# Stock and Index Futures Trading Behaviour of Individual and Institutional Investors

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# 1 Introduction

Market microstructure is concerned with the institutional set-up of an exchange and recognises that this design of trading mechanisms affects asset prices. Market frictions such as information asymmetries or transaction costs are taken into account, thereby extending the neoclassical asset pricing model but still assuming that investors process information rationally and thus make rational investment decisions. Information asymmetries do not only influence asset prices but also affect trading volume, trade size, and the timing of trades. As a result, the order flow potentially contains information about future stock prices. However, since the early 1980s, empirical results for financial markets have been documented that are inconsistent with the market efficiency hypothesis or a fully rational asset pricing model. Among the most prominent of such anomalies are the Monday and the January effects.[1] In this thesis, individual investors are separated from institutional traders by applying findings from the market microstructure literature. Specifically, the effects of information asymmetries between these two investor groups on order flow and asset pricing are investigated. Furthermore, the presence of a few aspects of potentially irrational trading behaviour, in particular exhibited by individuals, is tested empirically.

This thesis starts with an investigation of two trading platforms at the Frankfurt Stock Exchange from the traders' perspective. Specifically, the second chapter contributes to the debate about the relative qualities of floor and electronic trading systems by analysing the effects of bringing forward the Xetra closing time from 8.00pm to 5.30pm in November 2003, while the Frankfurt floor remains open until 8.00pm. This natural experiment lends itself to an investigation of the trading quality on both platforms for the same stocks in the same country before and after the event. It is hypothesised that anonymous electronic trading systems provide less favourable conditions for investors than the non-anonymous floor due to higher adverse selection costs in the anonymous system. In fact, the empirical evidence implies that investors remain with Xetra for informed trading. It can be concluded that a trading platform should be non-anonymous in order to avert informed trading. This finding casts doubt on the

[1] Recent empirical studies find these anomalies to have fully disappeared or weakened (Schwert (2003), Rubinstein (2001), Connolly (1989), Marquering et al. (2006), Steeley (2001), Sullivan et al. (2001), Szakmary and Kiefer (2004)). Since these studies focus on developed financial markets, their results are not necessarily applicable to the Polish stock and futures markets.

justifiability of abolishing floor trading systems. If the floor has already been closed, the remaining electronic exchange benefits from a broker-facilitated upstairs market.

In the next step, individual investors' trading behaviour is examined on the Polish stock market. Individuals are separated from institutions by using data from two trading mechanisms with vastly different investor structures: continuous trading and a call auction system. Well-informed institutional investors prefer the continuous trading platform over the periodic auction, since the larger trading volume in the continuous system offers greater market depth, lower price impact, immediate trade execution, and larger profits from private information. Likewise, individuals are likely to choose a batch market over continuous trading, since in the former liquidity is concentrated and adverse selection costs are small. While most existing studies focus on institutional investors' trading in developed markets, chapter 3 of this thesis tests for the presence of herding during market up- and down-swings on an emerging market. The empirical results suggest that individuals engage in herding during market downswings, while there is no evidence of imitating trading behaviour in bullish markets. Regardless of the state of the market, institutions' trading behaviour does not appear to exhibit herd behaviour.

Investigating the existence of anomalies on the Polish WIG20 index futures market yields further insights about individual investors' trading behaviour since they dominate this market. In chapter 4, the presence of Monday and January anomalies is tested, which both are well established in the literature and are at least partially attributed to individual investors' trading activities. While earlier studies of financial market anomalies refer to regularities in returns, more recent publications include a broader range of variables when testing for anomalies. In the context of the Polish futures market, these are trading volume, open interest, returns, and return volatility. Furthermore, with the intraday dataset, inference about the time of the day driving potential anomalies is possible. No evidence of the Monday effect is detected. Turning to a calendar month anomaly, a significantly low trading volume in the expiration months March, June, September, and December is observed. This apparent quarter-end month anomaly can be fully explained by the delivery cycle. It can be concluded that the contribution of individuals to market anomalies is rather overstated in the literature. Hence, individual investors' trading on the Polish futures market surpasses the prediction by the majority of investigations for mature stock markets.

Chapter 5 links the Polish stock and derivatives markets by examining the impact of the introduction of derivatives trading on the conditional volatility of the underlying instruments. The theoretical argument about this impact hinges upon the degree of information of spot traders relative to the arriving futures and options traders. If the debut of futures or options has a stabilising effect on the corresponding cash markets, this is indicative of well informed traders on the derivatives market. Overall, the empirical evidence suggests that the introduction of derivatives trading had a stabilising effect on the stock market. In light of the unique investor structure on the Polish derivatives market, which is dominated by individuals, we conclude that individuals entering the derivatives market are better informed than the literature on individual investors' trading behaviour suggests.

# 2 Forestalling Floor Closure: Evidence from a Natural Experiment on the German Stock Market

## 2.1 Introduction

On 3 November 2003, the closing time of the German electronic trading platform Xetra was brought forward from 8.00pm to 5.30pm, while the Frankfurt floor remained open until 8.00pm. Deutsche Boerse announced this change in opening hours in a press release on 3 September 2003. This release claims that market participants prefer uniform trading hours across Europe as stock trading becomes increasingly international (Deutsche Boerse (2003)).

We analyse the effects of this event on the trading qualities on both platforms, thereby overcoming the limitations of Venkataraman (2001) as pointed out by Madhavan (2001). Venkataraman (2001) analyses the trade execution costs for the non-anonymous New York Stock Exchange (NYSE) compared with the anonymous Paris Bourse for large and liquid stocks. He finds trading costs in Paris to be higher than at the NYSE by 0.14 percent of the trading volume and concludes that human intermediation may increase liquidity on a stock exchange. In a critical discussion, Madhavan (2001) demonstrates several substantial difficulties with this analysis: Venkataraman (2001) examines two stock exchanges in different countries with different regulatory settings and different sets of stocks that are matched using various algorithms. Moreover, two auction markets are investigated which makes the interpretation of the spreads ambiguous. As we compare the same stocks traded simultaneously on both platforms in continuous trading at the same stock exchange, we are able to report more reliable results than Venkataraman (2001).

Moreover, our direct comparison of the electronic trading system with the floor provides further evidence regarding the Seppi (1990) hypothesis that broker-facilitated upstairs markets are preferred to electronic downstairs markets by those traders who can credibly convey that their trades are uninformed. Bessembinder and Venkataraman (2004) find empirical evidence supporting Seppi (1990) and report total execution costs, and their adverse selection component, to be lower in the upstairs market than downstairs. They argue that the presence of brokers drives down transaction costs in part because these brokers have information about unexpressed liquidity (Grossman

(1992)), and in part because the information asymmetry is lower in a non-anonymous market. Bessembinder and Venkataraman (2004) conclude that an electronic exchange needs an upstairs market.

By presenting empirical evidence on the comparison of two trading systems in a clean institutional setting, we also contribute to the more general debate on whether anonymous electronic trading systems provide more or less favourable conditions for investors than the non-anonymous floor. While a few studies find evidence for the electronic system offering lower execution costs than the floor (Pirrong (1996), Domowitz and Steil (1999)), the majority of authors argue that higher information asymmetries in computerised trading lead to higher transaction costs (Venkataraman (2001), Theissen (2002), Barclay et al. (2003), Jain et al. (2006)).

Previous studies either compare floor and electronic trading platforms at the same time (Venkataraman (2001), Grammig et al. (2001), Theissen (2002)), or they investigate how the market properties change over time when an electronic system is introduced instead of the existing trading floor (Gilbert and Rijken (2006)). In our study, this is reversed in that part of the trading time in the *electronic* system is abolished. This reversal is intriguing in itself as one might expect the traditional floor trading to be more prone to cuts in opening hours than highly automated electronic trading platforms. Moreover, this setting provides a natural experiment to study potential transfers of investors from Xetra to the floor as it enables us to examine continuous trading of the same stocks in two trading mechanisms at the same stock exchange.

Generally, the higher the information asymmetry is, the less liquid and less deep a market. While traders on the floor have better knowledge about the order flow and the identity of their trading counterparties, those who trade on a computerised system have easier access to fundamental information and prices on other markets (Pirrong (1996)). Pirrong compares theoretically and empirically the liquidity of German Bund Futures contracts traded simultaneously on the open-outcry platform LIFFE and electronically on Deutsche Terminboerse DTB. He finds that the computerised system offers lower spreads and is more liquid and deeper than the floor system.

Domowitz and Steil (1999) examine the total execution costs on various U.S. trading platforms and hypothesise that electronic trading systems compete for traders with floor-based ones. The degree of automation and the resulting lower running costs of a computerised platform should lead to lower overall execution costs in an electronic system than the floor can offer. In fact, they find that electronic markets provide more favourable conditions to investors than the floor for trading in over-the-counter stocks. As for trading listed issues, commissions for traditional brokers are so high that they over-compensate the lower implicit execution costs on the floor.

In contrast to these studies, there is evidence for the floor offering lower execution costs and hence more favourable conditions for investors than electronic trading systems. Theissen (2002) compares the transaction costs on the Frankfurt floor with those in the electronic system (then IBIS, now Xetra) and finds the electronic system to offer lower bid-ask spreads for actively traded stocks. The floor, however, offers more favourable conditions for less frequently traded stocks, with the market share of less liquid stocks being lower in the electronic system than on the floor. Theissen attributes the higher execution costs on the electronic platform to the adverse selection component of the spread.

Several related studies investigate the influence of market makers on information asymmetry. Jain et al. (2006) examine the price impact for stocks traded parallel in the electronic system SETS and on the dealer market at the London Stock Exchange. They find empirical evidence for the computerised trading system to attract relatively more informed trades than the non-anonymous dealer market. Similarly, Barclay et al. (2003) conclude for Nasdaq stocks that informed traders prefer electronic systems over market makers. Benveniste et al. (1992) construct a theoretical model for the spread whose primary implication is that information asymmetries are lower in a non-anonymous market. However, Lehmann and Modest (1994) examine empirically the Tokyo Stock Exchange's success in providing liquidity without a specialist on the floor and the electronic system. They conclude that the Tokyo Stock Exchange is a well-functioning, liquid market despite the lack of market makers. Ding and Lau (2001) investigate how the Stock Exchange of Singapore - which includes a screen-based dealer system that has no specialist - performs relative to the NYSE and Nasdaq. They find, to a large extent, similarities between the Singapore Stock Exchange and the NYSE and Nasdaq.

Bringing forward the closing time of Xetra is not an endogenous variable (Deutsche Boerse (2003)) and therefore provides an ideal institutional setting to study the extent to which investors transfer from Xetra to the floor, and to ascertain the type of investors that accept trading on a non-anonymous system when the anonymous one closes earlier. This should yield insights into the perceptions of traders regarding the relative market qualities of both trading platforms. As investors choose the platform through which to route their orders, the 'selection bias' is an integral part of this study and does not need to be corrected for or explicitly modelled empirically. Since information asymmetry impacts directly on market quality, we examine whether it is primarily uninformed investors that accept the floor as a substitute of the electronic system. Theissen (2002) finds differences in relative execution costs between large and small stocks. This is consistent with Dennis and Weston (2001), who suggest that institutional investors are generally better informed than individual ones, and Falkenstein (1996), who concludes that mutual funds prefer large stocks. We therefore conduct our analysis separately for large and for small stocks, which might give further indications regarding the type of investors that transfer to the floor. Finally, we draw conclusions regarding the design of a trading platform.

We expect trading volume to increase sharply on the floor in November 2003 after 5.30pm, driven by uninformed trades which can thereby be settled at a time when Xetra is closed. As informed traders prefer the anonymity of the electronic system (e.g. Barclay et al. (2003)), this might lead, under otherwise equal conditions, to a higher fraction of informed traders in Xetra, thereby increasing the adverse selection costs and hence making the computerised platform less favourable for investors. This might induce further transfers to the floor. Alternatively, it is possible that the fraction of informed traders increases on the floor if the transferring traders are a representative subset of all traders in Xetra. If primarily institutional (individual) investors move to the floor, we expect especially trading volume for large (small) stocks to increase there in November 2003. If mostly uninformed traders transfer to the floor, we conclude that a trading platform should be non-anonymous in order to avert informed trading. This latter finding might shed light on the justifiability of abolishing floor trading systems from the perspective of market microstructure.

In order to empirically analyse the relative market quality on both trading platforms over time, section 2 introduces the dataset and the methodology before section 3 describes the empirical results. Section 4 summarises our findings and concludes.

## 2.2 Data and Methodology

### 2.2.1 Data

Our dataset captures three months prior to, and after, the bringing forward of the Xetra closing time on 3 November 2003 from 8.00pm to 5.30pm. This results in 66 trading days from August 2003 to October 2003 and 60 trading days from November 2003 to January 2004. The data comprise transactions and quotes data for 136 shares traded contemporaneously on both Xetra and the floor. This portfolio captures roughly 90 percent of the equities market in Xetra (Deutsche Boerse (2004)). The transactions data include timestamp, price, and number of shares. They were obtained from the University of Karlsruhe database and the quotes data from Deutsche Boerse AG.

The 136 stocks were selected based on the instrument groups set up by Deutsche Boerse which contain predominantly German companies' shares. The DAX index comprises 30 blue-chip stocks, the MDAX contains 50 stocks whose size ranks immediately below that of the DAX ones, the TecDAX covers 30 medium-sized stocks in the technology sector, and the SDAX consists of 50 small-cap stocks. Out of these four indices, we choose those shares that were traded on both platforms throughout the six months under investigation.

Quotes are only available for Xetra as this platform has one orderbook from which we received the data. On the floor, by contrast, several market makers operate who are not obliged to publish their orderbooks. For this institutional reason, it is impossible to obtain a comprehensive set of quotes for the floor. Quotes data for Xetra comprise bid and ask prices with timestamps and the respective number of shares. The relative spreads, which are reported multiplied with 100, are calculated as the difference between ask and bid prices divided by the spread midpoint.

We conduct common plausibility checks on the data (Madhavan et al. (1997), Chung and Van Ness (2001)) and eliminate implausible observations with negative spreads or with negative or zero trading volume, as well as overnight returns. There were no entries with changes in absolute spreads, spread midpoints or returns larger than 50 percent. We only use data from continuous trading, i.e. we exclude auctions and observations outside the trading times. This results in a dataset containing 1,106,147 transactions for the floor, 10,376,549 transactions for Xetra, and 28,165,410 quotes.

Transactions that market makers settle in their own accounts should also be eliminated since they do not pay spreads to themselves. However, we cannot identify such transactions in the dataset, and their impact on overall trading volume should be negligible for large stocks in which institutional investors trade actively. Since our results are driven by large stocks, we do not pursue this further.

### 2.2.2 Methodology

In order to analyse the anonymous and the non-anonymous trading platforms over time, we apply descriptive methods from the market microstructure literature, and we decompose the bid-ask spreads following George et al. (1991). The methodology of Venkataraman (2001) cannot be applied here because quotes data are not available for both markets that we are comparing. For the descriptive analysis, we choose the turnover as a proxy for trading volume, transaction size as an indicator for the presence of institutional investors, and return volatility (standard deviation as in Madhavan et al. (1997) or Ding and Lau (2001)) and the relative bid-ask spread (Glosten and Milgrom (1985)) to reflect information asymmetry. The trading time is split into 15-minute intervals, and within each interval the average is calculated per share on each trading day following Abhyankar et al. (1997). Rather than aggregating the shares into a portfolio, this method preserves the characteristics of each stock in each interval.

Turnover is calculated as the cumulative product of price and number of shares, transaction size gives the number of shares per trade, and return volatility is computed cumulatively across each interval with the return being $(p_t - p_{t-1})/p_{t-1}$.[2] The volatility and the spreads are reported in percent in Table 1. We employ t-tests to determine whether the means in the indicators have changed significantly over time. Statistically, this is identical to estimating dummy regressions and t-testing the estimated coefficients.

As there are no quotes data available for the floor, we estimate the spread following Roll (1984). Alternatively, transaction costs could be approximated as in Lesmond et al. (1999). Their results are strongly correlated with those of Roll (1984) so that the choice of model will have very little impact on the interpretation of the estimates in our setting. The basis of the spread estimation in Roll (1984) is the autocovariance $\gamma_T$

[2] For the descriptive analysis, we follow Roll (1984) and do not take the logarithm of the prices.

of the returns:

$$Spread_T = \sqrt{(-4)\gamma_T} \ , \tag{1}$$

where $T$ is the last period for which a return observation is available. $Spread_T$ can be interpreted as the average relative spread since the returns that feed into the estimation are relative. In case of $\gamma_T > 0$ it is not defined.

George at al. (1991) propose two methods for decomposing the spread into its order processing and adverse selection cost components. Under the first approach, the realised return of an individual stock $R_{i,t} = \ln(p_{i,t}/p_{i,t-1})$ over each 15-minute interval needs to be purged of its time-varying expected return component that is approximated by the return of an equal-weighted size-based portfolio $R_p$ to which stock $i$ belongs. We use the four portfolios DAX, MDAX, TecDAX, and SDAX described in section 2.1. The regression

$$R_{i,t} = \alpha_0 + \alpha_1 R_{p,t} + u_{i,t} \tag{2}$$

is used to extract the expected return of stock $i$. $u_{i,t}$ are the residuals, whose autocovariance across 2-hour intervals form the basis of the synthetic spread $Spread_{calc,i,t}$ which is otherwise calculated as in equation (1). In order to decompose the observed spread into its order processing and adverse selection cost components, we estimate the regression

$$Spread_{calc,i,t} = \beta_0 + \beta_1 Spread_{obs,i,t} + \epsilon_{i,t} \tag{3}$$

where $Spread_{obs,i,t}$ is the average observed spread across each 2-hour interval. $\beta_1$ measures the order processing costs and $(1 - \beta_1)$ are the adverse selection costs. While the constant has to be included in the model specification (George et al. (1991)), it is not needed to determine the estimated components of the spread. When $\hat{\beta}_1 < 0$ then the adverse selection costs are set to 1. As there are no observed spread data $Spread_{obs,i,t}$ available for the floor, we can only decompose the spreads from Xetra.

The starting point of the second method proposed by George et al. (1991) is the difference between $R_i$ and the logarithm of the bid price return to compute a synthetic spread $Spread_{calc}$. Roll's (1984) spread measure as given in equation (1) can only be used as $Spread_{calc}$ if the expected return of a security is constant over time, and if the adverse selection costs in the market equal zero.

George et al. (1991) test their models with daily and weekly data of stocks traded on the NYSE and on Nasdaq from 1983 to 1987. Their major result is that adverse selection costs are smaller than previously reported in the literature and account for 8 to 13 percent of the observed spread. George et al. (1991) conclude that order processing costs are the predominant component of the quoted spread.

If the aim of this paper was to directly compare spreads between the two trading platforms, we would need to report the Roll (1984) measure for Xetra as well. However, we observe spreads before and after bringing forward the Xetra closing time for each trading system separately, so that it is not meaningful to analyse an inferior proxy spread measure (i.e. Roll (1984)) for Xetra when observed spreads are available.

## 2.3 Empirical Results

We expected a sharp increase in trading volume on the floor in November 2003 after 5.30pm. In fact, turnover almost doubles there in the evening. As can be seen from Panel A in Table 1, it increases slightly in the daytime but grows from approximately 15,400 Euros in the evening in October to 29,700 Euros at the same time in November. This increase coincides with bringing forward the closing time in Xetra on 3 November 2003, which we view as empirical evidence for investors transferring to the floor rather than remaining with the electronic trading platform and trading in the daytime instead.

Table 1 about here

The results of the cross-sectional analysis, which are not reported here in detail but are available on request, suggest that the sharp growth in trading volume on the floor is driven by large stocks, while daytime turnover in Xetra for small stocks increases. This is an indication that primarily institutional investors transfer to the floor in the evening, while individual investors trading in small stocks remain with the electronic trading platform and adjust their trading time (see Falkenstein (1996) for the relationship between the size of stocks and investor type).

In Xetra, the trading volume increases steadily from August 2003 to November 2003, drops in December 2003 and grows strongly in January 2004. This time series behaviour, along with the fact that only a small fraction of pre-event evening trading volume in Xetra is visible on the floor post-event, suggests that other factors play a part in Xetra in addition to bringing forward its closing time.

Since transactions in Xetra tend to be larger than those settled on the floor, an increase in transaction size on the floor could be interpreted as further evidence for investors transferring to the floor when Xetra is closed. As Panel B of Table 1 shows, the average number of shares traded per transaction on the floor increases significantly from about 394 to 535 in November 2003 after 5.30pm. On average, transactions in the evening are then larger than during the daytime. Thus, the substantial increase in trading volume on the floor is driven by the growth in transaction size, and is interpreted as further evidence for the increased trading volume originating from Xetra. Similarly to turnover, transactions in Xetra grow steadily from August 2003 to October 2003, drop in size in November 2003 and resume growing thereafter.

The transaction size on the floor increases substantially for large stocks in November 2003 after 5.30pm, while the transaction size in Xetra grows slowly across the six months under investigation. We conclude that investors trading in large stocks transfer to the floor when Xetra closes earlier. As a larger fraction of market participants in Xetra are informed traders than on the floor (Barclay et al. (2003)), and since those traders that appear to have transferred tend to be well informed, we expect this movement of investors to increase information asymmetry on the floor in November 2003. We investigate this by analysing return volatility and the bid-ask spread.

However, the volatility decreased on both trading systems, with the floor showing a significant reduction in the daytime and in the evening (Panel C, Table 1). Following Barclay and Hendershott (2003), we interpret this as a reduction in asymmetric information on the floor. It therefore appears that the transfer of investors from Xetra to the floor does not result in higher information asymmetries on the floor. This can be explained in two ways: Either those investors that are prepared to transfer to the floor are not informed, or they are informed but the trades they choose to settle on the floor are not information-based. Either way, this transfer should increase information asymmetry in Xetra under otherwise equal conditions. Since we are investigating a dynamic market across six months, holding everything else equal is too restrictive an assumption. Therefore, we also observe an overall reduction in volatility in Xetra which could be attributed to a growth in liquidity shown in Panels A and D of Table 1.

The bid-ask spread is another measure of information asymmetry as it contains a component that compensates the market maker for losses incurred when trading against informed investors. The overall spread decreases in both trading systems, with the reduction being particularly sharp on the floor in the evening in November 2003 (Panel D, Table 1). For actively traded stocks, the decrease in the spread is so large that the usual pattern of lower spreads in the daytime than in the evening reverses. Thus, for large stocks, the daytime spread is larger than that in the evening from November 2003 onwards. The reduction in spreads in Xetra could be driven by the increase in liquidity or other factors beyond the transfer of trades to the floor.

As explained in section 2.2, the adverse selection component of the spread can be analysed for Xetra only. Table 2 shows the mean adverse selection costs for the first version of the spread decomposition according to George et al. (1991). For DAX and MDAX shares, the adverse selection costs before November 2003 are smaller in the evening than in the daytime. Thus, the trades that are affected by bringing forward the closing time of Xetra are informed to a smaller extent than the trades in the daytime. We therefore expect transfers inside Xetra from the evening to the daytime to lower adverse selection costs under otherwise equal conditions. Indeed, we observe minor, though statistically significant reductions in adverse selection costs for large and medium-size stocks, with the changes for small stocks being insignificant. This is plausible since small shares are not actively traded in Xetra in the evening, which implies that they are not much affected by shortening the Xetra trading time. While the changes are very small, their statistical significance gives an indication of the direction in which adverse selection costs have changed over time.

In light of the results of the descriptive analysis, one might expect an increase in adverse selection costs in November 2003, since primarily informed investors appear to remain with Xetra, while uninformed ones prefer the floor. However, liquidity in Xetra increased over time, which reduces spreads and adverse selection costs. While the adverse selection costs for the TecDAX stocks decrease over the six months under investigation, there is no significant effect at the time when Xetra begins to close earlier.

The level of the adverse selection costs across all four portfolios is suprisingly high. George et al. (1991) report that only about 10 percent of the spread compensate the market maker for adverse selection costs, and their results change substantially when varying interval lengths. However, our results are robust against the choice of interval length and the decomposition approach as we also followed Roll (1984) and the second method presented by George et al. (1991). This discrepancy between our results and those of George et al. (1991) could be attributed to technical innovations in the past 20 years lowering order processing costs, thereby increasing the fraction of the spread that is driven by information asymmetries.

Table 2 about here

It should be noted that the German stock market is fragmented from 9.00am to 5.30pm into floor and Xetra trading platforms. After 5.30pm, only the floor exists, which enables market makers to observe the entire market more easily than in the daytime. They can therefore learn faster, so that information is incorporated more promptly into quotes. This will also make floor trading in the evening more attractive than before November 2003 and might thus account for some of the observed transfers.

For turnover, transaction size, return volatility and spread, large stocks drive the empirical results. There are at least two possible explanations for this finding. First, Xetra has a much larger market share in large stocks than in smaller ones. It is therefore plausible that primarily large stocks are affected by bringing forward the Xetra closing time, which is what we see reflected in the data. Second, consistent with this interpretation is Falkenstein's (1996) result that institutional investors prefer large stocks over small ones. Therefore it is likely that primarily institutional investors transferred to the floor in November 2003, but continued to settle informed trades on the anonymous electronic platform. It can be concluded that non-anonymous trading platforms offer favourable conditions to uninformed traders, while the anonymity of a computerised platform is preferred for settling informed trades.

As a robustness check, we conducted our analysis of turnover, transaction size, volatility, spread and the spread decomposition for each of the six months from August 2003 to January 2004 separately for either trading platform. The results are not reported in detail but are available from the authors on request. The prominent changes in all these time series occurred in November 2003, which we regard as support for our attributing those changes to the earlier closing time in Xetra.

## 2.4 Summary and Conclusions

The aim of this paper is to contribute to the debate about the relative qualities of floor and electronic trading systems. This issue is investigated in a natural experiment on the German stock market: The trading hours on the anonymous electronic trading system Xetra are reduced, while the non-anonymous floor remains open from 9.00am to 8.00pm. Previous studies either compare both trading platforms operating parallel, or they examine how the market properties change over time when a computerised system is introduced to replace the trading floor. Our setting enables us to observe potential transfers of investors from Xetra to the floor, and it overcomes the limitations of Venkataraman (2001) as pointed out by Madhavan (2001).

We find empirical evidence for primarily investors trading in liquid shares transferring to the floor after 5.30pm when Xetra closes early. The transactions they settle on the floor are, on average, not informed. Our insights are consistent with Barclay et al. (2003), Jain et al. (2006), Benveniste et al. (1992), and Venkataraman (2001) who find that informed traders prefer the anonymity of the electronic trading system. Uninformed investors should choose non-anonymous trading systems, and they should settle their transactions before 5.30pm. The lack of fragmentation in the German stock market after 5.30pm from November 2003 onwards further contributes to lower transaction costs as market makers learn faster when the entire market can be observed more easily.

Likewise, if information-based trading is to be reduced, the trading platform should not be anonymous. This implies the recommendation to stock exchanges to refrain from closing floor trading even if highly automated electronic systems have lower running costs than the floor. However, there are exchanges that have completely abolished floor trading, e.g. Italy. Like Bessembinder and Venkataraman (2004), we argue that an electronic exchange benefits from a broker-facilitated upstairs market, especially if the floor has already been closed.

There are various alleys for methodological extensions of this paper. Firstly, a model as in Easley et al. (1996) could be estimated. However, this approach is based on the assumption that information events occur only *outside* the trading hours, and the market maker learns the information throughout the trading day. As a result, splitting the trading time into 9.00am to 5.30pm and 5.31pm to 8.00pm is not meaningful.

In light of our empirical results, which underscore the sharp differences on the floor between daytime and evening, we would not be able to interpret the probabilities of informed trading with respect to the research questions in this paper.

Secondly, the price impact of a trade could be estimated as in Hasbrouck (1991). The core of this method is to model the interactions between trades and quotes. As quotes data are not available for the floor, this can only be estimated for Xetra. Like with the spread decomposition performed above, this means that results cannot be compared between the floor and the electronic trading platforms, which is the primary scope of this paper. Thirdly, the effective spread could be used for the descriptive analysis and for the spread decomposition separately to the quoted spreads. This spread measure allows for trade executions within the quoted spread (Venkataraman (2001)). Once again, this would only be possible for Xetra. Finally, depth is another indicator of market quality and could also be examined in the context of this paper. However, Lee et al. (1993) find that spreads are negatively correlated with depth so that qualitative results regarding the latter can be inferred from our analysis of spreads.

More generally, further empirical research should take into account the explicit trading costs as well. Fees and commissions that investors face for transactions they settle on the floor might outweigh the relative benefits of the non-anonymous trading platform (Domowitz and Steil (1999)). Since institutional investors tend to have their own dealers on the floor, they might be able to save on those fees. This could be another reason why we observe primarily institutional investors transferring to the floor.

## 2.5 Tables

Table 1: Descriptive Statistics for the Frankfurt Stock Exchange

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | **Panel A: Turnover** | | | | | | |
| | | **Floor** | | | | **Xetra** | | |
| | | | $H_0$: equal means | | | | $H_0$: equal means | |
| | | mean | $t$-test | $P$-value | | mean | $t$-test | $P$-value |
| Aug03-Oct03 | daytime | 34,135.45 | 2.57 | 0.01 | | 915,752.10 | 9.87 | $< 0.0001$ |
| Nov03-Jan04 | daytime | 34,989.55 | | | | 1,000,625.36 | | |
| Aug03-Oct03 | evening | 16,417.06 | 19.47 | $< 0.0001$ | | 198,846.24 | | |
| Nov03-Jan04 | evening | 28,527.03 | | | | not applicable | | |
| Oct03 | evening | 15,444.56 | 12.74 | $< 0.0001$ | daytime | 947,214.42 | 2.86 | 0.004 |
| Nov03 | evening | 29,712.98 | | | daytime | 990,182.64 | | |
| | | **Panel B: Transaction Size** | | | | | | |
| | | **Floor** | | | | **Xetra** | | |
| | | | $H_0$: equal means | | | | $H_0$: equal means | |
| | | mean | $t$-test | $P$-value | | mean | $t$-test | $P$-value |
| Aug03-Oct03 | daytime | 493.85 | −4.00 | $< 0.0001$ | | 768.33 | −0.72 | 0.47 |
| Nov03-Jan04 | daytime | 478.49 | | | | 765.25 | | |
| Aug03-Oct03 | evening | 420.31 | 8.59 | $< 0.0001$ | | 629.00 | | |
| Nov03-Jan04 | evening | 512.23 | | | | not applicable | | |
| Oct03 | evening | 394.23 | 7.13 | $< 0.0001$ | daytime | 782.88 | −4.57 | $< 0.0001$ |
| Nov03 | evening | 534.66 | | | daytime | 756.32 | | |

Table 1 (continued): Descriptive Statistics for the Frankfurt Stock Exchange

| | | **Panel C: Return Volatility** | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | **Floor** | | | | **Xetra** | | |
| | | | $H_0$: equal means | | | | $H_0$: equal means | |
| | | mean | $t$-test | $P$-value | | mean | $t$-test | $P$-value |
| Aug03-Oct03 | daytime | 0.286 | −26.45 | < 0.0001 | | 0.187 | −20.04 | < 0.0001 |
| Nov03-Jan04 | daytime | 0.245 | | | | 0.168 | | |
| Aug03-Oct03 | evening | 0.274 | −18.49 | < 0.0001 | | 0.232 | | |
| Nov03-Jan04 | evening | 0.199 | | | | | not applicable | |
| Oct03 | evening | 0.249 | −6.63 | < 0.0001 | daytime | 0.173 | 0.76 | 0.45 |
| Nov03 | evening | 0.205 | | | daytime | 0.174 | | |

| | | **Panel D: Bid-Ask Spread** | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | **Floor** | | | | **Xetra** | | |
| | | | $H_0$: equal means | | | | $H_0$: equal means | |
| | | mean | $t$-test | $P$-value | | mean | $t$-test | $P$-value |
| Aug03-Oct03 | daytime | 0.356 | −21.12 | < 0.0001 | | 0.636 | −36.54 | < 0.0001 |
| Nov03-Jan04 | daytime | 0.307 | | | | 0.553 | | |
| Aug03-Oct03 | evening | 0.350 | −16.46 | < 0.0001 | | 0.778 | | |
| Nov03-Jan04 | evening | 0.252 | | | | | not applicable | |
| Oct03 | evening | 0.322 | −6.21 | < 0.0001 | daytime | 0.618 | −12.26 | < 0.0001 |
| Nov03 | evening | 0.262 | | | daytime | 0.571 | | |

Table 2: Relative Adverse Selection Costs (George et al. (1991)) for equal-weighted size-based portfolios in Xetra

| | | **DAX** | | | **MDAX** | | | **TecDAX** | | | **SDAX** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $H_0$: equal means | | | $H_0$: equal means | | | $H_0$: equal means | | | $H_0$: equal means | |
| | | mean | $t$-test | $P$-value | mean | $t$-test | $P$-value | mean | $t$-test | $P$-value | mean | $t$-test | $P$-value |
| Aug03-Oct03 | daytime | 0.9945 | -2.7407 | 0.0062 | 0.9935 | -3.6298 | 0.0003 | 0.9864 | -4.1547 | <0.0001 | 0.9949 | 0.4796 | 0.6315 |
| Nov03-Jan04 | daytime | 0.9942 | | | 0.9924 | | | 0.9826 | | | 0.9953 | | |
| Aug03-Oct03 | evening | 0.9924 | | | 0.9932 | | | 0.9871 | | | 0.9948 | | |
| Oct03 | daytime | 0.9948 | -10.8685 | <0.0001 | 0.9949 | -187.8081 | <0.0001 | 0.9821 | 0.3150 | 0.7528 | 0.9943 | -0.2416 | 0.8091 |
| Nov03 | daytime | 0.9924 | | | 0.9009 | | | 0.9864 | | | 0.9940 | | |

# 3 Together We Invest: Individual Investors' Trading Behaviour in Poland

## 3.1 Introduction

There are two paths in the empirical literature investigating herding behaviour. The first one is broader and examines institutional investors, while the second strand focusses on individual investors. There is mixed evidence regarding which investor type exhibits herd behaviour more strongly, since flocking together can be rational or irrational. The primary reasons for rational, or spurious, herding are incentives for fund managers, shared preferences for particular stocks, and common reactions to the same news (Griffin et al. (2003)), leading to efficient outcomes (Bikhchandani and Sharma (2001)). Irrational, or intentional herding, by contrast, refers to trading activities that simply imitate others' trading decisions regardless of prior information (Bikhchandani and Sharma (2001)). Individuals have been shown in the literature to be more prone to intentional herding behaviour than institutions (Kim and Wei (1999)), while institutions are more likely to engage in spurious herding (Wermers (1999)). Interestingly, Tan et al. (2008) find evidence of herding in both market segments and at both stock exchanges in China, suggesting that the Chinese stock market exhibits herding independently of investor structure. This paper contributes empirical evidence on individual investors' herding behaviour, and on whether this is exhibited more strongly during market upswings or downswings. Our unique dataset enables us to test for herding on two trading platforms which differ in investor structure, thereby gaining insights into the investor type that is particularly prone to imitating trading behaviour.

The literature offers various definitions and economic explanations for herd behaviour. Intentional herding refers to buying or selling the same stocks simultaneously with other market participants regardless of prior beliefs or information about asset prices. If this is purely sentiment-driven, then such behaviour results in market prices failing to reflect fundamental information, with mis-pricing potentially leading to bubbles and crashes on financial markets. However, observed flocking together can also lead to news being incorporated in stock prices faster, for example if traders react to correlated information (Froot et al. (1992)). Similarly, Lakonishok et al. (1992) report that institutions' trading activities have a stabilising effect on stock prices. In fact, herding can be rational at a single trader's level for either individual or institutional investors. Copying others' trading actions is beneficial for individual investors if the collective trading behaviour contains more information than one trader alone has (Banerjee (1992), Welch (1992), Bikhchandani et al. (1992)), and it can be rational for institutional investors if a reputation among fund managers is to be maintained (Scharfstein and Stein (1990), Graham (1999)). Similarly, investors share preferences for stocks with certain characteristics (Falkenstein (1996)). Collective investments in such securities are not intentional herding because they do consider prior beliefs.

A more detailed analysis of herding reveals that imitating trading behaviour can depend on the state of the overall market. In fact, there is growing empirical evidence that stock traders' responses to good and bad news are asymmetric (Grinblatt et al. (1995), Keim and Madhavan (1995)). In particular, McQueen et al. (1996) first document that cross-autocorrelation in stock returns is asymmetric in up- and downmarkets. Likewise, there is mixed empirical evidence on herding in market upswings compared to downswings. Chang et al. (2000) find herding in Taiwan to be more severe in bull markets than during bear phases, while there is no difference in herding between these two states of the markets in the U.S., Hong Kong, Japan, and South Korea. Christie and Huang (1995) report the U.S. stock market to be in accordance with rational asset pricing models even during periods of market stress. Hwang and Salmon (2004) examine the relative changes of herding activity over time for the U.S. and South Korea and find herding to be present in up- and downswings in both markets. Specifically, they observe a return to fundamentals during market downturns, which they refer to as 'adverse herd behaviour'.

Institutional investors' trading decisions are believed to be less biased by behavioural aspects than those taken by individuals (Barber and Odean (2008), Kamesaka et al. (2003), Ekholm and Pasternack (2008), Shiller (1984)), so that institutions are, in general, less prone to intentional herding. However, most of the empirical literature investigating herding behaviour by institutional investors reports mixed evidence. While some studies find that institutions hardly exhibit herd behaviour (Lakonishok et al. (1992), Grinblatt et al. (1995)), others report evidence of institutions flocking together (Nofsinger and Sias (1999), Dennis and Strickland (2002)). Apparent institutions' herding can be attributed to the peer review system that fund managers are subject to, or to correlated information flows that these investors follow. As institutional investors collectively trade on these news, they speed up the incorporation of new information in asset prices and hence stabilise the market (Wermers (1999), Sias (2002), Jones et al. (1999), Graham (1999)). Further research shows that herd behaviour differs across institution types (Lakonishok et al. (1992), Badrinath and Wahal (2002)). Specifically, pension funds are less likely to herd than other institutions.

On the other hand, research on individual investors' behaviour discovers that these traders may engage in spurious herding if they follow the same signals (Shleifer and Summers (1990)). However, herding due to overreaction to recent news is classified as intentional herding, which individuals are likely to exhibit. According to Kim and Wei (1999), who investigate the Korean Stock Exchange, herding behaviour by individuals is more prominent than for institutions. However, Ekholm and Pasternack (2008) show Finnish individual investors to be more overconfident than institutions. The higher the degree of overconfidence, the less likely investors are to rely on others' behaviour rather than their own beliefs when making investment decisions. It can therefore be concluded that Finnish individuals are less prone to herding than institutions. Since institutional investors prefer large-capitalisation stocks (Falkenstein (1996)), imitating trading behaviour is particularly prominent in these stocks, for which signals are not as noisy as for smaller stocks. There is, however, evidence of herding in smaller stocks (Wermers (1999), Lakonishok et al. (1992)), which could be an indication of herding behaviour by individual investors. In light of the mixed evidence on individuals' herding presented in previous studies, this paper contributes to a better understanding of this phenomenon. Our unique dataset enables us to conduct the analysis separately for small stocks concentrated in the auction system, and for large stocks dominating continuous trading.

The Polish stock market lends itself to an investigation of individuals' trading activities for a number of reasons. First and foremost, two quotation systems are operated in parallel by the Warsaw Stock Exchange (WSE) which enable us to separate institutional from individual investors. These trading platforms are a single-price auction which has existed since the exchange was opened on 16 April 1991, and a continuous trading system, introduced in July 1996. In this continuous system, only large liquid shares were traded, and a minimum trade size applied. As a result, individuals are concentrated in the auction system, while institutions prefer continuous trading. The co-existence of these two trading mechanisms enables us to separate individuals from institutional investors and to compare the trading behaviour of these investor groups. Secondly, small local investors played a comparatively important role on the Polish stock market until large open-end pension funds entered the market in May 1999 as a result of the Polish pension system reform. Thirdly, the Polish stock market is an emerging market, on which herding is more likely to be observed than on mature markets due to incomplete information disclosure in emerging markets (Chang et al. (2000)).

We test for the presence of herding behaviour in the single-price auction, where individual investors are concentrated, and in continuous trading with mostly institutions. In light of Wermers (1999), Lakonishok et al. (1992), Kim and Wei (1999), and Chang et al. (2000), we expect to find empirical evidence of Polish individual investors engaging in herding behaviour. By contrast, should there be no indication of herds, this would imply that Polish individual investors are as proficient as institutional investors in mature markets. In addition, we investigate whether herding is exhibited more strongly during up- or downswings of the market, as Chang et al. (2000) and Christie and Huang (1995) report contrary findings for this.

In order to give a better understanding of our testing setup, section 2 describes the institutional background of the Polish stock market and introduces the dataset. Section 3 explains the methodology before section 4 presents the empirical results. Section 5 summarises our findings and concludes.

## 3.2 Trading Systems and Institutional Setting at the Warsaw Stock Exchange

The organisation of stock trading has been shown in the literature to have a substantial influence on the behaviour of traders, transaction volume, and stock prices. While in a continuous trading system the market is cleared at almost all times, in a call auction orders are batched together. Thus, in the latter system, the market is only consolidated and cleared at discrete points in time with a specialist determining the market clearing price. The WSE re-opened in 1991 and initially, stocks were traded in one auction per week. Subsequently, trading has been extended and from 1994 onwards, a daily auction was carried out. In 1996, a continuous trading platform for stocks was introduced. As a result, all stocks we traded in the call auction and the most liquid securities were additionally traded in the continuous trading system. In this system, a minimum trade size applied which amounted to the equivalent of about 3,000 US$ and hence virtually excluded individual investors. With the launch of WARSET on 17 November 2000, liquid stocks were taken out of the auction trading, the minimum trade size requirement in the continuous trading system was dropped, and specialists started to provide liquidity in the continuous trading mechanism. This event therefore ends the period during which stocks were traded parallel in a call auction and a purely order-driven electronic limit order book system.

Both trading mechanisms at the WSE are order-driven, implying that traders submit orders without knowing a firm price, which is determined multilaterally in an auction. These order-driven platforms can be further divided by clearing frequency into continuous and periodic auctions. In a continuous auction, orders are executed upon arrival. For periodic auctions, orders are accumulated and executed simultaneously at a single market clearing price. By contrast, in a quote-driven dealer market, the dealers' profits are generated with the difference between the transaction price and the expected (fundamental) value of the asset. Competition among dealers drives down their profits, so that quotes and subsequently transaction prices move towards their fair values. As information asymmetry goes up, public information signals are imprecise, and dealers do not successfully learn from the order flow, their expected profits become negative, and they withdraw from the market. This potential collapse of trading is a market failure from which auction systems do not suffer. Instead, in a periodic auction, traders share the risk resulting from information asymmetries among themselves. In general, this yields lower adverse selection costs in auction systems than in dealer markets. In order to facilitate the incorporation of new information in prices and to prevent market failure, many continuous markets open with a call aution in the morning (Amihud et al. (1990)).

The optimal clearing frequency of a market is determined by the trade-off between two parts of liquidity risk (Garbade and Silber (1979)). The first part captures the risk of changes in fair values during the time between the decision to trade is made and the time the trade is executed. This part of liquidity risk is minimised in a continuous trading system. The second part of liquidity risk is caused by transient random deviations of prices from their fair values due to the fact that prices are set by a subset of traders. In a continuous system, these subsets are very small, while the consolidated market in an auction covers the entire market. As a result, the second part of liquidity risk is minimised in an auction. The larger the price volatility of a security, and the larger the number of market participants, the higher the optimal clearing frequency. Moreover, institutional investors hold well-diversified portfolios and trade often, so that random price fluctuations cancel out in the long run. Individual investors, by contrast, only trade infrequently and hold less diversified investments, which are, on balance, adversely affected by random price changes in the continuous system. Dealer presence reduces the time to trade completion and stabilises prices, implying that the liquidity risk on a dealer market is lower than on a purely public market under otherwise equal conditions.

In light of Garbade and Silber (1979), a well-informed, well-diversified institutional investor will prefer the continuous trading platform over the periodic auction, since the larger trading volume in the continuous system offers greater market depth (Kyle (1985)), hence lower price impact, immediate trade execution, and hence larger profits from private information. Moreover, like in any quote-driven market, the price is known at the time of order submission, relieving investors of the risk that other contemporaneous orders unfavourably influence the price. The flip side of this conclusion is the insight that individuals are likely to choose a batch market over continuous trading, so that liquidity is concentrated at particular points in time, adverse selection costs are small, and prices are nearer their fair values. Furthermore, Falkenstein (1996) finds that institutions prefer large stocks. Consistently with this, Madhavan (1992) reports that large liquid stocks are generally traded continuously, while smaller stocks dominate trading in periodic auctions. This distinction between trading systems enables us to investigate trading behaviour on a platform that institutions tend to prefer compared with a system that is more favourable towards individuals.

Both trading systems on the WSE have had daily price variation limits of 10% in place. A transaction price for shares in continuous trading had to lie inside a 10%-corridor around the opening price, and for shares traded in the auction system the benchmark value was the previous day's price. When the stock price hits these limits, the specialist broker appointed by the exchange intervenes by trying to balance the market through buying or selling securities in his own account. If it is impossible to find the market clearing price in this way, the size of the order imbalance is estimated. For imbalances between supply and demand of 5:1 and larger, trading is suspended, and for smaller imbalances the submitted orders are subject to proportional reduction by the prevailing side of the market (Warsaw Stock Exchange (2000)).

## 3.3 Methodology and Data

We base our analysis on the mean cross-sectional absolute deviation of individual stock returns $r_{it}$ from the market average $R_{m,t}$ at time $t$ (Christie and Huang (1995), Chang et al. (2000)):

$$S_t^* = \frac{\sum_{i=1}^{n} |r_{it} - R_{m,t}|}{n} \quad , \tag{4}$$

where $n$ is the number of stocks in the sample on each day $t$. The mean absolute deviation $S_t^*$ does not measure the variation in each stock over time, nor does it capture the dispersion of each individual return from its expected value. Thus, it cannot be viewed as the portfolio volatility. When herd behaviour is present, investors' decisions are driven by the market movements rather than by their own heterogenous beliefs, and hence individual stock returns are nearer the market average than under a rational asset pricing model. Among these models are the CAPM (Black (1972)) and the market timing model proposed by Treynor and Mazuy (1966). Rational asset pricing models predict differences among stock returns in their sensitivity towards the market return, resulting in return dispersion $S_t^*$ increasing linearly with the absolute value of the market return. Therefore, Chang et al. (2000) argue that $S_t^*$ by itself cannot be used to detect herding. Rather, the relationship between $S_t^*$ and $R_{m,t}$ should be examined. In the presence of herding, $S_t^*$ increases at a non-linear rate as the absolute market return increases, because $S_t^*$ deviates downwards from the linear relationship. Thus, in order to detect herding, we estimate the regression

$$S_t^* = \alpha + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + \epsilon_t \quad , \tag{5}$$

where a statistically significantly negative $\hat{\beta}_2$ indicates herd behaviour. When $\hat{\beta}_2$ is insignificant, $S_t^*$ increases linearly with the absolute value of the market return, and we conclude that herding is absent.

This regression analysis is conducted separately for down- and up-markets to detect potential differences in trading behaviour between these two states of the market. If the daily market return is positive (negative) on any given day, the market is classified as an up- (down-) market (Chang et al. (2000), Kurov (2008)). Since the absolute value of the market return is used in the estimation, $\hat{\beta}_2$ can be directly compared between the down-market and the up-market. We apply an $F$-test to detect statistically significant differences in all estimated coefficients between periods of market stress and bullish phases. Thus, the null hypothesis to test the entire regression line is $H_0$: $\alpha^{up} = \alpha^{down}$ and $\beta_1^{up} = \beta_1^{down}$ and $\beta_2^{up} = \beta_2^{down}$, and the test statistic is calculated as

$$F = \frac{(SSE_T - SSE_S)/q}{SSE_S/DF_S} \tag{6}$$

where $SSE_T$ denotes the sum of squared errors in the regression across all states of the market, while $SSE_S = SSE_{up} + SSE_{down}$ and thus refers to the sum of squared errors for market upswings and downswings. $q$ is the number of parameters that are being estimated, whereas $DF_S$ equals the total number of observations less the number of parameters estimated in the regressions for market upturns and downturns. The test statistic follows an $F$ distribution with $q$ and $DF_S$ degrees of freedom.

In order to test $H_0 : \beta_2^{up} = \beta_2^{down}$ rather than equality of the entire regression line, we estimate

$$S_t^* = \alpha + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + D_t \cdot (\gamma_0 + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2) + \epsilon_t \ , \tag{7}$$

where $D_t$ equals zero in market downswings and takes the value of one otherwise. A statistically significant $\gamma_2$ coefficient indicates differences in herding between market upswings and bear phases. A negative $\gamma_2$ parameter suggests more prominent herding during upswings than downswings.

Finally, it can be hypothesised that herding diminishes across the 4-year sample period. This could be due to smoother information flows on the Polish stock market, or it could result from investors becoming more experienced and hence less sentiment-driven, or both. We therefore examine the time series behaviour of herding in both trading systems and estimate

$$|\hat{\beta}_{2t}| = \zeta_0 + \zeta_1 t + \zeta_2 D_t + \epsilon_t \tag{8}$$

where $\hat{\beta}_{2t}$ is taken from regression (5) which is run for moving windows of 100 trading days each. $t$ is the time variable, and $D_t$ takes the value of zero if there are more bear market days than market upswings in any 100-trading-day window and the value of one otherwise. $D_t$ is included in the model specification because the estimation results from regression (5) indicate that $\beta_{2t}$ differs between up- and downmarkets. A statistically significant and negative $\hat{\zeta}_1$ coefficient implies that the market moves towards the prediction of rational asset pricing models, and hence herding becomes less prominent in case it was present at the outset. $\hat{\zeta}_2$ captures the difference in the time series behaviour of herding between market up- and downswings. All regressions are estimated with OLS, and the statistical inference is based on Newey and West (1987) standard errors which are corrected for heteroskedasticity and serial correlation in the error term.

The WSE provided time series of daily close prices for all traded stocks in each of the two trading systems from 9 July 1996 to 16 November 2000. This is the period when stocks were traded parallel in one single-price auction per day and in continuous trading and yields $1,088$ daily return observations. Christie and Huang (1995) hypothesise that data frequency might influence whether herding is detected empirically. Moreover, Lakonishok et al. (1992) argue that herding in individual stocks only shows up in daily or weekly data. Daily data assume that herding is short-lived, while monthly data let returns move away from, or cluster around, the market over longer time horizons. However, Christie and Huang (1995) find no empirical deviation between monthly and daily data for the New York Stock Exchange. Based on this finding, information does not appear to be lost when using daily data. We therefore follow Chang et al. (2000) in conducting the analysis with daily data.

After calculating continuously compounded returns $r_t = ln(P_t/P_{t-1})$ and accounting for stock splits and dividend payments, we obtain 182,861 observations for the call auction and 70,476 data points for continuous trading. At the beginning of the sample period, only five stocks were traded per day in the continuous system, while in November 2000, 102 companies were quoted and traded actively in the continuous trading system. By contrast, the auction was more heavily used with trading in 75 shares per day in July 1996 and transactions in 223 shares at the end of the sample period.

Table 3 presents summary statistics of daily returns for both trading platforms. The individual stocks' returns are, on average, negative in both systems. Interestingly, even though the market is consolidated in the call auctions and there are more than twice as many observations than for continuous trading, the return volatility in the auction market is larger than in continuous trading and substantially larger than the return volatilities reported by Chang et al. (2000) for mature markets (e.g. the U.S.) or for emerging markets (e.g. South Korea or Taiwan) for a 20-year period ending in 1995. This larger volatility in Poland could be attributed to higher information asymmetries on this market (Barclay and Hendershott (2003)), potentially driven by the large share of individual investors. Moreover, individual investors are a less homogeneous group than institutional investors and are thus less likely to agree on fair asset prices. Consistently with these arguments, we find return volatility in the auction system to be slighlty larger than in continuous trading, which is preferred by institutional investors.

Table 3 about here

We compute the market return $R_{m,t}$ in three different ways. First, we use the performance index WIG as a proxy for the market, which is an all-stocks value-weighted index. Second, the WIG20 price index captures the 20 large cap stocks; and third, we calculate equally weighted market portfolios across all shares traded on any one day for each trading system separately. While the WIG and the WIG20 indexes are observable for traders, the equally weighted market portfolios are not known to investors. By calculating $S_t^*$ with the equally weighted market portfolio which does not overrepresent any class of stocks, we measure how far the stocks traded on any given day move away from their own average return rather than from the overall market. The value-weighted indexes WIG and WIG20 are dominated by large-cap stocks, whose prices have been shown to incorporate new information more quickly, leading to a higher information content of large stocks (Gebka (2008)).

In addition to separating individual investors from institutions by examining two different trading systems, we distinguish these investor types by market capitalisation within either trading platform. Thus, we assume that institutional investors prefer large stocks, while individuals tend to be over-represented in small stocks (Falkenstein (1996)). Specifically, we create three size portfolios from all stocks traded on any given day based on the average market capitalisation of each stock across one month. By taking the average market capitalisation rather than the daily market capitalisation, we exclude short-term switches of stocks between two size groups resulting from highly volatile stock prices. In fact, these price movements should be captured in $S_t^*$, for which the respective stocks have to remain in the same size portfolio. The small stock portfolio comprises the smallest third of stocks across one month, the medium size group includes the next-largest third, with the remaining stocks being allocated to the large-capitalisation portfolio. Within each portfolio, $S_t^*$ is calculated, and regression (5) is estimated as described above.

## 3.4 Empirical Results

The primary goal of this paper is to determine whether individual investors on the Polish stock market engage in herding behaviour. Moreover, we test whether potential herding is different during market upswings and downswings. Across the four-year period under investigation, individuals are the dominating trader type at the WSE, contributing 43% of total turnover value. Furthermore, we distinguish between institutions and individuals by examining two trading platforms separately, and by splitting the stocks in our sample into three size portfolios. Overall, the empirical evidence suggests that individual investors' trading behaviour exhibits herding during market downswings, while institutions do not engage in flocking together regardless of the state of the market. Furthermore, herding behaviour appears to have become less pronounced over time.

Table 4 summarises the results for both trading platforms. A statistically significant negative $\hat{\beta}_2$ indicates herd behaviour. By contrast, when $\hat{\beta}_2$ is insignificant, we conclude that herding is absent. In the single-price auction, there is no herding in market upswings, but substantial herding during bear phases. These differences between market states are highlighted by the $F$-test and the $t$-test statistics. While the $F$-test tests for equality of the regression lines in up- and downmarkets, the $t$-test tests specifically for equal $\beta_2$-parameters in bull and bear periods. Chang et al. (2000) report significant herding in South Korea and Taiwan, while mature markets like the U.S. and Hong Kong do not show evidence of herds. Thus, during bull markets, individuals transacting in the single-price auction exhibit trading behaviour similar to institutional investors in the U.S. or Hong Kong. While Chang et al. (2000) find Taiwanese investors to exhibit more severe herding behaviour during upswings than downswings, our results suggest that individuals show herding behaviour during periods of market stress, which is also contrary to Hwang and Salmon (2004).

However, our findings are consistent with individuals being more overconfident during market upswings than downswings (Daniel et al. (1998), Gervais and Odean (2001), Statman et al. (2006)) as they follow their own assessment in the up markets but tend to ignore it during the down phases. This could be driven by the market rewarding behaviour that is based on prior beliefs during upswings, while investors are more likely to doubt their knowledge during market stress. Alternatively, investors could be reluctant to realise losses as the market goes down (Tversky and Kahneman (1991), Odean (1998)). Hence, rather than selling stocks when the market return becomes negative, they continue to hold them, which results in small return dispersion as a downward pressure on asset prices does not materialise.

Table 4 about here

For continuous trading, however, our results of no herding are in accordance with those reported by Chang et al. (2000) for mature markets, which are dominated by institutions and do not exhibit herding. Panel B in Table 4 shows a linear relationship between $S_t^*$ and the market return, with the quadratic term being statistically insignificant. When we use the equal-weighted index of all traded stocks on any given day as the market, the $\beta_2$ parameter is statistically significant and positive, implying that the deviation of individual stock returns from the market is larger than rational asset pricing models predict. This can be viewed as evidence in favour of investors strongly relying on their own anaylses rather than information revealed by others' trading behaviour. Overall, this finding can be interpreted as evidence against the existence of herding among institutional investors regardless of the state of the market, since the $t$-test of $\beta_2^{up} = \beta_2^{down}$ generates insignificant results. This is in accordance with Gebka et al. (2006) documenting a stabilising effect of institutional investors entering the Polish stock market.

In the next step, we test whether herding is more pronounced in small stocks than large ones. For this, we split the stocks within either trading platform into three size portfolios based on monthly average market capitalisation. Table 5 presents the results for the single-price auction, while Table 6 shows those for continuous trading. The overall evidence for the auction system, where individuals are overrepresented, suggests that there is significant herding in stocks of all sizes during market downturns, as indicated by significantly negative $\beta_2^{down}$ coefficients. For large stocks, however, we also find imitating trading patterns during market upswings ($\beta_2^{up}$ negative and significant), with herding in downswings being more severe (as indicated by the significant $t$-test statistic of $H_0 : \beta_2^{up} = \beta_2^{down}$). Thus, the insights summarised in Table 4 are confirmed, while the aggregates shown there hide the peculariaty in large stocks during bullish market periods. The results presented in Table 5 suggest that individuals trading in small and medium-sized stocks in the single-price auction refer, during periods of market stress, to others' investment decisions rather than their own prior beliefs. This is contrary to the return to fundamentals during market downswings found in Hwang and Salmon (2004). Those who trade in large stocks, however, appear to follow the market regardless of its current state.

Table 5 about here

Table 6 about here

The evidence for continuous trading, which is dominated by institutions, is consistent with Chang et al. (2000) for the U.S. and Hong Kong. In fact, there is no sign of herd behaviour independent of bullish or bearish market phases and across all stock sizes (Table 6). While the Polish stock market is an emerging capital market, its institutional investors' trading behaviour is similar to that observed in the U.S., as indicated by insignificant $\beta_2$ parameters. This suggests that institutions trading in the continuous system are as advanced as investors on mature markets, and the accuracy and availability of the information on the Polish stock market are as good as on mature markets. In light of this insight, the Polish stock market is no more likely to suffer from mis-pricing and the formation of bubbles than more advanced markets. Moreover, when the equal-weighted index of all traded stocks represents the market, the herding parameter $\beta_2$ is significant and positive in downmarkets. This implies that, during market stress, institutional investors transacting in the continuous trading system base their investment decisions mainly on their own beliefs and prior knowledge rather than on others' trading behaviour.

Table 7 summarises the time series behaviour of herding for both trading platforms. A statistically signifcant and negative $\hat{\zeta}_1$ parameter suggests that the market is complying more fully with rational asset pricing models towards the end of the sample period than at the outset. In the single-price auction, it appears that herding has become less pronounced over time except when the WIG20 index represents the market. Since $\zeta_2$ is significant and negative for the WIG as market index, it can be concluded that this development took place during market upswings rather than downswings. This is plausible as herding persists in the latter market state which is consistent with the results presented in Table 4. Thus, during market stress, individuals continue to exhibit herding behaviour, while they have learnt to trust their own information and beliefs as the market return rises.

Table 7 about here

In continuous trading, by contrast, we detect no evidence of herding (Table 4) and hence no significant changes in herding behaviour over time when the WIG or WIG20 indexes represent the market. When the equal-weighted index of all traded stocks is used, however, Table 4 reports that individual stock returns are even farther from the negative market return than rational asset pricing models predict, implying a cross-sectional return dispersion that is larger than predicted by these models. This effect has become less pronounced over time, since $\zeta_1$ is significant and negative for the equal-weighted index as market return. $\zeta_2$ is significant and positive, implying that this development took place primarily during market downswings. This is consistent with the results presented in Table 4, according to which deviations from the predicitions by rational asset pricing models only occur during market down-phases.

It can be argued that the existence of price limits, as discussed in section 3.2, can potentially bias our results. However, by investigating close-to-close spot returns rather than intraday price changes, we largely exclude the potentially decreasing effect of price variation limits on the cross-sectional deviation of stock returns from the market return. Moreover, herding implies that individual stock returns cluster around the market rather than deviating from it. Detecting herding is hence unaffected by price variation limits.

In essence, the empirical evidence suggests that individual investors transacting in the single-price auction engage in herding during market downswings, while their investment behaviour exhibits no herding during market upswings. This herding behaviour has become less pronounced over the sample period. Institutional investors in the continuous trading system do not show signs of flocking together regardless of the state of the market. These differences in herding by investor type are contrary to Tan et al. (2008) who find evidence of herd behaviour for both Chinese individuals and foreign institutions.

## 3.5 Summary and Conclusions

This paper investigates individual investors' trading behaviour by testing for the presence of herding on the Polish stock market from July 1996 to November 2000. In order to distinguish between individuals and institutions, we examine two trading platforms separately where stocks can be traded in a single-price call auction and a continuous system. While the former is dominated by individuals (Madhavan (1992)), institutions prefer the continuous system (Kyle (1985)). A further mechanism to differentiate between individuals and institutions is market capitalisation (Falkenstein (1996)). We therefore conduct the analysis by size portfolio for either trading platform.

The empirical results suggest that individual investors exhibit herding during market downswings, while institutions do not engage in flocking together regardless of the state of the market. This suggests that individuals' investment decisions are prone to sentiment during market stress, while they trust their beliefs and information when stock prices rise. By constrast, we find no evidence of herding among institutional investors. In fact, Polish institutions trading in the continuous system appear to be as experienced as investors on mature markets, and the information flows on the Polish stock market seem as good as on mature markets. Our insights imply for investments in stocks primarily traded by individuals that a larger number of stocks is necessary than in a market that is dominated by experienced institutional investors in order to achieve the same level of diversification (Chang et al. (2000)). In a market with herding, asset prices are more strongly correlated than in a market without imitating trading activities. As a result of this raised return correlation, investors need more stocks for the same level of diversification as in a scenario without herding.

The empirical evidence suggests that the trading patterns differ between individuals and institutions across the sample period, with individuals being prone to sentiment-driven investment decisions when the market return declines. This could be attributed to the Polish stock market being an emerging capital market throughout the period under investigation. During more favourable market phases, however, individuals' trading behaviour results in market outcomes that are consistent with the predictions of rational asset pricing models. Having identified a tendency towards diminishing herd behaviour by individuals, and in light of the lack of evidence in favour of herding among institutions, we conclude that the Polish stock market has become more efficient throughout the sample period. Trading systems that foster smooth information flows aid especially individuals in exhibiting investment behaviour that is consistent with rational asset pricing models.

## 3.6 Tables

Table 3: Descriptive Statistics for Stock Trading under the Single-Price Auction and the Continuous Trading Mechanisms in Poland

| | $R_i$ | $R_{WIG}$ | $R_{WIG20}$ | $R_{equal}$ |
|---|---|---|---|---|
| Panel A: Single-Price Auction | | | | |
| Mean | $-0.0563$ | 0.0135 | 0.0078 | $-0.0448$ |
| Median | 0.0000 | 0.0553 | 0.0099 | $-0.0018$ |
| Standard Deviation | 3.4402 | 1.8460 | 2.0702 | 1.6701 |
| No of observations | 182,861 | 1,090 | 1,090 | 182,861 |
| Panel B: Continuous Trading | | | | |
| Mean | $-0.0389$ | 0.0135 | 0.0078 | $-0.0279$ |
| Median | 0.0000 | 0.0553 | 0.0099 | $-0.0059$ |
| Standard Deviation | 3.3609 | 1.8460 | 2.0702 | 2.18952 |
| No of observations | 70,476 | 1,090 | 1,090 | 70,476 |

All returns are daily, continuously compounded and given in percent. $R_i$ is the individual stocks' return, while $R_{WIG}$ is the return of the performance index WIG, and $R_{WIG20}$ is the return of the price index WIG20. $R_{equal}$ is measured as the return of the equal-weighted index of all stocks traded on any given day. The sample period runs from 9 July 1996 to 16 November 2000.

Table 4: Regression Results of the Daily Cross-sectional Absolute Deviation of Stock Returns on the Linear and Squared Terms of the Market Return in Poland

| | Up-Market $S_t^* = \alpha^{up} + \beta_1^{up}\lvert R_{m,t}\rvert + \beta_2^{up} R_{m,t}^2 + \epsilon_t$ | | | | Down-Market $S_t^* = \alpha^{down} + \beta_1^{down}\lvert R_{m,t}\rvert + \beta_2^{down} R_{m,t}^2 + \epsilon_t$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\alpha^{up}$ | $\beta_1^{up}$ | $\beta_2^{up}$ | Adj $R^2$ | $\alpha^{down}$ | $\beta_1^{down}$ | $\beta_2^{down}$ | Adj $R^2$ | $F$-Test | $\beta_2^{up} - \beta_2^{down}$ |
| Panel A: Single-Price Auction | | | | | | | | | | |
| $R_m = R_{WIG}$ | 0.019 | 0.222 | 0.336 | 0.277 | 0.017 | 0.465 | −4.269 | 0.312 | 8.018 | 4.605 |
| $p$-value | 0.000*** | 0.000*** | 0.710 | | 0.000*** | 0.000*** | 0.000*** | | 0.000*** | 0.000*** |
| $R_m = R_{WIG20}$ | 0.018 | 0.281 | 0.062 | 0.380 | 0.017 | 0.463 | −3.775 | 0.344 | 6.312 | 3.837 |
| $p$-value | 0.000*** | 0.000*** | 0.954 | | 0.000*** | 0.000*** | 0.000*** | | 0.000*** | 0.000*** |
| $R_m = R_{equal}$ | 0.019 | 0.227 | −0.321 | 0.174 | 0.018 | 0.273 | 0.306 | 0.282 | 2.468 | −0.622 |
| $p$-value | 0.000*** | 0.000*** | 0.850 | | 0.000*** | 0.047** | 0.929 | | 0.061* | 0.839 |
| Panel B: Continuous Trading | | | | | | | | | | |
| $R_m = R_{WIG}$ | 0.018 | 0.336 | 2.086 | 0.297 | 0.016 | 0.450 | 0.438 | 0.419 | 3.487 | 1.648 |
| $p$-value | 0.000*** | 0.000*** | 0.381 | | 0.000*** | 0.000*** | 0.690 | | 0.015** | 0.584 |
| $R_m = R_{WIG20}$ | 0.018 | 0.396 | 1.229 | 0.357 | 0.016 | 0.462 | 0.246 | 0.448 | 2.695 | 0.982 |
| $p$-value | 0.000*** | 0.000*** | 0.561 | | 0.000*** | 0.000*** | 0.808 | | 0.045** | 0.702 |
| $R_m = R_{equal}$ | 0.014 | 0.437 | 0.487 | 0.531 | 0.013 | 0.439 | 1.838 | 0.805 | 4.658 | −1.352 |
| $p$-value | 0.000*** | 0.000*** | 0.652 | | 0.000*** | 0.000*** | 0.000*** | | 0.003*** | 0.210 |

The coefficients are estimated with OLS, and the $p$-values are based on standard errors corrected for heteroskedasticity and autocorrelation up to five lags with the Newey and West (1987) method. Three different proxies for the market are used: the performance index WIG, the price index WIG20, and the equal-weighted index of all stocks traded on any given day. The respective returns are daily and continuously compounded. $S_t^*$ gives the daily cross-sectional absolute deviation of the individual stocks' returns from the market return. The sample period runs from 9 July 1996 to 16 November 2000. A trading day is classified as up-market when $R_m \geq 0$ and as down-market when $R_m < 0$. The $F$-test tests for equality of the regression lines for the up and down markets, i.e. $H_0$: $\alpha^{up} = \alpha^{down}$ and $\beta_1^{up} = \beta_1^{down}$ and $\beta_2^{up} = \beta_2^{down}$. $H_0$ for the $t$-Test is $\beta_2^{up} = \beta_2^{down}$, which is tested in the dummy regression $S_t^* = \alpha + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + D_t \cdot (\gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2) + \epsilon_t$ where $D_t = 0$ in market downswings and $D_t = 1$ otherwise. We report $\hat{\gamma}_2 = \beta_2^{up} - \beta_2^{down}$ and the corresponding $p$-value. *,** ,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5: Regression Results of the Daily Cross-sectional Absolute Deviation of Stock Returns on the Linear and Squared Terms of the Market Return in Poland by Market Capitalisation for the Single-Price Auction

| | Up-Market $S_t^* = \alpha^{up} + \beta_1^{up}\lvert R_{m,t}\rvert + \beta_2^{up} R_{m,t}^2 + \epsilon_t$ | | | | Down-Market $S_t^* = \alpha^{down} + \beta_1^{down}\lvert R_{m,t}\rvert + \beta_2^{down} R_{m,t}^2 + \epsilon_t$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\alpha^{up}$ | $\beta_1^{up}$ | $\beta_2^{up}$ | Adj $R^2$ | $\alpha^{down}$ | $\beta_1^{down}$ | $\beta_2^{down}$ | Adj $R^2$ | $F$-Test | $\beta_2^{up} - \beta_2^{down}$ |
| Small Stocks | | | | | | | | | | |
| $R_m = R_{WIG}$ | 0.022 | 0.135 | 2.239 | 0.180 | 0.020 | 0.479 | −4.829 | 0.191 | 10.434 | 7.040 |
| $p$-value | 0.000*** | 0.029** | 0.088* | | 0.000*** | 0.000*** | 0.000*** | | 0.000*** | 0.000*** |
| $R_m = R_{WIG20}$ | 0.021 | 0.206 | 1.599 | 0.267 | 0.020 | 0.478 | −4.298 | 0.216 | 8.851 | 5.889 |
| $p$-value | 0.000*** | 0.004*** | 0.255 | | 0.000*** | 0.000*** | 0.000*** | | 0.000*** | 0.000*** |
| $R_m = R_{equal}$ | 0.021 | 0.154 | 1.109 | 0.090 | 0.021 | 0.257 | −0.072 | 0.171 | 1.791 | 1.200 |
| $p$-value | 0.000*** | 0.070* | 0.645 | | 0.000*** | 0.051* | 0.982 | | 0.147 | 0.705 |
| Medium-sized Stocks | | | | | | | | | | |
| $R_m = R_{WIG}$ | 0.019 | 0.206 | 0.523 | 0.222 | 0.017 | 0.449 | −3.704 | 0.251 | 5.732 | 4.227 |
| $p$-value | 0.000*** | 0.000*** | 0.659 | | 0.000*** | 0.000*** | 0.002*** | | 0.001*** | 0.001*** |
| $R_m = R_{WIG20}$ | 0.018 | 0.251 | 0.653 | 0.326 | 0.017 | 0.443 | −3.164 | 0.284 | 4.764 | 3.816 |
| $p$-value | 0.000*** | 0.000*** | 0.616 | | 0.000*** | 0.000*** | 0.012** | | 0.003*** | 0.002*** |
| $R_m = R_{equal}$ | 0.019 | 0.199 | −0.480 | 0.109 | 0.018 | 0.284 | 0.357 | 0.263 | 4.912 | −0.838 |
| $p$-value | 0.000*** | 0.002*** | 0.755 | | 0.000*** | 0.040** | 0.917 | | 0.002*** | 0.782 |
| Large Stocks | | | | | | | | | | |
| $R_m = R_{WIG}$ | 0.015 | 0.320 | −1.616 | 0.269 | 0.014 | 0.468 | −4.309 | 0.351 | 2.998 | 2.693 |
| $p$-value | 0.000*** | 0.000*** | 0.046** | | 0.000*** | 0.000*** | 0.000*** | | 0.030** | 0.002*** |
| $R_m = R_{WIG20}$ | 0.015 | 0.380 | −1.939 | 0.363 | 0.014 | 0.470 | −3.899 | 0.392 | 1.689 | 1.960 |
| $p$-value | 0.000*** | 0.000*** | 0.031** | | 0.000*** | 0.000*** | 0.000*** | | 0.168 | 0.034** |
| $R_m = R_{equal}$ | 0.016 | 0.326 | −1.556 | 0.227 | 0.016 | 0.277 | 0.633 | 0.306 | 1.457 | −2.194 |
| $p$-value | 0.000*** | 0.000*** | 0.292 | | 0.000*** | 0.059* | 0.864 | | 0.225 | 0.501 |

The size portfolios are based on the monthly average market capitalisation of each stock. The coefficients are estimated with OLS, and the $p$-values are based on standard errors corrected for heteroskedasticity and autocorrelation up to five lags with the Newey and West (1987) method. Three different proxies for the market are used: the performance index WIG, the price index WIG20, and the equal-weighted index of all stocks traded on any given day. The respective returns are daily and continuously compounded. $S_t^*$ gives the daily cross-sectional absolute deviation of the individual stocks' returns from the market return. The sample period runs from 9 July 1996 to 16 November 2000. A trading day is classified as up-market when $R_m \geq 0$ and as down-market when $R_m < 0$. The $F$-test tests for equality of the regression lines for the up and down markets, i.e. $H_0$: $\alpha^{up} = \alpha^{down}$ and $\beta_1^{up} = \beta_1^{down}$ and $\beta_2^{up} = \beta_2^{down}$. $H_0$ for the $t$-Test is $\beta_2^{up} = \beta_2^{down}$, which is tested in the dummy regression $S_t^* = \alpha + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + D_t \cdot (\gamma_0 + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2) + \epsilon_t$ where $D_t = 0$ in market downswings and $D_t = 1$ otherwise. We report $\hat{\gamma}_2 = \beta_2^{up} - \beta_2^{down}$ and the corresponding $p$-value. $^{*}$,$^{**}$,$^{***}$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 6: Regression Results of the Daily Cross-sectional Absolute Deviation of Stock Returns on the Linear and Squared Terms of the Market Return in Poland by Market Capitalisation for Continuous Trading

| | Up-Market $S_t^* = \alpha^{up} + \beta_1^{up}\lvert R_{m,t}\rvert + \beta_2^{up} R_{m,t}^2 + \epsilon_t$ | | | | Down-Market $S_t^* = \alpha^{down} + \beta_1^{down}\lvert R_{m,t}\rvert + \beta_2^{down} R_{m,t}^2 + \epsilon_t$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\alpha^{up}$ | $\beta_1^{up}$ | $\beta_2^{up}$ | Adj $R^2$ | $\alpha^{down}$ | $\beta_1^{down}$ | $\beta_2^{down}$ | Adj $R^2$ | $F$-Test | $\beta_2^{up} - \beta_2^{down}$ |
| Small Stocks | | | | | | | | | | |
| $R_m = R_{WIG}$ | 0.019 | 0.416 | 1.394 | 0.257 | 0.018 | 0.365 | 1.387 | 0.284 | 2.457 | 0.007 |
| $p$-value | 0.000*** | 0.000*** | 0.598 | | 0.000*** | 0.000*** | 0.235 | | 0.062* | 0.998 |
| $R_m = R_{WIG20}$ | 0.018 | 0.431 | 1.228 | 0.301 | 0.018 | 0.393 | 1.091 | 0.323 | 2.166 | 0.137 |
| $p$-value | 0.000*** | 0.000*** | 0.600 | | 0.000*** | 0.000*** | 0.305 | | 0.090* | 0.961 |
| $R_m = R_{equal}$ | 0.016 | 0.378 | 0.806 | 0.325 | 0.015 | 0.402 | 2.040 | 0.698 | 3.353 | −1.234 |
| $p$-value | 0.000*** | 0.000*** | 0.512 | | 0.000*** | 0.000*** | 0.000*** | | 0.018** | 0.322 |
| Medium-sized Stocks | | | | | | | | | | |
| $R_m = R_{WIG}$ | 0.019 | 0.278 | 3.893 | 0.239 | 0.015 | 0.535 | −0.515 | 0.371 | 4.212 | 4.420 |
| $p$-value | 0.000*** | 0.001*** | 0.024** | | 0.000*** | 0.000*** | 0.580 | | 0.006*** | 0.046** |
| $R_m = R_{WIG20}$ | 0.018 | 0.334 | 2.966 | 0.284 | 0.015 | 0.556 | −0.647 | 0.428 | 3.624 | 3.613 |
| $p$-value | 0.000*** | 0.001*** | 0.099 | | 0.000*** | 0.000*** | 0.452 | | 0.013** | 0.088 |
| $R_m = R_{equal}$ | 0.014 | 0.471 | 0.209 | 0.471 | 0.013 | 0.517 | 1.534 | 0.738 | 6.324 | −1.324 |
| $p$-value | 0.000*** | 0.000*** | 0.830 | | 0.000*** | 0.000*** | 0.000*** | | 0.000*** | 0.193 |
| Large Stocks | | | | | | | | | | |
| $R_m = R_{WIG}$ | 0.018 | 0.328 | 0.760 | 0.160 | 0.015 | 0.450 | 0.416 | 0.317 | 3.441 | 0.338 |
| $p$-value | 0.000*** | 0.008*** | 0.814 | | 0.000*** | 0.000*** | 0.785 | | 0.016** | 0.931 |
| $R_m = R_{WIG20}$ | 0.017 | 0.421 | −0.503 | 0.219 | 0.015 | 0.428 | 0.382 | 0.318 | 1.807 | −0.884 |
| $p$-value | 0.000*** | 0.001*** | 0.863 | | 0.000*** | 0.000**** | 0.792 | | 0.144 | 0.792 |
| $R_m = R_{equal}$ | 0.012 | 0.432 | 1.112 | 0.502 | 0.013 | 0.381 | 2.025 | 0.753 | 0.496 | −0.912 |
| $p$-value | 0.000*** | 0.000*** | 0.482 | | 0.000*** | 0.000*** | 0.000*** | | 0.685 | 0.562 |

The size portfolios are based on the monthly average market capitalisation of each stock. The coefficients are estimated with OLS, and the $p$-values are based on standard errors corrected for heteroskedasticity and autocorrelation up to five lags with the Newey and West (1987) method. Three different proxies for the market are used: the performance index WIG, the price index WIG20, and the equal-weighted index of all stocks traded on any given day. The respective returns are daily and continuously compounded. $S_t^*$ gives the daily cross-sectional absolute deviation of the individual stocks' returns from the market return. The sample period runs from 9 July 1996 to 16 November 2000. A trading day is classified as up-market when $R_m \geq 0$ and as down-market when $R_m < 0$. The $F$-test tests for equality of the regression lines for the up and down markets, i.e. $H_0$: $\alpha^{up} = \alpha^{down}$ and $\beta_1^{up} = \beta_1^{down}$ and $\beta_2^{up} = \beta_2^{down}$. $H_0$ for the $t$-Test is $\beta_2^{up} = \beta_2^{down}$, which is tested in the dummy regression $S_t^* = \alpha + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + D_t \cdot (\gamma_0 + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2) + \epsilon_t$ where $D_t = 0$ in market downswings and $D_t = 1$ otherwise. We report $\hat{\gamma}_2 = \beta_2^{up} - \beta_2^{down}$ and the corresponding $p$-value. $^{*}$,$^{**}$,$^{***}$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 7: Regression Results for the time-series behaviour of herding in Poland

| | $\lvert\hat{\beta}_{2t}\rvert = \zeta_0 + \zeta_1 t + \zeta_2 D_t + \epsilon_t$ | | | |
|---|---|---|---|---|
| | $\zeta_0$ | $\zeta_1$ | $\zeta_2$ | Adj $R^2$ |
| Panel A: Single-Price Auction | | | | |
| $R_m = R_{WIG}$ | 4.770 | $-2.263$ | $-1.109$ | 0.114 |
| $p$-value | 0.000∗∗∗ | 0.000∗∗∗ | 0.000∗∗∗ | |
| $R_m = R_{WIG20}$ | 3.416 | 0.745 | $-0.695$ | 0.029 |
| $p$-value | 0.000∗∗∗ | 0.158 | 0.041∗∗ | |
| $R_m = R_{equal}$ | 7.204 | $-6.653$ | 0.646 | 0.289 |
| $p$-value | 0.000∗∗∗ | 0.000∗∗∗ | 0.127 | |
| Panel B: Continuous Trading | | | | |
| $R_m = R_{WIG}$ | 5.106 | $-0.814$ | $-1.924$ | 0.088 |
| $p$-value | 0.000∗∗∗ | 0.214 | 0.000∗∗∗ | |
| $R_m = R_{WIG20}$ | 3.026 | 1.030 | $-0.355$ | 0.021 |
| $p$-value | 0.000∗∗∗ | 0.134 | 0.243 | |
| $R_m = R_{equal}$ | 3.213 | $-1.559$ | 1.205 | 0.075 |
| $p$-value | 0.000∗∗∗ | 0.024∗∗ | 0.000∗∗∗ | |

The coefficients are estimated with OLS, and the $p$-values are based on standard errors corrected for heteroskedasticity and autocorrelation up to five lags with the Newey and West (1987) method. $\hat{\zeta}_1$ is reported in thousands. Three different proxies for the market are used: the performance index WIG, the price index WIG20, and the equal-weighted index of all stocks traded on any given day. The regression $\lvert\hat{\beta}_{2t}\rvert = \zeta_0+\zeta_1 t+\zeta_2 D_t + \epsilon_t$ is estimated for moving windows of 100 trading days each. $D_t$ takes the value of zero if there are more bear market days than market upswings in any 100-trading-day window and the value of one otherwise. $\hat{\beta}_2$ is estimated in $S_t^* = \alpha + \beta_1\lvert\bar{r}_t\rvert + \beta_2\bar{r}_t^2 + \epsilon_t$. $^{*}$,$^{**}$,$^{***}$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

# 4 Individual Investors Surpass their Reputation: Trading Behaviour on the Polish Futures Market

## 4.1 Introduction

A number of studies analyse investment decisions by individual traders, with the majority of authors arguing that these investors tend to be uninformed regarding fundamentals and therefore exhibit sentiment-driven trading behaviour. Moreover, some of the evidence suggests that stock market anomalies such as the Monday and January effects can be at least partly attributed to individual investors. As stock market transactions cannot, in general, be separated into those initiated by individuals and those originating from institutions, it is difficult to test empirically which investor type is the driving force behind calendar anomalies. However, the Polish futures market offers an extraordinary testing ground for analysing individual investors' trading behaviour, since the vast majority of trading activity in Polish stock index futures is attributed to individuals. We investigate the Monday and January effects on the Polish WIG20 stock index futures market with a comprehensive set of variables covering trading volume, open interest, return, and return volatility.

On the Polish futures market, two thirds of the trading volume are accounted for by individual investors, turning them into the predominant trader type. Moreover, basket securities as underlyings are traded, for which adverse selection costs tend to be lower than in markets for individual securities (Subrahmanyam (1991)). As low adverse selection costs are especially attractive for uninformed investors, they tend to prefer basket securities over individual securities. Thus, the WIG20 futures market is likely to have an even higher share of individual traders than the overall futures market.

In contrast to individual investors, institutions employ financial analysts that gather firm-specific and macroeconomic information. As a result, institutions tend to be better informed than individuals (Dennis and Weston (2001)) and can exploit economies of scale in data processing. They therefore prefer stocks that a large amount of information is published about (Falkenstein (1996)). These are large, liquid stocks, for which research on fundamentals is profitable. By contrast, individual investors are generally employed in activities other than fundamental research and therefore tend to invest in attention-grabbing stocks (Barber and Odean (2008), Nofsinger (2001)). Moreover, individuals' trading decisions are more biased by behavioural aspects than institutions' investment strategies, which also contributes to institutions outperforming individuals (Kamesaka et al. (2003)).

In this study, we focus on two well-established anomalies, the Monday effect and the January effect. The former refers to the observation that stock returns on Mondays are statistically significantly lower than on the other days of the week, with Monday returns often being negative. This anomaly can be explained with the particularly high costs to individuals of conducting fundamental research on weekdays. Instead, they defer their investment decisions to the weekend. As a result, individual investors are more active traders Monday morning than on other days (Abraham and Ikenberry (1994)). At the same time, institutional investors devote Monday morning to strategically planning the remaining week, thereby being less active traders than usual (Lakonishok and Maberly (1990)). Abraham and Ikenberry (1994) argue further that brokers will issue primarily buy recommendations during the week, while individuals make their sell decisions over the weekend. The relative weight of individuals' transactions on Mondays and their bias towards sell orders are an explanation for the Monday effect being driven by individuals, which is supported by the empirical evidence of Brooks and Kim (1997).

The second stock market anomaly is the January effect, which describes the phenomenon of significantly high returns for small stocks in January. Dyl and Maberly (1992) find that it can partly be explained by the tax-loss-selling argument, according to which individual investors sell poorly performing stocks at the end of the year in order to deduct the losses from their tax burdens. In January, individuals re-invest in the same stocks, thereby increasing stock returns. In between these transactions, the proceeds are parked (Ritter (1988)). The window-dressing hypothesis predicts returns to move in the same direction, as institutional investors re-balance their portfolios towards the end of the year by selling 'losers' and buying 'winners'. However, Sias and Starks (1997) find that primarily individuals cause the January effect.

More recent studies find that the Monday and the January effects have become weaker or disappeared altogether since these phenomena became widely known. In particular, Marquering et al. (2006) examine anomalies before and after they were published. The empirical evidence suggests that both anomalies have vanished in the U.S. market at the time of the relevant academic publications. Szakmary and Kiefer

(2004) add the finding that the January effect in the U.S. cash and futures markets is no longer present after 1993, with the Monday effect having vanished in the U.S. post 1975 (Connolly (1989)). However, Dubois and Louvet (1996) report evidence of a persisting Monday effect for West European markets. All of these studies focus on developed financial markets that are dominated by institutional investors, whereas we investigate a market with an investor structure vastly different to this. It can therefore be hypothesised that either anomaly continues to exist on the Polish futures market where individual investors are the major trader type.

While the studies mentioned above examine the spot market, there is only a limited number of investigations of the futures market. Among these is Cornell (1985), who finds no empirical evidence for a day-of-the-week effect for returns of S&P500 index futures contracts. He therefore concludes that the prices on the futures market are consistent with the efficient market hypothesis, while returns of the S&P500 stock index exhibit a significant Monday effect. This apparent discrepancy in market efficiency between the spot and the futures market cannot be explained by the latter offering lower transactions costs since transactions could be timed such that sells are settled on Fridays and buys on Mondays without raising transactions costs. Furthermore, positive errors in prices on Friday could be reversed on Monday, thereby causing the Monday effect. However, Keim and Stambaugh (1984) show that this measurement error does not account for the Monday effect because of a high correlation between Friday and Monday returns.

Chiang and Tapley (1983) test for the presence of a day-of-the-week effect in return, trading volume, and open interest for commodity futures listed on the Chicago Board of Trade. While the results differ across contracts, the average return on Mondays is negative, volume scores the highest percentage change on Tuesdays, whereas open interest shows no day-of-the-week effect. This insight for the return on the futures market is consistent with the findings of studies examining the spot market (e.g. French (1980)). Potential anomalies in the Dow Jones spot and futures commodity indexes returns are studied in Chang and Kim (1988). They report persistent negative Monday spot returns, while the day-of-the-week effect in the corresponding futures market has completely vanished since 1982.

For the variables under scrutiny in this paper, empirical evidence regarding the spot market suggests a higher trading volume on Monday mornings than on the other four days of the week (Lakonishok and Maberly (1990), Abraham and Ikenberry (1994)). Moreover, return volatility can be expected to be higher on Mondays than during the rest of the week (Foster and Viswanathan (1990)). Harris (1986) finds significantly negative stock returns arising from the first 45 trading minutes on Monday morning. In case of a January effect, we expect higher spot returns in January than in the other eleven months (Keim (1983)). As for futures markets, by contrast, the existing literature gives rise to the conjecture that neither a Monday nor a January anomaly exists. In light of Grossman (1977), one might attribute the lack of a Monday effect on the futures market to the larger fraction of informed institutional investors there than on the spot market, who have arbitraged away anomalies. This argument does not hold for the Polish futures market though, since it is dominated by individual traders. Thus, should the empirical results for the Polish futures market reject the existence of an anomaly, it can be concluded that Polish individuals' trading behaviour is far less sentiment-driven than the literature predicts for developed spot markets.

In order to empirically investigate individuals' trading behaviour on the Polish futures market, section 2 describes the institutional design of this market, section 3 introduces the dataset and the methodology, before section 4 presents and interprets the empirical results. Section 5 summarises our findings and concludes.

## 4.2 Institutional Background

The first exchange in Warsaw was founded in 1817. Having been closed during World War II and the communist era, the Polish stock market was re-opened on 16 April 1991. Exactly three years later, the WIG20 stock price index was launched.[3] This index reflects the performance of twenty blue chip stocks listed on the main market of the Warsaw Stock Exchange (WSE). The mWIG40 (until 18 March 2007, MIDWIG), a mid-cap price index, followed on 21 September 1998, and the TechWIG price index, representing innovative technogogies, on 31 December 1999. The Polish stock market has been growing rapidly in part because formerly state-owned companies were privatised and listed on the WSE, with the first foreign company (Bank Austria Cred-

[3] All information about the Warsaw Stock Exchange is taken from the annual fact books. Regulatory details about shortsales can be obtained from Art.141-142 in the Act of 28 August 1997, 'About the organization and functioning of pension funds (OFE)' (Dz.U. 1997 Nr 139 poz. 934 with amendments).

itanstalt AG) being listed on 14 October 2003. Since 1 May 2004, the exchange's market structure has been complying with EU standards, i.e. securities trading has two segments, the main market and the regulated unofficial parallel market.

Initially, there was a spot market only. Futures contracts on the WIG20 have been traded at the WSE since 16 January 1998. This was the first derivative product introduced by the exchange, which quickly became very popular among Polish investors. During 1999, the trading volume in the WIG20 futures market rose over eightfold relative to the previous year, and in 2000 the growth in turnover was sevenfold compared to 1999. The number of contracts traded has been growing by 20% per year on average. In 2005, the trading volume for the stock index futures market at the WSE, measured as the number of contracts traded, reached 5.2 millions. This compares to a trading volume of 4.9 million contracts at the Borsa Italiana, while the leading European derivatives trading platform Eurex reports 185 million contracts traded. Relating trade in WIG20 futures contracts at the WSE to trade in futures on major stock exchanges throughout Europe by the number of contracts, the WSE ranked about seventh during the period under investigation here.

On 1 August 2000, futures contracts on the TechWIG index were introduced, with contracts on the MIDWIG index following on 18 February 2002. Futures contracts on individual stocks were first launched on 22 January 2001, while futures contracts on US$ debuted on 25 September 1998 already, followed by futures on the Euro on 1 May 1999. T-note futures were launched on 14 February 2005. Ordinary warrants started trading on 9 March 1998, with American-style warrants on WIG20 futures contracts joining in on 24 September 2001. Convertible bonds were first quoted on 25 April 2002. Put and call options with the WIG20 as underlying were introduced on 22 September 2003, and stock options started trading on 17 October 2005.

Derivatives are traded in the continuous trading system, whose trading hours were 10.15am to 4.00pm prior to the introduction of the quotation system WARSET on 17 November 2000. Thereafter, derivatives were traded from 9.00am to 4.10pm. Since 3 October 2005, the derivatives market has been closing at 4.20pm, with an auction being held at opening and closing. The contracts expire in March, June, September, and December, with the last trading day of any given contract being the third Friday of its expiry month, or the last trading day prior to that Friday in case of public holidays.

Market makers provide liquidity by placing their own orders in the order book. Price variation limits are in place and amount to 10% for stock index and individual stock futures (Warsaw Stock Exchange (2000)). These limits refer both to the difference between the opening price and the settlement price on the previous day, and to the variations during a trading day.

According to annual surveys conducted by the WSE, the fraction of turnover value attributed to individual investors has ranged from 66 to 85% in the past seven years. This dominance of individual investors is due to three factors: First, the value of a futures contract equals the product of the multiplier and the price of the underlying. The former was set to only 10 zl, which currently equals about 2.75 US$. This small multiplier makes WIG20 index futures affordable for small investors. Second, individual investors who wish to trade on the Polish futures market can easily register to do so without formal barriers. Third, institutional investors such as Polish pension funds or mutual funds are not permitted to trade in derivatives, which ceteris paribus raises the fraction of individuals engaging in futures trading.

## 4.3 Data and Methodology

We conduct an intraday analysis of futures contracts on the WIG20 stock index from December 2000 to June 2007. The electronic trading platform WARSET was launched on 17 November 2000, where all derivatives instruments have been traded in a continuous trading mechanism. Our dataset starts with the first full month after the introduction of WARSET, which results in 47,553 observations. Since we base our analysis on intraday observations, we can identify the trading time driving the empirical results. In particular, we are able to pinpoint the time of day causing a potential day-of-the-week anomaly.

Intraday analyses are common in the market microstructure literature, and their starting point is almost always the splitting of the trading time into separate 15-minute intervals (Abhyankar et al. (1997), Pirrong (1996), Ding and Lau (2001)). Up until 4.15pm, trades occur on every day in the sample, while trading activity is much reduced after 4.15pm. In fact, a closing auction is held at 4.20pm. Therefore, the final interval which we analyse ends at 4.15pm, leading to a total of 29 intervals per day.

The six variables to be investigated are selected based on previous studies such as

Foster and Viswanathan (1990), Abhyankar et al. (1997), Brooks and Kim (1997), and Johnston et al. (1991). For the futures market, these variables are the number of contracts traded, open interest, and two measures of both the price change and its volatility. The number of contracts is a proxy for trading volume $TV$ and is accumulated inside each interval.

Open interest $OI$ refers to the total number of contracts transacted less those that could not be matched after a transaction has been settled. For the calculations, we take the relative contribution of the transactions inside an interval to the level of open interest $OI_I = (OI_I^E - OI_I^B)/(OI_I^B)$, with $B$ referring to the first transaction in the interval $I$, and $E$ denoting the last transaction in the same interval.

The change in contract price $p$ is the return $R_I$, which can either be measured continuously compounded inside each interval $R_{1,I} = log(p_I^E/p_I^B)$, or as the simple return $R_{2,I} = p_I^E - p_I^B$. Dyl and Maberly (1986) argue that the compounded returns in Cornell (1985) are the inappropriate variable for an investigation of the futures market, because investors do not face a downpayment. Hence, they cannot make a return on the investment. However, Cornell (1985) aimed to report results that are directly comparable to those of other studies examining the cash market. In light of this debate, we analyse both return variables.

Like for returns, we also use two different approaches to estimate the return volatility. The first one follows Pirrong (1996) in taking the difference between the highest and the lowest price within each interval $\sigma_{1,I} = p_I^{max} - p_I^{min}$. While this is a simple measure of price variation, it suppresses any movements inside an interval. Therefore, we also take full advantage of our transaction-by-transaction data and follow Ding and Lau (2001) and Madhavan et al. (1997) in calculating a second volatility measure. It is the standard deviation of the continuously compounded return $R_1$. Since transactions on the Polish futures market are not frequent enough to calculate this measure for each interval, we measure the volatility across all intervals of each day $d$.[4] For this, the continuously compounded return $R_{1,t}$ for any two consecutive transactions is calculated, with the standard deviation of these returns measuring the return volatility on a daily

[4]Alternatively, returns can be calculated within an interval, with its volatility being computed across days per interval (Barclay and Hendershott (2003), Wood et al. (1985)). This approach is not meaningful in our context as we study the day-of-the-week effect.

basis $\sigma_{2,d} = \sqrt{\sum_{t=1}^{T}(R_{1,t} - \bar{R}_{1,d})^2/(T-1)}$, where $t$ denotes the individual transactions.

The dataset was obtained from the WSE and comprises intraday observations on prices, the number of contracts traded, and open interest for futures contracts on the WIG20 index. Cornell (1985), Dyl and Maberly (1986), and Johnston et al. (1991) exclude potentially highly volatile observations around the delivery date by switching to the next most distant contract during the entire delivery month of the nearby contract. We report all results based on this dataset construction.

We run all regressions with all observations, and excluding those from 21 to 31 December as trading volume drops substantially over Christmas and New Year's. The latter dataset is used as a robustness check, ensuring that an apparent January effect is not driven by the reduction in trading activity over the holiday period. Furthermore, as a second robustness check, we conduct the analysis with the dataset comprising only observations for the contract nearest to delivery.

Table 8 presents summary statistics for the overall dataset for all six variables. On average, each transaction comprises 496 contracts, with the number of contracts that remain unmatched after each transaction increasing by 0.02% per transaction on average, which is an indicator of liquidity in this index futures market and broadly in line with the results reported in Chiang and Tapley (1983). The transaction-by-transaction returns are negative regardless of how they are measured, which is consistent with the daily returns reported in Chiang and Tapley (1983).

Table 8 about here

There are two types of $F$-tests to detect a potential Monday (January) effect. In order to conduct these tests, each of the six variables $V_j$, $j = 1, ..., 6$, is regressed, by interval, on a set of dummy variables. The details of these tests are set out below for the Monday effect only, as they work analogously for the January effect. The first type of $F$-tests is based on the underlying model with an intercept so that the point estimates of the $\beta$-coefficients can be interpreted as differential values (French (1980) and Keim (1983)):

$$V_{j,I,t} = \alpha_{j,I} + \beta_{2,j,I} D_{Tues,t} + \beta_{3,j,I} D_{Wed,t} + \beta_{4,j,I} D_{Thurs,t} + \beta_{5,j,I} D_{Fri,t} + \epsilon_{j,t} \quad . \tag{9}$$

$I$ denotes the interval, $j$ refers to the variable $V$, while $t$ is the time index of each transaction. $D_{Tues}$ equals one on all Tuesdays and zero otherwise. The other dummy variables are defined analogously. For instance, $\hat{\beta}_{2,j,I}$ shows by how much the Tuesday average of $V_j$ differs from that for Mondays, which is treated as a benchmark and captured by $\hat{\alpha}_{j,I}$. The $F$-test statistic of $H_0 : \beta_{2,j,I} = \beta_{3,j,I} = \beta_{4,j,I} = \beta_{5,j,I} = 0$, i.e. the presence of a Monday effect, is denoted with $F_1$ and becomes statistically significant if the index futures market exhibits a Monday effect.[5]

The second type of $F$-tests is closely related to the first one, although it is less restrictive. The underlying model specification is equation (9), and the null is $H_0 : \beta_{2,j,I} = \beta_{3,j,I} = \beta_{4,j,I} = \beta_{5,j,I}$ (Johnston et al. (1991)). This test with the test statistic $F_2$ determines whether Tuesday through Friday have an equal (differential) effect on $V_j$ without imposing that this effect be nonexistent.

While $F_1$ shows whether Monday is significantly different from the other four days of the week as a whole, $F_2$ is an indicator of the variation among Tuesday through Friday and hence of the day of the week driving $F_1$ to be statistically significant. For example, it is conceivable that the Polish index futures market exhibits a Friday effect, while Monday through Thursday have roughly equal mean $V_j$. In this case, $F_1$ would still be significant, implying a Monday effect. At the same time, $F_2$ would be significant, pointing away from the Monday effect by highlighting the difference among Tuesday through Friday. Thus, by conducting both $F$-tests, we do not only investigate a Monday effect but rather a day-of-the-week effect. Likewise, this test setup captures calendar month anomalies that could be caused by the delivery cycle of futures contracts since it is not limited to testing for a January effect. The importance of this comprehensive test approach is heightened by the broad spectrum of variables that we cover, as trading volume is likely to be more affected by the delivery cycle than the return.

As the regression analysis is conducted separately for each interval $I$, a potential weekday effect can be characterised by the trading time driving this effect. However, regression (9) cannot be estimated *by interval* for the second measure of return volatility $\sigma_{2,d}$ since it is calculated across intervals $I$ for each trading day $d$. Testing for a Monday effect is equally possible with daily data though.

[5] As a robustness check, we additionally estimate the regression $V_{j,I,t} = \alpha_{j,I} + \beta_{2,j,I} D_{Tues,t} + \cdots + \beta_{5,j,I} D_{Fri,t} + \beta_{6,j,I} D_{Hal,t} + \epsilon_{j,t}$, where $D_{Hal,t}$ equals one for all observations in November through April and zero otherwise. Thus, we control for the Halloween effect. The empirical results are the same as those for regression (9) and are therefore not reported or discussed here.

The January effect is investigated in the same dummy regression framework for the variables $V_j$ (Reinganum (1983) and Keim (1983)). We first examine a calendar-month effect estimating the equivalent of regression (9):

$$V_{j,I,t} = \alpha_{j,I} + \beta_{2,j,I} D_{Feb,t} + \beta_{3,j,I} D_{Mar,t} + \cdots + \beta_{12,j,I} D_{Dec,t} + \epsilon_{j,t} \quad . \tag{10}$$

As a robustness check, we determine whether the findings persist when the half year that January falls into is controlled for (Jacobsen et al. (2005)). During the winter months November to April, stock index returns tend to be significantly higher than during the summer months May to October. This market-wide phenomenon is referred to as the Halloween effect and could cause both $F$-tests to be significant.[6] We therefore ascertain the existence of a January effect once the Halloween effect has been separated by estimating the regression

$$V_{j,I,t} = \alpha_{j,I} + \beta_{1,j,I} D_{Hal,t} + \beta_{2,j,I} D_{Jan,t} + \epsilon_{j,t} \tag{11}$$

where $D_{Hal,t} = 1$ during the winter months November to April and zero otherwise. $D_{Jan,t}$ takes the value one in January and zero throughout the rest of the year. $\hat{\alpha}_j$ gives the mean $V_j$ over the six summer months, and the estimated $\beta$-coefficients indicate the difference in this mean due to the Halloween and the January effects, respectively, based on $t$-tests. A statistically significant $\beta_{1,j}$ coefficient indicates that the mean of $V_j$ is different in winter compared to its value over the summer. If $F_1$ suggests the presence of a January effect, but $\beta_{2,j}$ becomes insignificant in regression (11), then the driving force behind the significant $F_1$ is the Halloween effect rather than the January effect.

As in most previous studies (e.g. Harris (1986), Johnston et al. (1991), Keim (1983)), the point estimates in the models are estimated with OLS. The statistical inference, however, is based on Newey and West (1987) standard errors which are corrected for heteroskedasticity and serial correlation in the error term. While we do not estimate a cross-section of futures contracts, White (1980) tests yield ambiguous results regarding the presence of heteroskedasticity. These test results are not reported here but are available on request. Moreover, if we aim to test for the presence of a

[6]The Halloween effect is generally explained by changes in risk aversion due to vacation time, seasonal affective disorder or temperature changes (Bouman and Jacobsen (2002), Kamstra et al. (2003), Garrett et al. (2005)). Furthermore, changing liquidity preferences due to the holiday time might cause investors to sell their stocks, driving down stock prices and hence returns.

Monday effect, we need to explicitly allow the observations on consecutive Mondays to be correlated. Thus, we set the lag length to five, thereby correcting the estimated standard errors of the point estimates for potential autocorrelation in the previous five days. Raising the maximum lag length further would introduce a higher estimation error, with the benefit for the goodness-of-fit being at least questionable. As the investigation of the January effect is also based on daily data, the lag length remains five.

## 4.4 Empirical Results

### 4.4.1 Monday Effect

Table 9 presents the evidence regarding the day-of-the-week effect for all intervals from 9.00am to 4.15pm. While large $p$-values for $F_1$ indicate the lack of a day-of-the-week effect, small $p$-values imply the existence of an anomaly. For such cases, the $F_2$ columns provide further insights as to which day of the week is driving this anomaly. Large $p$-values for $F_2$ support the hypothesis that Tuesday through Friday are equal, turning the day-of-the-week effect into a Monday effect. By contrast, small $p$-values for $F_2$ convey that any one, or a combination, of the four days Tuesday through Friday are causing the day-of-the-week effect.

Table 9 about here

Trading volume appears to exhibit a day-of-the-week effect in 23 of the 29 intervals, which represent almost the entire trading time. The trading activity on Mondays is significantly lower than on Tuesday, Wednesday, or Thursday across the trading day (not reported in the table). Moreover, the trading volume on Friday afternoon from 2.30pm onwards is statistically significantly higher than at the same time on Mondays. In the morning and around lunch time, however, the trading volume is not significantly different between Mondays and Fridays. Accordingly, the $p$-values in the $F_2$ column of Table 9 indicate equality in average trading volume among Tuesday through Friday for some intervals, and inequality for others. As the dataset excludes expiring contracts on their delivery date, the raised trading activity on Friday afternoon cannot be driven by expiration day effects.

In contrast to Lakonishok and Maberly (1990) and Abraham and Ikenberry (1994), the empirical evidence suggests that traders on the Polish futures market are generally less active on Mondays than Tuesday through Friday. This implies that those individuals who choose to trade on the Polish futures market do not exhibit the same behavioural patterns as individuals transacting on mature spot markets. Instead, these individuals have adopted institutions' trading times.

Another indicator of liquidity on the futures market is open interest. While trading volume is lower on Mondays than on the other four days of the week, the contribution of unmatched contracts is not any different throughout the five weekdays. This implies that weak trading activity on Mondays does not yield fewer unmatched positions than larger trading volume does on Tuesday to Thursday.

The evidence for the price change and its volatility confirms this insight. If individuals were uninformed, their dominating presence on the Polish futures market should drive up the volatility of returns, expressing larger uncertainty or information asymmetry on the market. In fact, neither the return nor its volatility vary statistically significantly across the five trading days of the week. Thus, even if individuals are trading particularly strongly or weakly on any given day, their impact on futures price changes' volatility is nonexistent. This is consistent with Cornell's (1985) findings for the S&P500 index futures market, even though individual investors on the young Polish market might have been expected to be less well informed about a complex financial product like futures than traders on a mature market. It can therefore be concluded that the individuals transacting on the Polish futures market surpass their reputation.

### 4.4.2 January Effect

Table 10 shows trading volume in January to be statistically significantly different from its average across the remaining eleven months ($F_1$), with February through December recording significantly different mean trading volumes ($F_2$). In fact, January records a signifcantly higher trading activity than the quarter-end months March, June, September, and December, while the number of contracts traded is not significantly different among January, February, April, May, July, August, October, and November. Thus, the anomaly whose presence Table 10 suggests is actually not a January one, but rather a delivery month phenomenon. In these months, the dataset comprises observations on the next-nearest-to-delivery futures contract, in which trading volume is relatively low while the transactions are concentrated in the nearest-to-delivery contract that expires in that month. In fact, this apparent quarter-end effect vanishes when the dataset consists, at all times, of observations on the nearest-to-delivery contract. However, December then still scores a particularly low trading volume even when excluding the trading days around Christmas and New Year's. The tax-loss selling hypothesis predicts high trading activity in December and in January. Our findings are not consistent with this argument, as it is a less important motive for trading in futures contracts than for spot deals with substantial downpayments.

Table 10 about here

Open interest also shows a strong calendar-month effect. The contribution to unmatched contracts is highest in the quarter-end months March, June, September, and December because these are the months when new contracts are introduced into the dataset. By definition, open interest has to drop towards the expiration date. Upon switching to contracts that have longer to live, we observe a rise in open interest. Consistently with this, we find significantly lower open interest in quarter-end months when the dataset consists of nearest-to-delivery contracts which expire in those months. These results are robust against the ommission of the end-December observations.

The volatility of price changes measured as in Pirrong (1996) is significantly higher in January than in December, regardless of the inclusion of the trading days around the Christmas holiday period. This could be attributed to more news releases being disseminated, and reflected in the prices, after the holiday period than before. In fact, when omitting the end-December observations, the volatility in January is significantly higher than in March, April, and December. Regarding these two spring months, the results appear to respond strongly to changes in the dataset. Moreover, when the analysis is based on the nearest-to-delivery contracts, any differences in return volatility among calendar months disappear. In summary, the empirical results for return volatility vary strongly with changes in the dataset. The returns exhibit no calendar-month anomaly.

As a robustness check, we test for the existence of the January effect once controlled for the half year that January happens to fall into. For trading volume, both the January and the Halloween dummy variables are significant, as shown in Table 11.

Since the apparent January effect ($F_1$ in Table 10) is not actually driven by January, but rather by the four quarter-end months, this persists when effectively controlling for two of the four quarter-end months.

Table 11 about here

Likewise for open interest, the apparent January effect remains when controlling for the Halloween effect. In fact, the six winter months included in the Halloween dummy variable do not score significantly different open interest contributions compared with the six summer months. However, open interest in January is significantly lower than over the summer, which includes two quarter-end months.

In essence, Monday records lower trading volume than Tuesday through Friday, which is not mirrored by open interest. This is consistent with trading patterns of institutional investors on mature spot markets (Abraham and Ikenberry (1994), Lakonishok and Maberly (1990)). Returns and their volatility exhibit no day-of-the-week effect independently of how these variables are measured. Regarding the January effect, the unusual months are March, June, September, and December with lower trading volume and higher open interest than in the remaining months. This effect can be explained by the delivery cycle of futures contracts and is not a calendar-month anomaly. The tax-loss selling argument predicts high trading volume on the spot market in December and January. This cannot be observed on the futures market as there is no downpayment for the investment, but rather the exchange of margin payments. Overall, the Polish futures market is not affected by the well established Monday or January anomalies. One caveat with this analysis is that the sample period only spans six and a half years, which is a narrow basis to investigate a yearly effect.

## 4.5 Summary and Conclusions

The aim of this paper is to investigate whether the Monday and January anomalies exist on the Polish futures market, where individuals are the dominating investor type. Previous empirical evidence for mature futures markets is sparse and suggests that such markets do not exhibit the well established Monday or January effects, while the corresponding spot markets are affected by these anomalies. The presence of these phenomena is primarily attributed to individual investors whose trading behaviour is generally regarded as more sentiment-driven than that of institutions. On the Polish futures market, individual investors account for three quarters of the trading volume. An intraday analysis of trading volume, open interest, return, and return volatility in this unique setting of the Polish WIG20 index futures market enables us to contribute to the debate about the extent to which individuals' trading behaviour is sentiment-driven compared with institutions' trading activities.

In fact, we find that individuals surpass their reputation on the Polish futures market. Our results support the conclusion of Cornell (1985) that futures returns are consistent with the market efficiency hypothesis. This is in line with the results of Chang and Kim (1988) but contradicts Johnston et al. (1991) who report negative Monday returns before 1982 and positive Tuesday returns after 1984 for GNMA, T-bond, and T-note futures contracts traded over the Chicago Board of Trade. Likewise, we find return volatility on the Polish futures market shows no sign of a day-of-the-week anomaly. Moreover, trading volume on Mondays is lower than on Tuesday through Friday, which further underscores that individuals do not engage in more active trading after the weekend and contradicts the evidence in Abraham and Ikenberry (1994) who argue that individuals drive the Monday effect.

As for a calendar month anomaly, we observe a significantly low trading volume in the expiration months March, June, September, and December. In these months, the dataset comprises second-to-nearest-to-delivery futures contracts, while the trading activity concentrates on expiring contracts. Thus, this apparent quarter-end month anomaly can be fully explained by the delivery cycle and the construction of the dataset. It can be concluded that individuals' trading activities are less sentiment-driven than the existing literature for mature markets predicts.

Futures contracts are complex financial products, and the Polish market for these is a very young one. Despite this, we observe a remarkably efficient market for WIG20 index futures. One can hypothesise that this is due to a self-selection among individual investors. Those who decide to engage in futures trading are far more informed about these instruments than those who choose to not trade in derivatives. This could be an explanation for the lack of anomalies on the Polish futures market.

This conclusion raises two further questions. First, why do we observe anomalies on spot markets, while the corresponding futures markets do not appear to be affected by these phenomena? Differences in investor structure between mature spot and the corresponding futures markets could partially account for differences in observed anomalies. If uninformed individuals prefer straight-forward spot deals over complex futures trading, then they will be concentrated on the cash market. This results in institutions trading among themselves in futures markets, where anomalies have been arbitraged away. Future research could focus on a direct comparison in investor structure between a spot market with anomalies and a futures market without such regularities. Since the Polish spot market does not appear to exhibit a day-of-the-week effect from 1992 to 2003 (Basher and Sadorsky (2006)), the analysis should be conducted in a broader context.

And second, could this shed light on the mechanism relating the spot and futures markets? It can be conjectured that the mechanism relating the spot and futures markets is affected by anomalies or measurement errors that cancel out the transmission of particular regularities from the cash market to the futures market. Further research could place an emphasis on this.

## 4.6 Tables

Table 8: Descriptive Statistics for Futures Trading on the WIG20 Stock Index in Poland

| | $TV$ | $OI$ | $R_1$ | $R_2$ | $\sigma_1$ | $\sigma_2$ |
|---|---|---|---|---|---|---|
| Mean | 496.470 | 0.159 | −0.009 | −0.018 | 5.608 | 0.505 |
| Median | 338.000 | 0.688 | 0.000 | 0.000 | 4.000 | 0.446 |
| Std Dev | 529.860 | 9.729 | 2.235 | 4.424 | 4.955 | 0.256 |
| No of obs | 47,553 | 47,553 | 47,553 | 47,553 | 47,553 | 1,650 |

Trading volume $TV$ is measured as the number of contracts traded, open interest is calculated as $OI_t = (OI_t - OI_{t-1})/OI_{t-1}$, the continuously compounded return is defined as $R_{1,t} = log(p_t/p_{t-1})$, the simple return is computed as $R_{2,t} = p_t - p_{t-1}$, the volatility following Pirrong (1996) is $\sigma_{1,t} = p_t^{max} - p_t^{min}$, while the volatility in Madhavan et al. (1997), $\sigma_2$, is measured as the standard deviation of $R_1$ over each day. $OI$, $R_1$, and $\sigma_2$ are reported in thousands. The simple return and $\sigma_1$ are given in zlotys. The sample period runs from December 2000 to June 2007.

Table 9: Monday Effect on the Polish Futures Market

| Interval $I$ | $TV_I$ $F_1$ | $TV_I$ $F_2$ | $OI_I$ $F_1$ | $OI_I$ $F_2$ | $R_{1,I}$ $F_1$ | $R_{1,I}$ $F_2$ | $R_{2,I}$ $F_1$ | $R_{2,I}$ $F_2$ | $\sigma_{1,I}$ $F_1$ | $\sigma_{1,I}$ $F_2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 9.00-9.15 | 0.000*** | 0.000*** | 0.484 | 0.328 | 0.761 | 0.778 | 0.916 | 0.906 | 0.238 | 0.245 |
| 9.16-9.30 | 0.132 | 0.246 | 0.378 | 0.242 | 0.235 | 0.175 | 0.322 | 0.230 | 0.692 | 0.871 |
| 9.31-9.45 | 0.055* | 0.085* | 0.382 | 0.247 | 0.954 | 0.904 | 0.716 | 0.552 | 0.951 | 0.878 |
| 9.46-10.00 | 0.003*** | 0.062* | 0.859 | 0.782 | 0.779 | 0.855 | 0.924 | 0.942 | 0.676 | 0.508 |
| 10.01-10.15 | 0.001*** | 0.102 | 0.308 | 0.189 | 0.001*** | 0.001*** | 0.002*** | 0.001*** | 0.416 | 0.294 |
| 10.16-10.30 | 0.000*** | 0.041** | 0.631 | 0.992 | 0.946 | 0.874 | 0.928 | 0.850 | 0.028** | 0.325 |
| 10.31-10.45 | 0.000*** | 0.003** | 0.481 | 0.657 | 0.541 | 0.858 | 0.420 | 0.882 | 0.242 | 0.225 |
| 10.46-11.00 | 0.001*** | 0.219 | 0.016** | 0.007*** | 0.575 | 0.775 | 0.464 | 0.459 | 0.509 | 0.768 |
| 11.01-11.15 | 0.002*** | 0.060* | 0.010*** | 0.012** | 0.047** | 0.029** | 0.338 | 0.223 | 0.182 | 0.159 |
| 11.16-11.30 | 0.011** | 0.565 | 0.237 | 0.218 | 0.158 | 0.451 | 0.092* | 0.541 | 0.279 | 0.499 |
| 11.31-11.45 | 0.018** | 0.781 | 0.866 | 0.826 | 0.919 | 0.822 | 0.988 | 0.955 | 0.885 | 0.777 |
| 11.46-12.00 | 0.007*** | 0.363 | 0.034** | 0.721 | 0.640 | 0.691 | 0.395 | 0.461 | 0.343 | 0.299 |
| 12.01-12.15 | 0.229 | 0.466 | 0.213 | 0.185 | 0.739 | 0.772 | 0.775 | 0.858 | 0.777 | 0.955 |
| 12.16-12.30 | 0.037** | 0.028** | 0.014** | 0.027** | 0.805 | 0.657 | 0.799 | 0.667 | 0.362 | 0.533 |
| 12.31-12.45 | 0.032** | 0.020** | 0.187 | 0.119 | 0.136 | 0.353 | 0.208 | 0.611 | 0.856 | 0.767 |
| 12.46-13.00 | 0.010*** | 0.017** | 0.380 | 0.399 | 0.204 | 0.115 | 0.269 | 0.163 | 0.609 | 0.459 |
| 13.01-13.15 | 0.024** | 0.029** | 0.048** | 0.047** | 0.296 | 0.403 | 0.549 | 0.767 | 0.429 | 0.381 |
| 13.16-13.30 | 0.043** | 0.213 | 0.318 | 0.731 | 0.827 | 0.892 | 0.873 | 0.963 | 0.695 | 0.809 |
| 13.31-13.45 | 0.010*** | 0.012** | 0.173 | 0.441 | 0.687 | 0.537 | 0.508 | 0.402 | 0.338 | 0.288 |
| 13.46-14.00 | 0.077* | 0.188 | 0.201 | 0.181 | 0.946 | 0.880 | 0.822 | 0.683 | 0.486 | 0.625 |
| 14.01-14.15 | 0.261 | 0.580 | 0.759 | 0.602 | 0.690 | 0.953 | 0.863 | 0.960 | 0.679 | 0.524 |
| 14.16-14.30 | 0.280 | 0.619 | 0.631 | 0.464 | 0.245 | 0.202 | 0.412 | 0.282 | 0.002*** | 0.002*** |
| 14.31-14.45 | 0.000*** | 0.184 | 0.055* | 0.335 | 0.432 | 0.375 | 0.578 | 0.551 | 0.000*** | 0.005*** |
| 14.46-15.00 | 0.000*** | 0.048** | 0.024** | 0.013** | 0.696 | 0.535 | 0.691 | 0.561 | 0.001*** | 0.228 |
| 15.01-15.15 | 0.000*** | 0.012** | 0.170 | 0.387 | 0.288 | 0.275 | 0.179 | 0.191 | 0.171 | 0.298 |
| 15.16-15.30 | 0.000*** | 0.112 | 0.213 | 0.149 | 0.065* | 0.032** | 0.071* | 0.035** | 0.462 | 0.613 |
| 15.31-15.45 | 0.001*** | 0.160 | 0.030** | 0.159 | 0.316 | 0.317 | 0.403 | 0.462 | 0.282 | 0.312 |
| 15.46-16.00 | 0.000*** | 0.056* | 0.395 | 0.419 | 0.898 | 0.790 | 0.739 | 0.620 | 0.535 | 0.459 |
| 16.01-16.15 | 0.018** | 0.840 | 0.692 | 0.542 | 0.560 | 0.408 | 0.523 | 0.383 | 0.857 | 0.889 |

Trading volume $TV$ is measured as the number of contracts traded, open interest is calculated as $OI_t = (OI_t - OI_{t-1})/OI_{t-1}$, the continuously compounded return is defined as $R_{1,I} = log(p_I^E/p_I^B)$, the simple return is computed as $R_{2,I} = p_I^E - p_I^B$, and the volatility following Pirrong (1996) is $\sigma_{1,I} = p_I^{max} - p_I^{min}$. Estimation of the regression $V_{j,I,t} = \alpha_{j,I} + \beta_{2,j,I} D_{Tues,t} + \beta_{3,j,I} D_{Wed,t} + \beta_{4,j,I} D_{Thurs,t} + \beta_{5,j,I} D_{Fri,t} + \epsilon_{j,t}$ with OLS, standard errors are corrected for heteroskedasticity and autocorrelation with Newey and West (1987). $F_1$ tests for equality of all five days of the week, whereas $F_2$ tests for equality among Tuesday through Friday. Reported are the $p$-values implied by these $F$-tests. Large $p$-values indicate the absence of a Monday anomaly. $^{*}$,$^{**}$,$^{***}$ denote statistical significance at the 10%, 5% and 1% levels, respectively. $\sigma_2$ is measured as the standard deviation of $R_1$ over each day, with the respective $p$-value for $F_1$ amounting to 0.290 and for $F_2$ to 0.971.

Table 10: January Effect on the Polish Futures Market

| Interval $I$ | $TV_I$ $F_1$ | $TV_I$ $F_2$ | $OI_I$ $F_1$ | $OI_I$ $F_2$ | $R_{1,I}$ $F_1$ | $R_{1,I}$ $F_2$ | $R_{2,I}$ $F_1$ | $R_{2,I}$ $F_2$ | $\sigma_{1,I}$ $F_1$ | $\sigma_{1,I}$ $F_2$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 9.00-9.15 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.645 | 0.778 | 0.584 | 0.621 | 0.426 | 0.342 |
| 9.16-9.30 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.073* | 0.066* | 0.041** | 0.036** | 0.371 | 0.357 |
| 9.31-9.45 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.152 | 0.111 | 0.182 | 0.135 | 0.371 | 0.329 |
| 9.46-10.00 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.569 | 0.528 | 0.663 | 0.579 | 0.084* | 0.073* |
| 10.01-10.15 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.748 | 0.769 | 0.922 | 0.891 | 0.000*** | 0.000*** |
| 10.16-10.30 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.147 | 0.173 | 0.037** | 0.070* | 0.002*** | 0.004*** |
| 10.31-10.45 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.987 | 0.981 | 0.927 | 0.908 | 0.059* | 0.041** |
| 10.46-11.00 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.673 | 0.586 | 0.711 | 0.634 | 0.001*** | 0.001*** |
| 11.01-11.15 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.451 | 0.404 | 0.420 | 0.374 | 0.018** | 0.018** |
| 11.16-11.30 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.158 | 0.171 | 0.216 | 0.230 | 0.000*** | 0.000*** |
| 11.31-11.45 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.589 | 0.504 | 0.367 | 0.303 | 0.052∗ | 0.090∗ |
| 11.46-12.00 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.820 | 0.750 | 0.663 | 0.575 | 0.007*** | 0.012** |
| 12.01-12.15 | 0.000*** | 0.009*** | 0.000*** | 0.000*** | 0.572 | 0.854 | 0.740 | 0.955 | 0.043** | 0.087* |
| 12.16-12.30 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.109 | 0.109 | 0.378 | 0.316 | 0.003*** | 0.006*** |
| 12.31-12.45 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.387 | 0.479 | 0.174 | 0.235 | 0.005*** | 0.006*** |
| 12.46-13.00 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.013** | 0.009*** | 0.048** | 0.032** | 0.001*** | 0.001*** |
| 13.01-13.15 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.315 | 0.262 | 0.191 | 0.152 | 0.000*** | 0.000*** |
| 13.16-13.30 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.245 | 0.232 | 0.663 | 0.595 | 0.020** | 0.033** |
| 13.31-13.45 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.183 | 0.173 | 0.098* | 0.083* | 0.012** | 0.018** |
| 13.46-14.00 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.307 | 0.346 | 0.278 | 0.312 | 0.002*** | 0.005*** |
| 14.01-14.15 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.163 | 0.121 | 0.104 | 0.072* | 0.065* | 0.044** |
| 14.16-14.30 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.625 | 0.538 | 0.492 | 0.414 | 0.092* | 0.075* |
| 14.31-14.45 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.082* | 0.084* | 0.075* | 0.066* | 0.043** | 0.048** |
| 14.46-15.00 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.306 | 0.294 | 0.550 | 0.559 | 0.127 | 0.101 |
| 15.01-15.15 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.738 | 0.838 | 0.842 | 0.904 | 0.180 | 0.203 |
| 15.16-15.30 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.834 | 0.844 | 0.770 | 0.816 | 0.227 | 0.233 |
| 15.31-15.45 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.073* | 0.066* | 0.136 | 0.111 | 0.021** | 0.041** |
| 15.46-16.00 | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.770 | 0.736 | 0.779 | 0.739 | 0.420 | 0.580 |
| 16.01-16.15 | 0.000*** | 0.000*** | 0.842 | 0.778 | 0.523 | 0.440 | 0.500 | 0.418 | 0.869 | 0.822 |

Trading volume $TV$ is measured as the number of contracts traded, open interest is calculated as $OI_t = (OI_t - OI_{t-1})/OI_{t-1}$, the continuously compounded return is defined as $R_{1,I} = log(p_I^E/p_I^B)$, the simple return is computed as $R_{2,I} = p_I^E - p_I^B$, and the volatility following Pirrong (1996) is $\sigma_{1,I} = p_I^{max} - p_I^{min}$. Estimation of the regression $V_{j,I,t} = \alpha_{j,I} + \beta_{2,j,I} D_{Feb,t} + \beta_{3,j,I} D_{Mar,t} + \beta_{4,j,I} D_{Apr,t} + \cdots + \beta_{12,j,I} D_{Dec,t} + \epsilon_{j,t}$ with OLS, standard errors are corrected for heteroskedasticity and autocorrelation with Newey and West (1987). $F_1$ tests for equality of all twelve calendar months, whereas $F_2$ tests for equality among February through December. Reported are the $p$-values implied by these F-tests. Large $p$-values indicate the absence of a January anomaly. *,**,*** denote statistical significance at the 10%, 5% and 1% levels, respectively. $\sigma_2$ is measured as the standard deviation of $R_1$ over each day, with the respective $p$-value for $F_1$ amounting to 0.000 and for $F_2$ to 0.000.

Table 11: January Effect on the Polish Futures Market, controlled for the Halloween Effect

| | $TV_I$ | | $OI_I$ | | $R_{1,I}$ | | $R_{2,I}$ | | $\sigma_{1,I}$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| Interval $I$ | Hal | Jan | Hal | Jan | Hal | Jan | Hal | Jan | Hal | Jan |
| 9.00-9.15 | 0.008*** | 0.060* | 0.990 | 0.017** | 0.407 | 0.216 | 0.154 | 0.556 | 0.310 | 0.854 |
| 9.16-9.30 | 0.012** | 0.034** | 0.903 | 0.000*** | 0.180 | 0.187 | 0.132 | 0.164 | 0.094* | 0.240 |
| 9.31-9.45 | 0.066* | 0.188 | 0.241 | 0.016** | 0.535 | 0.530 | 0.587 | 0.863 | 0.386 | 0.538 |
| 9.46-10.00 | 0.025** | 0.056* | 0.951 | 0.011** | 0.385 | 0.391 | 0.132 | 0.685 | 0.067* | 0.312 |
| 10.01-10.15 | 0.001*** | 0.000*** | 0.647 | 0.079* | 0.698 | 0.344 | 0.367 | 0.843 | 0.005*** | 0.007*** |
| 10.16-10.30 | 0.000*** | 0.000*** | 0.154 | 0.022** | 0.110 | 0.148 | 0.134 | 0.048** | 0.033** | 0.022** |
| 10.31-10.45 | 0.004*** | 0.115 | 0.975 | 0.490 | 0.365 | 0.490 | 0.337 | 0.440 | 0.095* | 0.408 |
| 10.46-11.00 | 0.001*** | 0.013** | 0.601 | 0.970 | 0.402 | 0.852 | 0.773 | 0.830 | 0.034** | 0.103 |
| 11.01-11.15 | 0.000*** | 0.004*** | 0.177 | 0.333 | 0.829 | 0.472 | 0.729 | 0.521 | 0.036** | 0.122 |
| 11.16-11.30 | 0.001*** | 0.014** | 0.954 | 0.097* | 0.764 | 0.163 | 0.947 | 0.164 | 0.022** | 0.135 |
| 11.31-11.45 | 0.047** | 0.001*** | 0.736 | 0.052* | 0.690 | 0.927 | 0.535 | 0.793 | 0.103 | 0.047** |
| 11.46-12.00 | 0.000*** | 0.001*** | 0.461 | 0.000*** | 0.223 | 0.740 | 0.237 | 0.653 | 0.037** | 0.035** |
| 12.01-12.15 | 0.038** | 0.006*** | 0.288 | 0.034** | 0.821 | 0.047** | 0.965 | 0.056* | 0.099* | 0.032** |
| 12.16-12.30 | 0.038** | 0.006*** | 0.851 | 0.010*** | 0.039** | 0.441 | 0.177 | 0.741 | 0.110 | 0.063* |
| 12.31-12.45 | 0.002*** | 0.008*** | 0.839 | 0.001*** | 0.366 | 0.202 | 0.487 | 0.130 | 0.050** | 0.072* |
| 12.46-13.00 | 0.005*** | 0.004*** | 0.119 | 0.005*** | 0.456 | 0.576 | 0.542 | 0.790 | 0.008*** | 0.053* |
| 13.01-13.15 | 0.002*** | 0.008*** | 0.331 | 0.024** | 0.270 | 0.555 | 0.911 | 0.774 | 0.011** | 0.047** |
| 13.16-13.30 | 0.000*** | 0.002*** | 0.632 | 0.044** | 0.834 | 0.412 | 0.818 | 0.618 | 0.023** | 0.056* |
| 13.31-13.45 | 0.001*** | 0.001*** | 0.850 | 0.001*** | 0.519 | 0.294 | 0.337 | 0.315 | 0.028** | 0.063* |
| 13.46-14.00 | 0.004*** | 0.005*** | 0.695 | 0.048** | 0.700 | 0.171 | 0.883 | 0.187 | 0.073* | 0.035** |
| 14.01-14.15 | 0.059* | 0.333 | 0.267 | 0.013** | 0.004*** | 0.284 | 0.016** | 0.368 | 0.164 | 0.743 |
| 14.16-14.30 | 0.028** | 0.108 | 0.972 | 0.072* | 0.528 | 0.839 | 0.598 | 0.975 | 0.186 | 0.343 |
| 14.31-14.45 | 0.093* | 0.032** | 0.364 | 0.000*** | 0.466 | 0.188 | 0.428 | 0.281 | 0.228 | 0.156 |
| 14.46-15.00 | 0.047** | 0.066* | 0.316 | 0.045** | 0.179 | 0.275 | 0.101 | 0.230 | 0.065* | 0.314 |
| 15.01-15.15 | 0.010*** | 0.021** | 0.027** | 0.000*** | 0.426 | 0.247 | 0.639 | 0.265 | 0.104 | 0.111 |
| 15.16-15.30 | 0.071* | 0.033** | 0.236 | 0.000*** | 0.368 | 0.246 | 0.354 | 0.168 | 0.703 | 0.562 |
| 15.31-15.45 | 0.033** | 0.000*** | 0.369 | 0.000*** | 0.785 | 0.266 | 0.554 | 0.342 | 0.221 | 0.066* |
| 15.46-16.00 | 0.010*** | 0.000*** | 0.077* | 0.000*** | 0.925 | 0.485 | 0.816 | 0.428 | 0.466 | 0.095* |
| 16.01-16.15 | 0.025** | 0.002*** | 0.631 | 0.306 | 0.402 | 0.567 | 0.398 | 0.540 | 0.545 | 0.799 |

Trading volume $TV$ is measured as the number of contracts traded, open interest is calculated as $OI_t = (OI_t - OI_{t-1})/OI_{t-1}$, the continuously compounded return is defined as $R_{1,I} = log(p_I^E/p_I^B)$, the simple return is computed as $R_{2,I} = p_I^E - p_I^B$, and the volatility following Pirrong (1996) is $\sigma_{1,I} = p_I^{max} - p_I^{min}$. Estimation of the regression $V_{j,I,t} = \alpha_{j,I} + \beta_{1,j,I} D_{Hal,t} + \beta_{2,j,I} D_{Jan,t} + \epsilon_{j,t}$ with OLS, standard errors are corrected for heteroskedasticity and autocorrelation with Newey and West (1987). Reported are the $p$-values implied by $t$-tests. Large $p$-values indicate the absence of a January or Halloween anomaly, respectively. $^{*}$,$^{**}$,$^{***}$ denote statistical significance at the 10%, 5% and 1% levels, respectively. $\sigma_2$ is measured as the standard deviation of $R_1$ over each day, with the respective $p$-value for $t_{Hal}$ amounting to 0.634 and for $t_{Jan}$ to 0.033.

# 5 Do Individual Investors on the Futures Market Induce higher Spot Market Volatility?

## 5.1 Introduction

There are two strands of theoretical and empirical literature on the impact of the introduction of derivatives trading on spot market volatility. One of them argues that derivatives trading increases the corresponding spot market volatility, while the other strand finds the opposite effect on return volatility of the underlying instrument. A key argument in this debate is the extent to which traders on the derivatives market are informed relative to those on the spot market (Stein (1987), Cox (1976)). We investigate the impact of the introduction of Polish futures and options on the conditional return volatility of the underlyings. Since individuals account for more than three quarters of trading volume on the Polish futures market and 73% of turnover value in options across the most recent years, the reaction of the cash market volatility following the introduction of derivatives trading is indicative of the degree to which Polish individuals transacting on the derivatives market are informed relative to the traders on the spot market. Moreover, the impact of derivatives trading on the cash market is of interest to regulators since a destabilising effect might justify restrictions on derivatives trading.[7]

The spot and futures markets are interlinked through the cost-of-carry relation which states that the arbitrage-free futures price equals the cost of holding the cash position and delivering it into the forward contract. Calls and puts enable investors to create synthetic futures contracts, resulting in options to have an impact on cash market volatility that is analogous to that of the futures market. Moreover, Sarris (1984) argues that some investors who used to transact on the cash market before derivatives were introduced will trade on both markets once derivatives are launched. As a result, they will change their spot market holdings and thus change cash market dynamics.

Among the theoretical studies arguing that derivatives trading can destabilise the underlying spot market are Ross (1989), Stein (1987), and Hart and Kreps (1986). On the one hand, if objective new information is effectively transmitted from the futures

[7]In the U.S., trading in futures on most agricultural products was regulated until 1974 in order to limit spot price fluctuations.

market to the cash market and hence the information flow onto the spot market is improved following the onset of futures trading, spot market volatility should increase (Ross (1989)). Therefore, Edwards (1988b) argues that higher stock return volatility can be a sign of a well-functioning spot market. On the other hand, Figlewski (1981) shows empirically that futures traders who are less well informed than spot market participants destabilise the cash market.

Stein (1987) proposes a theoretical model in which the impact of the introduction of a derivatives market on spot price variability depends on the degree to which derivatives traders are informed relative to spot traders. If derivatives traders are perfectly informed or completely uninformed, derivatives trading has a stabilising effect on the cash market where traders are fully informed. In the former case, the debut of derivatives simply adds more investors of the same degree of information to the market. The intuition behind the latter case is that spot traders correctly anticipate the actions of derivatives traders and trade against these, because uninformed derivatives traders do not alter the perfect information held by spot traders. Releasing this assumption yields a more realistic intermediate scenario with somewhat informed participants in both spot and derivatives markets. Uninformed spot traders destabilise the spot market, and uninformed derivatives traders introduce additional uncertainty that cannot be 'stabilised away' by equally uninformed spot traders. Thus, an observed destabilising effect of derivatives trading implies that spot and derivatives traders are equally informed, while a stabilising effect indicates an information differential between spot and derivatives traders. While the model introduced by Stein (1987) cannot be tested directly, it provides a theoretical foundation for the interpretation of our empirical results.

Moreover, Hart and Kreps (1986) argue that speculative activity is likely to destabilise prices regardless of how well these speculators are informed. Speculators will buy when the chance of rising prices increases, and they will sell as the likelihood of falling prices goes up. This trading behaviour raises price variability in the short term under otherwise equal conditions. Thus, if derivatives traders have mostly speculative motives, the cash market is likely destabilised following the introduction of futures or options.

By contrast, a number of theoretical studies show that derivatives trading has a stabilising effect on spot prices (Peck (1976), Sarris (1984), Turnovsky (1983)). In particular, Danthine (1978) argues that futures traders are better informed than spot traders, and hence futures prices transmit information to relatively uninformed spot traders. This results in a stabilised cash market. Cox (1976) and Hiraki et al. (1995) present empirical evidence for futures traders to be better informed than spot traders. Empirically, the market completion achieved through the introduction of derivatives trading improves risk-sharing in the spot market (Gulen and Mayhew (2000)), enhances market efficiency there (Bologna and Cavallo (2002)) and has thus a stabilising overall effect on the cash market.

The ambiguity of theoretical arguments about the effect of derivatives trading on conditional spot market volatility has lead to an ongoing empirical debate, yielding equally mixed evidence. While Antoniou and Holmes (1995), Bae et al. (2004), and Butterworth (2000) find a destabilising effect, Edwards (1988a,b), Gulen and Mayhew (2000), Raju and Karande (2003), and Antoniou et al. (2005) report decreased spot market volatility following the introduction of futures trading. Similarly, several studies find the introduction of options trading to decrease return volatility of the underlying stocks (Damodaran and Lim (1991), Conrad (1989), Skinner (1989)). In these studies, conditional spot market volatility is examined around the dates when futures or options are launched, since direct empirical tests of theoretical models such as the one proposed by Stein (1987) are impossible.

While most empirical investigations focus on mature markets (e.g. Antoniou and Holmes (1995), Edwards (1988a,b), Cox (1976)), Gulen and Mayhew (2000) provide international evidence for 17 markets excluding Poland, as the post-event time series for the Polish market was too short at the time. These mature markets are dominated by well informed institutional investors, whereas individuals account for more than three quarters of trading volume on the Polish futures market. This institutional peculiarity of the Polish derivatives market enables us to empirically test more directly than in previous studies the theoretical argument that the impact of derivatives trading on conditional spot market volatility depends on the degree to which futures and options traders are informed compared to spot market participants. Cohen et al. (2002) show that institutional investors' trading decisions are based on fundamental information. Thus, institutions drive stock prices to their fair values by trading against individuals, thereby stabilising stock prices. Moreover, individuals are less well informed than institutions (Dennis and Weston (2001)), and individuals' trading decisions are more biased by behavioural aspects than institutions' trading activities (Kamesaka et al. (2003)). This is consistent with Figlewski (1981) who reports that uninformed futures traders destabilise the cash market.

In essence, theoretical arguments regarding the impact of the introduction of futures and options trading on the spot market volatility are ambiguous, leaving the subject to empirical investigation. Specifically, we raise three research questions. First, we examine the effect of the debut of futures and options trading on the conditional volatility of the corresponding underlying instrument on the cash market. Since the Polish derivatives market is dominated by individuals who are generally perceived as being less well informed than institutions, we expect to find higher conditional volatility on the spot market following the introduction of futures and options trading. This destabilising hypothesis is consistent with Figlewski (1981) and the argument that uninformed individuals transacting on the derivatives market introduce noisy price signals into the underlying spot market. However, if our empirical findings support the stabilising hypothesis, this can be viewed as evidence against individual investors' trading decisions being generally sentiment-driven.

Second, we ascertain whether the spot market's reaction to the arrival of news changed when derivatives trading commenced. The GARCH model suggested by Glosten et al. (1993) enables us to explicitly capture asymmetric responses on the spot market to positive and negative return shocks. Antoniou et al. (1998) find asymmetries to transfer from the spot market to the futures market when the latter is introduced, while McKenzie et al. (2001) report mixed evidence regarding the direction of the change in asymmetries. Third, we check whether observed changes in conditional spot market volatility coincide with the introduction of derivatives. Bologna and Cavallo (2002) confirm this coincidence for the Italian stock market. We investigate a wide range of introduction dates of futures and options, and we shrink the sample period around these dates in order to exclude the effect of other events near the launch dates of the derivatives.

In order to empirically investigate the impact of individuals' derivatives trading on the spot market volatility in Poland, section 2 describes the institutional background of these two markets. Section 3 introduces the methodology and the dataset, before section 4 presents and interprets the empirical results. Section 5 summarises our findings and concludes.

## 5.2 The Polish Spot and Derivatives Markets

The first stock exchange in Warsaw was founded in 1817. Having been closed during World War II and the communist era, the Polish stock market was re-opened on 16 April 1991. Exactly three years later, the WIG20 stock price index was launched.[8] This index reflects the performance of twenty blue chip stocks listed on the main market of the Warsaw Stock Exchange (WSE). The mWIG40 (called MIDWIG until 18 March 2007), a mid-cap price index, followed on 21 September 1998, and the TechWIG price index, representing innovative technologies, on 31 December 1999.

Being a medium-size stock exchange in Europe, the WSE ranks first in market capitalisation and turnover value among the exchanges in the 12 states that joined the European Union (EU) in 2004 and 2007. The total value of share trading at the WSE in 2006 amounted to 55,702 million US$, which compares to 30,909 million US$ at the Budapest Stock Exchange and 82,049 million US$ at the Vienna Stock Exchange, which is among the smaller West-European exchanges. For the WSE, this represents an 83% increase relative to 2005, while the Budapest Stock Exchange only grew by 28%. The Polish stock market has been growing rapidly in part because formerly state-owned companies were privatised and listed on the WSE. The first foreign company (Bank Austria Creditanstalt AG) was listed at the WSE on 14 October 2003. Since 1 May 2004, the exchange's market structure has been complying with EU standards, i.e. securities trading has two segments, the main market and the regulated unofficial parallel market.

Initially, there was a spot market only. Futures contracts on the WIG20 have been traded at the WSE since 16 January 1998. This was the first derivative product introduced by the exchange, which quickly became very popular among Polish investors. During 1999, the trading volume in the WIG20 futures market rose over eightfold relative to the previous year, and in 2000 the growth in turnover was sevenfold compared

[8] All information about the Warsaw Stock Exchange is taken from the annual fact books. The comparisons of the Warsaw Stock Exchange with other exchanges are based on the World Federation of Exchanges Annual Report 2006.

to 1999. In 2006, the trading volume for the stock index futures market at the WSE, measured as the number of contracts traded, reached 6.3 millions. This compares to a trading volume of 1.9 million contracts at the Budapest Stock Exchange and 155,000 at the Vienna Stock Exchange, while the leading European derivatives trading platform Eurex reports 270 million contracts traded.

On 1 August 2000, futures contracts on the TechWIG index were introduced, with contracts on the mWIG40 index following on 18 February 2002. Futures contracts on individual stocks were first launched on 22 January 2001. Put and call options with the WIG20 as underlying were introduced on 22 September 2003, and stock options started trading on 17 October 2005. Table 12 gives an overview of these events. Moreover, trading has been suspended in futures on three individual stocks.[9]

Table 12 about here

Derivatives are traded in the continuous trading system, whose trading hours were 10.15am to 4.00pm prior to the introduction of the quotation system WARSET on 17 November 2000. Thereafter, derivatives were traded from 9.00am to 4.10pm. Since 3 October 2005, the derivatives market has been closing at 4.20pm, with an auction being held at opening and closing. The contracts expire in March, June, September, and December. The last trading day of any given contract is the third Friday of its expiry month, or the last trading day prior to that Friday in case of public holidays.

Price variation limits for shares, futures, and options are in place at the WSE. Potentially relevant to our empirical investigation are the price limits on the cash market. A transaction price for shares in continuous trading had to lie inside a 10%-corridor around the opening price, and for shares traded in the auction system the benchmark value was the previous day's price. When the stock price hits these limits, the specialist broker appointed by the exchange intervenes by trying to balance the market through buying or selling securities in his own account. If it is impossible to find the market clearing price in this way, the size of the order imbalance is estimated. For imbalances between supply and demand of 5:1 and larger, trading is suspended, and for smaller imbalances the submitted orders are subject to proportional reduction

[9] For completeness: Futures contracts on US$ debuted on 25 September 1998, followed by futures on the Euro on 1 May 1999. T-note futures were launched on 14 February 2005. Ordinary warrants started trading on 9 March 1998, with American-style warrants on WIG20 futures contracts joining in on 24 September 2001. Convertible bonds were first quoted on 25 April 2002.

by the prevailing side of the market. Thus, by investigating close-to-close spot returns rather than intraday price changes, we largely exclude the potentially decreasing effect of price variation limits on stock market volatility. Moreover, most studies find price variation limits to merely delay price adjustments to the next trading day, thereby transferring stock return volatility to the following day (Kim and Rhee (1997), Henke and Voronkova (2005)). Regarding price variation limits for futures and options, the empirical results are largely unaffected by these since we base our analysis on stock returns rather than derivatives prices.

More relevant to our research questions is the unique investor structure on the Polish derivatives market. On the futures and options markets, individual investors are the dominating trader type, accounting for about 75% of turnover value on average over the past eight years, with domestic institutions contributing 20%, while the remaining 5% were allocated to foreign investors. This dominance of individual investors is due to three factors: First, small transactions can be settled at the Polish derivatives market. For example, the value of an index futures contract equals the product of the multiplier and the price of the underlying. The former was set to only 10 zl, which currently equals about 2.75 US$. This small multiplier makes WIG20 index futures affordable for small investors. Second, individual investors who wish to trade on the Polish futures market can easily register to do so without formal barriers. Third, institutional investors such as Polish pension funds or mutual funds are not permitted to trade in derivatives. Interestingly, the fraction of turnover value attributed to individuals on the derivatives market is about twice as large as their share on the spot market. The share of cash market trading volume originating from foreign investors, domestic institutional investors, and domestic individual investors is about one third each.

## 5.3 Methodology and Data

In order to empirically investigate the impact of the introduction of futures and options on stock market volatility we rely on the asymmetric GARCH model proposed by Glosten et al. (1993) (GJR-GARCH). Its mean equation takes into account first-order autocorrelation in stock returns, a structural change in the autoregressive structure after the introduction of futures or options, international interdependence of the Polish stock market, and a day-of-the-week-effect. Specifically, we estimate the mean equation:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 D_t r_{t-1} + \alpha_3 r^f_{t-1} + \sum_{i=4}^{7} \alpha_i DoW_{it} + \epsilon_t \ . \tag{12}$$

The daily spot return is defined as the logarithmic difference $r_t = \ln(P_t) - \ln(P_{t-1})$, and $\epsilon_t = N(0, h_t)$ denotes the unpredictable component of spot returns. With the dummy variable $D_t$ we model the structural change induced by the introduction of futures or options on the Polish stock market at time $\tau$. $D_t$ takes the value of zero up until futures or options are launched (and after their suspension) and the value of one from the day after their introduction onwards. A statistically significant coefficient $\alpha_2$ indicates a structural change in the autocorrelation pattern of stock returns after $\tau$. In particular, while $\alpha_1$ measures the extent of autocorrelation during the period before the introduction of futures and options, the sum $(\alpha_1 + \alpha_2)$ provides an autocorrelation measure for the period afterwards. $r^f_{t-1}$ denotes the lagged logarithmic return on a foreign stock market index. Finally, $\sum_{i=4}^{7} DoW_{it}$ are dummy variables for Tuesday, Wednesday, Thursday and Friday.

In the volatility equation of the GJR-GARCH model, positive and negative shocks can have different effects on subsequent volatility:

$$h_t = (1 + \gamma_D D_t)(\gamma_0 + \gamma_1 h_{t-1} + \gamma_2 \epsilon^2_{t-1} + \gamma_3 \epsilon^2_{t-1} I_t) \ , \tag{13}$$

where $I_t$ takes on the value of zero when the return innovation is zero or positive, i.e. $\epsilon_{t-1} \geq 0$, and the value of one in case of negative return shocks, i.e. $\epsilon_{t-1} < 0$. This is a parsimonious model specification with only one lagged term of $h_t$ and $\epsilon^2_t$. A statistically significant and positive $\gamma_3$ coefficient indicates that negative return shocks increase the conditional variance more strongly than positive return shocks. Setting the asymmetry coefficient $\gamma_3$ equal to zero yields the conventional GARCH(1,1) specification as a special case of the GJR-GARCH model.

Relevant to the first research question about the impact of the introduction of derivatives on spot market volatility is the estimated parameter $\hat{\gamma_D}$ on the multiplicative dummy variable $D_t$, which captures the differences in volatility between the time before the introduction of derivatives contracts and thereafter. This coefficient provides, thus, a measure of the shift in the conditional volatility process. A statistically significant and positive $\hat{\gamma_D}$ parameter suggests that the spot market volatility is higher after the introduction of derivatives contracts than before, thereby providing evidence in favour of the destabilising hypothesis. If $\hat{\gamma_D}$ is statistically significant but negative, futures or options exhibit a dampening influence on volatility.

In order to answer the second research question regarding changes in the asymmetric pattern of the impact of positive and negative return shocks on conditional volatility, we estimate the volatility equation (2) in a different specification:

$$h_t = (1 + \zeta_D D_t)(\zeta_0 + \zeta_1 h_{t-1} + \zeta_2 \epsilon_{t-1}^2) + \zeta_3 \epsilon_{t-1}^2 I_t + \zeta_4 D_t \epsilon_{t-1}^2 I_t \ , \tag{14}$$

where $\zeta_4$ captures differences in the volatility response to negative return shocks between before the introduction of derivatives and thereafter. $\zeta_3$ measures the impact of negative return shocks before the introduction of derivatives (and after their suspension), whereas the influence of negative return shocks after the launch of futures or options equals $\zeta_3 + \zeta_4$. A statistically significant negative (positive) $\zeta_4$ parameter implies that this asymmetry has decreased (increased) due to the introduction of futures or options.

Other institutional changes and shocks to the Polish stock market such as international financial crises and the collapse of the dotcom stock price bubble might have had an effect on stock return volatility. To take into account this aspect and to answer the third research question, two shorter sample periods than the original one are investigated. The first one captures two calendar years around the introduction date, whereas the second sample period includes a 12-month period before and after the event. The broad spectrum of introduction dates in our dataset provides a further robustness check against other factors potentially driving changes in spot market volatility.

Equations (1) and (2), and equations (1) and (3), are jointly estimated via maximum likelihood using the Bernd et al. (1974) algorithm. $p$-values based on Bollerslev and Wooldridge (1992) robust standard errors with six lags are reported. We present the estimation results for the complete mean equation (1), and, as a robustness check, excluding the four day-of-the-week dummy variables.

Our dataset, which was obtained from Datastream, comprises time series of daily close price observations ($P_t$) on the WIG20, mWIG40, and TechWIG stock price indexes as well as on the individual stocks listed in Table 12. The sample period starts on 1 November 1994, which is the first complete month with five trading days per week, and it ends on 29 July 2007. The TechWIG price index was introduced on 19 May

2000 and back-calculated to 31 December 1999. We include in our sample TechWIG data from 31 December 1999. For data availability reasons, the time series for Bank Millenium only starts on 16 July 1996. Options on individual stocks were introduced on 17 October 2005, and futures on PKO BP were launched on 11 July 2005, resulting in post-event time series too short to draw reliable conclusions. We therefore omit the corresponding spot returns from the analysis. In order to control for international influence on the Polish stock market, we further include daily close prices of the S&P500 index in our dataset.

It can be argued that expiration day effects on the futures market raise stock market volatility. However, Illueca and LaFuente (2006) show that the S&P500 spot return volatility is not higher at the expiration date of the corresponding futures contracts. Therefore we do not adjust the observed spot returns for potential expiration day effects after the futures introduction dates.

## 5.4 Empirical Results

Table 13 presents the estimation results of the GJR-GARCH model for the full sample period. While autocorrelation ($\alpha_1$) in stock indexes can be explained by time-varying expected returns, non-synchronous trading, transaction costs, or feedback trading, serial correlation in individual stocks could be indicative of market inefficiency. We find return autocorrelation of order one for three individual stocks, the WIG20 index, and the mWIG40 index. The impact of the introduction of futures and options on stock return autocorrelation is statistically insignificant ($\alpha_2$) for most underlying instruments. However, for WIG20 futures and for WIG20 options, stock return autocorrelation diminishes following the debut of these derivatives. This finding holds also for the individual stock Bank Zachodni WBK. The reduction in stock return autocorrelation can be viewed as evidence in favour of more efficient spot markets with improved information flows once the derivatives markets are established. Holden and Subrahmanyam (2002) show that sequential information acquisition leads to return autocorrelation, implying that the reduction in serial correlation was at least partially driven by improved information flows once derivatives started trading. Nevertheless, the estimated $\alpha_2$ parameters for the mWIG40 index and the Elektrim stock are positive and significant. The Polish stock market is significantly positively correlated with the S&P500 market ($\alpha_3$), while the Polish cash market for most instruments under investigation exhibits no day-of-the-week effect ($\alpha_4$ to $\alpha_7$).

When looking at the estimated coefficients describing the conditional volatility process, we find that all estimated $\gamma_1$ and $\gamma_2$ are significant and show a high degree of persistence. The results for the asymmetry coefficient $\gamma_3$ are mixed. In most cases, the estimated $\gamma_3$ parameter is insignificant suggesting that positive and negative shocks affect the conditional cash market volatility equally. This indicates that a simple GARCH(1,1) specification sufficiently models the conditional volatility process. For the TechWIG and for individual stocks, volatility is higher in periods of market decline than during market upturns due to a positive and significant $\gamma_3$ parameter. The significant asymmetry in conditional variance following positive and negative return innovations is consistent with Glosten et al. (1993).

Table 13 about here

Our primary goal is to determine the impact of futures and options trading on the conditional volatility of the underlying instrument, which is measured by the coefficient $\gamma_D$. Surprisingly, for the vast majority of instruments, the introduction of futures and options trading seems to stabilise spot returns, which is in contradiction to the hypothesis that uninformed individual investors on the derivatives market introduce noisy price signals into the cash market. This empirical finding is in accordance with the results reported in Edwards (1988a) for the U.S., with the insights in Gulen and Mayhew (2000) for most mature markets, and with the evidence of Raju and Karande (2003) for India but is contrary to Bae et al. (2004)'s findings for Korea. Thus, individuals transacting on the Polish derivatives market appear as informed and rational as institutional traders dominating mature futures markets. For only three out of 15 derivatives, their launches appear statistically insignificant (futures on the WIG20 index, on PKN Orlen, and on Bank Zachodni WBK).

Interestingly, the introduction of futures trading with the WIG20 stock price index as underlying has no significant effect on the conditional volatility of the WIG20. This is in accordance with Edwards (1988b) who reports the absence of significant changes in Value Line index volatility following the introduction of such index futures. Around the introduction date of WIG20 futures, individual investors were the most active trader group on both cash and futures markets, resulting in comparatively low information differentials between spot and futures traders. It could be conjectured that the absence of an effect of futures trading on spot market volatility results, in part, from this setting. Later on, after 2000, the difference in investor structure between the cash and futures markets grew, and thus the information differential between these two markets increased. At that time, futures on the mWIG40, on the TechWIG, on individual stocks as well as options on the WIG20 were introduced. Their debut stabilises the corresponding spot returns, implying that the arrival of individual investors on the derivatives market lead to improved information flows into the cash market. Again, this result suggests that Polish individuals trading in derivatives are better informed than the literature indicates for mature markets.

Next, as our second research question, we examine potential changes in asymmetry in the spot market responses to positive and negative return shocks. A significantly positive $\zeta_4$ coefficient shown in Table 14 indicates that negative return shocks increase the conditional spot volatility after the introduction of derivatives more than before. For futures on the TechWIG and on two individual stocks, this asymmetry in cash market responses to positive and negative shocks has increased following the launch of derivatives trading, while the spot market responses to such shocks for two other individual stocks have become less asymmetric after their corresponding futures were introduced. Whereas no significant change in asymmetry can be detected for the WIG20 conditional volatility following the introduction of WIG20 futures, the launch of WIG20 options reduces the asymmetric responses on the spot market to positive and negative shocks. This is consistent with Antoniou et al. (1998) who find a statistically significant reduction in the asymmetric response of spot market volatility following the introduction of stock index futures in Germany, Japan, and the U.S.

Table 14 about here

Our third research question revolves around the coincidence between changes in conditional spot market volatility and the introduction of derivatives. In order to eliminate the effect of other events near the launch dates of the derivatives, we present in Table 15 estimation results based on shorter samples for the shift $\gamma_D$ in conditional spot market volatility following the launch of derivatives.[10]

[10]In addition, we shrink the sample period around the suspension dates for futures on Elektrim, Bank BPH, and Bank Millenium. For the former, the effect of the suspension on conditional volatility

Table 15 about here

Overall, the findings reported in Table 13 are confirmed. Moreover, the introduction dates of derivatives examined in this paper range from January 1998 to July 2005. The empirical results are consistent across this 7-year period, providing a further robustness check against other factors potentially driving changes in spot market volatility. Interestingly, while the impact of trading in WIG20 futures on conditional WIG20 volatility is insignificant across the entire sample period, the introduction of WIG20 futures appears to raise the corresponding conditional spot market volatility in the shorter sample. Launched in January 1998, this futures contract was the first derivatives instrument at the WSE. It can be conjectured that individual investors trading in financial products as complex as derivatives contracts had to learn profitable trading strategies in the first months after their introduction. During this learning process, unreliable price signals were conveyed to the cash market, resulting in a temporarily destabilised spot market.

In essence, we investigate the impact of the introduction of derivatives trading on the conditional volatility of the underlying cash market. Since the Polish derivatives market is dominated by individual investors, we hypothesise that derivatives traders are uninformed relative to spot market traders. Consistently with this view, derivatives trading should have increased spot market volatility. However, the introduction of futures and options has stabilised the underlying cash market, implying that the individuals transacting on the Polish derivatives market are better informed than the literature on individual investors' trading behaviour suggests for mature markets. While the empirical results regarding changes in asymmetry in cash market responses to positive and negative return shocks are ambiguous, the WIG20 stock index volatility becomes less asymmetric after WIG20 options are launched. This is further evidence supporting the favourable influence of individuals trading in derivatives on the cash market.

is insignificant, while the maximisation procedure for the latter two shares does not converge. This is likely to be due to the small number of observations since the recent suspension date.

## 5.5 Summary and Conclusions

The aim of this paper is to investigate the impact of the introduction of derivatives trading in Poland on the conditional return volatility of the underlyings. This impact primarily depends on how well informed futures and options traders are relative to investors transacting on the corresponding spot market. Since the Polish derivatives market is dominated by individuals, we expect a destabilising effect on the spot market (Dennis and Weston (2001), Figlewski (1981)). However, derivatives trading has a stabilising effect on the Polish stock market, implying that Polish individuals transacting in derivatives are better informed and more rational traders than the literature suggests for individuals on mature markets. The introduction of futures and options trading therefore leads to better information flows into the cash market and hence to a more efficient spot market. This evidence does not justify the regulation of derivatives trading in order to stabilise the cash market.

## 5.6 Tables

Table 12: Overview of the Polish Futures and Options Markets

| Name | Listing of underlying spot | Introduction of derivatives contract | Trading suspended |
|---|---|---|---|
| Futures | | | |
| WIG20 | 16 April 1994 | 16 January 1998 | – |
| mWIG40 | 21 September 1998 | 18 February 2002 | – |
| TechWIG | 19 May 2000 | 1 August 2000 | – |
| Telekomunikacja Polska | 18 November 1998 | 22 January 2001 | – |
| PKN Orlen | 26 November 1999 | 22 January 2001 | – |
| Elektrim | 26 March 1992 | 22 January 2001 | 17 November 2003 |
| Bank Pekao | 30 June 1998 | 22 October 2001 | – |
| KGHM Polska Miedz | 18 July 1997 | 22 October 2001 | – |
| Bre Bank | 26 September 1996 | 22 October 2001 | – |
| Agora | 20 April 1999 | 22 October 2001 | – |
| Prokom Software | 20 April 1998 | 22 October 2001 | – |
| Bank BPH | 16 September 1996 | 18 March 2002 | 5 July 2006 |
| Bank Millenium | 13 August 1992 | 24 March 2003 | 5 July 2006 |
| Bank Zachodni WBK | 2 July 2001 | 24 March 2003 | – |
| PKO BP | 9 November 2004 | 11 July 2005 | – |
| Options | | | |
| WIG20 | 16 April 1994 | 22 September 2003 | – |
| PKN Orlen | 26 November 1999 | 17 October 2005 | – |
| Bank Pekao | 30 June 1998 | 17 October 2005 | – |
| Telekomunikacja Polska | 18 November 1998 | 17 October 2005 | – |
| KGHM Polska Miedz | 18 July 1997 | 17 October 2005 | – |
| Prokom Software | 20 April 1998 | 17 October 2005 | – |

Table 13: Estimation Results for Mean and Volatility Equations

| Name of underlying | Regression coefficients ($p$-values) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $r_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 D_t r_{t-1} + \alpha_3 r^f_{t-1} + \sum_{i=4}^{7} \alpha_i DoW_{it} + \epsilon_t$ | | | | | | | | $h_t = (1 + \gamma_D D_t)(\gamma_0 + \gamma_1 h_{t-1} + \gamma_2 \epsilon^2_{t-1} + \gamma_3 \epsilon^2_{t-1} I_t)$ | | | | |
| | $\alpha_0$ | $\alpha_1$ | $\alpha_2$ | $\alpha_3$ | $\alpha_4$ | $\alpha_5$ | $\alpha_6$ | $\alpha_7$ | $\gamma_D$ | $\gamma_0$ | $\gamma_1$ | $\gamma_2$ | $\gamma_3$ |
| Panel A: Futures | | | | | | | | | | | | | |
| WIG20 | 0.137 | 0.199 | −0.180 | 0.451 | −0.214 | −0.232 | −0.046 | 0.011 | −0.005 | 0.081 | 0.878 | 0.091 | 0.018 |
| | (0.019)** | (0.000)*** | (0.000)*** | (0.000)*** | (0.008)*** | (0.008)*** | (0.559) | (0.880) | (0.378) | (0.000)*** | (0.000)*** | (0.000)*** | (0.185) |
| | 0.039 | 0.202 | −0.183 | 0.449 | – | – | – | – | −0.005 | 0.079 | 0.880 | 0.090 | 0.015 |
| | (0.152) | (0.000)*** | (0.000)*** | (0.000)*** | | | | | (0.364) | (0.000)*** | (0.000)*** | (0.000)*** | (0.236) |
| mWIG40 | 0.048 | 0.081 | 0.077 | 0.196 | −0.053 | −0.043 | 0.055 | 0.100 | −0.011 | 0.017 | 0.888 | 0.122 | −0.022 |
| | (0.265) | (0.002)*** | (0.052)* | (0.000)*** | (0.350) | (0.451) | (0.297) | (0.075)* | (0.042)** | (0.000)*** | (0.000)*** | (0.000)*** | (0.081)* |
| | 0.062 | 0.084 | 0.072 | 0.197 | – | – | – | – | −0.012 | 0.018 | 0.884 | 0.127 | −0.025 |
| | (0.004)*** | (0.002)*** | (0.075)* | (0.000)*** | | | | | (0.026)** | (0.000)*** | (0.000)*** | (0.000)*** | (0.044)** |
| TechWIG | 0.249 | 0.170 | −0.138 | 0.278 | −0.455 | −0.319 | −0.100 | −0.024 | −0.106 | 0.306 | 0.815 | 0.169 | 0.075 |
| | (0.001)*** | (0.187) | (0.294) | (0.000)*** | (0.000)*** | (0.005)*** | (0.300) | (0.838) | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.009)*** |
| | 0.062 | 0.169 | −0.139 | 0.281 | – | – | – | – | −0.104 | 0.310 | 0.816 | 0.172 | 0.061 |
| | (0.125) | (0.195) | (0.298) | (0.000)*** | | | | | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.029)** |
| Telekomunikacja Polska | 0.148 | 0.005 | −0.038 | 0.307 | −0.283 | −0.185 | −0.053 | −0.046 | −0.015 | 0.113 | 0.921 | 0.066 | 0.008 |
| | (0.117) | (0.885) | (0.371) | (0.000)*** | (0.039)** | (0.168) | (0.700) | (0.722) | (0.003)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.578) |
| | 0.035 | 0.005 | −0.037 | 0.306 | – | – | – | – | −0.015 | 0.112 | 0.923 | 0.065 | 0.006 |
| | (0.439) | (0.878) | (0.375) | (0.000)*** | | | | | (0.003)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.668) |
| PKN Orlen | 0.127 | −0.001 | −0.000 | 0.246 | −0.178 | −0.100 | −0.096 | 0.061 | 0.004 | 0.535 | 0.778 | 0.060 | 0.024 |
| | (0.179) | (0.982) | (0.999) | (0.000)*** | (0.208) | (0.478) | (0.440) | (0.633) | (0.837) | (0.000)*** | (0.000)*** | (0.000)*** | (0.285) |
| | 0.063 | −0.001 | −0.001 | 0.247 | – | – | – | – | 0.007 | 0.555 | 0.770 | 0.061 | 0.022 |
| | (0.116) | (0.991) | (0.987) | (0.000)*** | | | | | (0.755) | (0.000)*** | (0.000)*** | (0.000)*** | (0.324) |
| Elektrim | −0.090 | 0.032 | 0.091 | 0.317 | 0.239 | 0.053 | 0.118 | 0.208 | −0.007 | 0.328 | 0.929 | 0.048 | 0.034 |
| | (0.515) | (0.097)* | (0.024)** | (0.000)*** | (0.253) | (0.791) | (0.550) | (0.304) | (0.007)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| | 0.034 | 0.032 | 0.090 | 0.315 | – | – | – | – | −0.007 | 0.323 | 0.930 | 0.047 | 0.033 |
| | (0.605) | (0.098)* | (0.023)** | (0.000)*** | | | | | (0.005)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| Bank Pekao | 0.232 | −0.055 | 0.005 | 0.349 | −0.281 | −0.292 | −0.097 | −0.135 | −0.035 | 0.610 | 0.758 | 0.129 | 0.005 |
| | (0.012)** | (0.062)* | (0.902) | (0.000)*** | (0.047)** | (0.016)** | (0.465) | (0.274) | (0.005)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.856) |
| | 0.072 | −0.054 | 0.004 | 0.348 | – | – | – | – | −0.033 | 0.593 | 0.762 | 0.127 | 0.006 |
| | (0.086)* | (0.066)* | (0.931) | (0.000)*** | | | | | (0.007)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.811) |
| KGHM Polska Miedz | 0.089 | 0.017 | 0.010 | 0.374 | −0.150 | −0.241 | 0.013 | 0.134 | −0.017 | 0.359 | 0.878 | 0.071 | 0.035 |
| | (0.461) | (0.566) | (0.801) | (0.000)*** | (0.400) | (0.137) | (0.928) | (0.357) | (0.005)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.027)** |
| | 0.037 | 0.020 | 0.007 | 0.369 | – | – | – | – | −0.018 | 0.378 | 0.873 | 0.074 | 0.033 |
| | (0.479) | (0.496) | (0.863) | (0.000)*** | | | | | (0.005)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.035)** |
| Bre Bank | 0.116 | −0.007 | 0.055 | 0.332 | −0.031 | −0.138 | −0.043 | −0.021 | −0.023 | 0.153 | 0.928 | 0.040 | 0.033 |
| | (0.209) | (0.771) | (0.155) | (0.000)*** | (0.815) | (0.291) | (0.734) | (0.861) | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| | 0.068 | −0.007 | 0.054 | 0.332 | – | – | – | – | −0.022 | 0.151 | 0.929 | 0.040 | 0.033 |
| | (0.101) | (0.793) | (0.164) | (0.000)*** | | | | | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| Agora | −0.109 | 0.038 | 0.037 | 0.249 | −0.048 | 0.067 | 0.293 | 0.176 | −0.018 | 0.160 | 0.892 | 0.092 | 0.003 |
| | (0.229) | (0.233) | (0.365) | (0.000)*** | (0.708) | (0.615) | (0.021)** | (0.209) | (0.028)** | (0.000)*** | (0.000)*** | (0.000)*** | (0.839) |

Table 13 (continued): Estimation Results for Mean and Volatility Equations

| Name of underlying | Regression coefficients ($p$-values) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $r_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 D_t r_{t-1} + \alpha_3 r^f_{t-1} + \sum_{i=4}^{7} \alpha_i DoW_{it} + \epsilon_t$ | | | | | | | | $h_t = (1 + \gamma_D D_t)(\gamma_0 + \gamma_1 h_{t-1} + \gamma_2 \epsilon^2_{t-1} + \gamma_3 \epsilon^2_{t-1} I_t)$ | | | | |
| | $\alpha_0$ | $\alpha_1$ | $\alpha_2$ | $\alpha_3$ | $\alpha_4$ | $\alpha_5$ | $\alpha_6$ | $\alpha_7$ | $\gamma_D$ | $\gamma_0$ | $\gamma_1$ | $\gamma_2$ | $\gamma_3$ |
| | −0.011 | 0.041 | 0.035 | 0.252 | – | – | – | – | −0.017 | 0.153 | 0.894 | 0.090 | 0.003 |
| | (0.804) | (0.196) | (0.389) | (0.000)*** | | | | | (0.031)** | (0.000)*** | (0.000)*** | (0.000)*** | (0.844) |
| Prokom Software | 0.218 | −0.020 | 0.039 | 0.341 | −0.374 | −0.431 | −0.167 | 0.018 | −0.038 | 0.303 | 0.887 | 0.094 | −0.008 |
| | (0.048)** | (0.606) | (0.410) | (0.000)*** | (0.015)** | (0.004)*** | (0.282) | (0.905) | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.613) |
| | 0.021 | −0.016 | 0.037 | 0.340 | – | – | – | – | −0.041 | 0.329 | 0.884 | 0.095 | −0.010 |
| | (0.683) | (0.688) | (0.439) | (0.000)*** | | | | | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.554) |
| Bank BPH | 0.081 | −0.014 | 0.022 | 0.285 | −0.107 | −0.169 | 0.123 | 0.019 | −0.105 | 0.849 | 0.774 | 0.071 | 0.078 |
| | (0.391) | (0.615) | (0.569) | (0.000)*** | (0.433) | (0.209) | (0.310) | (0.889) | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| | 0.053 | −0.013 | 0.018 | 0.287 | – | – | – | – | −0.106 | 0.856 | 0.773 | 0.074 | 0.075 |
| | (0.214) | (0.647) | (0.639) | (0.000)*** | | | | | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| Bank Millenium | 0.165 | 0.014 | 0.022 | 0.211 | −0.150 | −0.255 | −0.090 | 0.052 | −0.125 | 1.196 | 0.758 | 0.136 | 0.026 |
| | (0.152) | (0.654) | (0.630) | (0.000)*** | (0.305) | (0.133) | (0.585) | (0.717) | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.130) |
| | 0.076 | 0.016 | 0.018 | 0.211 | – | – | – | – | −0.125 | 1.200 | 0.759 | 0.135 | 0.025 |
| | (0.180) | (0.610) | (0.691) | (0.000)*** | | | | | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.140) |
| Bank Zachodni WBK | 0.247 | 0.099 | −0.094 | 0.206 | −0.095 | −0.365 | −0.109 | 0.039 | −0.003 | 0.203 | 0.872 | 0.093 | −0.015 |
| | (0.034)** | (0.007)*** | (0.053)* | (0.000)*** | (0.555) | (0.020)** | (0.520) | (0.779) | (0.716) | (0.000)*** | (0.000)*** | (0.000)*** | (0.554) |
| | 0.141 | 0.100 | −0.095 | 0.209 | – | – | – | – | −0.004 | 0.229 | 0.862 | 0.097 | −0.015 |
| | (0.004)*** | (0.007)*** | (0.048)** | (0.000)*** | | | | | (0.716) | (0.000)*** | (0.000)*** | (0.000)*** | (0.553) |
| Panel B: Options | | | | | | | | | | | | | |
| WIG20 | 0.146 | 0.087 | −0.069 | 0.446 | −0.221 | −0.238 | −0.049 | 0.001 | −0.027 | 0.107 | 0.872 | 0.089 | 0.018 |
| | (0.013)** | (0.000)*** | (0.084)* | (0.000)*** | (0.006)*** | (0.006)*** | (0.529) | (0.987) | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.211) |
| | 0.043 | 0.089 | −0.075 | 0.444 | – | – | – | – | −0.026 | 0.105 | 0.875 | 0.088 | 0.015 |
| | (0.117) | (0.000)*** | (0.057)* | (0.000)*** | | | | | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.272) |

Notes: The sample period starts on 1 November 1994, which is the first complete month with five trading days per week, and it ends on 29 July 2007. See table 1 for an overview of listing dates of stock market indices and individual stocks after 1 November 1994. For data availability reasons, the time series for Bank Millenium only starts on 16 July 1996. *,**,*** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 14: Estimation Results of Asymmetric Effects

| Name of underlying | Regression coefficients ($p$-values) | | | | | |
|---|---|---|---|---|---|---|
| | $h_t = (1+\zeta_D D_t)(\zeta_0 + \zeta_1 h_{t-1} + \zeta_2 \epsilon^2_{t-1}) + \zeta_3 \epsilon^2_{t-1} I_t + \zeta_4 D_t \epsilon^2_{t-1} I_t$ | | | | | |
| | $\zeta_D$ | $\zeta_0$ | $\zeta_1$ | $\zeta_2$ | $\zeta_3$ | $\zeta_4$ |
| Panel A: Futures | | | | | | |
| WIG20 | 0.008 | 0.075 | 0.875 | 0.089 | 0.036 | −0.031 |
| | (0.489) | (0.000)*** | (0.000)*** | (0.000)*** | (0.113) | (0.247) |
| mWIG40 | −0.003 | 0.017 | 0.881 | 0.126 | −0.013 | −0.022 |
| | (0.807) | (0.000)*** | (0.000)*** | (0.000)*** | (0.515) | (0.326) |
| TechWIG | −0.167 | 0.354 | 0.862 | 0.183 | −0.122 | 0.202 |
| | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.122) | (0.012)** |
| Telekomunikacja Polska | −0.043 | 0.150 | 0.931 | 0.066 | −0.032 | 0.064 |
| | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.059)* | (0.008)*** |
| PKN Orlen | 0.014 | 0.556 | 0.764 | 0.061 | 0.037 | −0.017 |
| | (0.746) | (0.000)*** | (0.000)*** | (0.000)*** | (0.701) | (0.861) |
| Elektrim | −0.154 | 0.213 | 0.950 | 0.050 | −0.015 | 0.470 |
| | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.015)** | (0.000)*** |
| Bank Pekao | 0.024 | 0.557 | 0.747 | 0.119 | 0.086 | −0.148 |
| | (0.173) | (0.000)*** | (0.000)*** | (0.000)*** | (0.028)** | (0.000)*** |
| KGHM Polska Miedz | 0.046 | 0.291 | 0.853 | 0.069 | 0.123 | −0.150 |
| | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| Bre Bank | −0.013 | 0.148 | 0.926 | 0.039 | 0.042 | −0.023 |
| | (0.093)* | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.151) |
| Agora | −0.003 | 0.145 | 0.887 | 0.090 | 0.024 | −0.034 |
| | (0.832) | (0.000)*** | (0.000)*** | (0.000)*** | (0.289) | (0.225) |
| Prokom Software | −0.046 | 0.330 | 0.887 | 0.094 | −0.016 | 0.013 |
| | (0.006)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.416) | (0.656) |
| Bank BPH | −0.112 | 0.861 | 0.774 | 0.074 | 0.068 | 0.009 |
| | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.001)*** | (0.772) |
| Bank Millenium | −0.113 | 1.180 | 0.760 | 0.133 | 0.033 | −0.037 |
| | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.097)* | (0.158) |
| Bank Zachodni WBK | 0.035 | 0.093 | 0.893 | 0.080 | 0.030 | −0.088 |
| | (0.018)** | (0.005)*** | (0.000)*** | (0.000)*** | (0.331) | (0.006) |
| Panel B: Options | | | | | | |
| WIG20 | −0.008 | 0.095 | 0.875 | 0.087 | 0.024 | −0.042 |
| | (0.486) | (0.000)*** | (0.000)*** | (0.000)*** | (0.130) | (0.072)* |

Notes: The estimated mean equation without day-of-the-week dummies is $r_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 D_t r_{t-1} + \alpha_3 r^f_{t-1} + \epsilon_t$. The sample period starts on 1 November 1994, which is the first complete month with five trading days per week, and it ends on 29 July 2007. See table 1 for an overview of listing dates of stock market indices and individual stocks after 1 November 1994. For data availability reasons, the time series for Bank Millenium only starts on 16 July 1996. *,** ,*** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 15: Estimation Results for shorter sample periods

| Name of underlying | Sample period | $\gamma_D$ ($p$-value) |
|---|---|---|
| Panel A: Futures | | |
| WIG20 | 1996:01:02 - 2000:12:19 | 0.054 (0.033)$^{**}$ |
| | 1997:01:02 - 1999:01:29 | 0.197 (0.034)$^{**}$ |
| mWIG40 | 2000:01:03 - 2004:12:31 | $-0.037$ (0.034)$^{**}$ |
| | 2001:02:01 - 2003:02:28 | $-0.166$ (0.007)$^{***}$ |
| TechWIG | 2000:05:19 - 2002:12:31 | $-0.210$ (0.000)$^{**}$ |
| | 2000:05:19 - 2003:02:28 | $-0.277$ (0.001)$^{***}$ |
| Telekomunikacja Polska | 1999:01:04 - 2003:12:31 | $-0.101$ (0.002)$^{***}$ |
| | 2000:01:03 - 2002:01:31 | $-0.060$ (0.757) |
| PKN Orlen | 1999:11:29 - 2003:12:31 | 0.004 (0.938) |
| | 2000:01:03 - 2002:01:31 | 0.224 (0.206) |
| Elektrim | 1999:01:04 - 2003:12:31 | 0.035 (0.004)$^{***}$ |
| | 2000:01:03 - 2002:01:31 | 0.038 (0.175) |
| Bank Pekao | 1999:01:04 - 2003:12:31 | $-0.088$ (0.071)$^{*}$ |
| | 2000:10:02 - 2002:10:31 | 0.006 (0.926) |
| KGHM Polska Miedz | 1999:01:04 - 2003:12:31 | $-0.011$ (0.343) |
| | 2000:10:02 - 2002:10:31 | $-0.003$ (0.852) |
| Bre Bank | 1999:01:04 - 2003:12:31 | $-0.206$ (0.000)$^{***}$ |
| | 2000:10:02 - 2002:10:31 | 0.234 (0.314) |
| Agora | 1999:04:21 - 2003:12:31 | $-0.044$ (0.050)$^{**}$ |
| | 2000:10:02 - 2002:10:31 | $-0.113$ (0.042)$^{**}$ |
| Prokom Software | 1999:01:04 - 2003:12:31 | $-0.141$ (0.000)$^{***}$ |
| | 2000:10:02 - 2002:10:31 | $-0.064$ (0.084)$^{*}$ |
| Bank BPH | 2000:01:03 - 2004:12:31 | $-0.061$ (0.020)$^{**}$ |
| | 2001:03:01 - 2003:03:31 | $-0.116$ (0.177) |
| Bank Millenium | 2001:01:02 - 2005:12:30 | $-0.240$ (0.000)$^{***}$ |
| | 2001:03:01 - 2004:03:31 | 0.034 (0.618) |
| Bank Zachodni WBK | 2001:07:03 - 2005:12:30 | $-0.081$ (0.035)$^{**}$ |
| | 2002:03:01 - 2004:03:31 | 0.025 (0.506) |
| Panel B: Options | | |
| WIG20 | 2001:01:02 - 2005:12:30 | $-0.052$ (0.000)$^{***}$ |
| | 2002:09:02 - 2004:09:30 | $-0.010$ (0.023)$^{**}$ |

Notes: The estimated mean equation without day-of-the-week dummies is $r_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 D_t r_{t-1} + \alpha_3 r^f_{t-1} + \epsilon_t$ and the estimated conditional variance equation is $h_t = (1+\gamma_D D_t)(\gamma_0 + \gamma_1 h_{t-1} + \gamma_2 \epsilon^2_{t-1} + \gamma_3 \epsilon^2_{t-1} I_t)$. $^{*}$,$^{**}$,$^{***}$ denote statistical significance at the 10%, 5% and 1% level, respectively.

# 6 Conclusion

The aim of this thesis is to contribute empirical evidence on individual investors' trading behaviour. It is often asserted that individuals are less well informed than institutions, and that individuals' investment decisions are more sentiment-driven than institutions' trading activities. This investigation starts with an analysis of the market microstructure of the anonymous electronic trading platform Xetra compared with the non-anonymous floor trading at the Frankfurt Stock Exchange. The main conclusion of this chapter is that uninformed individuals find more favourable trading conditions on a non-anonymous platform, while the anonymous system offers a more advantageous environment for informed trading. It is therefore argued against closing floor trading systems. If the floor has already been abolished, the electronic exchange benefits from a non-anonymous broker-facilitated upstairs market.

The remainder of this thesis investigates the extent to which individual investors are informed, and whether their trading activities tend to be driven by behavioural aspects. As a testing ground, the Polish stock and derivatives markets are chosen, because individuals can be separated from institutions there. In the third chapter, the presence of herding during up- and downswings on the Polish stock market is tested, and significant herd behaviour by individuals is found in market downturns, while institutions do not appear to engage in herding regardless of the state of the market. If individuals are generally uninformed, it is rational for them to follow the market rather than their own prior beliefs which are likely unreliable. However, it is hard to maintain this argument considering the difference in herd behaviour between periods of market stress and bullish phases.

By contrast, the following chapter testing for the presence of the Monday and January effects on the Polish futures market suggests that individuals are better than their reputation. The Polish futures market, which is dominated by individuals, shows no sign of a Monday effect. Furthermore, the calendar month effect that we detect is associated with the delivery cycle and hence does not constitute an anomaly.

Moreover, the final chapter concludes that individuals trading in Polish derivatives are better informed than the literature on individual investors' trading behaviour on mature markets suggests. The introduction of futures and options trading at the Warsaw Stock Exchange had a stabilising effect on the underlying spot market. If futures traders are better informed than cash market participants, the launch of derivatives improves the information flow into the underlying spot market and thus raises market efficiency there.

In summary, the empirical evidence regarding individual investors' trading behaviour is mixed. The absence of the Monday and January anomalies on the Polish futures market suggests that individuals transacting there are as mature as institutional investors. Moreover, we find evidence of informed and rational individuals when investigating the effect of derivatives trading on conditional spot market volatility. However, individual investors' trading behaviour exhibits herding during periods of market stress. Considering that the Polish stock market only re-opened in 1991 and has been a rapidly growing emerging market, it is not surprising that individuals have had to gain experience with complex financial products. As market participants learn, and as trading behaviour and anomalies receive attention in the academic literature, market efficiency is further promoted.

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# Versicherung

Ich versichere an Eides statt, dass ich die eingereichte Dissertation "Stock and Index Futures Trading Behaviour of Individual and Institutional Investors" selbständig verfasst habe. Anderer als der von mir angegebenen Quellen und Hilfsmittel habe ich mich nicht bedient. Alle wörtlich oder sinngemäß den Schriften anderer Autoren entnommenen Stellen habe ich kenntlich gemacht. Die Dissertation wurde nicht bereits anderweitig als Prüfungsarbeit vorgelegt.

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# Publikationen

1. Goodfellow, Christiane, Martin T. Bohl und Dirk Schiereck (2006), Vorteilhaftigkeit des börslichen Abendhandels für Privatanleger, Wissenschaft für die Praxis 61, 11-13.

2. Goodfellow, Christiane, Martin T. Bohl und Dirk Schiereck, Vorteilhaftigkeit des börslichen Abendhandels aus Anlegersicht, Kredit und Kapital, erscheint demnächst.

# Working Paper

1. Goodfellow, Christiane and Martin T. Bohl, Forestalling Floor Closure: Evidence from a Natural Experiment on the German Stock Market, under review.

2. Bohl, Martin T., Christiane Goodfellow, and Jedrzej Bialkowski, Individual Investors Surpass their Reputation: Trading Behaviour on the Polish Futures Market, under review.

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4. Bohl, Martin T., Christiane Goodfellow, and Christian A. Salm, Do Individual Investors on the Futures Market Induce higher Spot Market Volatility?, working paper.

5. Löffler, Gunter, Peter N. Posch, and Christiane Schoene, Bayesian Methods for Improving Credit Scoring Models, working paper.

# Vorträge auf Nationalen und Internationalen Konferenzen

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