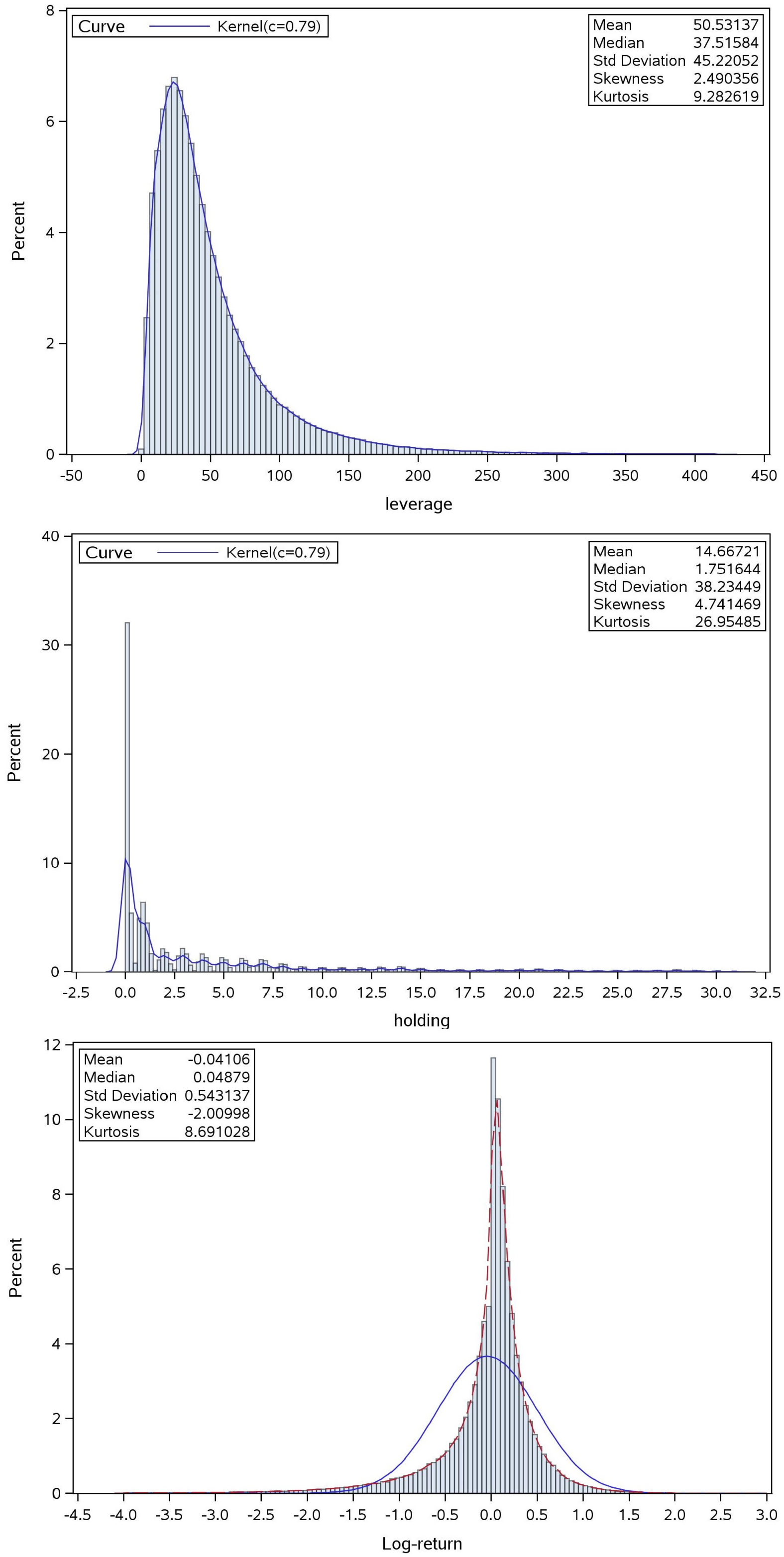

Figure 2: Characteristics of round-trip trades.

The figures shows the distribution of log-returns, holding duration, and leverage (at purchase) of RI's round-trip trades in KO products and warrants.

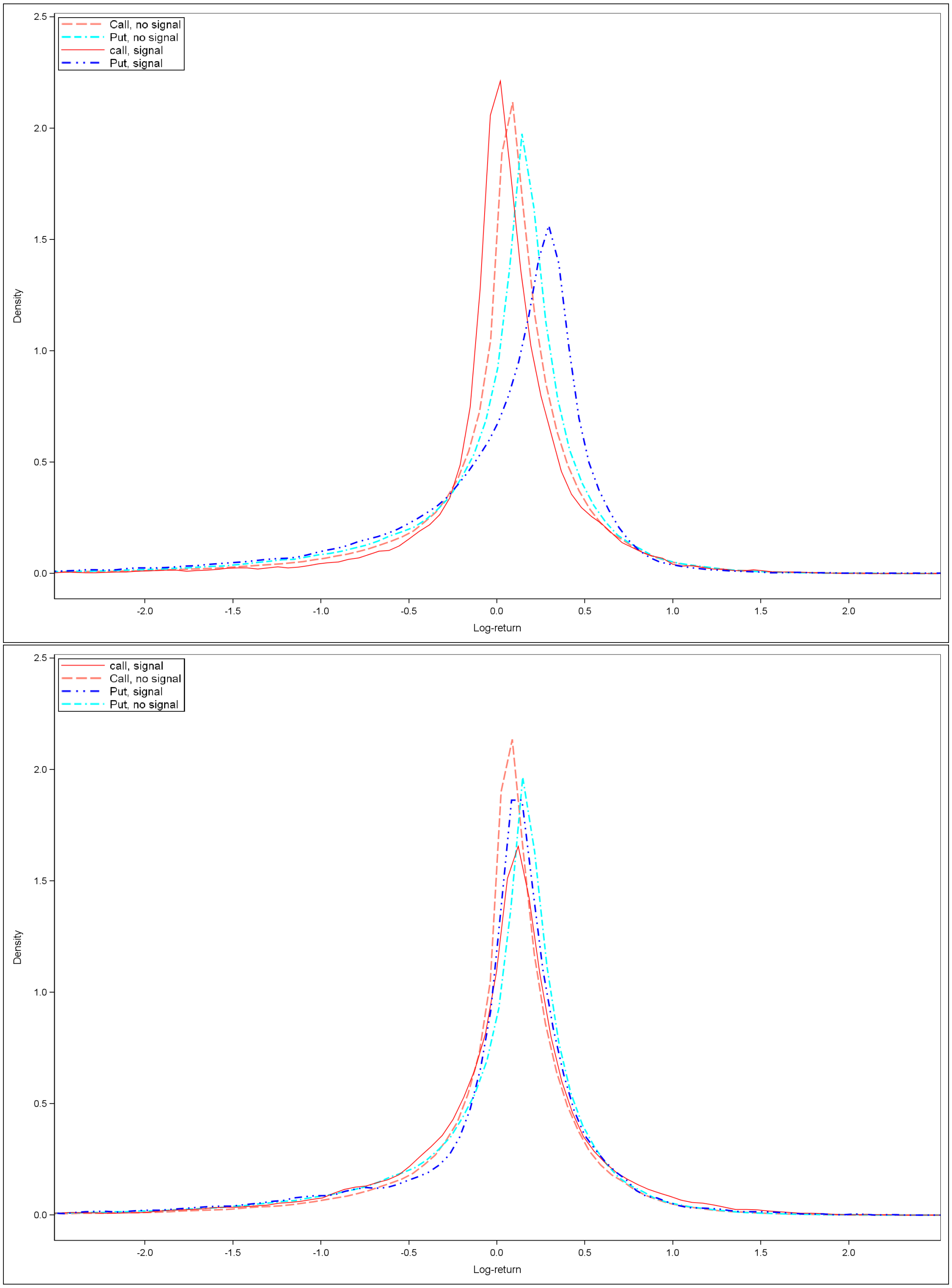

Figure 3: Skewness of realized returns.

The figures shows kernel density of the empirical log-return distributions of call and put round-trip trades on signal and non-signal days, respectively. The upper plot depicts the trade classification based on buy signals and the bottom plot on sell signals. For each group the mean is subtracted to improve the comparability between the density graphs.

Table 6: Excess trading long-short imbalance on TA signal days.

We regress the excess trading long-short imbalance on trading signals applying the following regression specification: $\delta_t^{(j)} = \alpha + \beta * Psig_t^{(j)} + \gamma * MAsig_t^{(j)} + \xi_t^{(j)}$, where $\epsilon_t^{(j)}$ is the excess turnover in stock j on day t, $Psig_t^{(j)}$and $MAsig_t^{(j)}$ equal 1 if a TA and MA signal occurred in underlying j on day t or are zero, else. Column (1) shows a regression specification using aggregated TA signals. In column (2) each TA signal type is used separately, coded as a dummy variable which is 1 if a trading signal occured. For both regressions we apply Thompson (2011) clustered standard errors. *, **, and *** denote significance on the 5%, 1%, and 0.1% level.

	Excess long short imbalance			
	(1)		(2)	
	Estimate	Std. Error	Estimate	Std. Error
Intercept	-0.0161	0.0119	-0.0164	0.0119
Buy signal	0.1072	0.1193		
Sell signal	-0.0737	0.1301		
Head and shoulders			-0.1162	0.2555
Inv. Head and shoulders			0.3694	0.2964
Double top			0.2334	0.5287
Double bottom			0.0443	0.3116
Rectangle top			-0.3375	0.4019
Rectangle bottom			-0.0173	0.3077
SMA200 long			0.0738	0.4019
SMA200 short			-0.0698	0.3077
Number of observations	36301		36301	
R-Square	0.0001		0.0001	

Table 7: Trading performance of round-trip trades.

This table presents estimation results from regression model (7) which is defined as $r_i = \beta_1 * buysig_i * c_i + \beta_2 * buysig_i * p_i + \gamma_1 * sellsig_i * c_i + \gamma_2 * sellsig_i * p_i + \delta_1 * holding_i * c_i + \delta_2 * holding_i * p_i + \eta * market_i + \zeta * ko_i + controls + \epsilon_i$, where c_i and p_i are dummy variables for call and put, $holding_i$ denotes the duration of trade i in days, $market_i$ is a dummy for market buy order, and ko_i indicates trades in knock-out products. The term $controls$ is defined as $\sum_j \left(ul_i^{(j)} * c_i + ul_i^{(j)} * p_i \right)$, where dummy $ul_i^{(j)}$ equals 1 if the underlying of $trade_i$ is j. We regress three return measures, i.e. raw log-return, risk-adjusted return, and excess return, which are reported in column (1), (2), and (3), respectively. For each regressions we apply Thompson (2011) clustered standard errors. *, **, and *** denote significance on the 5%, 1%, and 0.1% level.

	Round-trip trade performance					
	log-return		risk-adjusted return		risk-adj. excess return	
	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Buy signal * call	8.2668**	2.7153	1.1130**	0.4115	0.0528*	0.0284
Buy signal * put	-13.986***	1.2242	-1.9780***	0.2201	-0.0652***	0.0187
Sell signal * call	-3.2263**	1.2234	-0.1654	0.2305	-0.0096	0.0203
Sell signal * put	5.2310***	0.9175	-1.0733***	0.2573	-0.0348	0.0257
Holding * call	-0.2450***	0.0356	-0.0628***	0.0092	-0.0074**	0.0025
Holding * put	-0.6815***	0.0323	-0.2502***	0.0114	-0.0151***	0.0026
market order	-0.6821***	0.2116	-0.1781***	0.0463	-0.0141**	0.0049
knock-out product	0.5163	0.7381	2.1506***	0.0664	-0.0792***	0.0254
Controls	underlying*put, underlying*call		underlying*put, underlying*call		underlying*put, underlying*call	
Number of Obs.	1085349		1085349		1085349	
R-Square	0.0785		0.1499		0.1188	

Table 8: Trading characteristics of round trip trades.

This table shows results from two regression models using (log-) leverage and holding duration as independent variables. The model is defined as $y_i = \beta_1 * buysig_i * c_i + \beta_2 * buysig_i * p_i + \gamma_1 * sellsig_i * c_i + \gamma_2 * sellsig_i * p_i + \eta * market_i + \zeta * ko_i + \delta ul_v ola_i + controls + \epsilon_i$, where c_i and p_i are dummy variables for call and put, $holding_i$ denotes the duration of trade i in days, $market_i$ is a dummy for market buy order, and ko_i indicates trades in knock-out products. In case of holding duration a dummy variable for call products and the leverage at purchase are added to the equation. In case of leverage as independent variable, the term $controls$ is defined as $\sum_j \left(ul_i^{(j)} * c_i + ul_i^{(j)} * p_i \right)$, where dummy $ul_i^{(j)}$ equals 1 if the underlying of $trade_i$ is j. In case of holding duration we only use control dummies per stock. Results for leverage is reported in column (1) and for holding duration in column (2). In both regressions we apply Thompson (2011) clustered standard errors. *, **, and *** denote significance on the 5%, 1%, and 0.1% level.

	Round-trip trade characteristics			
	Log. leverage		Log. holding duration	
	Estimate	Std. Error	Estimate	Std. Error
Buy signal * call	-0.1077**	0.0405	-0.2158***	0.0181
Buy signal * put	-0.1011***	0.0163	0.3667***	0.0178
Sell signal * call	0.0525***	0.0148	0.1269***	0.0285
Sell signal * put	-0.2644***	0.0178	-0.7433***	0.0527
Call	-	-	-0.2063*	0.1076
Log. leverage	-	-	-0.8990***	0.0378
Market order	-0.2091***	0.0046	0.2236***	0.0592
Knock-out product	-0.1840***	0.0061	-2.1629***	0.0748
Underlying vola.	-1.6850***	0.3105	-1.8639***	0.3360
Controls	underlying * put, underlying * call		underlying	
Number of Obs.	1085349		1085349	
R-Square	0.9476		0.3093	

Table 9: Skewness of realized returns.

The table reports robust skewness measures of log-return distributions grouped by TA signal events and option type. Panel A reports buy signals and analogues Panel B sell signals. Cloumn 2 and 3 show Groeneveld/Meeden skewness measure and Bowley coefficient, respectively. Absolute diff.s between the call bought on buy signal group and the other groups are validated by bootstrapping from the overall sample (one-sided). 99.9 % confidence internals are reported in parentheses. Column 4 shows two-sample Kolmogorov-Smirnov test statistics and p-value based on the standardized (by mean and standard deviation) empirical return distributions of buy signal call (panel A) and sell signal put group compared to the particular other groups.

Panel A - Buy Signals

	# trades	GM skewness		Bowley skewness		Kolmogorov-Smirnov	
		Estimate	Abs. diff.	Estimate	Abs. diff.	KS statistic	p-value
Signal, Call	9407	-0.1048	-	0.1993	-	-	-
No Signal, Call	564528	-0.2403	0.1356	-0.0456	0.2449	0.1115	<0.0001
			(0.0444)		(0.0606)		
Signal, Put	16286	-0.4482	0.3434	-0.3825	0.5819	0.2080	<0.0001
			(0.0470)		(0.0648)		
No Signal, Put	495128	-0.3560	0.2512	-0.2615	0.4608	0.1776	<0.0001
			(0.0378)		(0.0556)		

Panel B - Sell Signals

	# trades	GM skewness		Bowley skewness		Kolmogorov-Smirnov	
		Estimate	Abs. diff.	Estimate	Abs. diff.	KS statistic	p-value
Signal, Put	8498	-0.3035	-	-0.1092	-	-	-
No Signal, Put	502916	-0.3628	0.0593	-0.2739	0.1647	0.054128	<0.0001
			(0.0391)		(0.0575)		
Signal, Call	22157	-0.2453	0.0582	-0.1666	0.0574	0.056365	<0.0001
			(0.0506)		(0.0717)		
No Signal, Call	551778	-0.2374	0.0661	-0.0363	0.0728	0.171503	<0.0001
			(0.0478)		(0.0652)		