

Trading Systems, Volatility, and the Regulation of Stock Markets: An Investigation of the Microstructure of the Warsaw Stock Exchange

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Contents

1	Introduction	6
2	Trading Volume and Stock Market Volatility: The Polish Case	11
2.1	Introduction	11
2.2	Mixture of Distributions Hypothesis and Econometric Methodology	12
2.3	Data, Empirical Results, and Comparison With Available Evidence	15
2.4	Conclusion	19
2.5	Tables	21
3	Introducing Continuous Trading in an Emerging Market: The Case of Poland	27
3.1	Introduction	27
3.2	Trading Systems on the Warsaw Stock Exchange	30
3.2.1	Call Auction	30
3.2.2	Continuous Trading	31
3.3	Data and Methodology	32
3.3.1	Data	32
3.3.2	Market Liquidity	33
3.3.3	Price Efficiency	34
3.3.4	Price Effects of the Transfers	36
3.4	Empirical Results	37
3.4.1	Use of the Continuous Trading System	37
3.4.2	Market Liquidity	38
3.4.3	Price Efficiency	39
3.4.4	Price Effects	40
3.5	Discussion	41
3.6	Conclusion	43
3.7	Figures and Tables	46

4	When Continuous Trading Becomes Continuous: The Impact of Institutional Trading on the Continuous Trading System of the Warsaw Stock Exchange	52
4.1	Introduction	52
4.2	The Polish Stock Market and the Pension Reform of 1999 . . .	55
4.3	Theory and Testable Implications	58
4.4	Methodology and Results	64
4.4.1	Data	64
4.4.2	Empirical results for the stock groups	66
4.4.3	Empirical results of cross-sectional tests	72
4.5	Conclusion	74
4.6	Figures and Tables	76
5	Price Limits on a Call Auction Market: Evidence from the Warsaw Stock Exchange	83
5.1	Introduction	83
5.2	Trading Structure and Price Limits on the Warsaw Stock Exchange	86
5.3	Research Hypotheses and Data	88
5.4	Empirical Results	90
5.4.1	Volatility	90
5.4.2	Return Autocorrelation	93
5.4.3	Discussion	96
5.5	Summary and Concluding Remarks	98
5.6	Figures and Tables	100
6	Conclusion	106

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1 Introduction

In recent years, a growing number of empirical finance studies focus on emerging stock markets all over the world. This research is mainly motivated by three reasons. First, there was a drastic increase of capital flows to securities markets during the last decade. As emerging capital markets offer higher expected returns and are therefore an attractive investment opportunity, researchers are interested in the functioning of these markets, in the way returns and volatility behave there, and whether the well-established principles found on mature markets also hold in young fast-growing emerging markets.

Second, as the higher expected returns on emerging markets also correspond to higher risk, the understanding of risk factors and their correlation across markets has also attracted considerable attention. Financial crises such as the one in East Asia (1997), Russia (1998), or Argentina (2001) and the contagion to other emerging markets have cost investors large amounts of money and made them more sensitive to the dangers of these investments. Finally, as some of the stock markets in emerging markets were newly established, the exchanges used state-of-the-art technology for their trading platforms and included the insights from financial research into the design and regulation of the trading process. Thus, these markets provide natural experiments to research questions asked before but in many cases not answered yet.

The present thesis is driven by the last motive. In the following research papers, the focus is on the microstructure of the Warsaw Stock Exchange (WSE). Consequently, this thesis aims to answer several research problems of market microstructure theory. For some of them, the WSE offers a rare, for some even a unique investigation opportunity. Details of the research questions are outlined below.

An analysis of emerging stock markets always has to take care that the market under scrutiny can indeed be viewed as a functioning stock market instead of a casino or an empty shape without any trading going on. Or, put differently, while certain structural features of a stock market may be worth

investigating, the thinness of the market may devalue any findings from a scientific point of view.

The WSE on which the present studies focus, however, is considered as a successful implementation of a stock market in an emerging economy. E.g., Steil (2001) notes that the WSE successfully concentrated liquidity by first trading stocks only once per week in a call auction after the launch of trading in 1991. The market switched to one daily auction not earlier than October 1994. Continuous trading was introduced in July 1996, approximately five years after trading started in Warsaw. In the first days of continuous trading, only the five most liquid stocks were traded in this system, while more stocks were introduced only gradually. The WSE did not develop its own trading platform, but used the well-established NSC platform of the Paris Bourse. Finally, according to Steil (2001), the large share of domestic investors in the market during the nineties is also indicative of a successful development. The market was open and attractive to foreign investors, nevertheless domestic investors held the majority of stocks.

The following articles focus on several aspects of the trading process, institutional details, and stock market reactions around microstructure events. The first article deals with the interaction of stock return volatility and trading volume of the corresponding stock. While most financial time series are characterized by autoregressive conditional heteroscedasticity (which can be modelled using GARCH-type models), there is no consensus of the reasons for its appearance. Several competing theories explain the occurrence of GARCH effects in return series.

One of the most prominent theories is the so-called 'Mixture of distributions' (MDH) hypothesis. This theory states that dependent on information flow there exist a random number of equilibrium returns during a trading day. If information flow is serially correlated, it can be shown that this translates into an autoregressive structure of the return variance.

In an important paper, Lamoureux and Lastrapes (1990) argue that this information flow can be proxied by trading volume. Therefore, incorporating trading volume in the conditional variance equation of a GARCH model should remove the GARCH effects and display a positive and significant im-

pect of volume on volatility. Several empirical studies have explored this issue and found evidence in favor of the MDH.

We show that the same effect can be found for many stocks on the WSE. Highly persistent GARCH effects are present in daily volatility series. The incorporation of trading volume in the conditional variance equation removes these GARCH effects in a majority of cases. However, in a few cases the GARCH effects remain present and trading volume does not seem to capture useful information for the modelling of return volatility. Therefore, we conclude that the modelling of stock return volatility on the WSE may partly follow processes different from those on developed stock markets.

The second study explores the choice of the trading structure for the listed stocks. In the time period from July 1996 to November 2000, a continuous trading system and an auction system with one daily call auction operated side-by-side. While all stocks were traded in the call auction system during this period, the WSE additionally transferred the most liquid stocks to the continuous trading system. Based on the seminal paper by Amihud, Mendelson, and Lauterbach (1997), there is some evidence that continuous trading improves the liquidity and the efficiency with which the stock is priced relative to liquidity and price efficiency in a call auction mechanism. Moreover, as higher liquidity reduces risk premia and, therefore, expected returns, several studies report positive abnormal returns around transfer announcements and transfers of stocks from a call auction to continuous trading.

Previous evidence exclusively focuses on the stock exchanges in Israel and France. The second article of this collection focuses on the transfers of around seventy stocks from the call auction to continuous trading on the WSE. The results contradict previous findings. The continuous trading system was only infrequently used and attracted only a small share of overall trading volume. Liquidity is not improved and price efficiency suffers. Moreover, there is no permanent price reaction of the transferred stocks.

The article discusses several reasons for these results. While it does not seem to be the case that the WSE is too illiquid to need multiple trading rounds during a trading day, a possible explanation is the investor structure of the WSE. While other markets are dominated by institutional investors,

the WSE was at that time mainly characterized by small domestic investors. For them, continuous trading may not have been a valuable alternative.

This last point deserves further attention. Interestingly, an event on the Polish stock market enables a further exploration of this question. This is done in the third paper in this thesis. In 1999, a pension reform took place and citizens were forced to transfer part of their gross income to privately managed pension funds. These large funds entered the market and induced a considerable change in the investor composition on the WSE.

First, the model of Garbade and Silber (1979) is adopted and modified according to the trading structure on the WSE. Testable hypothesis regarding the use of continuous trading relative to the call auction and on stock liquidity are derived. These hypotheses are tested in an event study-type analysis. The results show that only those stocks that were subject to pension fund trading experience a more frequent use and consequently higher liquidity in the continuous trading system. Moreover, the evidence suggests that small domestic investors and large pension fund traders interact.

The last article of this collection deals with the price limit regulation of the WSE. On many security markets in the world price movements are restricted to a certain maximum and minimum return per day. A rationale frequently put forward by stock exchange officials is that such price limits prevent the markets from overreacting. If in case of new information asset prices start to rise (fall), the increase (decrease) stops at the upper (lower) price limit. If investors overreact or panic, these limits prevent large price changes as trading will be suspended and traders receive time to contact their principals or evaluate the content of their information. Thus, overreaction will be mitigated, prices reverse after limit moves and volatility decreases.

While this view is controversial and empirical evidence is not in agreement with this theory, existing studies focus exclusively on continuously trading markets. On the WSE, however, price limits also apply to the call auction system. While they may prevent overreaction and panic in a continuous trading system, this argument is questionable in a call auction. As in the call auction system orders are collected during the day, the time-out feature of price limits is inherently included in the auction as there is a one-day

break between two consecutive auctions. Thus, there is no rationale for the application of price limits in the call auction system of the WSE.

In the study, we test whether the effects attributed to price limits apply in this system. We find volatility spill-overs to the following trading day in agreement with the hypothesis that price limits merely delay price adjustment to equilibrium. Similarly, we find extremely large positive autocorrelation in returns on days subsequent to limit moves. This indicates that prices tend to continue moving in the same direction after limit hits.

This evidence questions the necessity of price limits in the call auction system of the WSE. To exclude other potentially beneficial effects of price limits not stated officially by stock exchange officials, we attach a discussion of their use to mitigate or prevent price manipulation and insider trading and to be a substitute for higher margin requirements. Our general assessment is that price limits in the given market structure harm investors more than they provide offsetting benefits.

2 Trading Volume and Stock Market Volatility: The Polish Case

2.1 Introduction

Recent studies on the volatility of stock returns have been dominated by time series models of conditional heteroscedasticity and have found strong support for GARCH effects. These findings are important to the field of applied finance for at least three reasons. First, the estimated return variances are used as risk measures and enter directly into Black-Scholes type derivative pricing formulas. Second, heteroscedasticity must be taken into account for tests of market efficiency to produce reliable test statistics. Third, most asset pricing theories relate expected returns to the joint second order movements of returns, as well as, other stochastic processes and, therefore, efficient estimating and testing must take into account the heteroscedasticity property of returns.

While a large number of studies has found evidence in favor of GARCH effects in stock returns, there is no consensus on the underlying economic explanations for the autoregressive effect on the conditional variance. One of the possible theoretical explanations is the mixture of distributions hypothesis (MDH) put forward by Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983), and more recently Lamoureux and Lastrapes (1990).¹ According to the MDH, a serially correlated mixing variable measuring the rate at which information arrives to the market explains the GARCH effect in the returns. This linkage has been documented, among others, for the US stock market by Lamoureux and Lastrapes (1990), Kim and Kon (1994), Andersen (1996), Gallo and Pacini (2000), and the UK stock market by Omran and McKenzie (2000). In general, the bulk of empirical studies have found evidence that the inclusion of trading volume in GARCH models for returns results in a decrease of the estimated persistence or even causes it to vanish.

¹Alternative explanations are the existence of autocorrelation in the news arrival process (Diebold and Nerlove (1989)), agents' slow adaption to news (Brock and LeBaron (1996)), market microstructure effects (Bollerslev and Domowitz (1991)), and parameter instability (Tsay (1987)).

While a fair amount of empirical evidence on the daily return-volume relationship exists for developed, highly liquid stock markets in industrial countries, to our knowledge the current literature does not provide findings on this issue for Central and Eastern European capital markets.² Hence, the purpose of this paper is to provide initial evidence for one of the developing stock markets in Central and Eastern Europe, namely the Polish stock market.³ Relying on a sample of 20 individual stocks for the period from January 4, 1999 to October 31, 2000, we investigate the issue of whether GARCH effects in daily stock returns capture the effects of temporal dependence in daily trading volume for stocks in the Polish market. We examine the return-volume relationship for Polish stocks to determine whether there are differences between developed markets and one emerging market.

The remainder of this section is organized as follows: Subsection 2.2 outlines the theoretical foundation and the methodology. A description of the data, the empirical results for the Polish stocks, and the findings of existing investigations are contained in Subsection 2.3, while Subsection 2.4 concludes.

2.2 Mixture of Distributions Hypothesis and Econometric Methodology

The MDH (e.g., Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983)) provides one theoretical explanation for the success of GARCH models in finance. According to this model the return over the full trading

²The only empirical evidence on the return-volume relationship for an emerging market is provided by Pyun, Lee, and Nam (2000) who investigate 15 individual shares in the Korean stock market. Furthermore, Brailsford (1996) analyzes the effect of information arrivals on volatility persistence in the Australian stock market and Lange (1999) for the small Vancouver stock exchange.

³The number of studies on the Polish stock market is limited, focusing primarily on market efficiency and volatility. Gordon and Rittenberg (1995) and Rockinger and Urga (2000) provide evidence on market efficiency and market integration, Shields (1997), Scheicher (1999), and Kasch-Haroutounian and Price (2001) apply various univariate and multivariate GARCH models, and Charemza and Majerowska (2000) analyze the risk reduction effect of price limits.

day, R_t , is the sum of $i = 1, 2, \dots, n_t$ intraday equilibrium returns, δ_i

$$R_t = \sum_{i=1}^{n_t} \delta_{it}, \quad (1)$$

where the random variable n_t represents the number of information arrivals to the market on day t and each δ_{it} is independently and identically distributed with mean zero and variance σ^2 , $N(0, \sigma^2)$. Since the number of intraday returns is random, daily returns follow a mixture of normals with n_t as the mixture variable. According to equation (1), the daily returns are generated by a subordinated stochastic process in which R_t is subordinate to δ_i and n_t is the directing process.

If the intraday equilibrium returns δ_i are independently and identically distributed, $N(0, \sigma^2)$, and the number of information arrivals, n_t , is sufficiently large, then conditional on n_t the daily returns can be written as

$$R_t | n_t \sim N(0, \sigma^2 n_t). \quad (2)$$

The daily returns conditional on the number of information arrivals are normally distributed with mean zero and a variance term, which reflects the intensity of information arrivals.

Next, we assume that the number of information arrivals follows an autoregressive process

$$n_t = \alpha + \theta(L)n_{t-1} + u_t, \quad (3)$$

where $\theta(L)$ is a polynomial in the lag operator L and u_t denotes the error term. Defining the conditional variance of the daily return R_t as

$$\sigma_{R_t|n_t}^2 = E(R_t^2 | n_t) = \sigma^2 n_t \quad (4)$$

and substituting the autoregressive process (3) into equation (4) yields

$$\sigma_{R_t|n_t}^2 = \sigma^2 \alpha + \theta(L)\sigma_{R_{t-1}|n_{t-1}}^2 + \sigma^2 u_t. \quad (5)$$

As can be seen from equation (5), the autoregressive structure of the mixing variable is translated into the conditional variance of R_t generating the typical GARCH structure. Time-varying volatility in returns of a stock is

attributed to time-varying news arrivals about the share. The more news arrive about the share, the more investors will interpret the effects of the news differently, and the more investors have an incentive to trade the share as their expectations on future returns diverge. Following this economic argument, GARCH behavior in the stock's return is generated by the serially correlated news arrival process where news arrivals can be proxied by the volume of trade.⁴

Based on the previously outlined theoretical underpinnings, we first empirically analyze the characteristics of the individual trading volume time series. The trading volume serves as a proxy measure of the unobservable amount of information that flows into the market (e.g., Lamoureux and Lastrapes (1990), Andersen (1996)).⁵ The existence of autocorrelation in the volume time series is essential, since the MDH implies that serial correlation in volume causes conditional heteroscedasticity in stock returns. The serial correlation structure of the trading volume is analyzed using autocorrelation coefficients and Ljung-Box statistics (Ljung and Box (1978)). Moreover, augmented Dickey-Fuller statistics (Dickey and Fuller (1981)) are shown testing the null hypothesis of instationarity. The application of a unit root test is important because subsequent tests for the effect of trading volume on the conditional variance may be invalid if the volume time series is instationary.

Second, following Lamoureux and Lastrapes (1990), we investigate the GARCH-cum-volume model for daily returns

$$R_t = \alpha_0 + \alpha_1(L)R_{t-1} + \varepsilon_t \quad (6)$$

and

$$h_t = \beta_0 + \beta_1(L)\varepsilon_{t-1}^2 + \beta_2(L)h_{t-1} + \beta_3V_t, \quad (7)$$

⁴A detailed derivation of the MDH and its statistical foundations is beyond the scope of this paper. For more details see Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983), and Lamoureux and Lastrapes (1990).

⁵Note that we have a broad definition of the number of news arrivals, n_t , in this paper. This variable does not only contain firm-specific news but all information that lead to changes in the stock prices like news about connected firms, changes in other asset prices like exchange rates, and information about other stock markets. Due to this broad definition, n_t is large enough to justify the derivation of the MDH from asymptotic theory.

where $\alpha_1(L)$, $\beta_1(L)$, and $\beta_2(L)$ represent polynomials in the lag operator L , $\varepsilon_t \sim N(0, h_t)$ denotes the unpredictable component of the returns, and V_t represents the trading volume. Equation (6) allows for an autoregression in the mean of returns. Hence, we take into account the possibility of a low order linear autoregressive process in returns of the individual stocks.

Equation (7) models the variance of the unexpected returns as a GARCH process including the daily total volume of stocks traded, V_t , from close at $t - 1$ to close of t as a proxy of information arrivals. First, a restricted version of equation (7) is analyzed by setting the coefficient of the volume of trade to zero, $\beta_3 = 0$. If the parameters of the lag polynomials $\beta_1(L)$ and $\beta_2(L)$ are positive, then volatility shocks persist over time where the degree of persistence is determined by the magnitude of these parameters. Second, the unrestricted version of equation (7) is investigated. If the trading volume is autocorrelated and approximates information arrivals to the stock market, then it can be expected that $\beta_3 > 0$ and the persistence in volatility measured by $\beta_1(L)$ and $\beta_2(L)$ becomes negligible.

2.3 Data, Empirical Results, and Comparison With Available Evidence

To investigate the return-volume relationship we consider daily returns and the trading volume for 20 stocks listed on the Warsaw Stock Exchange (WSE) over the period from January 4, 1999 to October 31, 2000. Return and volume data are provided directly by the WSE. The time series contain only a few missing values, so our empirical scrutiny relies on about 455 observations for each of the 20 shares.

We made several attempts to take into account the price limits imposed on price changes in the Polish stock market (for example, using dummy variables and excluding individual data points) and we finally ended up applying the econometric techniques to the original, unadjusted data set for two reasons. First, in the sample under investigation daily stock returns rarely reached the price limits, so we can expect no major influence on our empirical results. Second, the consequences of price limits on stock price behavior are not

clear. According to the popular view among regulators, price limits serve to reduce stock market volatility. However, several researchers (for example Kyle (1988), Fama (1989), Subrahmanyam (1994), and Kim (2001)) provide both theoretical arguments and empirical findings that price limits not only do not moderate but may even increase stock market volatility.

The returns are defined by the formula

$$R_t = 100 \cdot \ln(P_t/P_{t-1}), \quad (8)$$

where P_t denotes the end of day t closing price of the individual stock. Summary statistics for daily stock returns of individual companies are presented in Table 1. An inspection of Table 1 reveals that the various time series behave in a complex manner. The mean of daily returns ranges between -0.149% and $+0.288\%$ and the standard deviation between 2.166% and 4.3% . Furthermore, all time series show excess kurtosis implying fat tails of the returns distribution.

[Insert Table 1 here]

In addition to the return time series, our data set contains time series on trading volume for the 20 individual stocks. For the period under scrutiny the WSE provides volume data for the auction trading and the continuous trading system separately, which allows to undertake a sensitivity analysis in terms of different volume time series. We provide evidence relying solely on volume data from the continuous trading system, as well as, the aggregate volume from both trading systems.

Tables 2 and 3 contain autocorrelation coefficients of up to five lags, Ljung-Box statistics and Dickey-Fuller test statistics for the individual trading volume time series. When looking at both tables, the autocorrelation coefficients and the Ljung-Box statistics show that all trading volume time series exhibit serial correlation and all Ljung-Box statistics are significant at the 1% level. Hence, for the 20 Polish stocks, the rate of information arrival measured by the trading volume is serially correlated. In addition, the Dickey-Fuller statistics are significant at the 1% level providing evidence in favor of the stationarity of the individual volume time series. The empirical

findings on autocorrelation coefficients, Ljung-Box statistics, and augmented Dickey-Fuller tests are insensitive to the inclusion of auction volume. To receive an impression of the number of news arrivals per day, Tables 2 and 3 also report the average trading volume per day.

[Insert Tables 2 and 3 here]

We now turn to the estimation results of the GARCH models. First, we estimate equation (6) to look for possible autoregressive effects in the mean of daily returns. The results (not presented) show that there is in general no statistically significant autocorrelation structure in the returns. Consequently, we rely on a parsimonious specification of equation (6) setting the α_1 s to zero. Next, a restricted version of equation (7) is estimated excluding the volume of trade, V_t , and applying the usual GARCH(1,1) parameterisation. Table 4 contains the estimated parameters $\hat{\beta}_1$ and $\hat{\beta}_2$ together with corresponding standard errors, as well as the sums $\hat{\beta}_1 + \hat{\beta}_2$ to evaluate the degree of persistence in volatility. Furthermore, we calculate the Bayesian Information Criterion (BIC) to provide the basis for a comparison of the standard GARCH models and the GARCH-cum-volume models. With only one exception, the estimated coefficients $\hat{\beta}_1$ and $\hat{\beta}_2$ are significant at least at the 5% level, and the sums $\hat{\beta}_1 + \hat{\beta}_2$ are in the majority of cases higher than 0.950, which indicates a high degree of persistence in the volatility series of all stocks.

[Insert Table 4 here]

The presented findings on GARCH(1,1) models corresponds to the results in Scheicher (1999) and Shields (1997). For daily returns of three Polish stocks (BSK, BRE, and WBK) in the sample from August 12, 1994 to August 13, 1996, Scheicher finds no first order autocorrelation and statistically significant GARCH coefficients, which imply a high degree of volatility persistence. Kasch-Haroutounian and Price (2001) confirm this finding for the WIG index relying on the sample of daily returns from June 1992 to March 1998. Shields receives a similar result on the daily returns of Tonsil's share prices for the period from April 1991 to March 1995. Furthermore, our

empirical results are comparable to the findings of the studies for developed stock markets in industrial countries. Lamoureux and Lastrapes (1990), Kim and Kon (1994), Gallo and Pacini (2000), and Omran and McKenzie (2000) have found a high degree of volatility persistence for US and UK stocks.

Tables 5 and 6 present the empirical results of the GARCH-cum-volume models. In 30 out of 40 cases the coefficients on the trading volume are statistically significant at the 1% level in both tables and for nearly all these stocks we observe a substantial reduction in the volatility persistence. For the remaining cases the coefficients on trading volume are either statistically significantly different from zero at the 5% level, or statistically insignificant from zero. Including trading volume in the conditional variance equation does not result in a reduction of volatility persistence for these stocks. The sums of the estimated parameters $\hat{\beta}_1$ and $\hat{\beta}_2$ are only slightly lower than the estimated coefficients of the GARCH models without trading volume. Again the empirical findings are in general insensitive to the inclusion of the auction trading volume data. When looking at the BIC measures in Tables 5 and 6, the comparison with the BIC measures in Table 4 reveals that in the majority of cases the BIC measure for the GARCH-cum-volume models is lower. Hence, the inclusion of trading volume in a standard GARCH model results in a reduction of the BICs.⁶

[Insert Tables 5 and 6 here]

Compared with the available evidence on the return-volume relationship for the US and the UK stock markets, the findings on Polish stocks are not unanimously favorable for the testable implications of the MDH. In general, if trading volume is included in the conditional variance equation, the evidence for US and UK stocks analyzed in the papers mentioned above provides a more clear-cut picture in terms of a substantial reduction in volatility persistence for nearly all stocks under investigation. Moreover, the evidence

⁶In addition to the BIC, Akaike's AIC measure was calculated for all models. The empirical results are qualitatively the same. Moreover, the coefficients were estimated using the usual nonnegativity restrictions that require β_i ($i = 0, \dots, 3$) to be positive, in order to prohibit the conditional variance to become negative. After dropping this nonnegativity restriction, some parameters became negative, but the results did not essentially change.

provided in Pyun, Lee, and Nam (2000) for 15 individual shares in the Korean stock market shows for all stocks a statistically significant positive volume effect implying a dramatic reduction of return volatility persistence.

2.4 Conclusion

An appealing theoretical explanation for the presence of GARCH effects in stock returns is based on the hypothesis that daily stock returns are generated by a stochastic mixing variable reflecting the rate of daily information arrivals to the market. According to the so-called mixture of distributions hypothesis (MDH) GARCH behavior in stock returns might capture the autocorrelation properties of trading volume used as an observable measure for the mixing variable. While the return-volume relationship has been broadly confirmed for individual shares of developed stock markets like the US and the UK market, there is no empirical evidence for Central and Eastern European countries. Hence, the purpose of this paper is twofold. First, we examine the validity of the MDH for Polish stocks during the period from January 4, 1999 to October 31, 2000. Second, we determine whether the evidence on the Polish stock market parallels the evidence found for developed stock markets in industrial countries.

Our evidence on individual Polish stocks supports, to a large extent, the implications of the MDH. In most cases the inclusion of trading volume as an explanatory variable in the conditional variance equation results in a substantial reduction of volatility persistence in daily returns. Hence, serially correlated news arrival processes are a source of GARCH effects in the Polish stock market and the implications of the MDH provide to a large extent a valid theoretical explanation for Polish stock market volatility. This finding corresponds to the results found for highly liquid developed stock markets (e.g., Lamoureux and Lastrapes (1990), Kim and Kon (1994), Gallo and Pacini (2000), Omran and McKenzie (2000)) and the Korean emerging stock market (Pyun, Lee, and Nam (2000)). While we have found strong support in favor of the implications of the MDH, for some of the stocks under investigation, however, the inclusion of trading volume has no significant effect on

volatility persistence, which encourages future research on the Polish stock market.

Scope for future research is given by the challenge of investigating alternative proxies for trading activities in the Polish stock market. Using the contemporaneous trading volume as the mixing variable, we assume that trading volume can be considered weakly exogenous with respect to returns. Furthermore, extensions of the standard GARCH model including trading volume can be applied to analyze possible asymmetric effects and effects of stock price regulation. Another useful route to pursue in future research on the Polish stock market, as well as, other stock markets in Central and Eastern Europe is the analysis of modifications to the standard MDH.

2.5 Tables

Table 1: Descriptive statistics of daily stock returns

Stock	Mean (%)	Std. Dev. (%)	Skewness	Excess Kurtosis
AMICA	.116	3.394	.301	4.227
BRE	.035	2.978	.259	1.935
BSK	.002	2.370	.089	1.247
COMPLAND	.197	3.960	.500	2.760
DEBICA	-.088	2.166	.292	1.827
ELBUDOWA	-.149	2.631	.128	1.614
ELEKTRIM	-.023	3.636	.169	3.072
HANDLOWY	.015	2.631	.418	3.061
JELFA	-.014	2.834	.605	4.043
JUTRZENKA	-.003	3.285	.970	4.565
KGHM	.148	3.176	1.019	4.236
MOSTALEX	.034	3.036	.292	1.798
OPTIMUS	.288	4.300	.474	2.047
ORBIS	-.051	2.234	.478	2.170
PBK	.010	2.504	.148	1.842
PEKAO	.000	2.240	.213	2.485
PROKOM	.071	3.761	.612	4.320
ROLIMPEX	-.149	3.185	1.586	8.010
STALEXP	.027	3.153	.214	1.844
TPSA	.054	2.919	.284	1.380

Note: The time series are directly from the WSE and cover the period from January 4, 1999 to October 31, 2000.

Table 2: Autocorrelation and stationarity of volume series
(continuous trading only)

Stock	Lags					ADF	Avg. daily trading volume
	1	2	3	4	5	Lag 5	
AMICA	.736 (37.2)	.592 (50.4)	.573 (50.1)	.515 (63.3)	.495 (67.5)	-.259 (-4.94)	18282
BRE	.686 (57.8)	.627 (70.5)	.564 (79.9)	.554 (95.8)	.559 (108.9)	-.282 (-5.55)	18565
BSK	.557 (51.8)	.531 (61.8)	.473 (65.6)	.443 (77.8)	.466 (78.1)	-.450 (-6.34)	3869
COMPLAND	.793 (54.9)	.746 (64.7)	.650 (83.6)	.599 (95.9)	.567 (106.9)	-.278 (-5.93)	21259
DĘBICA	.749 (94.7)	.632 (131.7)	.602 (145.1)	.588 (151.3)	.564 (165.8)	-.413 (-6.47)	27179
ELBUDOWA	.784 (52.2)	.676 (74.4)	.632 (96.2)	.610 (108.1)	.635 (108.7)	-.259 (-4.92)	21074
ELEKTRIM	.801 (100.4)	.744 (131.5)	.739 (139.2)	.736 (144.3)	.712 (153.6)	-.198 (-4.28)	267086
HANDLOWY	.712 (37.3)	.635 (44.3)	.562 (61.0)	.530 (64.9)	.521 (65.1)	-.293 (-5.73)	76788
JELFA	.815 (69.8)	.748 (82.3)	.714 (89.7)	.719 (91.6)	.658 (104.7)	-.193 (-4.76)	20800
JUTRZENKA	.800 (54.1)	.664 (77.7)	.608 (90.2)	.590 (99.4)	.552 (112.9)	-.256 (-5.43)	38765
KGHM	.720 (30.9)	.608 (51.9)	.588 (59.5)	.586 (63.4)	.557 (69.1)	-.288 (-5.56)	112628
MOSTALEX	.800 (62.4)	.719 (72.2)	.663 (89.3)	.644 (96.4)	.634 (99.7)	-.234 (-4.93)	244844
OPTIMUS	.836 (98.1)	.785 (106.6)	.721 (113.6)	.685 (120.6)	.690 (120.9)	-.207 (-4.76)	42434
ORBIS	.705 (47.5)	.648 (74.9)	.610 (82.5)	.603 (85.6)	.561 (98.7)	-.279 (-4.88)	40567
PBK	.747 (78.7)	.683 (93.9)	.693 (99.8)	.671 (102.9)	.672 (104.0)	-.222 (-4.43)	15920
PEKAO	.515 (75.9)	.514 (96.0)	.455 (108.7)	.428 (109.1)	.434 (121.1)	-.578 (-7.13)	35915
PROKOM	.768 (55.8)	.746 (59.2)	.686 (62.7)	.663 (66.1)	.630 (69.0)	-.188 (-4.47)	20435
ROLIMPEX	.669 (51.3)	.566 (93.5)	.524 (124.3)	.504 (141.1)	.481 (149.4)	-.534 (-7.44)	52332
STALEXP	.839 (114.8)	.767 (133.7)	.724 (150.2)	.713 (152.9)	.720 (155.6)	-.213 (-4.41)	53815
TPSA	.752 (123.2)	.729 (133.9)	.712 (135.3)	.711 (138.2)	.666 (145.7)	-.346 (-5.64)	228282

Note: Autocorrelation coefficients contain up to five lags and Ljung-Box (1978) statistics are shown in parentheses. The augmented Dickey-Fuller (1981) regressions contain a constant term and their augmentations are determined according to the Schwert (1989) formula. The ADF t-statistics are shown in parentheses below the coefficients. All statistics are significant at the 1% level.

Table 3: Autocorrelation and stationarity of volume series
(auction and continuous trading)

Stock	Lags					ADF	Trading
	1	2	3	4	5	Lag 5	Volume
AMICA	.858 (69.3)	.808 (70.5)	.756 (76.4)	.735 (78.1)	.705 (81.7)	-.128 (-3.56)	40908
BRE	.826 (130.7)	.772 (149.0)	.733 (164.5)	.739 (180.1)	.760 (183.2)	-.289 (-5.15)	47410
BSK	.706 (67.2)	.636 (82.7)	.645 (83.4)	.598 (88.1)	.604 (95.6)	-.287 (-4.97)	13659
COMPLAND	.871 (93.3)	.815 (102.7)	.775 (106.9)	.739 (119.1)	.698 (132.7)	-.217 (-5.33)	42791
DEBICA	.856 (124.2)	.742 (179.3)	.716 (193.2)	.694 (207.7)	.686 (215.1)	-.354 (-6.57)	55243
ELBUDOWA	.833 (96.1)	.751 (131.0)	.717 (152.4)	.705 (166.1)	.708 (166.7)	-.267 (-5.04)	40990
ELEKTRIM	.882 (152.2)	.843 (170.5)	.840 (173.7)	.825 (179.0)	.812 (186.9)	-.190 (-4.49)	486584
HANDLOWY	.789 (54.6)	.722 (70.6)	.658 (97.3)	.651 (98.3)	.649 (100.7)	-.203 (-4.43)	145531
JELFA	.887 (105.3)	.843 (112.1)	.818 (116.5)	.791 (123.2)	.769 (130.1)	-.142 (-4.24)	42322
JUTRZENKA	.856 (85.3)	.771 (101.0)	.733 (115.7)	.704 (125.1)	.693 (131.5)	-.186 (-4.59)	20065
KGHM	.821 (48.4)	.724 (68.9)	.686 (89.4)	.676 (97.0)	.654 (107.6)	-.289 (-5.95)	262561
MOSTALEX	.790 (87.5)	.741 (107.3)	.749 (108.6)	.737 (110.5)	.676 (135.1)	-.268 (-5.40)	200653
OPTIMUS	.852 (117.6)	.800 (128.4)	.761 (136.0)	.730 (142.9)	.717 (148.4)	-.213 (-4.80)	78494
ORBIS	.814 (102.4)	.762 (136.7)	.749 (139.2)	.739 (140.2)	.699 (150.3)	-.262 (-4.95)	98568
PBK	.849 (111.4)	.798 (128.5)	.772 (137.1)	.776 (139.6)	.791 (139.8)	-.171 (-3.93)	43064
PEKAO	.676 (83.2)	.616 (120.2)	.573 (138.7)	.571 (149.1)	.553 (178.0)	-.501 (-6.89)	94550
PROKOM	.843 (74.6)	.801 (80.7)	.773 (86.0)	.755 (89.9)	.740 (92.2)	-.145 (-3.80)	37964
ROLIMPEX	.689 (81.86)	.620 (114.9)	.571 (145.3)	.564 (158.5)	.556 (160.7)	-.492 (-6.93)	93390
STALEXP	.878 (142.8)	.829 (155.6)	.781 (179.0)	.769 (185.8)	.760 (189.0)	-.209 (-4.64)	93920
TPSA	.849 (134.6)	.836 (143.5)	.813 (148.3)	.818 (148.6)	.778 (149.4)	-.233 (-4.77)	466896

Note: see comments in Table 2.

Table 4: Results of GARCH(1,1) Models

Stock	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_1 + \hat{\beta}_2$	BIC
AMICA	.867 ^a (.022)	.131 ^a (.025)	.998	2353.04
BRE	.934 ^a (.024)	.050 ^b (.020)	.984	2373.13
BSK	.802 ^a (.064)	.114 ^a (.004)	.916	2142.12
COMPLAND	.827 ^a (.056)	.126 ^b (.043)	.953	2587.65
DĘBICA	.458 ^a (.110)	.243 ^a (.074)	.701	2056.79
ELBUDOWA	.592 (.317)	.112 (.078)	.704	2261.67
ELEKTRIM	.926 ^a (.022)	.056 ^a (.018)	.982	2524.95
HANDLOWY	.757 ^a (.054)	.207 ^a (.055)	.964	2181.71
JELFA	.883 ^a (.020)	.106 ^a (.024)	.989	2215.17
JUTRZENKA	.903 ^a (.026)	.084 ^a (.025)	.987	2390.40
KGHM	.825 ^a (.043)	.155 ^a (.041)	.980	2376.00
MOSTALEX	.877 ^a (.036)	.084 ^a (.027)	.961	2360.58
OPTIMUS	.926 ^a (.017)	.064 ^a (.016)	.990	2614.36
ORBIS	.664 ^a (.136)	.111 ^b (.049)	.775	2112.42
PBK	.787 ^a (.054)	.133 ^a (.041)	.920	2174.81
PEKAO	.782 ^a (.084)	.129 ^b (.047)	.911	2075.58
PROKOM	.883 ^a (.032)	.106 ^a (.030)	.989	2446.38
ROLIMPEX	.932 ^a (.025)	.027 ^b (.014)	.959	2439.96
STALEXP	.482 ^a (.150)	.188 ^b (.072)	.670	2413.93
TPSA	.913 ^a (.035)	.058 ^b (.021)	.971	2340.04

Note: $\hat{\beta}_1$ and $\hat{\beta}_2$ represent the estimated parameters of the model $h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}$. Standard errors are in parentheses and BIC denotes the Bayesian information criterion. The time series are directly from WSE and cover the period from January 4, 1999 to October 31, 2000. ^a and ^b denote statistically significant parameters at the 1% and 5% level, respectively.

Table 5: Results of GARCH(1,1)-Cum-Volume Models
(continuous trading only)

Stock	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3 \times 10,000$	$\hat{\beta}_1 + \hat{\beta}_2$	BIC
AMICA	.024 (.074)	.149 ^b (.063)	4.813 ^a (.718)	.173	2251.92
BRE	.000 (.000)	.119 ^b (.051)	2.880 ^a (.578)	.119	2340.85
BSK	.509 (.270)	.154 ^a (.050)	2.309 (2.085)	.663	2143.98
COMPLAND	.000 (.000)	.107 (.057)	5.776 ^a (.861)	.107	2536.81
DEBICA	.105 (.107)	.166 ^b (.062)	1.097 ^a (.223)	.271	1976.30
ELBUDOWA	.030 (.074)	.049 (.057)	2.425 ^a (.412)	.079	2211.45
ELEKTRIM	.000 (.000)	.038 (.043)	.342 ^a (.052)	.038	2475.77
HANDLOWY	.764 ^a (.062)	.186 ^a (.052)	.022 (.018)	.950	2185.20
JELFA	.000 (.000)	.066 (.052)	3.418 ^a (.420)	.066	2132.81
JUTRZENKA	.000 (.000)	.183 ^a (.059)	4.915 ^a (.537)	.183	2265.56
KGHM	.842 ^a (.042)	.131 ^a (.038)	.020 (.013)	.973	2379.32
MOSTALEX	.000 (.000)	.035 (.041)	.283 ^a (.034)	.035	2277.89
OPTIMUS	.000 (.000)	.008 (.030)	4.631 ^a (.345)	.008	2478.92
ORBIS	.428 ^a (.112)	.156 ^a (.051)	.252 ^b (.093)	.584	2105.18
PBK	.271 ^a (.085)	.192 (.560)	2.678 ^a (.545)	.463	2114.74
PEKAO	.768 ^a (.092)	.139 ^b (.053)	.028 (.043)	.907	2081.29
PROKOM	.000 (.000)	.021 (.029)	6.950 ^a (.771)	.021	2384.20
ROLIMPEX	.000 (.000)	.044 (.026)	1.944 ^a (.187)	.044	2254.40
STALEXP	.000 (.000)	.001 (.042)	1.964 ^a (.167)	.001	2245.52
TPSA	.000 (.000)	.076 (.042)	.405 ^a (.045)	.076	2271.39

Note: $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ represent the estimated parameters of the model $h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 V_t$ with V as trading volume only from continuous trading. Standard errors are in parentheses and BIC denotes the Bayesian information criterion. The time series are directly from WSE and cover the period from January 4, 1999 to October 31, 2000. ^a and ^b denote statistically significant parameters at the 1% and 5% level, respectively.

Table 6: Results of GARCH(1,1)-Cum-Volume Models
(auction and continuous trading)

Stock	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3 \times 10,000$	$\hat{\beta}_1 + \hat{\beta}_2$	BIC
AMICA	.000 (.148)	.139 ^b (.058)	2.502 ^a (.278)	.139	2288.58
BRE	.868 ^a (.073)	.049 ^b (.023)	.130 (.085)	.917	2371.62
BSK	.832 ^a (.062)	.101 ^b (.039)	-.090 (.076)	.933	2147.33
COMPLAND	.311 ^b (.116)	.147 ^b (.063)	2.065 ^a (.549)	.458	2550.48
DEBICA	.174 ^b (.081)	.193 ^a (.064)	.496 ^a (.093)	.367	2001.94
ELBUDOWA	.000 (.000)	.031 (.057)	1.744 ^a (.273)	.031	2207.99
ELEKTRIM	.382 ^a (.108)	.071 (.046)	.153 ^a (.032)	.453	2484.34
HANDLOWY	.754 ^a (.063)	.184 ^a (.053)	.015 (.012)	.938	2185.21
JELFA	.000 (.000)	.074 (.053)	1.674 ^a (.189)	.074	2161.40
JUTRZENKA	.000 (.000)	.163 ^a (.054)	2.727 ^a (.289)	.163	2292.20
KGHM	.136 (.151)	.218 ^b (.073)	.189 ^a (.054)	.354	2378.25
MOSTALEX	.338 ^a (.102)	.144 ^b (.061)	.221 ^a (.050)	.482	2325.15
OPTIMUS	.000 (.000)	.073 (.053)	2.353 ^a (.196)	.073	2529.12
ORBIS	.431 ^a (.104)	.151 ^a (.049)	.174 ^a (.053)	.582	2099.91
PBK	.393 ^a (.108)	.180 ^b (.062)	.824 ^a (.216)	.573	2137.85
PEKAO	.779 ^a (.092)	.128 ^b (.052)	-.007 (.042)	.907	2081.60
PROKOM	.865 ^a (.043)	.046 (.028)	.318 ^b (.132)	.911	2431.38
ROLIMPEX	.000 (.000)	.022 (.031)	1.117 ^a (.082)	.022	2268.49
STALEXP	.000 (.000)	.000 (.000)	1.111 ^a (.074)	.000	2275.62
TPSA	.000 (.000)	.065 (.046)	.174 ^a (.030)	.065	2322.94

Note: $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ represent the estimated parameters of the model $h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1} + \beta_3 V_t$ with V as trading volume including auction trading. Standard errors are in parentheses and BIC denotes the Bayesian information criterion. The time series are directly from WSE and cover the period from January 4, 1999 to October 31, 2000. ^a and ^b denote statistically significant parameters at the 1% and 5% level, respectively.

3 Introducing Continuous Trading in an Emerging Market: The Case of Poland

3.1 Introduction

A disputed issue in financial economics is the choice of the best trading system for stocks. There exists a considerable amount of research, both empirical and theoretical, on the relative advantages and disadvantages of different trading systems. This debate also preoccupies practitioners of stock exchanges all over the world where the microstructure changes over time. Stock exchanges are continuously trying to improve market quality in order to attract traders.

In general, there are two kinds of trading systems. Trading can be organized as a call auction, where orders are batched together and the market clears at discrete points in time. In an auction submitted buy and sell orders form demand and supply schedules and the intersection of these curves determines the market clearing price at which all trades are executed. Alternatively, there exists continuous trading systems, where limit orders are placed in an order book and await execution (order-driven system) or where a market maker quotes bid and ask prices at which he is willing to buy and sell the stock (quote-driven system).

In principle, a continuous trading system provides immediate execution of trades. In a call auction the trader has to wait until the next market clearing. Moreover, the price at which all trades are executed in a call auction is not known when investors submit their orders, so the determination of the auction price provides new information to them. If they want to adjust their portfolios after the announcement of the auction price they have to wait until the next market clearing.

These problems do not arise in a continuous trading system. Best bid and ask quotes in the order book or the quotes of a market maker are usually known to investors and portfolio adjustment can take place immediately. If, however, the liquidity of a stock is low, the costs of immediate execution of

a trade may be large due to larger bid-ask spreads and larger price impacts of trades. Trading illiquid stocks in call auctions and thereby concentrating liquidity at certain points in time may mitigate this problem.

A number of theoretical models support the view that it is optimal to trade highly liquid stocks in a continuous trading system and to batch order illiquid stocks in call auctions (Garbade and Silber (1979), Mendelson (1985)). Another argument in favor of an auction trading system is the problem of asymmetric information in the market. A call auction was found to be a more robust trading mechanism in the case of a large number of informed traders in the market (Madhavan (1992)). Moreover, uninformed traders suffer smaller losses in an auction trading system compared to a continuous trading mechanism (Kyle (1985), Pagano and Roell (1996)).

Empirical studies, however, focusing on the effects of the introduction of continuous variable price trading and the transfers of stocks from a call auction to a continuous trading system generally report the inferiority of the auction mechanism. Studies of changes in the microstructure of the Israeli and the French stock markets⁷ report higher liquidity and price efficiency as well as a permanent price increase of 5-6% following the introduction of a continuous trading system. Stocks that were dropped from continuous trading mirror these reactions.

The available empirical evidence focuses exclusively on the stock markets in Israel and France. These markets are relatively liquid, have a long history, and attract a considerable number of internationally experienced investors. No rigorous evidence of the impact of the introduction of continuous trading, however, is available from smaller emerging markets. Therefore, we ask the question whether continuous trading is also preferable on the young central eastern European stock market of Poland.

An investigation of this question can yield interesting insights. If we find positive effects of the introduction of continuous trading on the Polish stock market, we will have additional evidence on the benefits of continuous trading from a central eastern European market. If we do not find positive

⁷See Amihud, Mendelson, and Lauterbach (1997), Lauterbach (2001), Muscarella and Piwowar (2001), and Kalay, Wei, and Wohl (2002).

effects of stock liquidity and prices upon transfer to the continuous trading system, an analysis of the major differences between the Polish and other markets (that successfully introduced continuous trading) may enhance our understanding of the conditions for the success of different trading systems and outline directions for future research.

We analyze the transfers of 68 stocks from a daily call auction to a semi-continuous trading segment on the Warsaw Stock Exchange (WSE). After the introduction of a continuous trading system in July 1996, the call auction was followed by continuous trading for the most liquid stocks on the exchange. The continuous trading system attracted only about 18% of the stocks' total trading volume on average and the number of transactions per day was low.

Contrary to previous studies, we do not find that liquidity measures improve after stock transfers to continuous trading. The changes in relative trading volume and liquidity ratios are negative for the majority of stocks. Moreover, price efficiency decreases in the continuous trading system. Relative return dispersions across stocks increase and the majority of stocks display a higher residual variance of returns after transfer to continuous trading. Upon transfers, cumulative abnormal returns amount to 4.5%, but this price effect is not permanent and is completely reversed after 30 trading days following the transfers.

We also discuss several possible reasons for our results. One explanation is that the Polish stock market was not liquid enough and did not need multiple trading rounds during the trading day. We find, however, that the least liquid stocks profitted most from the introduction of continuous trading. A second explanation focuses on the investor structure of the WSE. Since small and unexperienced local investors dominated the Polish stock market, continuous trading may have been less beneficial compared to other markets with a higher degree of institutional traders. E.g., the restrictive minimum trade size requirements in the continuous trading system may have excluded small traders. Finally, we discuss a possible 'non-liquidity' explanation for the introduction of continuous trading in Poland.

The remainder of this section is organized as follows. Subsection 3.2 de-

scribes both the call auction and the continuous trading systems of the WSE in detail. The methodology used in this paper is reviewed in Subsection 3.3. Subsection 3.4 presents the empirical results, while we discuss our empirical results in 3.5. Subsection 3.6 concludes.

3.2 Trading Systems on the Warsaw Stock Exchange

This section describes the trading mechanisms and the regulations of the WSE in both the auction system and the continuous trading system. These systems were in place until November 17, 2000, when a new trading system called "WARSET" was launched. After the introduction of WARSET each stock was only traded in one segment: either in one call auction per day, two auctions per day, or in the continuous trading system. Before WARSET, however, all stocks were traded on the WSE in a call auction once per day. Additionally, the more liquid stocks were also traded in a continuous trading system. More liquid stocks were gradually introduced to this new continuous trading system where trading took place after the daily auction. We will now describe these two trading systems in more detail.

3.2.1 Call Auction

Trading started on the WSE in 1991 with one call auction once per week. The number of trading days per week gradually increased and by October 1994 a call auction took place every day. Buy and sell orders were submitted to the exchange prior to the auction. Then, the order book was closed and a specialist determined the price that maximized trading volume, minimized the difference between demand and supply, and minimized price changes relative to the previous session. Moreover, this price was subject to a price variation limit and could not vary by more than 10% in either direction compared to the price of the previous auction.

When there was an imbalance in the market the specialist determined the size of the imbalance and could intervene by trading on his own account or attracting offsetting orders from market participants. After the market had been balanced, the auction price was announced. In the case the market

remained unbalanced, a non-transactional price was determined at the upper or lower price limit.

After the determination of the auction price, investors could submit additional buy or sell orders at that price and post-auction trading took place. In the post-auction trading period, no price changes occurred and all trades were executed at the auction price. The timetable of the single price auction is displayed in Table 7.

[Insert Table 7 here]

3.2.2 Continuous Trading

In July 1996, a fully computerized, order-driven continuous trading mechanism was introduced on the WSE. Following the launch of the continuous trading system, the most liquid stocks were gradually transferred to this system. All stocks that were listed in the continuous trading system were also traded in the call auction. Whereas only five stocks were traded using this mechanism at its inception in July 1996, by the beginning of 2000 the system included around one hundred stocks.

Continuous trading started with an opening auction. Prior to this auction, investors were only allowed to submit limit orders to the order book. In the auction, an opening price was determined using the procedure of the call auction system. As in the auction system, a price variation limit applied to the opening price of the continuous trading system. The price was allowed to vary by not more than 5% compared to the last available price.

Contrary to the call auction, no specialist intervention took place in the continuous trading system. During continuous trading, traders could submit market and limit orders to the electronic open limit order book. A trade was executed when two matching orders met. Orders were prioritized on the book in terms of price, then time. During continuous trading stock prices should not move by more than 10% compared to the opening price.

In the continuous trading system, only round lots of a stock could be traded. The lot size was determined for every stock on an individual basis

and was equal to an amount of several thousand zlotys.⁸ The timetable of the continuous trading system is also shown in Table 7.

3.3 Data and Methodology

We investigate the effects of a change in trading systems on the WSE for 68 stocks in the period between July 1996, when the continuous trading system was launched, and October 1999.⁹ Since the transfer of stocks to the continuous trading system is a pure microstructure event exogenous to all firms¹⁰ that did not change their fundamentals, any change in the characteristics of transferred stocks can be interpreted as a direct consequence of this transfer.

3.3.1 Data

During the period under consideration, stocks were transferred to continuous trading in 16 batches, where the mean (median) number of stocks per batch was 4.6 (5). Information on announcement and transfer dates were provided by the WSE for all transfers since July 1997. Information on the transfers prior to this date were obtained from the archive of the Polish daily newspaper "Rzeczpospolita". For one batch, we were not able to determine the announcement day of the transfer and therefore dropped the corresponding five stocks from our sample. We denote the announcement and transfer days A and T for every batch, respectively.

For the stocks in our sample, the WSE provided data on prices and trading volumes in both trading systems. In the pre-event period, returns are calculated as the logarithmic price difference between the single auction prices of two consecutive trading days. Daily trading volume is the turnover of the

⁸At the start of the continuous trading system in July 1996, the Polish Zloty(PLN)-U.S.Dollar(USD) exchange rate was 2.73 PLN/USD. On the day of the last transfer in our sample in October 1999 it was 4.08 PLN/USD.

⁹We do not consider the stocks transferred after October 1999 to ensure that the post-event window is not contaminated by the structural break caused by the introduction of the new trading system WARSET in November 2000.

¹⁰The Executive Board of the WSE decided which stocks were to be transferred to the continuous trading system.

auction and the post-auction trading at the single price measured in zlotys.¹¹

In the post-event period, returns are computed as the difference between the logarithms of the last price observations of a stock on two consecutive trading days. We choose the price of the last transaction in this system as the closing price. If stocks are not traded in the continuous trading system on a particular day, we use the auction price established earlier that day as its final price observation. All stock returns are adjusted for stock splits. Daily trading volume in the post-event period is the sum of turnover (in zlotys) in the call auction, in post-auction trading, and in the continuous trading system.

3.3.2 Market Liquidity

First, we investigate the consequences of the new trading system for market liquidity using the methodology of Amihud, Mendelson, and Lauterbach (1997). Liquidity is measured by a stock's trading frequency and by the depth of the market for that stock. There exist, of course, other measures of liquidity such as the bid-ask spread, but intraday data from this time period are not available to us.

The trading frequency of a stock is expressed by its relative trading volume. The relative instead of the absolute trading volume is used in order to account for a possible market-wide trend in trading volume. The liquidity effect of the transfer of a stock to the continuous trading system is its change in relative trading volume from the pre-event to the post-event period. An increase in the relative trading volume of a stock is typically associated with an increase in the stock's liquidity.¹² The pre-event period comprises 120 trading days, from day 150 to day 31 prior to the transfer announcement. Since data on individual stock returns and volume is available since January 1996, the pre-event period for the stocks in the first batch starts on day $A - 121$. The post-event period starts 31 days after the transfer and covers

¹¹Our data do not allow us to distinguish between the volumes of auction and post-auction trading. According to WSE (1999), the share of post-auction trading in total trading volume in the auction system was around 28% in 1998.

¹²See Amihud and Mendelson (1986).

120 trading days until $T + 150$.

The change in relative trading volume of stock j is measured as

$$DVOL_j = \log(V_j/VM)_{AFTER} - \log(V_j/VM)_{BEFORE}, \quad (9)$$

where V_j and VM are the average daily trading volume of stock j and of the market, respectively. Market volume is calculated as aggregated trading volume of all stocks ignoring those stocks that were newly listed or delisted during the event period.¹³ The indices *AFTER* and *BEFORE* denote the periods $T + 31$ to $T + 150$ and $A - 150$ to $A - 31$, respectively.

Market depth is measured using the liquidity ratio (LR), the so-called Amivest ratio, defined as

$$LR_j = \sum_t V_{jt} / \sum_t |R_{jt}|,$$

where V_{jt} and R_{jt} are the trading volume and the return of stock j at day t , respectively. The liquidity ratio measures the trading volume that is necessary to move stock prices by one percentage point. A higher value of LR_j , therefore, can be interpreted as higher depth of the market for stock j . The change in the liquidity ratio is defined as

$$DLR_j = \log(LR_{j,AFTER}/LR_{j,BEFORE}). \quad (10)$$

The subscripts are the same as in equation (9).

3.3.3 Price Efficiency

In the studies of Amihud, Mendelson, and Lauterbach (1997) and Muscarella and Piwowar (2001), the introduction of a continuous trading segment is reported to increase price efficiency. The reason for this is that

¹³The number of stocks listed on the WSE increased dramatically in the period under consideration. While there were 65 stocks listed at the beginning of 1996, the number rose to 83, 143, 198, and 221 at the beginning of the years 1997-2000, respectively. Since the period of our investigation starts 150 days prior to a transfer announcement and ends 150 days after the transfer is completed, the number of listings and the corresponding market share of newly listed stocks in this period is of considerable magnitude. By excluding newly listed stocks from the calculation of market volume, we ensure that the growing number of stocks does not impact our relative volume measure.

continuous trading enables investors to react to new information and to adjust their portfolios immediately. Therefore, new information is incorporated into prices quickly and prices are closer to their true values.

One measure of price efficiency is the relative return dispersion (RRD), which is defined as the cross-sectional average of the variances of the residuals of a market model estimated separately for all stocks in the sample. The market-wide WIG stock index was used as a proxy for the market index. The RRD of event day s is defined as

$$RRD_s = (1/J) \sum_{j=1}^J \varepsilon_{js}^2, \quad (11)$$

where ε_{js} is the day s residual of a market model estimated for stock j and J is the number of stocks in the sample. A lower value of RRD_s corresponds to lower pricing errors with respect to the market model and therefore to a higher degree of price efficiency in the stock market.

To ensure that our results are not driven by the assumption about the return-generating process, we applied several robustness checks. We repeated all analyses using the returns on the WIG20 index instead of the market-wide WIG index as a proxy for the market returns. The WIG20 includes the twenty largest stocks in terms of turnover value and market capitalization. All results were the same, which is not surprising given the high correlation between both indices. Since the twenty large stocks of the WIG 20 index also dominate the WIG index, correlation coefficients between both indices are close to unity. Moreover, to account for infrequent trading, we also estimated the market model using the beta estimates of Scholes and Williams (1977), as well as the estimates of Dimson (1979). Again, all results were virtually the same.

A measure of the relative price efficiency of a particular stock is the variance of the stock's market model residuals. This measure is calculated separately for both the pre-event and the post-event periods and is defined as

$$VARE_j = (1/120) \cdot \sum_{s=1}^{120} \varepsilon_{js}^2,$$

where the residual variance of stock j , $VARE_j$, is calculated over both the 120 trading days of the pre-event and post-event periods. A measure of the change in price efficiency of stock j is then

$$DVARE_j = \log(VARE_{j,AFTER}/VARE_{j,BEFORE}). \quad (12)$$

Again, the subscripts describe the same periods as explained in equation (9). A positive value of $DVARE_j$ indicates an increase in price variance of stock j in the post-event period and therefore a decrease in price efficiency.

3.3.4 Price Effects of the Transfers

We calculate cumulative abnormal returns (CARs) for those stocks that were introduced to the continuous trading segment. The event window ranges from day $A - 10$ to $T + 30$ where A is the day of the announcement of the transfer and T is the event day. The event period starts 10 days prior to the announcements of the transfers to account for possible information leakages. Moreover, because the transfer decisions of the Executive Board of the WSE were based on parameters like market capitalization and trading volume that were known to market participants, the choice of stocks for transfer was not a complete surprise and investors may have been able to forecast them to some extent. We choose a 30-days period after the transfer to investigate whether a possible price effect is permanent or transitory.

We estimate risk-adjusted returns for every transferred stock using the simple market regression model¹⁴

$$R_{js} = \alpha_j + \beta_j R_{Ms} + \varepsilon_{js},$$

where R_{js} is the return of stock j at day s , R_{Ms} is the return on the broad stock index WIG at day s , α_j and β_j are the parameters of the market model, and ε_{js} is the residual. The market model is estimated over the days $T + 31$ to $T + 150$. We use post-event data for regression analysis in order to avoid a possible selection bias. The decision of the WSE regarding which stocks

¹⁴Note that the assumption of a market model as the return-generating process does not necessarily imply the validity of the CAPM on the market or the existence of a risk-free rate of interest.

to transfer is based on characteristics such as high trading volume and high market capitalization, so these stocks may have performed especially well in the pre-event period. The use of pre-event data could then bias the results.

Abnormal returns are calculated for every day in the event period as

$$AR_{js} = R_{js} - \alpha_j - \beta_j R_{Ms},$$

where AR_{js} is the abnormal return of stock j at event day s ($s = A - 10, \dots, T + 30$) and α_j and β_j are the estimated parameters from the market model.¹⁵

CARs are then calculated for every stock j as

$$CAR_{js} = \sum_{t=A-10}^s AR_{jt}$$

with $s = A - 10, \dots, T + 30$. The CAR of event day s is the average CAR over all stocks.

To calculate the t -statistics for the average CAR on event day s the usual event study methodology yields potentially biased results. Since the WSE transferred stocks in batches to the continuous trading segment, the returns of stocks from the same batch may not be independent. We, therefore, construct portfolios from all stocks of the same batch. Portfolio CARs are calculated as equally weighted CARs of all stocks of the same batch. The t -statistic on day s is then calculated from the weighted average of portfolio t -statistics with the number of stocks in the portfolios as the weighting factors.

3.4 Empirical Results

3.4.1 Use of the Continuous Trading System

First, some descriptive statistics of the continuous trading system are presented. An important characteristic of this new system was that trades occurred only infrequently. Although the system provided the possibility of continuous trading, trading in the new system did not take place continuously. The average number of trades per stock and day for the 68 stocks of

¹⁵Again, we try different specifications of the return-generating process to make sure that our results are robust to the model specification.

our sample was 14.13 in the post-event period from $T + 31$ to $T + 150$ and the median was only 7.36. On the other hand, the average number of days in which no trade in a particular stock took place was 27.38 (median 17.5) in this period covering 120 days. These figures do not show that these stocks were illiquid in general, but rather that most of their volume was generated in the auction system. On average, the volume traded in the continuous trading system amounted to only 18.3% (median 18.3%) of the total trading volume.

3.4.2 Market Liquidity

We analyze the effect of the introduction of the new trading system on market liquidity by calculating the trading frequency measure $DVOL_j$ defined in equation (9) for all stocks in the sample. This measure is positive for only 29 stocks and it is negative for 39. The cross-sectional average of the relative volume change is negative and marginally significant with the mean relative trading volume change of -0.187 (t-value -1.72) and the median -0.224. The calculation of the average relative volume of each event day yields a small and insignificant increase in relative trading volume in the post-event period as shown in Figure 1.

[Insert Figure 1 here]

Furthermore, we use the changes in the Amivest ratios, DLR , as defined in equation (10) to investigate the effect of the new trading system on the depth of the market. The results are qualitatively very similar to the measure of trading frequency. Market depth increases for 31 stocks while it decreases for 36. The cross-sectional average of the changes in liquidity ratios indicates a decrease of market depth with a mean value of -0.185 (t-value -1.60) and a median of -0.129.

The results indicate that the introduction of a continuous trading system had a slightly negative influence on liquidity of the transferred stocks. These findings contradict the results of studies on other stock markets that find a significant increase in liquidity for those stocks that were transferred from a call auction to a continuous trading system.

3.4.3 Price Efficiency

We compute the RRD as a measure of price efficiency as defined in equation (11). We dropped one stock due to the large changes in its daily prices.¹⁶ The cross-sectional averages of the residual variances in the pre-event and post-event periods are shown in Figure 2.

[Insert Figure 2 here]

As can be seen from the figure, price variance increases after the introduction of continuous variable price trading. The mean value across days $A - 150$ to $A - 31$ is 7.09, while the average residual variance in the period $T + 31$ to $T + 150$ equals 10.81. This difference is significantly positive with a corresponding t -value of 4.39.

To investigate the effects of the introduction of the new trading system on particular stocks, we compute the change in price efficiency defined in equation (12) for all remaining stocks in the sample. This measure is positive for 43 stocks (indicating higher post-event residual variances) and negative for only 24 stocks. The cross-sectional mean of the efficiency measure $DVARE_j$ is 0.401 (t -value 4.21) and the median is 0.512. These results support the finding of higher relative return dispersions from Figure 2.

The decrease in price efficiency due to the introduction of a continuous trading segment contradicts the findings of other studies. Obviously, the infrequent use of the continuous trading system leads to greater price variation. Since trading in this system only takes place in a few transactions per day, the random noise component in continuous trading prices is larger and prices do not adjust to their true values quickly. Prices at which trades are executed in the continuous trading system are then, to some extent, random and price efficiency decreases.

¹⁶The price of this stock fell below one zloty and the large percentage price changes made it impossible to reliably estimate a market model.

3.4.4 Price Effects

We calculate cumulative abnormal returns (CARs) for each stock over the period $A-10$ to $T+30$.¹⁷ The CAR associated with day s is calculated as the cross-sectional average of the cumulative abnormal returns of all sample stocks on that day. The return behavior is shown in Figure 3.

[Insert Figure 3 here]

Figure 3 indicates that the announcement of a stock transfer to the continuous trading segment results in a CAR of about 4.5% until the transfer finally takes place. This is in line with the findings of the other studies mentioned above. Contrary to these studies, however, the price increase of transferred stocks on the WSE is not permanent, but the positive response disappears within 30 days following the transfers. Moreover, the t -values indicate that only the price reactions in the period from the announcement day until day 3 after the transfer are significantly positive, as can be seen from Table 8.¹⁸

[Insert Table 8 here]

An initially positive price response to the transfer announcement and the actual transfer of stocks to the continuous trading system is only transitory and quickly reversed.¹⁹

The findings of no permanent price reaction and no significant change in the measures of market quality are consistent with one another. The initial positive price reaction may be caused by uncertainty among investors as to whether or not the introduction of a stock to continuous trading leads to an improvement in liquidity and price efficiency. Although this effect is insignificant on average, the variation within the sample is of considerable magnitude. An investor, however, does not know, a priori, if a particular

¹⁷Again, we dropped one stock due to its large price fluctuations.

¹⁸The significantly positive CARs on days $A-7$ and $A-6$ are probably a result of random price changes and not caused by the transfer event.

¹⁹Again, using the WIG20 index instead of the WIG index does not impact our findings. Moreover, results from Scholes-Williams and Dimson beta estimates are very similar to those presented in the paper.

stock will perform well in the continuous trading system. The corresponding uncertainty may be the reason for the observed price reaction.

3.5 Discussion

The results presented in the previous section are in conflict with evidence on the introduction of continuous trading in Israel and France. We find that liquidity and price efficiency on the WSE decrease and the price reaction is only transitory after stock transfers to continuous trading. The question arises, why we do not observe a positive response upon transfer to continuous trading on the Polish market. Or, put differently, what distinguishes the WSE from its counterparts in Tel Aviv and Paris?

As empirical evidence so far is only available from three markets (France, Israel, and Poland), we are not able to determine which structural characteristics of markets support the development of continuous trading. In the remainder of this section, we discuss potential explanations and impact factors for our results. A rigorous examination of this issue in a multi-market study is left for future research.

A first explanation of our results is that the Polish market was too small and illiquid, at the time continuous trading was introduced, and that there was no need for additional trading rounds after the daily call auction. To investigate this question, we present mean and median pre-event volume for the transferred stocks grouped in deciles in Table 9.

[Insert Table 9 here]

While the seven stocks in the tenth decile have an average daily turnover of hardly more than 100,000 zlotys and the argument of illiquidity may hold for these stocks, it is unlikely to be an explanation for the stocks in decile 1. These stocks display a daily turnover of more than 2.7 million zlotys, which is comparable to stocks traded continuously on larger exchanges. Thus, the market was not illiquid for all transferred stocks.

If the overall liquidity of the market was too small to produce, on average, positive effects of continuous trading, we should observe positive effects increasing in the level of pre-transfer liquidity. Hence, we relate pre-event

volume to the change in volume due to the introduction of continuous trading. If the call auction mainly restricts trading for the most liquid stocks, we will observe a positive relationship between the change in relative volume due to the transfer to continuous trading and the level of pre-event volume. The results of GMM estimation are

$$DVOL_j = 0.01 - 0.018 \cdot VOL_{before,j},$$

$$(0.07)(-2.16)$$

where $VOL_{before,j}$ is the average pre-event turnover of stock j in million zlotys. t -values are in parentheses below the coefficient estimates. Contrary to what we expected, we see a negative relationship between the change in trading volume and the level of pre-event volume. Thus, we see that the less liquid stocks profitted most from the introduction of continuous trading in terms of liquidity gains.

Another measure of the success of continuous trading is the share of continuous trading volume. Thus, we run a second regression to capture the relationship between the share of continuous trading in the post-event period and pre-event volume levels. The calculation yields

$$CONSHARE_j = 0.220 - 0.075 \cdot VOL_{before,j}.$$

$$(12.73)(-3.88)$$

$CONSHARE_j$ is the ratio of continuous trading volume to overall trading volume in the post-event period for stock j . Again, the most frequently traded stocks show a relatively less frequent use of the continuous trading system. These puzzling findings are difficult to explain but at least they do not lend support to the hypothesis that the overall liquidity of the market was too low to generate a need for continuous trading, since the least liquid stocks clearly profitted from continuous trading.

A second explanation for our findings is that the differences between the Polish market and the markets investigated in previous studies may be due to differences in the investor structures. While large institutional investors with international experience, who were used to complex trading mechanisms, were present in Israel and France, the Polish market was dominated

by small and unexperienced domestic investors (see WSE (1999)). Therefore, although trading structure and regulation display many similarities, the effects on liquidity and securities values may differ across these markets.

An example of the impact of different investor structures is the minimum trade size requirement in this system. The necessary amounts that allow investors to use this system were too high for many small domestic traders. Thus, the call auction was attractive to small investors as no minimum order size applied to this system. This explanation is in line with Amihud, Mendelson, and Uno (1999) and Hauser and Lauterbach (2003) who find that the restrictiveness of trading lot sizes impacts stock liquidity. The dominance of small local investors in Poland may, therefore, explain why the effects differ on the WSE compared to the Israeli stock market although a similar trading size regulation applied there.

Finally, the WSE may have had 'non-liquidity' reasons for the introduction of continuous trading. The operation of a continuous market is costly and given the lack of success it is possible that the WSE had other goals than improving liquidity. A possible reason for the introduction of the continuous trading system is the pension reform that took place in Poland in 1999. Following this event, large pension funds entered the market and large amounts of money flowed into domestic stocks. Since the pension reform was based on a parliamentary decision, it was discussed for several years and the WSE was able to prepare its structure for the needs of these large institutional investors. Thus, the WSE may have introduced continuous trading in 1996 in anticipation of the arrival of large pension funds some years later. An investigation of this change in the investor structure on the WSE is also left for future research.

3.6 Conclusion

Stock exchanges around the world change their trading structures to improve trading opportunities for their listed stocks. Usually the introduction of a continuous trading system and a shift of stocks that were previously traded in a call auction to this new system is considered to be an improve-

ment.

While a continuous trading system is a superior trading mechanism for large, liquid stocks, theoretical studies give rise to the view that investors may be better off trading small, illiquid stocks in call auctions. In an auction, liquidity is concentrated at certain points in time and the possible losses of uninformed traders in the presence of agents with superior information on fundamental asset values are limited. Empirical studies on the effects of the transfer of stocks from a call auction to a continuous trading system find increases in market quality and prices of liquid stocks. The effects of transfers of illiquid stocks are mixed and evidence indicates that trading illiquid stocks in a call auction may not be a superior trading mechanism. These studies, however, focus exclusively on the relatively liquid stock markets in Israel and France.

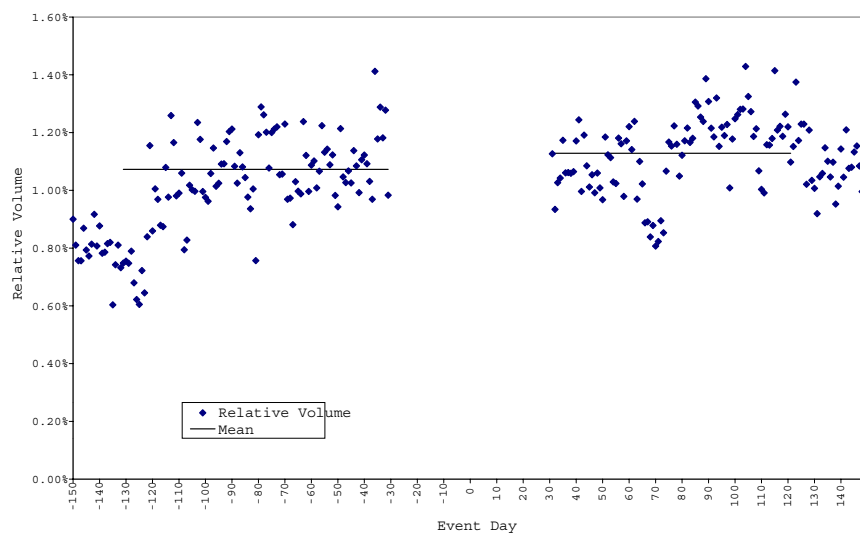
We extend the empirical literature on the introduction of continuous trading to the largest and most important stock market in the emerging economies in central eastern Europe, the WSE. The continuous trading system was only infrequently used on the WSE and did not attract a high share of trading volume. We find that liquidity and price efficiency decrease, on average, and a positive price reaction around the transfer of stocks to the continuous trading system is only transitory and quickly reversed.

We discuss several potential reasons for these results. First, the market does not seem to be too illiquid for continuous trading. If the overall liquidity was low, there may have been no need for a continuous trading opportunity. We find, however, that some of the stocks show considerably high liquidity. Moreover, it turns out that the least liquid stocks profited most from the introduction of continuous trading. Other reasons for the infrequent use of the continuous trading system may be the predominance of small unexperienced domestic investors on the market who were not used to complex trading mechanisms and were excluded from continuous trading by the minimum trade size requirement. Finally, the continuous trading system may have been launched to adjust the trading structure to the needs of large institutional investors who were expected to enter the market after the Polish pension reform in 1999.

In this study, we have shown that continuous trading was not a superior trading mechanism on the WSE contrary to evidence for the markets in France and Israel. Thus, the paper demonstrates that continuous trading may not have the same effects across markets. Other factors such as the investor structure may contribute to the success of changes in the microstructure. Future research may analyze the determinants for the success of continuous trading in a cross-country context to identify crucial factors determining liquidity and trading frequency in different trading systems.

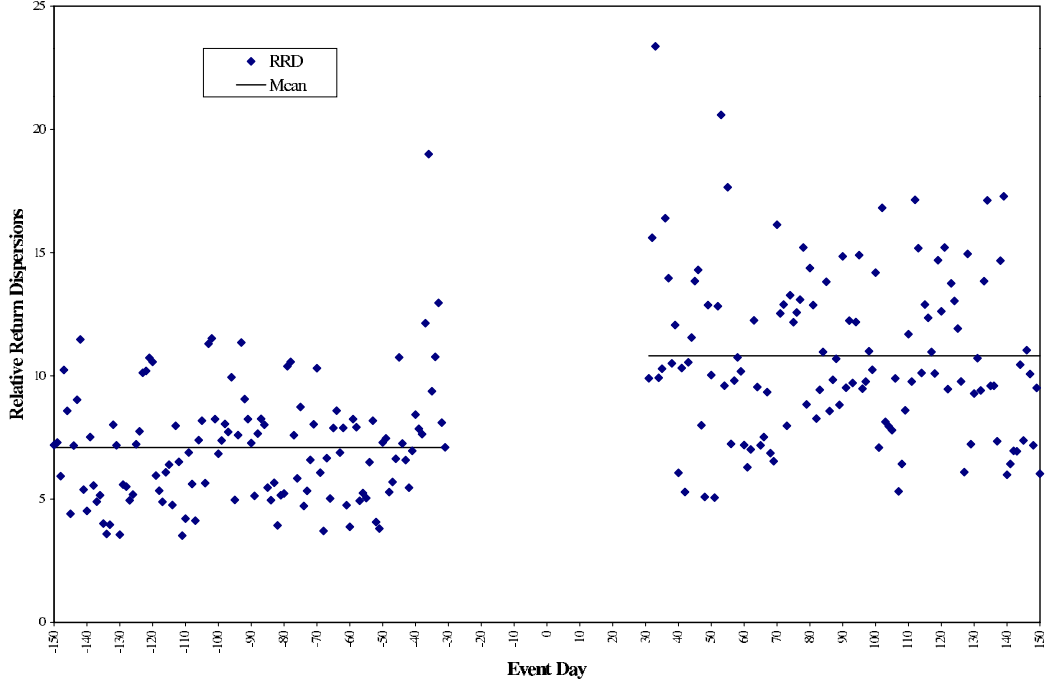
3.7 Figures and Tables

Figure 1: Average relative trading volumes for the pre-event and post-event periods



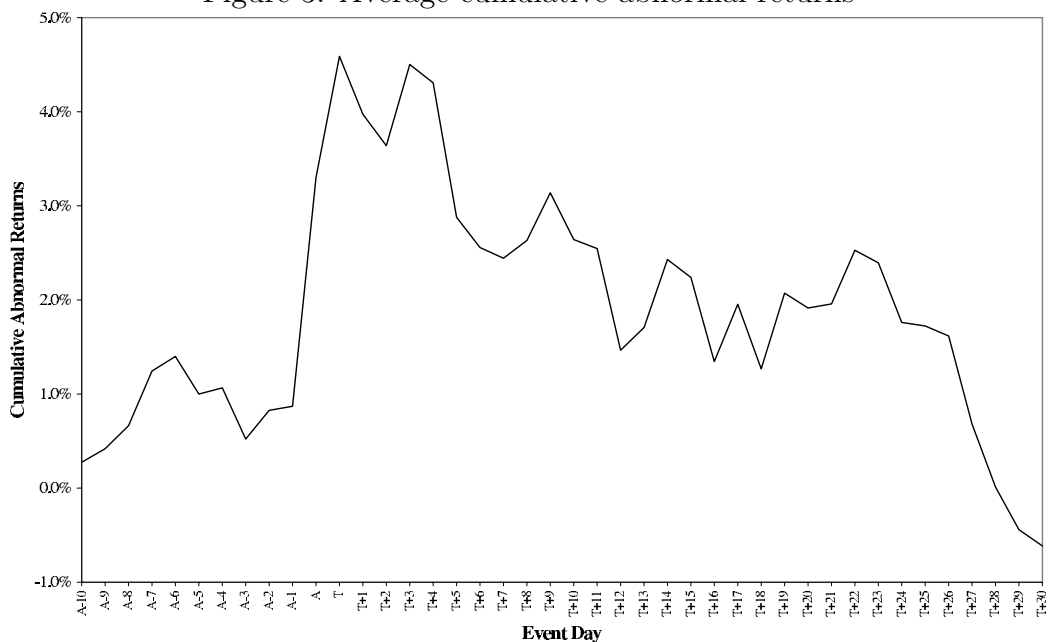
The figure shows average daily relative trading volume on event day s calculated as the average relative trading volume of all 68 sample stocks. The two steady lines show the average relative daily trading volumes in the periods $A - 121$ to $A - 31$ and $T + 31$ to $T + 121$, respectively. The period $A - 150$ to $A - 122$ is excluded because we do not have data for the five stocks of the first batch during these days.

Figure 2: Relative return dispersions for the pre-event and post-event periods



The figure displays relative return dispersions (RRD) of 67 stocks that were transferred from a daily call auction to a semi-continuous trading system on the WSE. RRD for event day s is the cross-sectional average of the residual variances of all stocks on that day, $RRD_s = (1/67) \cdot \sum_{i=1}^{67} \varepsilon_{is}^2$, where ε_{is} is the residual of stock i on day s from a market model. The market model is estimated in the pre-event ($A - 150$ to $A - 31$) and post-event periods ($T + 31$ to $T - 150$) separately, where A and T denote transfer and announcement days, respectively. The two steady lines are the pre-event and post-event averages.

Figure 3: Average cumulative abnormal returns



The graph shows average cumulative abnormal returns (CARs) for 67 stocks that were transferred in batches from the daily call auction to the semi-continuous trading system. Day T is the transfer day of the stocks. Since the time between the announcements of the transfers and the transfers itself varied across batches, the notation "A" in Figure 3 aggregates the CARs from the announcement day A to day $T - 1$. CARs are calculated during the period $A - 10$ to $T + 30$ from residuals of a market model that was estimated using return data during the period $T + 31$ to $T + 150$.

Table 7: Trading hours at the WSE in different trading systems

Time	Call auction	Continuous trading
08:00-11:00 ¹	pre-opening (placement of orders)	
08:00-13:00 ^{1,2}		pre-opening (placement of orders)
11:00-11:30 ³	price determination	
11:30-12:15 ³	post-auction trading	
13:00 ⁴		opening auction
13:00-16:00 ⁴		continuous trading

¹ After August 1999, the period ended one hour earlier.

² After May 2000, the pre-opening phase started at 08:30.

³ After August 1999, the period started and ended one hour earlier.

⁴ After August 1999, the opening auction and the start of continuous trading were at 12:00.

Table 8: Cumulative abnormal returns in the event period $A - 10$ to $T + 30$

Event Day	CAR	t-Statistics	Event Day	CAR	t-Statistics
A-10	.28	.79	T+10	2.64	.64
A-9	.42	.80	T+11	2.55	.65
A-8	.66	1.12	T+12	1.47	.35
A-7	1.24	2.19 ^b	T+13	1.71	.40
A-6	1.40	2.19 ^b	T+14	2.43	.60
A-5	1.00	1.01	T+15	2.24	.54
A-4	1.07	1.20	T+16	1.35	.31
A-3	.52	.53	T+17	1.95	.46
A-2	.83	.72	T+18	1.27	.30
A-1	.87	.66	T+19	2.07	.52
A	3.30	1.36 ^c	T+20	1.91	.50
T	4.59	1.72 ^c	T+21	1.96	.48
T+1	3.97	1.51 ^c	T+22	2.53	.62
T+2	3.64	1.35 ^c	T+23	2.39	.55
T+3	4.50	1.50 ^c	T+24	1.76	.40
T+4	4.31	1.33	T+25	1.72	.37
T+5	2.88	.84	T+26	1.62	.33
T+6	2.56	.70	T+27	.68	.14
T+7	2.44	.68	T+28	.01	.00
T+8	2.63	.67	T+29	-.44	-.09
T+9	3.14	.79	T+30	-.61	-.13

The table reports average cumulative abnormal returns (CARs) from day $A - 10$ to day $T + 30$ of stocks that were transferred to the continuous trading system. A denotes the announcement day and T the transfer day. The value on day A aggregates the CARs from days A to $T - 1$ because the length of this period differed across transfer batches. Abnormal returns are calculated from a market model that was estimated over the period $T + 31$ to $T + 150$ using the return of the WIG index as the market return. ^b (^c) indicate significance at the 5% (10%) level of significance (one-tailed test).

Table 9: Average daily pre-event level of trading volume of stocks transferred to continuous trading

Volume Decile	Mean pre-event volume (in zlotys)	Median pre-event volume (in zlotys)
1 (highest)	2700793	2410549
2	1329649	1208489
3	1010463	1012430
4	743181	735899
5	500380	493113
6	403940	401022
7	314294	307126
8	230934	228614
9	182041	172141
10 (lowest)	115612	99176

The table presents mean and median daily volume (in Polish zlotys) of 68 stocks transferred to continuous trading in the period $A - 150$ to $A - 31$, where A denotes the announcement day of transfers. For presentational purposes, the 68 stocks are grouped into deciles, where decile 1 contains the seven stocks with the largest and decile 10 with the smallest average pre-event volume.

4 When Continuous Trading Becomes Continuous: The Impact of Institutional Trading on the Continuous Trading System of the Warsaw Stock Exchange

4.1 Introduction

The rapid increase of funds invested on capital markets worldwide has forced stock exchanges to adjust their trading structures to the needs of investors. There is a global tendency among stock exchanges to adopt continuous trading mechanisms in order to provide immediate execution of trades.²⁰ Call auctions in which orders are batched together and the market clears at discrete points in time are being replaced by continuous trading systems. Call auctions are still used mainly for the opening procedure of the trading day and after trading halts, i.e., in situations when the uncertainty among investors is especially high.

Market microstructure theory suggests that it is optimal to trade highly liquid stocks continuously thereby providing the possibility of immediate execution of trades and lower information costs (Garbade and Silber (1979), Madhavan (1992)). On the other hand, in a call auction liquidity is concentrated and prices are closer to their fundamental values. A call auction is also more robust and is associated with smaller losses to uninformed traders in the case of large information asymmetries (Kyle (1985), Madhavan (1992), Pagano and Roell (1996)).

Empirical studies focusing on the stock markets in Israel and France on the effects of the transfer of stocks to continuous trading report a positive effect of trading in this system on stock prices, liquidity, and price discovery (Amihud, Mendelson, and Lauterbach (1997), Lauterbach (2001), Kalay, Wei, and Wohl (2002), Muscarella and Piwowar (2001)). We can, however, not conclude that continuous trading is superior on all markets. The Paris Bourse in France is a well-established stock market, while the Tel Aviv Stock

²⁰A good analysis of the development of European stock exchanges towards this structure is given by Pagano (1998).

Exchange is an important emerging market with a long tradition. On both markets, experienced investors are present who are used to advanced trading mechanisms. If we consider markets with a short history and a high share of local investors, the introduction of continuous trading may not be superior.

An example of such a market is the Warsaw Stock Exchange (WSE), a young stock market that was dominated by small private local investors (see WSE (1999) for a description of the historical investor structure). When the WSE was re-established in 1991, trading took place in a call auction system. Continuous trading was introduced in 1996 and the most liquid stocks were gradually transferred to this system. It attracted, however, little liquidity and only a few trades took place.

What is the difference between this and other stock markets, on which continuous trading was successful? We investigate, whether a certain investor structure is a necessary condition for the success of a continuous trading system. Contrary to the markets mentioned above, the WSE was a very young market dominated by small inexperienced local investors. We ask the question, whether a certain number of large professional investors is necessary for a continuous trading system to attract liquidity. The WSE allows us to investigate this question due to a special event on this market. In 1999, a pension reform took place in Poland and large open-ended pension funds entered the stock market. Many of these funds were established by Western European banks and insurance companies. Thus, we can investigate the impact of a large increase in the number of institutional traders on the performance of the continuous trading system.

We apply the model of Garbade and Silber (1979) with small modifications, which reflect the special structure of the Polish market, to derive testable implications regarding the impact of a large increase of the number of institutional traders on the performance of a continuous trading system. We show that the entrance of large liquidity traders (such as pension funds) on the market boosts the continuous trading system and trading shifts from the call auction to this system. Moreover, this has a positive impact on liquidity in the continuous trading system.

The impact on liquidity in the call auction system is not clear a priori.

The increase in institutional trading may cause investors to switch to the continuous trading system, which induces a decrease in liquidity in the call auction. Trading of pension funds may, however, also attract small investors who use the call auction for the stocks actively traded by the institutional investors. This would lead to an increase in liquidity even in the call auction system for actively traded stocks. If small investors turn their attention to these stocks, however, this will have a negative impact on liquidity in the call auction system of those stocks that are not traded by pension funds.

We investigate the validity of our theoretical predictions using Polish stock market data by comparing the period prior to the inflow of money from pension funds with the period after the appearance of these large players. In our empirical investigation, we distinguish between stocks that are most actively traded by pension funds and stocks that are not (or only to a small extent) traded by pension funds. We utilize a hand-collected data set of pension funds' activity on the Polish stock market.

We measure the share of continuous trading by the ratio of volume in the continuous trading system to the overall trading volume of a stock. Since intraday data are not available on the Polish stock market, we use liquidity measures based on daily data in our empirical investigation. The first measure reflecting general trading activity is trading volume measured as turnover in Polish zlotys. The second measure is the liquidity ratio (also known as the Amivest ratio), defined as trading volume during a certain time period divided by the sum of absolute daily returns during the same period. This is a measure of market depth and can be interpreted as the volume necessary to move prices by one percentage point. A larger value of the liquidity ratio is associated with higher depth of the market.

We find that the frequency with which the continuous trading system is used strongly and steadily increases after the entrance of pension funds on the market. The share of continuous trading volume increases significantly for the actively traded stocks and decreases for all other stocks. Furthermore, liquidity in the continuous trading system, measured by the two variables defined above, increases for the actively traded stocks and decreases for all other stocks. The actively traded stocks also display increased liquidity in

the call auction system, while the liquidity of other stocks in this system decreases. This indicates that institutional trading has an effect on the trading behavior of small investors as well. Our findings support the hypothesis that a certain number of experienced professional investors are necessary for the success of a continuous trading system.

The remainder of this section is organized as follows. The next subsection describes the trading systems of the Polish stock market and the reform of the pension system in Poland. In Subsection 4.3, using the model of Garbade and Silber (1979), we theoretically show the effects of an increase in the number of institutional traders on the frequency, with which the trading systems are used, and on their liquidity and derive testable hypotheses. Our methodology and the empirical results are reviewed in Subsection 4.4: 4.4.1 presents the data used in the investigation, 4.4.2 outlines the design and results of the tests for the two groups of stocks used in our study, while additional cross-sectional tests are presented in 4.4.3. Subsection 4.5 concludes.

4.2 The Polish Stock Market and the Pension Reform of 1999

In this section, we present a description of the Polish stock market and the pension reform of 1999. Trading in Poland takes place on the Warsaw Stock Exchange (WSE) that was re-established in 1991 with the trading structure taken from the Paris Bourse. Trading started with all stocks being traded in a single call auction once per week. Trading times were gradually extended and from October 1994, trading finally took place in one daily auction. Orders were collected in the morning until 11:00 a.m., when the order book was closed and the orders were batched together by a specialist to determine the market clearing price. This specialist was allowed to trade on his own account in order to balance the market and to provide additional liquidity to the system. Moreover, he could invite market participants to submit offsetting orders in case of an order imbalance. At 11:30 a.m. the market clearing price was announced. Investors who wanted to trade after price determination could do so in a 45 minute post-auction trading phase,

in which all buy and sell orders had to be submitted at the price determined in the auction before.

Continuous trading started in July 1996 and the most liquid stocks were gradually introduced into this system. Continuous trading took place in the afternoon after call auction trading. All stocks that were traded in the continuous trading system were still traded in the call auction in the morning. No specialist intervened in the continuous trading system, i.e., the system was a purely order-driven electronic open limit order book system, where liquidity was exclusively provided by limit order traders. A minimum trade size applied to orders in this system that was determined for each stock on an individual basis and amounted to between 7,000 and 11,000 zlotys.²¹ This minimum trade size requirement virtually excluded small private investors. Since these investors were the dominant group of traders on the market, the continuous trading system was infrequently used.²² As we are interested in stocks that are traded in both the continuous and the auction system, we focus our empirical investigation on the time period during which stocks were traded in both systems. During this period, no further changes in the microstructure of the trading systems took place that could potentially impact our event under consideration. In particular, there was no specialist participation in the continuous trading system at any time during our sample period.

On November 17, 2000, the new trading system "WARSET" was introduced and after that all stocks were only traded in either the call auction or the continuous trading system. The more liquid stocks were taken out of the call auction system and traded in the continuous trading system only, while the less liquid stocks were only traded in the call auction. The minimum transaction size requirement of the continuous trading system was abandoned and specialists supported the liquidity of most of the stocks. Since several microstructure changes took place simultaneously, it is difficult (if not im-

²¹At the start of the continuous trading system in July 1996, the Polish Zloty-U.S.Dollar exchange rate was 2.73.

²²Note that a similar minimum order size requirement was employed on the Israeli stock market. Nevertheless, the introduction of continuous trading increased liquidity and stock prices of transferred stocks (see, Amihud, Mendelson, and Lauterbach (1997)).

possible) to investigate one particular effect after November 2000. This date, therefore, naturally constitute the end of our investigation period.

The Polish stock market received a massive boost after the Polish pension reform of 1999. Beginning on January 1, 1999, Polish citizens could transfer 7.3% of their gross earnings to the Social Security Institution (ZUS), which channelled the money to professionally managed open-ended pension funds (OFE). This new private component of the pension system was attractive to citizens and widely used. Due to technical difficulties and the ZUS' financial problems, however, the first transfer of money to the OFEs did not take place until May 19, 1999, when the amount of 184,000 Polish zlotys was transferred. By the end of the year 1999, 2.3 billion Polish zlotys were channelled to the OFEs, and in the years 2000 and 2001, an amount of, on average, 675 million zlotys was transferred monthly.

The number of pension funds varied between 15 and 20 due to the liquidation of old funds and the establishment of new funds during our investigation period. The contributions of the four largest OFEs in the period from May 1999 to December 2001 amounted to 70% of the total contributions. The OFEs active on the market were either established by domestic or by Western European banks and insurance companies. There are regulations restricting the types of investments and their relative weights in the portfolios of the OFEs. No limitations apply for bonds issued by the State Treasury. A maximum of 40% can be invested in quoted stocks, while not more than 5% can be invested in foreign securities.²³ Stocks had a weight of between 20% and 30% in the OFEs' portfolios during our investigation period. This weight gradually increased over time. Furthermore, the funds had to guarantee a minimum return on the invested capital. Compliance with these regulations was supervised by the Superintendency of Pension Funds (UNFE).

The appearance of large, professionally managed pension funds supported the development of the Polish capital market. Anecdotal evidence recounts that the atmosphere on the trading floor strongly improved after OFE man-

²³Not only is the percentage of quoted stocks in the portfolios restricted, but further limitations apply for the relative weights invested in National Investment Funds (NFIs), the secondary stock market, closed-end funds, and open-end funds.

agers entered the market. Moreover, the appearance of OFEs and the large capital inflows into the market created a public sentiment expecting a strong development of the domestic stock market over the following years.

The appearance of the OFEs is interesting for the evaluation of the development of the continuous trading system on the WSE. In the next section, we provide a framework that models the effects on a continuous trading system as the number of institutional traders on a stock market increases.

4.3 Theory and Testable Implications

In this section, we apply the model of Garbade and Silber (1979) to the event under consideration. As a modification of the model, we distinguish between large and small liquidity traders and explicitly compare liquidity risk in a call auction with the liquidity risk in a continuous trading system.

Our model assumes L large and S small liquidity traders on the market. Each large and each small liquidity trader has an initial endowment, E_L and E_S , respectively. All traders are equally informed, i.e., private information about the asset's true value does not play any role. There are also two trading systems, a continuous trading system and a call auction. Large liquidity traders can trade in both systems, while small traders are only allowed to trade in the call auction.²⁴

The demand functions of all traders within the same group are assumed to be equal. All traders tender their full endowment to the market. The demand functions of the large and small liquidity traders in period t , $D_{it}(p_t)$ and $D_{jt}(p_t)$, are given by

$$D_{it}(p_t) = E_L + \alpha(r_{it} - p_t)$$

and

$$D_{jt}(p_t) = E_S + \alpha(r_{jt} - p_t),$$

²⁴This restriction reflects the minimum transaction size requirement in the continuous trading system of the Polish stock market that virtually excluded small private investors. Moreover, the absence of a market maker in the model mirrors the electronic limit order book structure without specialist participation of the WSE.

where p_t is the market clearing price in period t , α is the slope of the demand schedules (assumed to be identical for both groups of traders for simplicity), and r_{it} is the reservation price of trader i in period t .²⁵

Market clearing requires that total supply equals total demand or, formally,

$$LE_L + SE_S = \sum_{i=1}^L [E_L + \alpha(r_{it} - p_t)] + \sum_{j=1}^S [E_S + \alpha(r_{jt} - p_t)] \quad (13)$$

$$p_t = \frac{\sum_{i=1}^L r_{it} + \sum_{j=1}^S r_{jt}}{L + S} \equiv r_t. \quad (14)$$

From equation (13), we see that the liquidity of the market increases with the number of traders. Equilibrium condition (14) requires that the price in period t is an average over all traders' reservation prices.

We assume that the reservation prices of both the group of large and of small traders are uncorrelated and normally distributed with mean m_t and variances σ_L^2 and σ_S^2 , respectively, where m_t is the fundamental value of the asset at time t .²⁶ This fundamental value is assumed to follow a random walk, where the variance of the random walk innovation is $\tau\psi^2$. ψ^2 is the variance of the change in the fundamental value per unit time and τ is the time between market clearings. Adopting the assumption of Garbade and Silber (1979), over an interval of time of length τ , $\tau\omega_L$ large traders and $\tau\omega_S$ small traders arrive at the market. This arrival rate is exogenously given and

²⁵Note that this assumption does not mean that the demand functions between the two groups are identical. Identical slope coefficients suggest that investors react identically to deviations of the market price from their reservation prices. Since we assume that the reservation prices are uncorrelated across groups, however, we end up with uncorrelated demands for the risky asset. Obviously, we could assume a certain correlation structure of demands between the two groups, but as we don't have a theoretical prediction of this relationship, we attempt to answer this question empirically.

²⁶It is important to distinguish between the fundamental asset price and its variance on the one hand, and the quoted (market) price and its variance on the other hand. While the quoted price and its variance are observable variables and depend on the market structure, the fundamental value and its variance do not. The fundamental asset value reflects the true price of the asset dependent on the company's profitability and its future prospects, and the variance reflects changes in this fundamental value per unit time. This fundamental value is unobservable and exclusively depends on real economic variables. Therefore, it is reasonable to assume in the model that this price and its variance are exogenous.

constant over time.

Focusing on the interval $[t - 1, t]$, Garbade and Silber (1979) derive the liquidity risk of the market as the variance of the difference of the market clearing price at t , r_t , and the asset's equilibrium value at the time the average investor decides to trade, $m_{t-1/2}$. This variance can be written as

$$\text{Var}[r_t - m_{t-1/2}] = \text{Var}[(r_t - m_t) + (m_t - m_{t-1/2})].$$

In our example this variance becomes

$$\text{Var}[r_t - m_{t-1/2}] = \frac{\omega_L \sigma_L^2 + \omega_S \sigma_S^2}{\tau(\omega_L + \omega_S)^2} + \frac{1}{2} \tau \psi^2. \quad (15)$$

Liquidity risk consists of two terms: the first term is the difference between the market clearing price and the fundamental value at the time the market clears (the first term of (15)), which is a decreasing function of the time between two consecutive market clearings, τ ; second, liquidity risk increases with τ since the change of the fundamental value increases with time. This is captured by the second term of (15).

Since the time between two consecutive market clearings in the call auction system, τ , is exogenously given by the stock exchange, we normalize it to unity. Liquidity risk in this system, then, becomes

$$V_a = \frac{\omega_L \sigma_L^2 + \omega_S \sigma_S^2}{(\omega_L + \omega_S)^2} + \frac{1}{2} \psi^2. \quad (16)$$

Small investors cannot use the continuous trading system by assumption. Since no other restrictions apply and market participants can determine the optimal trading frequency in the system endogenously,²⁷ the variance in the continuous trading system is the same as in Garbade and Silber (1979), i.e.,

$$V_c = \sigma_L \psi \left(\frac{2}{\omega_L} \right)^{1/2}. \quad (17)$$

²⁷Note that the endogenous determination of the optimal clearing frequency does not mean that continuous trading is always optimal. The optimal market clearing frequency may be overcompensated by the lower number of market participants in this system, since small private investors only trade in the call auction. See the discussion of Figure 4 below for further details.

Both the variance in the call auction and the variance in the continuous trading system given in (16) and (17) depend on the number of large liquidity traders, ω_L . For large values of ω_L , liquidity risk in the call auction converges to $\frac{1}{2}\psi^2$, while liquidity risk in the continuous trading system converges to zero. Thus, if ω_L is sufficiently large, the continuous trading system will always be preferred by institutional investors. Figure 4 displays a graphic representation of the variances in both systems as a function of ω_L for certain parameter values.

[Figure 4 around here]

The figure shows that for a small number of large liquidity traders the call auction system has lower liquidity risk and is therefore preferred by all traders. Depending on the assumed parameter values, there exists a critical level of large traders beyond which continuous trading offers lower liquidity risk to large traders. This critical level depends on, among other things, the number of small liquidity traders on the market. In general, the larger this number, the higher the threshold level beyond which continuous trading is preferred by large investors.²⁸

Once the number of large traders increases beyond this threshold, they prefer the continuous trading system. Moreover, an increase in the number of large traders, ω_L , increases the trading volume in this trading system, as can be seen from equation (13).

Summarizing the results of the model, an increase in the number of large traders, *ceteris paribus*, makes the continuous trading system more attractive relative to the call auction. After the number of large players has reached a critical level, the trading of large traders shifts to this system, thereby increasing the liquidity of the corresponding stocks.

The model results rely on the assumption that small private investors do not trade in the continuous trading system. This assumption was valid for

²⁸For some combinations of parameter values, the continuous trading system always has a lower variance than the call auction and is therefore always preferred. Since we investigate a market, on which trading predominantly took place in the call auction system, we concentrate on the cases where the continuous trading system is preferred beyond some critical level of large institutional investors.

the WSE, but for other stock markets it may be reasonable as well. Many stock exchanges impose minimum transaction size requirements similar to the WSE. Moreover, small investors are more likely to lose to informed investors in continuous trading systems compared to call auctions. Posting limit orders in a continuous trading system provides "free options" to informed traders. This problem is especially severe in emerging markets that are frequently plagued by insider trades, which makes the continuous trading system less attractive there. It can only be mitigated by permanently monitoring the market, but this is rather costly. Thus, the assumption that small traders avoid the continuous trading system may be an accurate description of other emerging stock markets as well. Brooks and Su (1997) show that even in the U.S. small investors can reduce their trading costs by trading in the opening auction.

From the findings outlined above, we can derive testable implications. First, Figure 4 indicates that for those stocks actively traded by OFEs the continuous trading system is used more frequently after the arrival of institutional investors on the market. For the stocks not traded by OFEs, we do not expect an increase in trading intensity in the continuous trading system.

Second, equation (13) states a positive relationship between the number of institutional traders on the market and the liquidity in the continuous trading system. Thus, we expect an increase in liquidity in the continuous trading system for the actively traded stocks. This effect is supposed to be absent for the remaining stocks that are not subject to trading by OFEs.

Third, we focus on the performance of the call auction system after the entrance of OFE fund managers on the market. The effect of the event under investigation on the liquidity in the call auction is not clear a priori. After institutional investors change from the call auction to the continuous trading system, the liquidity of the call auction system may deteriorate for stocks actively traded by OFEs. On the other hand, professional investors' active trading in these stocks may attract private investors and increase trading in these stocks even in the call market. Note that an increase in the number of small traders in equation (13) has a positive impact on liquidity in the corresponding trading system. Moreover, some institutional investors may

still use the call auction system for some trades.

For stocks not traded by OFEs, liquidity in the call auction system may not change since the investor structure does not change for these stocks. If, however, private investors imitate the investment behavior of institutional traders, they may concentrate on the actively traded stocks and the liquidity of other stocks decreases. Kalay, Wei, and Wohl (2002) report that, on the Israeli stock market, stocks that remained in the call auction when others were transferred to the continuous trading system suffered decreases in liquidity. Thus, we also investigate the impact of institutional trading on liquidity in the call auction system. Since our model does not provide theoretical predictions on this question, we aim to answer it empirically.

Before we test the model's implications, however, it is important to note the shortcomings of the model and several caveats. First, the model completely abstracts from private information by assuming that all investors have the same information set. This, of course, does not mirror real-world stock markets, where some investors possess private information on the fundamental asset value or better skills to process information.

In this paper, however, we are mainly interested in the impact of the appearance of institutional traders on liquidity and the frequency with which the different trading systems are used and not on the degree of information asymmetry. While changes in asymmetric information can have impacts on liquidity, we believe that this effect will not dominate: If OFE managers are uninformed investors, the presence of insiders may impact their selection of stocks (which we do not model) but not the decision to invest at all as they had to invest their funds in order to maintain a minimum rate of return. If, on the other hand, OFE managers possess superior information and discourage other investors from trading, the effects found in our empirical study will underestimate the true impact on liquidity and are therefore a conservative estimator.

Second, the model assumes that the arrival time of investors is exogenous. While the demand for trading can, in principle, arise at any time during the day, it is unlikely that the trading decision is independent of the opening hours of the exchange. Investors are more likely to receive and evaluate in-

formation when they can trade on it. Moreover, professional investors' working hours and information releases by companies usually depend on opening hours of the exchange. Therefore, trading demands are more likely to arise at these times. Third, in reality there may not be such a strict distinction between continuous trading and the call auction. Different institutional investors may use the two trading systems in different ways due to variations in their demands for immediacy. Thus, there may not be such a strict distinction between the call auction and continuous trading as predicted by the model. The effects of the appearance of OFEs on the market may nevertheless influence our variables in the predicted way if a sufficiently large number of institutional traders acts as presumed by the model.

4.4 Methodology and Results

4.4.1 Data

We investigate the impact of the inflow of money from Polish OFEs to the local market. This inflow started on May 19, 1999 (event day zero). We compare the periods prior to and after the start of the inflow. Our pre-event period comprises 100 days from day -100 to day -1 (denoted Period *I*). Since stocks were gradually introduced to the continuous trading system after its launch in 1996, there exists a trade-off between the length of the pre-event period and the number of stocks in the sample. Starting on day -100 allows us to include most stocks that were actively traded by OFEs in our investigation. Additionally, we use a second pre-event window from -200 to -101 as a robustness check. The comparability of the results with those of later periods, however, is limited because the sample of stocks permanently listed in the continuous trading system during this period is considerably smaller.

The post-event period is divided into three sub-periods of 100 trading days each, $+1$ to $+100$ (Period *II*), $+101$ to $+200$ (Period *III*), and $+201$ to $+300$ (Period *IV*), respectively.²⁹ The post-event period consists of three

²⁹We end on day $+300$ (August 1, 2000) because of the institutional structural break introduced by the launch of the new trading system WARSET on November 17, 2000, as

subperiods because we want to investigate the evolution of the performance of the continuous trading system. As there was a steady flow of money to the market, we expect a permanent and ongoing increase in the use of the continuous trading system and in the liquidity of the most actively traded stocks.

During the entire event period, 57 stocks were listed in the continuous trading system.³⁰ When we focus on the effect of the appearance of pension fund managers on the market, we have to investigate the stocks that mainly were of interest to these large traders. For this purpose, we use a hand-collected data set consisting of the annual reports of the pension funds.

Pension funds in Poland are obliged to publish semi-annually all holdings that exceed 1% of their total funds invested. Moreover, they have to publish their complete portfolios annually. We requested all Polish pension funds and the superintendency (UNFE) to provide us with the reports of the funds' portfolio holdings. We received detailed portfolio information from 11 out of 19 OFEs. The other (mainly state-owned) OFEs and the UNFE did not answer. Although our information on pension fund portfolio holdings are thus incomplete, these shortcomings may not have a large effect for the following reasons. First, the holdings of the OFEs that responded to our request comprise about 75% of the overall holdings of all OFEs. Second, the two largest players (with an overall market share of about 50%) are in our sample. Finally, with one exception the missing OFEs are rather small players. Polish newspaper reports indicate that there was a tendency among small OFEs to simply copy the behavior of the large funds. Taking these arguments together, we believe that our sample consistently mirrors the investment behavior of Polish OFEs.³¹

outlined above.

³⁰We dropped the national investment funds (NFI) from our sample as their behavior may differ from those of ordinary stocks. Since the pension funds in our sample hardly invested at all in NFIs, this will not influence the results.

³¹We also found a data source on the internet providing information on the portfolio holdings of all pension funds (<http://emerytura.hoga.pl>, information available in Polish only). We do not present the results from the analysis of these data since we do not know whether or not they are reliable. If we classify the stocks according to these data, however, we still obtain virtually the same results.

Using the information provided by the pension funds, we are able to classify the 57 stocks of our investigation into two groups. Group 1 consists of 28 stocks that were most frequently traded by pension funds. Group 2 contains the remaining 29 stocks that were either not traded by OFEs or traded only to a small extent. Table 10 displays the characteristics of the two samples.

[Insert Table 10 here]

The table reports the sector classification of stocks within each group, average market capitalization and total turnover in Polish zlotys during the entire sample period. We calculate the mean, median, standard deviation and the range of market capitalization and turnover.

The results indicate that stocks in group 1 are larger and more frequently traded. Moreover, stocks from the financial and the service sectors are concentrated in group 1, while industry stocks dominate sector 2.³²

We will have to take into account these differences between the two samples in the cross-sectional analysis. First, however, we investigate the two groups of stocks separately. Our theory predicts that only the stocks of group 1 should have profited from the appearance of pension funds.

4.4.2 Empirical results for the stock groups

To measure the effect of an increase in the number of large traders on the use of the continuous trading system, we calculate the ratio of continuous trading volume (measured as turnover in zlotys) to total trading volume for all stocks separately and average the measure across stocks. We compute this measure for the pre-event and post-event periods separately and distinguish between the two groups of stocks.

Results for both groups of stocks are presented in Table 11. The table presents the share of the continuous trading system in the pre-event period

³²The WSE groups stocks into the macro sectors finance, industry, and services. Within each macro sector, there is a finer grid of fifteen sectors overall. We report the macro sectors since we use this classification for creating sector dummies in our multivariate cross-sectional regressions and the sample is too small to use dummy variables for fifteen sectors.

(*I*) and all post-event sub-periods (*II* to *IV*), as well as the change from the pre-event period to the j th sub-period ($j = II, III, IV$), $\Delta(j - I)$, defined as $\log(Share_j/Share_I)$.

[Insert Table 11 here]

For group 1 (the stocks actively traded by OFEs) the share of the continuous trading system increases from 31.8% in the pre-event period to more than 41% in the last post-event sub-period. The cross-sectional t -statistic and the paired t -test of the change in the share of continuous trading volume across all stocks in the group is statistically significant at the 1% level of significance. Non-parametric Wilcoxon signed-rank tests support this finding. Moreover, the increase in the share of continuous trading is positive for the majority of stocks. In the second and third post-event sub-periods (periods *III* and *IV*), 85.7% and 75% of stocks, respectively, display an increase in the relative use of the continuous trading system.

Contrary to the findings for group 1, we do not find an increased use of the continuous trading system for the stocks of group 2. The pre-event share of the continuous trading system is 31.1% and, thus, similar to the share of this system for the stocks of group 1. For the stocks of group 2, however, this share remains constant in the first post-event sub-periods and even decreases in the last sub-period. The percentage of stocks, for which the share of continuous trading volume increases, is not statistically significantly different from .5, which is the expected value in the case that the event under consideration had no effect on the use of the continuous trading system.

The findings documented in Table 11 confirm our first hypothesis that for stocks subject to trading by OFEs the continuous trading system is more frequently used, while we do not find a significant change for the stocks that are not traded by OFEs.

Our second testable implication is an increase in liquidity in the continuous trading system for the stocks of group 1 as indicated by equation (13), while we do not expect increased liquidity for group 2 stocks. We first use trading volume measured as turnover in zlotys as a liquidity measure. We calculate the monetary value of average daily trading volume in both

groups of stocks and compare this value in all post-event sub-periods with the value of the pre-event period. Specifically, the change in trading volume is calculated as

$$DVOL_{ij} = \log(VOL_{AFTER,ij}) - \log(VOL_{BEFORE,i}), \quad (18)$$

where $VOL_{AFTER,ij}$ denotes the average absolute trading volume of stock i in the continuous trading system in the j th sub-period ($j = II, III, IV$) and $VOL_{BEFORE,i}$ denotes stock i 's average trading volume in the continuous trading system in the pre-event period. Equation (18) is calculated for all stocks separately. An increase in trading volume corresponds to a positive value of $DVOL$.

In addition to trading volume, we use the depth of the market as a second measure of liquidity. Market depth is usually calculated as the liquidity ratio of stock i over a period of T days,

$$LR_{ij} = \frac{\sum_{t=1}^T VOL_{it}}{\sum_{t=1}^T |R_{it}|},$$

where R_{it} is the continuously compounded rate of return. We calculate returns and volume using closing prices and turnover of the continuous trading session. The liquidity ratio measures the volume that is necessary to move prices by one percentage point. The change in liquidity ratios, DLR , of stock i is given by

$$DLR_{ij} = \log(LR_{AFTER,ij}) - \log(LR_{BEFORE,i}) \quad (19)$$

The indices "AFTER", "BEFORE", and j are as defined in equation (18). Again, a positive value of DLR indicates an increase in the liquidity of stock i .

Table 12 displays summary statistics for the two liquidity measures outlined above such as mean, median, standard deviation, maximum, and minimum. Panel A reports results for group 1, panel B for group 2. Within each panel, results are reported, separately, for each period and each trading system under consideration.

[Insert Table 12 here]

The table shows that the liquidity changes are, on average, positive for group 1 stocks in all cases and, on average, negative for the stocks in group 2. Thus, a first look at the data reveals that, indeed, only stocks of group 1 seem to have profitted from the appearance of OFEs.

Significance tests of the changes in our liquidity measures, *DVOL* and *DLR* in the continuous trading system are presented in Table 13. The table reports test statistics of the changes in trading volume and liquidity ratios from the pre-event period to the first, second, and third post-event sub-periods (periods *II*, *III*, and *IV*), respectively. The upper half shows results for group 1 stocks, while results for group 2 stocks are presented in the lower half of the table.

[Insert Table 13 here]

For the stocks actively traded by OFEs (group 1), we see drastic increases in our liquidity measures. Absolute trading volume and liquidity ratios double over time and the parametric and non-parametric test statistics are significant in the overwhelming majority of cases. Moreover, the changes in the measures are positive for a highly significant majority of stocks.

Overall, we find support for our hypothesis that the liquidity in the continuous trading system of the stocks actively traded by OFEs strongly increases. For group 2, however, we do not find increased liquidity measures. The lower part of Table 13 displays significant decreases in trading volume for stocks in group 2 in periods *II* and *IV*, while the decrease is not significantly different from zero in period *III*. Liquidity ratios decrease as well, but with the exception of period *IV*, the decreases are not statistically significant. These findings support our second hypothesis that in the continuous trading system of the WSE only actively traded stocks display increased liquidity, while the other stocks do not. The findings indicate that the trading by institutional investors on the WSE had a significant effect on the performance of the continuous trading system.

Finally, we compute equations (18) and (19) again using price and volume data from the call auction system to test the impact of the appearance of a large number of institutional investors on the call auction system of the

WSE. As outlined in our research hypotheses, the impact of our event on the performance of the call auction system is not clear a priori and requires further investigation. For the stocks of group 1 liquidity may decrease when institutional traders withdraw from the call auction system. Alternatively, institutional trading in the stocks of group 1 may attract small private investors and thus even increase the liquidity of the call auction system. For the stocks in group 2, we also have two different hypotheses. We may not see a change in liquidity since the institutional trading in group 1 stocks has no impact on the stocks in group 2. Alternatively, if small traders are attracted by the appearance of OFEs and increase trading in the stocks of group 1, liquidity in the call auction system may even decrease for group 2 stocks.

Table 14 reports the changes in trading volume, *DVOL*, and in liquidity ratios, *DLR*, for groups 1 and 2 that are calculated from return and volume data of the call auction system.

[Insert Table 14 here]

The stocks of group 1 experience an increase in trading volume in the call auction that is significant in subperiod *III* and marginally significant in the two other post-event subperiods. The change in trading volume is positive for a (however insignificant) majority of stocks. Liquidity ratios on the other hand display an increase that is significant at the 5% level in all periods. Moreover, around 70% of all stocks in group 1 show increased liquidity ratios in the call auction. Interestingly, however, all liquidity improvements are smaller than the corresponding improvements in the continuous trading system. Thus, we can state that for group 1 stocks liquidity increases in both the call auction and the continuous trading system and the increase is more pronounced for continuous trading.

There are two explanations for this finding. First, some pension funds may also use the daily opening call auction to execute part of their trades and thus increase the liquidity in this system as well. Second, the increased liquidity in the call auction system may be caused by small private investors who are attracted by the trading of OFEs and thus increase their trading in the stocks of group 1. If the last explanation is valid, we should see negative

liquidity responses in the call auction system for the stocks of group 2 after the appearance of OFEs on the market.

The lower part of Table 14 presents changes in liquidity measures in the call auction system for group 2 stocks. Trading volume and liquidity ratios significantly decrease in all sub-periods. All parametric and non-parametric tests unanimously display highly significant decreases of all measures in all subperiods. Furthermore, the average changes in liquidity measures in the call auction system indicate a stronger decrease in liquidity in this system compared to the continuous trading system. The findings are comparable to those of Kalay, Wei, and Wohl (2002) who find that after some stocks were transferred to continuous trading other stocks that remained in the call auction system lost liquidity. Our findings suggest that the trades of OFE managers influence the trading behavior of small private investors. Thus, there are spill-over effects from institutional trading in the continuous trading system to liquidity in the call auction system.³³

As a robustness check, we also calculate the changes in liquidity using an earlier pre-event period (days -200 to -101). While the results are almost identical for the stocks of group 1, changes in liquidity measures increase for group 2 stocks. The difference between the two groups of stocks, however, remains statistically significant and is, therefore, in line with the results presented above. These results have to be interpreted with caution, however, because the sample size in the robustness check is much smaller (42 stocks). Since a number of stocks were transferred to continuous trading during this earlier pre-event period, comparability of the results is limited.

³³We additionally test whether the differences in liquidity changes and the use of the continuous trading system are significant between the two groups of stocks. We use parametric group comparison *t*-tests and non-parametric Kruskal-Wallis and Mann-Whitney tests. The results (not reported but available on request) indicate that liquidity changes are significantly larger at the 1% level for group 1 than for group 2 in both trading systems during all subperiods. The share of continuous trading is significantly larger for group 1 stocks in periods *III* and *IV*.

4.4.3 Empirical results of cross-sectional tests

So far, we have based our empirical evidence on the two groups of stocks separately. While the evidence indicates that liquidity increases for (and only for) stocks frequently traded by OFEs, it is premature to attribute these effects to the appearance of large institutional investors. We have seen in Table 10 that the two stock samples differ with respect to characteristics such as size and sector classification. Therefore, factors related to these variables could impact the two groups of stocks in different ways. To exclude possible competing explanations for our findings, we additionally investigate the impact of the appearance of OFEs on our liquidity change measures in cross-sectional regressions. This allows us to control for other factors that may drive our results.

First, we regress our liquidity change measures defined in equations (18) and (19) on a dummy variable, D^{Group} , that is equal to one if the stock is in group 1 and zero otherwise. The regression takes the form

$$DLIQ_{ij} = \alpha_0 + \alpha_1 D_i^{Group} + \varepsilon_i, \quad (20)$$

where $DLIQ_{ij}$ is the change in liquidity (either $DVOL$ or DLR) for stock i in period j ($j = II, III, IV$), α_0 and α_1 are parameters to be estimated, D_i^{Group} is the dummy defined above, and ε_i is the error term of the regression.

Second, we add other explanatory variables to regression (20). To control for possible sector effects, we add sector dummies. Since our stocks are grouped into three macro sectors (finance, industry, and services), we add two dummies. D_i^{Ind} is one if stock i is from the industrial sector and zero otherwise, while D_i^{Fin} equals one if stock i is from the financial sector and zero otherwise. Since stocks from group 1 are, on average, around seven times larger than group 2 stocks, we also include market capitalization in Polish zlotys as a control variable into the regression to capture other potential impact factors approximated by firm size. Finally, the average level of trading volume of stock i is captured by the variable VOL_i .

The multivariate regression takes the following form

$$DLIQ_{ij} = \alpha_0 + \alpha_1 D_i^{Group} + \alpha_2 D_i^{Ind} + \alpha_3 D_i^{Fin} + \alpha_4 Size_i + \alpha_5 VOL_i + \varepsilon_i, \quad (21)$$

where α_0 to α_5 are regression coefficients, $Size_i$ is the average market capitalization of stock i over the sample period, and all other variables are defined above.

Regression results of equations (20) and (21) are presented in Table 15. The upper half presents cross-sectional regression results for the two variables in the continuous trading system, the lower half for the two variables in the call auction.

[Insert Table 15 here]

As can be seen from the table, the coefficient of the group dummy in equation (20) is positive for both measures in all cases and significant at the 1% level without exception.

After controlling for other factors in equation (21), the coefficients decrease but remain significant at conventional levels of significance. The sector dummies are insignificant in most cases except for sub-period *IV*, where the industrial sector dummy is significant at the 10% level in two out of four cases. Thus, the differences in sector classification between the two groups do not seem to impact our findings significantly. Size generally exerts a positive influence on the liquidity measures, but the coefficients are only marginally significant, while cross-sectional differences in the level of trading volume do not seem to drive our results. Moreover, adjusted R^2 measures of the regression are between 0.2 and 0.4, which shows that the impact of our pension fund trading dummy, D^{Group} , explains a considerable fraction of the variance in the cross-section of the sample.³⁴

Finally, we use another cross-sectional test statistic put forward by Pagano and Schwartz (2003) to measure whether market quality has improved for the stocks of group 1 relative to those of group 2. While the other measures in this study are all related to turnover in Polish zlotys, the Pagano and Schwartz model focuses on the betas of the stocks and on the explanatory power of a market model. The results of the Pagano and Schwartz model (not reported

³⁴We checked the correlation coefficients between the explanatory variables in equation (21) to avoid the problem of multicollinearity. The highest correlation (between size and volume) is 0.38. Thus, multicollinearity does not seem to impact our findings. If we drop either size or volume from the regression, the results remain qualitatively unchanged.

but available on request) show that there is a significant difference in market quality changes after event day zero between the two groups of stocks. We find a highly significant decrease in market quality for the stocks of group 2, while market quality increases for group 1. Thus, using an alternative testing specification we obtain results in agreement with our previous tests.³⁵

4.5 Conclusion

The global trend toward continuous trading on stock markets also induced stock exchanges in emerging markets to introduce a continuous trading opportunity. Although several studies report the superiority of continuous trading in countries like Israel and France, on the Polish market it attracted only a few traders.

We argue that a critical number of experienced institutional investors are necessary for a frequent use of continuous trading and a positive impact on liquidity of the stocks attributed to this system. Applying the model of Garbade and Silber (1979), we show that a determinant of the success of a continuous trading system in attracting a high share of trading volume and improving liquidity is the existence of a certain number of large, institutional traders.

We investigate these findings empirically using data from the WSE. In Poland, the introduction of professionally managed private pension funds that invested large amounts of money in domestic stocks gave a massive boost to the stock market. We show that stocks that are actively traded by pension funds show a steady and significant increase in the share of this system. Other stocks that are not traded by pension funds do not exhibit a more frequent use of the continuous trading system.

Liquidity in the continuous trading system dramatically increases for the stocks of group 1, while we find (partly significant) decreases of liquidity in

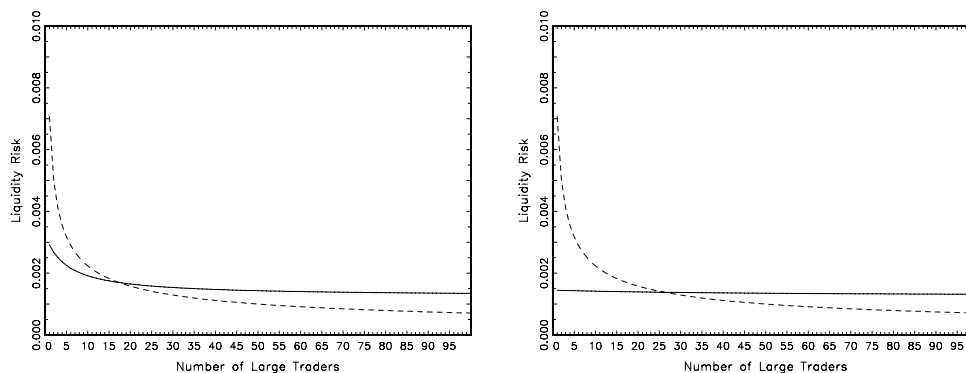
³⁵Some readers may ask whether there is a cross-sectional relationship between liquidity changes and abnormal returns in the spirit of Amihud and Mendelson (1986). In this paper, we do not address this question because we only have semi-annual reports of portfolio holdings by OFEs and we do not know when exactly during these six months OFE managers bought the stocks. Thus, we are not able to specify an exact event window to calculate abnormal returns with reasonable precision.

this system for group 2 stocks. Liquidity in the call auction also increases for group 1 stocks although to a smaller extent, while it drastically decreases for group 2 stocks.

We interpret our findings as evidence that the appearance of a large number of institutional traders on the Polish stock market boosts the continuous trading system and has effects on liquidity in the call auction system as well. Overall, the findings are consistent with the assessment that a continuous trading system may not be optimal on a market that is dominated by small inexperienced investors and that a certain number of experienced professional investors are necessary for the frequent use of a continuous trading system.

4.6 Figures and Tables

Figure 4: Liquidity risk in a call auction and in a continuous trading system



Note: The figure displays liquidity risk in trading systems with different market clearing frequencies. The solid and dashed lines show liquidity risk in a call auction and in a continuous trading system, respectively. The functions are calculated using the formulae in equations (16) and (17). The two figures show results for ω_S , the number of small liquidity traders, equaling 5 (left figure) and 50 (right figure), respectively. The values of the other parameters used in the calculation are $\psi = 0.05$, $\sigma_L = 0.1$, and $\sigma_S = 0.1$.

Table 10: Descriptive statistics of the sample

Group 1		Mean	Median	Std. Dev.	Maximum	Minimum
Macro sectors	Finance	8				
	Industry	8				
	Services	12				
Avg. size (million zlotys)		2904.0	1003.4	7005.6	38295.8	42.7
Total turnover (million zlotys)		17.282	9.831	19.667	100.029	.966
Group 2		Mean	Median	Std. Dev.	Maximum	Minimum
Macro sectors	Finance	3				
	Industry	21				
	Services	5				
Avg. size (million zlotys)		427.1	179.7	779.2	3776.6	38.6
Total turnover (million zlotys)		3.745	2.865	2.507	10.487	.769

Note: The table displays sector classification, size, and turnover of stocks frequently traded by OFEs (group 1) and stocks infrequently (or not at all) traded by OFEs (group 2). Average size is the average market capitalization of the sample stocks during the period -100 to +300. Total turnover in Polish zlotys reports turnover during the period -100 to +300 from both the continuous trading system and the call auction.

Table 11: Share of the continuous trading system

Sub-period	<i>I</i>	<i>II</i>	<i>III</i>	<i>IV</i>	$\Delta(II - I)$	$\Delta(III - I)$	$\Delta(IV - I)$
Group 1							
Share of continuous trading	.318	.365	.430	.412	.127	.303	.245
<i>t</i> -value of change in variable					2.65 ^a	5.40 ^a	3.43 ^a
Paired <i>t</i> -test of levels					3.02 ^a	5.75 ^a	4.03 ^a
Wilcoxon signed-rank test					2.32 ^b	3.87 ^a	3.03 ^a
% positive					.679	.857	.750
p-value % positive					.059	.000	.008
Group 2							
Share of continuous trading	.311	.315	.329	.268	.006	.033	-.234
<i>t</i> -value of change in variable					.08	.41	-2.09 ^b
Paired <i>t</i> -test of levels					.23	.90	-1.89 ^a
Wilcoxon signed-rank test					.49	.96	-.44
% positive					.517	.621	.414
p-value % positive					.853	.194	.353

Note: The table presents the share of the continuous trading system on the WSE in the pre-event period (*I*) and the three post-event sub-periods (*II*, *III*, and *IV*) as well as the changes from the pre-event period to the *j*th post-event sub-period ($j = II, III, IV$), $\Delta(j - I)$ calculated as $\log(Share_j / Share_I)$. Group 1 contains the stocks actively traded by OFEs, while the stocks in group 2 were not (or only to a small extent) subject to institutional trading. Parameter values are calculated for each stock separately and then averaged across all stocks in the particular group (with the same weights given to each stock). *t*-values of change in variable denote cross-sectional *t*-statistics of $\Delta(j - I)$. Paired *t*-tests test the equality of the means of the share of continuous trading for one group in the pre-event and the *j*th post-event periods. Wilcoxon signed-rank tests test whether the median of the distribution is different from zero. % positive is the percentage of stocks for which the corresponding measure increased, while p-value % positive denotes the p-value of a test with the null hypothesis that the percentage of stocks with positive values is .5. ^a and ^b denote statistical significance at the 1% and 5% level, respectively.

Table 12: Descriptive statistics of the changes in liquidity

Panel A: Group 1		Mean	Median	Std. Dev.	Maximum	Minimum
$\Delta II - I$						
Continuous trading	<i>DVOL</i>	.632	.567	1.323	3.229	-2.401
	<i>DLR</i>	.981	.579	1.296	3.467	-1.574
Call auction	<i>DVOL</i>	.443	.354	1.198	2.359	-2.242
	<i>DLR</i>	.802	.619	1.217	3.019	-1.799
$\Delta III - I$						
Continuous trading	<i>DVOL</i>	1.400	1.191	1.463	4.494	-1.126
	<i>DLR</i>	1.422	1.122	1.364	3.927	-.940
Call auction	<i>DVOL</i>	.817	.461	1.288	3.760	-1.251
	<i>DLR</i>	.837	.530	1.292	3.239	-1.400
$\Delta IV - I$						
Continuous trading	<i>DVOL</i>	.977	.966	1.633	4.789	-2.402
	<i>DLR</i>	1.164	.942	1.443	4.159	-1.881
Call auction	<i>DVOL</i>	.544	.146	1.364	3.815	-1.708
	<i>DLR</i>	.760	.557	1.274	3.269	-1.865
Panel B: Group 2		Mean	Median	Std. Dev.	Maximum	Minimum
$\Delta II - I$						
Continuous trading	<i>DVOL</i>	-.822	-.680	2.062	3.659	-4.706
	<i>DLR</i>	-.423	-.578	1.643	3.237	-4.095
Call auction	<i>DVOL</i>	-.998	-.912	1.548	2.271	-4.343
	<i>DLR</i>	-.670	-.490	1.474	2.076	-3.984
$\Delta III - I$						
Continuous trading	<i>DVOL</i>	-.571	-.180	2.000	3.613	-5.151
	<i>DLR</i>	-.299	-.290	1.615	3.242	-3.660
Call auction	<i>DVOL</i>	-.810	-.478	1.464	2.109	-3.733
	<i>DLR</i>	-.742	-.331	1.392	2.271	-3.460
$\Delta IV - I$						
Continuous trading	<i>DVOL</i>	-1.403	-.901	1.948	2.379	-5.813
	<i>DLR</i>	-.594	-.465	1.675	3.395	-3.732
Call auction	<i>DVOL</i>	-1.458	-1.201	1.411	1.257	-3.734
	<i>DLR</i>	-1.237	-.925	1.408	1.232	-3.940

Note: The table reports liquidity changes as defined in equations (18) and (19) for the stocks frequently traded by OFEs (Panel A) and infrequently or not at all traded by OFEs (Panel B). For each group, the table shows changes in variables from the pre-event period I to the j th period ($j = II, III, IV$) in both the call auction and the continuous trading system.

Table 13: Liquidity measures in the continuous trading system

Sub-period	Change from pre-event period		
	<i>II</i>	<i>III</i>	<i>IV</i>
Group 1			
<i>DVOL</i>	.632	1.400	.977
<i>t</i> -value of change in variable	2.53 ^a	5.06 ^a	3.17 ^a
Paired <i>t</i> -test of levels	.76	2.93 ^a	2.13 ^b
Wilcoxon signed-rank test	2.30 ^a	3.58 ^a	2.73 ^a
% positive	.714	.821	.643
p-value % positive	.023	.001	.131
<i>DLR</i>	.981	1.422	1.164
<i>t</i> -value of change in variable	4.01 ^a	5.52 ^a	4.27 ^a
Paired <i>t</i> -test of levels	1.95 ^c	3.87 ^a	2.94 ^a
Wilcoxon signed-rank test	3.17 ^a	4.05 ^a	3.58 ^a
% positive	.786	.857	.821
p-value % positive	.003	.000	.001
Group 2			
<i>DVOL</i>	-.822	-.571	-1.403
<i>t</i> -value of change in variable	-2.15 ^b	-1.54	-3.88 ^a
Paired <i>t</i> -test of levels	-1.85 ^c	-1.08	-3.47 ^a
Wilcoxon signed-rank test	-2.13 ^b	-1.26	-3.19 ^a
% positive	.310	.379	.276
p-value % positive	.041	.194	.016
<i>DLR</i>	-.423	-.299	-.594
<i>t</i> -value of change in variable	-1.39	-1.00	-1.91 ^c
Paired <i>t</i> -test of levels	-1.22	-.66	-.14
Wilcoxon signed-rank test	-1.57	-.83	-2.41 ^b
% positive	.414	.448	.207
p-value % positive	.353	.578	.002

Note: The table presents changes in liquidity measures in the continuous trading system from the pre-event period to the j th post-event sub-period ($j = II, III, IV$). Group 1 contains the stocks actively traded by OFEs, while the stocks in group 2 were not (or only to a small extent) subject to institutional trading. *DVOL* and *DLR* are the changes in absolute trading volume and in liquidity ratios as defined in equations (18) and (19), respectively. All parameter values are calculated for each stock separately and then averaged across all stocks in the particular group (with the same weights given to each stock). "*t*-values of change in variable" denote cross-sectional *t*-statistics of *DVOL* and *DLR*. Paired *t*-tests test the equality of the means of *VOL* and *LR* for one group in the pre-event and the j th post-event periods. Wilcoxon signed-rank tests test whether the median of the distribution is different from zero. % positive is the percentage of stocks for which the corresponding measure increased, while p-value % positive denotes the p-value of a test with the null hypothesis that the percentage of stocks with positive values is .5. ^a, ^b, and ^c denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 14: Liquidity measures in the call auction system

	Change from pre-event period		
Sub-period	<i>II</i>	<i>III</i>	<i>IV</i>
Group 1			
<i>DVOL</i>	.443	.817	.544
<i>t</i> -value of change in variable	1.96 ^c	3.36 ^a	2.11 ^b
Paired <i>t</i> -test of levels	.77	2.19 ^b	1.60
Wilcoxon signed-rank test	1.62	2.66 ^b	1.73 ^c
% positive	.536	.679	.571
p-value % positive	.706	.059	.450
<i>DLR</i>	.802	.837	.760
<i>t</i> -value of change in variable	3.49 ^a	3.43 ^a	3.16 ^a
Paired <i>t</i> -test of levels	2.61 ^b	2.35 ^b	2.42 ^b
Wilcoxon signed-rank test	2.82 ^a	2.69 ^a	2.69 ^a
% positive	.679	.679	.714
p-value % positive	.059	.059	.023
Group 2			
<i>DVOL</i>	-.998	-.810	-1.458
<i>t</i> -value of change in variable	-3.47 ^a	-2.98 ^a	-5.56 ^a
Paired <i>t</i> -test of levels	-3.04 ^a	-2.91 ^a	-4.05 ^a
Wilcoxon signed-rank test	-3.06 ^a	-2.48 ^b	-4.12 ^a
% positive	.207	.310	.172
p-value % positive	.002	.041	.000
<i>DLR</i>	-.670	-.742	-1.237
<i>t</i> -value of change in variable	-2.45 ^b	-2.87 ^a	-4.73 ^a
Paired <i>t</i> -test of levels	-2.47 ^b	-2.76 ^a	-3.70 ^a
Wilcoxon signed-rank test	-2.19 ^b	-2.41 ^b	-3.69 ^a
% positive	.310	.310	.207
p-value % positive	.041	.041	.002

Note: The table presents changes in liquidity measures in the call auction system from the pre-event period to the j th post-event sub-period ($j = II, III, IV$). Group 1 contains the stocks actively traded by OFEs, while the stocks in group 2 were not (or only to a small extent) subject to institutional trading. *DVOL* and *DLR* are the changes in absolute trading volume and liquidity ratios as defined in equations (18) and (19), respectively. All parameter values are calculated for each stock separately and then averaged across all stocks in the particular group (with the same weights given to each stock). "t-values of change in variable" denote cross-sectional *t*-statistics of *DVOL* and *DLR*. Paired *t*-tests test the equality of the means of *VOL* and *LR* for one group in the pre-event and the j th post-event periods. Wilcoxon signed-rank tests test whether the median of the distribution is different from zero. % positive is the percentage of stocks for which the corresponding measure increased, while p-value % positive denotes the p-value of a test with the null hypothesis that the percentage of stocks with positive values is .5. ^a, ^b, and ^c denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 15: Cross-sectional regression results

Panel A: Continuous Tr.	Dependent	Variables				
Independent Variables	$DVOL_2$	$DVOL_2$	$DVOL_3$	$DVOL_3$	$DVOL_4$	$DVOL_4$
Intercept	-.822 ^b	-.290	-.571 ^c	.017	-1.403 ^a	-.540
D^{Group}	1.454 ^a	1.106 ^c	1.971 ^a	1.566 ^a	2.38 ^a	1.774 ^a
D^{Ind}		-.688		-.728		-1.093 ^c
D^{Fin}		-.029		-.785		-.973
$Size(\times 10^{10})$.607		.428		.295
$Vol(\times 10^7)$		-.090		.072		.143
R^2	.13	.12	.23	.22	.29	.32
	DLR_2	DLR_2	DLR_3	DLR_3	DLR_4	DLR_4
Intercept	-.423	.008	-.299	.158	-.594 ^b	.020
D^{Group}	1.405 ^a	1.076 ^b	1.721 ^a	1.282 ^b	1.758 ^a	1.119 ^b
D^{Ind}		-.573		-.624		-.878
D^{Fin}		.121		-.172		.001
$Size(\times 10^{10})$.731		.549		.390
$Vol(\times 10^7)$		-.107		.029		.094
R^2	.17	.19	.23	.24	.23	.25
Panel B: Call auction	Dependent	Variables				
Independent Variables	$DVOL_2$	$DVOL_2$	$DVOL_3$	$DVOL_3$	$DVOL_4$	$DVOL_4$
Intercept	-.998 ^a	-.637	-.810 ^a	-.326	-1.458 ^a	-.787
D^{Group}	1.441 ^a	1.077 ^b	1.627 ^a	1.307 ^a	2.003 ^a	1.527 ^a
D^{Ind}		-.509		-.589		-.848 ^c
D^{Fin}		.110		-.668		-.744
$Size(\times 10^{10})$.581		.502		.382
$Vol(\times 10^7)$		-.030		.028		.085
R^2	.20	.20	.24	.25	.33	.36
	DLR_2	DLR_2	DLR_3	DLR_3	DLR_4	DLR_4
Intercept	-.670 ^b	-.334	-.742 ^a	-.447	-1.237 ^a	1.607
D^{Group}	1.472 ^a	1.102 ^b	1.579 ^a	1.314 ^a	1.997 ^a	1.607 ^a
D^{Ind}		-.479		-.381		-1.050
D^{Fin}		.105		-.287		-.250
$Size(\times 10^{10})$.674		.598		.496
$Vol(\times 10^7)$		-.032		-.008		.054
R^2	.21	.23	.24	.24	.34	.35

Note: The table presents cross-sectional regression results of equations (20) and (21). The dependent variables are given on top of columns two to seven, while the explanatory variables are displayed in column one. $DVOL_j$ and DLR_j ($j = II, III, IV$) are defined in equations (18) and (19). $Size$ is average market capitalization over the event period (measured in Polish zlotys). D^{Group} , D^{Ind} , and D^{Fin} are dummy variables that equal one if the corresponding stock belongs to group 1, to the industry sector, and the financial sector, respectively, and zero otherwise. R^2 is the adjusted R^2 of the regression. ^a, ^b, and ^c denote statistical significance at the 1%, 5%, and 10% level, respectively.

5 Price Limits on a Call Auction Market: Evidence from the Warsaw Stock Exchange

5.1 Introduction

A number of security markets worldwide impose limits on daily asset price movements. Among these markets are very liquid and important exchanges such as Paris Bourse/Euronext and the Tokyo Stock Exchange. A price limit rule restricts daily changes in asset prices by a defined percentage of a previous price. Depending on the regulatory framework in a particular market, trading is either suspended after a limit hit or continues, with subsequent prices fixed either at the limit or within the price limit bounds.

Since price limits directly interfere with asset price resolution, their influence is actively discussed by both practitioners and academic researchers. Price limit advocates consider them beneficial due to the following reasons. First, price limits prevent markets from overreacting by bounding the maximum price change during the trading day. Thus, until trading is resumed, investors may re-assess new information and adjust their beliefs about the asset's fundamental value accordingly. Second, price limits constitute an upper bound for daily volatility and thus reduce the risk that investors bear during turbulent trading days. Therefore, price limit mechanisms are supposed to ensure orderly markets and smooth prices.

However, the implementation of price limits is associated with tangible costs for market participants, which may outweigh their potential benefits. First, prices cannot adjust immediately to their equilibrium in case of large changes in the fundamental asset value because they are restricted by the allowed variation band. A second cost of price limits lies in their interference with liquidity. Since price limits restrict trading beyond certain price ranges and may cause trading halts, some investors are excluded from trading which may cause temporal inefficiency of portfolios and sub-optimal risk-sharing.

Whether the gains from price limit application exceed its costs is scrutinized in a number of studies of equity and futures markets. Evidence on the beneficial influence of price limits is provided by Ma, Rao, and Sears

(1989a), Ma, Dare, and Donaldson (1990), and Huang, Fu, and Ke (2001). Other studies (Gay, Kale, Kolb, and Noe (1994) and Chen (1998)) find no support for systematic overreaction by market participants, thus challenging the expected advantage of price limits. Another strand of the literature, analyzing the impact of price limits under different price limit regimes on particular markets, casts further doubt on the view that price bounds yield beneficial effects. These investigations document that tighter price limits do not necessarily result in lower volatility levels on the stock markets of Korea (Chung (1991)), Taiwan (Chen (1993), Kim (2001)), and Greece (Phylaktis, Kavussanos, and Manalis (1999)). A possible reason behind this finding is that price limits, bounding volatility on the limit hit day, merely transfer it to the subsequent day. Abnormally high volatility on the days following a limit move is reported by Kim and Rhee (1997) for the Tokyo Stock Exchange.³⁶ This volatility spill-over is accompanied by strong price continuation after limit hits, indicating that price limits retard price discovery (Kim and Rhee (1997), Shen and Wang (1998)). The available evidence thus indicates the lack of conformity between proposed and actual effects of price limits.

There are, however, marked differences in market architecture across exchanges and, therefore, price limits do not necessarily have the same effects across markets. The trading process, e.g., as one of the key characteristics of market organization, can be organized as periodic call auctions, continuous auctions, or as continuous dealer markets. The studies cited above all focus on markets where trading takes place continuously or the market clears frequently during operating hours.³⁷ To the best of our knowledge, no study of the impact of price limits on a call auction market with a low number of market clearings per day is available, although this market structure is widely used for at least a subset of stocks traded on various exchanges. In markets

³⁶Similar effects are reported for circuit breakers (Kuhn, Kurserk, and Locke (1991)) and trading halts on the NYSE (Lee, Ready, and Seguin (1994)). Ma, Rao, and Sears (1989b) find lower volatility after limit hitting days; their method was, however, subject to heavy criticism (Lehmann (1989), Miller (1989)).

³⁷In Taiwan, e.g., the market is organized as a periodic call auction with the time between market clearings varying between 60 and 90 seconds (see Kim and Limpaphayom (2000)).

with one or two auctions per day, where the period between two consecutive trading sessions is of considerable length, investors are provided with sufficient time to evaluate the importance of any new information. Extensive time-out periods between auctions serve the same purpose as the rationale behind the imposition of price limits that is usually put forward by regulators. Due to a time-out period inherently provided by the discrete market clearing frequency in a call auction, one will not expect that price limits will have additional effects on preventing overreaction and panic, and, therefore, there is no reason to assume that price limits offer the proposed advantages to market participants in this market setting.

Empirical evidence on the impact of price limits in such a market setting will be of interest for both market participants, who may suffer from inefficient price formation, and officials of stock exchanges, considering the implementation of similar trading regulation. Therefore, here we investigate the effects of price limits in the call auction segment of the Warsaw Stock Exchange (WSE), with trading taking place once per day and with price limits applied to the change of the daily auction price relative to the price on the previous trading day.

We investigate our hypothesis that price limits do not have the positive effects proposed by their proponents in this call auction market by focusing on the following two aspects. First, we do not expect a reduction in volatility after limit moves. On the contrary, if price limits merely hinder price adjustment, volatility will be passed on to the next trading day. Therefore, we examine whether estimated volatility after limit moves is higher than predicted by a model that does not explicitly incorporate price limit hits.

Second, if price limits have no additional effect on preventing overreaction and panic, we do not expect price reversals after limit moves either. Therefore, our second proposition is that price reversals will not occur after limit hits; rather one would observe continuation of price movements.

To examine the first assessment that price limits pass on volatility to the next day, we model daily stock return volatility in a GARCH framework. To capture additional volatility on the day following a limit hit, we include dummy variables in the conditional variance equation. The estimation re-

sults yield significant positive parameter values for excess volatility on the first day after limit hits. This indicates that price variability on these days is higher than predicted by a conventional GARCH model that discards the presence of price limits. This finding lends empirical substance to our conjecture that price limits do not moderate volatility but rather transfer it to the next trading day.

We investigate the second assessment that price limit hits are not followed by price reversals by focusing on the serial autocorrelation of daily stock returns. First-order autocorrelation turns out to be positive and highly significant on days following limit hitting days with parameter estimates ranging between .35 and .8. This finding supports our second hypothesis and enables us to infer that price limits in a call auction market do not succeed in preventing overreaction.

The remainder of this section is organized as follows. The next subsection presents the price limit and trading regulation on the Polish stock market. Subsection 5.3 describes the data and derives our research hypotheses. The empirical results are presented in Subection 5.4: the impact of price limit hits on volatility is investigated in 5.4.1 and the influence on return autocorrelation in 5.4.2. In 5.4.3, we identify other potential benefits of price limits and discuss why they are unlikely to apply in the considered market structure. Subsection 5.5 contains concluding remarks.

5.2 Trading Structure and Price Limits on the Warsaw Stock Exchange

Re-established in 1991, trading on the WSE initially took place in one daily call auction. In July 1996, an order-driven continuous trading system was launched and the most liquid stocks were gradually introduced to this system. These stocks were still traded in the daily call auction in the morning, but an additional continuous trading session took place in the afternoon. In November 2000, a new trading system was launched and all stocks were allocated to either the call auction system or the continuous trading system. Today, most stocks are traded continuously.

Since in our study of the WSE we focus on the influence of price limits on prices of stocks traded exclusively in the call auction system with one daily auction, we confine ourselves here to the outline of the trading procedure in this particular system. The most liquid stocks are additionally traded in the continuous trading system in the afternoon, but as we focus entirely on the effect of price limits in the call auction system, these stocks are excluded from our investigation. The call auction system consists of several phases: a pre-opening phase followed by possible interventions by the specialist, the auction itself, and post-auction trading. The trading day is concluded by the pre-opening order placement for the following trading day. This time schedule of trading of our sample stocks is displayed in Figure 5.

[Insert Figure 5 here]

The pre-opening procedure starts after the collection of orders. If there is an order imbalance, the pre-opening phase may be followed by interventions undertaken by the specialist who is appointed by the WSE and assigned to a particular stock. The specialist can intervene by either trading on his own account or by encouraging investors to submit additional offsetting orders.

After the intervention phase, the market price for a security is set. The price is determined under the principles of maximizing turnover, minimizing the demand and supply imbalance, and minimizing the difference between the determined and the reference prices. The reference price for a security is the price fixed in the previous session, i.e., on the previous day. After the call auction price is set, market participants can submit additional orders and trade at this price in a post-auction trading phase, which lasts 45 minutes.

The WSE imposes limits on call auction price fluctuations. According to this price limit rule the stock price may not vary by more than $\pm 10\%$ of the reference price. If a price cannot be determined within these price brackets the following procedure applies. If the imbalance of buy and sell orders (or vice versa) exceeds the ratio 5 : 1, no trade is executed and a non-transactional price is announced at the upper (lower) price limit in case of a buy (sell) order surplus. If the imbalance does not exceed this ratio, all buy (sell) orders are reduced proportionately and all transactions are executed

at the upper (lower) price limit. The WSE categorizes all prices determined in the call auction whether they arise from a balanced market, or whether demand or supply surpluses prevailed after price determination.³⁸

In some cases, the strict price limit rule is relaxed for a particular stock and the call auction price on this day is unrestricted. This can happen for two reasons. First, the price of a stock may experience price limit hits in the same direction on two or more consecutive trading days. In this case, the specialist may drop the limit rule and the price can adjust to its equilibrium. Second, when trading in a particular stock has been suspended for one or more days, the limit rule is dropped on the first day on which trading is resumed.

5.3 Research Hypotheses and Data

From the description of the periodic call market in Poland presented above it becomes clear that call auction systems with one daily market clearing and price limit mechanisms are essentially substitutional ways to counter panic and overreaction on a market. The call auction structure itself provides time-out periods that allow investors to cool off and re-assess their information. Therefore, we do not expect ex-ante additional benefits arising from the imposition of price limits in the call auction market under investigation. On the contrary, due to the delay of price adjustment, we expect to detect volatility spill-overs to the following day. To test whether price limits dampen volatility, we formulate the following hypothesis:

H1₀: On days subsequent to price limit hits, stock returns do not display excess volatility

against the alternative hypothesis

H1_A: Price limit hits cause excess return volatility on the next trading day.

If price limits prevent overreaction on a market, the price series should display reversal immediately after limit hits. If price limits are not beneficial in the sense that they delay price adjustment to equilibrium, we expect

³⁸In our empirical investigation, we use this indicator variable to determine price limit hits.

continuation of price movements. In this call auction market, we expect the latter effect to prevail. Therefore, if price limits are successful in mitigating overreaction, then

H2₀: On days subsequent to price limit hits, one will not observe price continuation for limit hitting stocks.

We test this hypothesis against the alternative hypothesis

H2_A: Price limit hits induce continuation of price movements on the following day.

We test the two research hypotheses using Polish stock market data. In our empirical study, we use daily stock return and trading volume series that are provided by the WSE. Our sample covers the period from January 1996 to November 2000. We use all stocks that are traded exclusively in the call auction system as described in the previous section.³⁹ With the introduction of a new trading system in November 2000, most stocks were transferred to the continuous trading segment that has different price limit restrictions. Therefore, this date naturally constitutes the end of our investigation period.

To be included in our sample, a stock has to meet the following conditions. First, we require at least one year of observations to permit a reliable estimation of model parameters. Second, to estimate the effect of price limit hits for a stock with sufficient accuracy we include only stocks with six or more price limit hits over the estimation window.⁴⁰ Our final sample contains 92 return series of individual stocks.

To facilitate the presentation of our results, we group the 92 stocks in our sample into three sub-samples. Group 1 contains 30 stocks with the highest number of price limit hits, while 30 stocks with the smallest number of limit hits are assigned to group 3. The remaining 32 stocks with a medium number

³⁹Once a stock is introduced to continuous trading, we exclude the following observations from our analysis. The data prior to the transfer to the continuous trading system, however, remain in our sample.

⁴⁰When excluding stocks with only few price limit hits, we face a trade-off between a larger number of stocks included in our study and a sufficiently large number of price limit hits in the individual return series. Although the cut-off point at six price limit hits is arbitrarily chosen, this number allows us to use a reasonable number of price limit hits in a sufficiently large sample. Small variations in the cut-off point do not essentially alter our findings.

of price limit hits are classified as group 2.

In the following section, we present results on the impact of price limit hits on volatility and return autocorrelation. We conduct the investigation in two ways. First, we estimate results for all stocks separately and report cross-sectional averages and t -statistics for the overall sample as well as for the three sub-groups. Second, we pool all observations into one sample and estimate results for this one large sample. Since the results are similar in both cases, we report only the cross-sectional averages from individual return series estimations. The pooled regression results as well as the results for individual stocks are available upon request.

5.4 Empirical Results

5.4.1 Volatility

First, we present descriptive statistics of our three groups of stocks as well as of the overall sample. The numbers are shown in Table 16.

[Insert Table 16 here]

Our sample stocks hit the price limits on 1.9% of all trading days and the average number of trading days with limit hits varies between 7.1 for group 3 and 24.4 for group 1. Average returns are positive for groups 1 and 2 and negative for group 3, which provides evidence that stocks with more frequent limit hits performed better during our estimation period. Standard deviation and excess kurtosis, indicating fat tails of the return distribution, increase from group 3 to group 1, which is consistent with the fact that the stocks in group 1 hit their price limits more frequently. Finally, the stocks with the highest number of limit hits are most actively traded.

We first investigate the hypothesis that price limits do not increase the expected volatility of returns on the day following limit hits. Therefore, we calculate the impact of price limits on stock return volatility taking into account the serially dependent nature of volatility. Serial dependence, which is a well-known feature of conditional return volatility, is usually captured by GARCH models (Bollerslev (1986)). To explicitly measure volatility on the

day following a price limit hit, we include dummy variables for this day in the GARCH framework. Specifically, volatility after price limit hits is captured by the following GARCH(1,1) model:⁴¹

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t \quad (22)$$

$$\varepsilon_t \sim (0, h_t) \quad (23)$$

$$h_t = \omega + \beta_1 h_{t-1} + \beta_2 \varepsilon_{t-1}^2 + \gamma_1 D_{t-1}^u + \delta_1 D_{t-1}^l + v_t. \quad (24)$$

The day t return, r_t , of a particular stock depends on the return of the previous trading day plus an error term, ε_t . This error term has zero mean and conditional variance h_t . The conditional variance depends on its value on the previous trading day, h_{t-1} , as well as on the squared lagged residual, ε_{t-1}^2 . Additionally, the conditional variance equation includes dummy variables that explicitly capture the change in conditional volatility attributable to a limit hit. D_{t-1}^u (D_{t-1}^l) equals one if the stock price hits the upper (lower) limit on day $t - 1$ and zero otherwise. Thus, the coefficient γ_1 (δ_1) measures the excess volatility on the first day after an upper (lower) limit hit.

First, we estimate a restricted version of (22) to (24) by setting γ_1 and δ_1 equal to zero. The results of this model serve as a benchmark for comparisons with the extended model. Second, we estimate the model with the upper and lower limit hit dummies. This extension explicitly captures excess volatility on the day following a price limit hit.

We use two measures to evaluate whether volatility on days after a price limit hit is higher or lower than average. First, we analyze the signs of the γ_1 and δ_1 coefficients. If $H1_0$ holds, then γ_1 (δ_1) should not be significantly larger than zero. A positive value of γ_1 implies higher (lower) volatility than expected on the first day after an upper limit hit given the serially dependent nature of volatility. The coefficient δ_1 for lower limit hits is interpreted analogously.⁴²

⁴¹We determined the optimal lag length of our GARCH specification using the information criteria of Schwartz and Akaike. These measures indicate the GARCH(1,1) specification as optimal for the overwhelming majority of stocks. To allow comparison across stocks, we rely on this specification for all securities in our sample.

⁴²Note that we have to drop the usual nonnegativity restriction for the coefficients in the conditional variance equation in order to determine whether volatility after price limit

Second, since the inclusion of the dummy variables may also change the estimated GARCH coefficients, we use the estimated unconditional variance to draw inferences about volatility on days after price limit hits. The unconditional variance of return residuals in a GARCH(1,1) model is given by

$$VAR = \frac{\omega}{1 - \beta_1 - \beta_2}, \quad (25)$$

where the ω and the two β coefficients are, respectively, the estimated intercept term and the GARCH coefficients of the variance equation (24). First, we calculate the measure in equation (25) for our restricted benchmark model (γ_i and δ_i are both set to zero). Then, we compute the same measure for the model with the dummy variables. In the latter case, equation (25) measures the unconditional variance of the return residual series *excluding* excess volatility on the day following a price limit hit. If unconditional variance decreases significantly after excluding the additional volatility attributed to limit hits, we can conclude that excess volatility is present on these days.

We estimate the two versions of the GARCH model (22) to (24) described above and present the results from the extended model in Table 17. Columns two to four display the results of equation (24) of the restricted model, while the coefficients of the unrestricted model are shown in columns five to nine. The model is estimated for each stock separately. The table presents cross-sectional means and t -statistics for the entire sample as well as for the three subgroups as defined in Section 4.4.1.

[Insert Table 17 here]

The results shown in the table reveal that the coefficients of the dummy variables are positive and highly significant across the sample. This finding indicates that volatility on days following a price limit hit is higher than predicted by a conventional GARCH(1,1) model that already captures serial dependence in the conditional variance. When investigating this effect for the

hits deviates from volatility in periods without limit hits. The nonnegativity restriction is usually placed on the coefficients to prevent the estimated variance from becoming negative. Our approach is justified by the fact that we apply it solely to historical data and do not use it for out-of-sample forecasts. A similar methodology is used in Cho, Russell, Tiao, and Tsay (2003) and Veld-Merkoulova (2003).

three sub-groups of stocks, we find that the coefficients γ_1 and δ_1 are positive in all cases with significance increasing with the number of limit hits. In group 3, however, both coefficients are still significant at the 5% level.

An explicit test of changes in the unconditional variance is reported in Table 18. The measure VAR is defined in equation (25) and the indices "0" and "1" indicate the number of lags of the limit hit dummy variables included in the conditional variance equation (24). For the model without dummy variables, VAR_0 denotes the unconditional variance in the return series, while for the model with one lag of the dummy variables VAR_1 is the unconditional variance excluding excess volatility on the first day after a limit hit. If price limits successfully mitigate volatility in a call auction, i.e., $H1_0$ holds, then VAR_1 should not be significantly lower than VAR_0 . That means that there is no excess volatility on the day following a limit hit day. To test the significance of the difference between VAR_1 and VAR_0 we apply a conventional t -test to the variable $DVAR$, which is defined as $Ln(Var_1/Var_0)$.

[Insert Table 18 here]

Across the sample, VAR_1 is significantly smaller than VAR_0 as indicated by the highly significantly negative $DVAR$ variable. In all three sub-groups, $DVAR$ is significant at the 1% level. Moreover, $DVAR$ is negative for the overwhelming majority of stocks, indicating excess volatility after limit moves.

All results presented in this section soundly reject our first hypothesis that price limit hits do not cause excess volatility on the next trading day. This finding provides the first piece of evidence in favor of our expectation that price limits are not beneficial in a call auction market with one daily auction. We now turn to the second research hypothesis and focus on price movements after limit hits.

5.4.2 Return Autocorrelation

We test our second hypothesis that price limits do not cause price continuation by focusing on the autocorrelation structure of the return series.

Following Shen and Wang (1998), we estimate return autocorrelation on the day following a price limit hit using the following two regressions:

$$r_t = \beta_0 + (\beta_1 + \beta_2 D_{t-1}^u + \beta_3 D_{t-1}^l) r_{t-1} + \varepsilon_t \quad (26)$$

$$r_t = \beta_0 + (\beta_4 + \beta_5 TO_{t-1} + \beta_6 D_{t-1}^u + \beta_7 D_{t-1}^l) r_{t-1} + \varepsilon_t. \quad (27)$$

In equation (26), we model return autocorrelation as an autoregressive process of the return series. We capture the impact of price limit hits on autocorrelation by including the dummy variables D_{t-1}^u and D_{t-1}^l as defined above. ε_t represents the error term of the regression. The estimated coefficient β_1 gauges first-order autocorrelation if no limit hit occurred on the previous day. In case of a hit of the upper (lower) limit on the previous day, autocorrelation is given by the coefficient sum of β_1 and β_2 (β_1 and β_3).

It has been shown empirically that trading volume may have an impact on return autocorrelation (see Boudoukh, Richardson, and Whitelaw (1994) for an overview). This 'volume effect' presumes a decrease in the extent of autocorrelation after periods of high trading activity. Thus, trading volume may compensate or reinforce the impact of price limits on return autocorrelation. To disentangle these effect, we include turnover, TO_{t-1} , as a proxy of trading volume in equation (27), defined as the number of shares traded on day $t - 1$ in all phases of the auction system divided by the number of shares outstanding on the same day. The coefficient β_5 in (27) evaluates the additional impact of volume on autocorrelation in the stock return series.

For $H2_0$ to hold, the coefficients of limit hit dummies ($\beta_2, \beta_3, \beta_6, \beta_7$) should not be significantly positive. Table 19 displays the estimation results of equations (26) and (27). We first estimate the equations using the regular OLS estimation technique. Next, we allow the error term to follow a GARCH(1,1) process and repeat the estimation of equations (26) and (27).⁴³ Since both methods yield qualitatively identical results, we report the simple OLS estimation results only.

[Insert Table 19 here]

⁴³Again, the information criteria indicate optimality of the GARCH(1,1) formulation.

We observe strong continuation in the stock return series after price limit hits reflected in a substantial degree of return autocorrelation. Results of equation (26) indicate that after a hit of the upper (lower) price limit the average return autocorrelation in the whole sample measured as the sum of β_1 and β_2 (β_1 and β_3) reaches .618 (.371). Such a considerable extent of serial dependence is found for all sub-groups of stocks with the highest value for the sub-group with the largest number of limit hits (group 1). For this group, return autocorrelation on the day immediately following upper and lower limit hits attains .703 and .585, respectively, while the estimates for group 3 equal .585 and .340.

Estimation results of equation (27) show that the coefficients of the dummy variables are only slightly reduced when volume is included in the regression, indicating the robustness of our results. Volume, measured as share turnover, exerts a positive influence on return autocorrelation. Correlation is higher on days subsequent to larger trading activity, although this finding is not significant in groups 1 and 2. The additional explanatory power of turnover, however, is rather small as can be seen from the modest increase in the average adjusted R^2 measure as reported in the table.

Contrary to other markets (Shen and Wang (1998)), we do not find a negative relationship between trading volume and autocorrelation. However, this does not necessarily mean that there is no information content in trading volume. It may be helpful to disaggregate our volume measure into volume realized in the auction phase and volume in post-auction trading. Especially, the latter may contain useful information and contribute to the explanation of autocorrelation in equation (27). If market participants expect prices to continue moving in the same direction on days after limit hits, we will observe only small or no volume in post-auction trading after the limit hit since all potential sellers prefer selling the stock at the expected higher price on the next trading day. On the other hand, if investors do not expect a certain direction of price movement on the next day, they may want to close down their positions to avoid the increased overnight risk after a limit hit. In this case, we would observe high trading volume. Thus, volume disaggregated into components from different phases of the auction process may contain

additional information.

Due to lack of data from the early years of the WSE, when only aggregated volume series were recorded, we are not able to distinguish between volume in the different phases of the call auction.⁴⁴ However, the inclusion of trading volume in equation (27) only serves as a robustness check. Moreover, none of our hypotheses are directly related to assumptions about trading volume. Therefore, the relationship between trading volume and autocorrelation should not essentially impact our conclusions.

The findings reported in Table 19 are consistent with our assessment that price limits simply distort the price adjustment process to equilibrium since strong positive autocorrelation can be found on the first day after price limit hits.

5.4.3 Discussion

Our empirical findings suggest that price limits in the call auction system of the WSE merely delay price adjustment and cause volatility spillovers. If the aim of their imposition was to curb overreaction and panic in periods of large price fluctuations, the results indicate that they fail to achieve it. The range of potential benefits of price limits may, however, be wider than this.

Price limits can substitute for higher margin requirements in futures trading, short selling, and credit for the purpose of buying stocks. Moreover, they can limit price manipulation and insider trading by investors with superior information on a stock. While these reasons can justify the implementation of price limits, we doubt that the benefits related to them can realize and thus outweigh the costs of price limit imposition on the WSE.

Price limits can lower transaction costs by substituting for higher margin requirements. This holds for futures trading as shown theoretically by Brennan (1986), Chowdhry and Nanda (1998), and Chou, Lin, and Yu (2000) and supported empirically by Chen (2002), for short selling, as well as for stocks bought on margin (Hardouvelis (1990), Hsieh and Miller (1990)). Since short

⁴⁴In personal discussion with WSE officials we obtained estimates for the share of post-auction trading varying from 10% to around one quarter of volume in the auction system.

positions are usually marked to the market, price limits prevent large changes in margins and, thus, limit the risk of a short position. Therefore, default risk decreases and regulators can decrease transaction costs by allowing lower margins. While this positive function of price limits is intuitively plausible, it cannot be applied to our sample stocks.

First, there are no interdependencies between the stocks used in our study and the futures market. The only futures contracts traded on the WSE that are linked to the stock market are contracts on the WIG 20 index that includes the twenty largest and most liquid stocks. Since these stocks are all traded continuously and are, therefore, not included in our sample, interdependencies between the cash and the futures market do not apply in this case and, therefore, do not justify the implementation of price limits for our sample stocks.

Moreover, the WSE prohibits short selling for almost all stocks (including all of our sample stocks). Thus, price limits in the call auction of the WSE cannot be justified as means of reducing margin requirements for short positions on the spot market either. Finally, buying stocks on margin is very unusual in Poland. In general, brokerage firms do not provide this service to investors. Thus, this rationale can be ruled out as well.

Another potentially beneficial aspect of price limits is the limitation of price manipulation and insider trading. An insider with superior private information on the stock value can make profits at the expense of small uninformed investors. Price limits restrict the potential gains of an insider and the degree of price manipulation and provide time-out periods that make possible the dissemination of information or investigations by regulators. This effect is especially pronounced for less liquid stocks like the stocks in our sample. Since the market is thin for these infrequently traded securities, large orders may lead to large price changes.

The beneficial role in the case of asymmetric information on the WSE is, however, doubtful. First, positive effects of price limits on information distribution are theoretically controversial. As outlined in Chan, Kim, and Rhee (2004), informed traders may be unwilling to trade in the presence of narrow price limits since they are not able to fully exploit their advantage.

This may even increase information asymmetry on the market.

Second, due to the specific structure of the call auction system under investigation the necessity of price limits as a protection against insider trading is questionable. Information is efficiently incorporated into securities prices in a call auction especially for illiquid stocks and the losses of small uninformed investors to better informed agents are lower compared to other market structures (Madhavan (1992), Pagano and Roell (1996)).

Finally, the market price is not simply determined by buy and sell orders but computed by a specialist who observes the content of the order book, may trade on his own account, and can encourage the submission of offsetting orders. Since each trader and his trade can be identified by stock exchange officials *before* the trade is executed, the problem of price manipulation is significantly mitigated since illegal practices can be easier identified and restricted.

The imposition of price limits entails severe costs to the market as shown in the previous subsections. The potential benefits as discussed in this section are questionable given the special structure of the market and we doubt that they can compensate for the disadvantages of price limit imposition.

5.5 Summary and Concluding Remarks

A number of stock markets in the world restrict daily stock price movements by applying price limit rules. The motivation behind this imposition is to mitigate daily volatility and to prevent markets from overreaction and panic by providing a time-out period that allows investors to cool down.

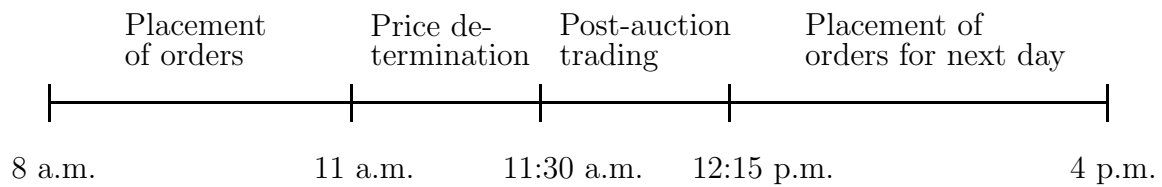
Several investigations have focused on the impact of price limits on markets characterized by continuous trading systems. Their results cast doubt on the suitability of price limits. This study, being the first attempt to extend the empirical evidence to a call auction market with low trading frequency, focuses on the call auction segment of the WSE with one daily auction. Since call auctions provide time-out periods between periodic market clearings, we expect that price limits do not provide additional benefits in terms of reduced volatility and reversed overreaction of stock prices.

Our empirical results sustain this assessment. We document strong evidence of volatility spill-overs to the day after a price limit hit. In our GARCH framework, dummy variables that capture excess volatility on the day following a price limit hit display positive and highly significant coefficients. We also discover strong autocorrelation induced by both upper and lower limit hits. Autocorrelation coefficients on the day subsequent to a limit move are .62 for upper limit hits and .37 for lower limit hits.

Our empirical findings clearly suggest that price limits in the call auction system of the WSE merely delay price adjustment and cause volatility spill-overs. If the aim of their imposition was to curb overreaction and panic in periods of large price fluctuations, the results indicate that they fail to achieve it. Other potential benefits (such as substitutes for higher margin requirements and the protection against insider trading and price manipulation) are also doubtful in this particular trading structure. Our results should be of interest for investors and regulators who are considering the imposition or abolition of price limits on stock markets with similar trading structures.

5.6 Figures and Tables

Figure 5: Time schedule of trading in the call auction system



Note: The figure displays the different phases of the call auction system of the WSE. In 1999, the time for order placement in the morning was reduced from three to two hours and all subsequent phases started one hour earlier.

Table 16: Descriptive statistics of the sample

Stock Group	% Limit Hits	Number Limit Hits	Return	Std. Dev.	Skewness	Excess Kurtosis	Average daily turnover (%)
Group 1	.029	24.4	.024	.042	-.293	6.18 ^a	.524
Group 2	.015	11.5	.026	.038	-.049	1.89 ^a	.264
Group 3	.010	7.1	-.029	.036	-.159 ^a	1.33 ^a	.291
All Stocks	.019	14.2	.008	.039	-.165 ^a	3.11 ^a	.358

Note: The table presents descriptive statistics of three groups of stocks on the WSE as well as of the entire sample. Group 1 consists of 30 stocks with the largest number of price limit hits, group 2 of 32 stocks with an intermediate number of price limit hits, and group 3 of 30 stocks with a small number of price limit hits. This number is displayed in the second column. The third column reports the average number of limit hits per group in the sample. The last column describes average daily turnover (in %), defined as the number of shares traded divided by the number of shares outstanding for a particular stock. ^a indicates that the corresponding value is significantly different from zero at the 1% level.

Table 17: Estimation results of conditional return volatility and the impact of price limit hits

	ω	β_1	β_2	ω	β_1	β_2	γ_1	δ_1
Group 1								
Coefficient	2.49	.636	.222	2.58	.652	.174	13.97	19.37
<i>t</i> -value	7.32 ^a	20.01 ^a	13.88 ^a	7.39 ^a	20.39 ^a	13.19 ^a	4.26 ^a	4.50 ^a
Group 2								
Coefficient	2.98	.581	.206	3.06	.591	.174	13.00	16.63
<i>t</i> -value	7.18 ^a	15.99 ^a	14.55 ^a	7.06 ^a	15.59 ^a	12.52 ^a	3.89 ^a	3.79 ^a
Group 3								
Coefficient	2.96	.575	.191	3.00	.584	.171	6.88	9.52
<i>t</i> -value	8.40 ^a	14.44 ^a	13.46 ^a	7.36 ^a	13.90 ^a	11.17 ^a	2.60 ^b	2.67 ^b
All Stocks								
Coefficient	2.81	.597	.207	2.88	.609	.173	11.32	15.21
<i>t</i> -value	12.99 ^a	28.32 ^a	23.89 ^a	12.42 ^a	27.77 ^a	21.17 ^a	6.19 ^a	6.29 ^a

Note: The table presents excerpts from the regression results of the GARCH model (22) to (24). Columns two to four display the results of equation (24) of the restricted model ($\gamma_1 = \delta_1 = 0$), while the coefficients of the unrestricted model are shown in columns five to nine. ω is the intercept term, β_1 is the GARCH parameter, and β_2 is the ARCH parameter of the conditional variance equation (24). γ_1 and δ_1 are coefficients of dummy variables that equal one on the day subsequent to an upper and a lower price limit hit, respectively, and zero otherwise. ^a and ^b denote significance at the 1% and 5% level, respectively.

Table 18: Results of the impact of price limits on unconditional return variance

	VAR ₀	VAR ₁	DVAR	% positive	p-value % positive
Group 1					
Coefficient	21.10	17.88	-.197	.069	<.0001
<i>t</i> -value			-4.16 ^a		
Group 2					
Coefficient	14.25	12.93	-.099	.129	<.0001
<i>t</i> -value			-4.05 ^a		
Group 3					
Coefficient	13.17	12.56	-.045	.103	<.0001
<i>t</i> -value			-2.77 ^a		
All Stocks					
Coefficient	16.13	14.42	-.113	.101	<.0001
<i>t</i> -value			-5.79 ^a		

Note: The table presents unconditional variance estimates as defined in equation (25) for two formulations of the conditional variance equation (24): A model without any dummy variables (indexed "0") and a model with one lag of the dummy variables (indexed "1"). *DVAR* denotes the cross-sectional mean of the change in unconditional variances defined as $Ln(VAR_1/VAR_0)$. % positive reports the percentage of stocks for which the estimated coefficient is positive, while the p-value of % positive is the p-value of a test with the null hypothesis that positive and negative coefficients are equally likely across the sample. ^a denotes significance at the 1% level.

Table 19: Estimation results of the impact of price limit hits on stock return autocorrelation

Group 1	β_1	β_2	β_3	β_4	β_5	β_6	β_7
Parameter	-.051	.754	.636	-.057	7.585	.747	.635
<i>t</i> -value	-2.94 ^a	20.17 ^a	11.81 ^a	-2.76 ^a	1.33	19.42 ^a	11.99 ^a
% positive	.333	1.000	1.000	.333	.633	1.000	1.000
p-value % positive	.068	.000	.000	.068	.144	.000	.000
% significant	.500	1.000	.900	.433	.133	1.000	.867
Adj <i>R</i> ²	.085			.086			
Group 2							
Parameter	-.094	.712	.340	-.113	6.144	.707	.358
<i>t</i> -value	-5.30 ^a	16.56 ^a	4.53 ^a	-5.21 ^a	1.04	15.56 ^a	4.77 ^a
% positive	.156	1.000	.844	.156	.656	1.000	.875
p-value % positive	.000	.000	.000	.000	.077	.000	.000
% significant	.500	.969	.688	.656	.406	.969	.594
Adj <i>R</i> ²	.072			.075			
Group 3							
Parameter	-.050	.585	.340	-.078	19.041	.571	.341
<i>t</i> -value	-2.57 ^b	11.44 ^a	4.54 ^a	-3.24 ^a	2.36 ^b	10.81 ^a	4.48 ^a
% positive	.300	.967	.800	.167	.700	.967	.800
p-value % positive	.029	.000	.001	.000	.029	.000	.001
% significant	.433	.800	.433	.467	.300	.833	.433
Adj <i>R</i> ²	.033			.038			

(Table 19 continued)

All stocks	β_1	β_2	β_3	β_4	β_5	β_6	β_7
Parameter	-.066	.684	.437	-.084	10.820	.676	.443
t -value	-6.18 ^a	26.02 ^a	10.40 ^a	-6.47 ^a	2.82 ^a	24.68 ^a	10.55 ^a
Adj R^2	.063			.067			
% positive	.261	.989	.880	.217	.663	.989	.891
p-value % positive	.000	.000	.000	.000	.002	.000	.000
% significant	.478	.924	.674	.522	.283	.935	.630

Note: The table presents estimation results of the models (26) and (27). The four panels show results for groups 1 to 3 as well as for the entire sample. t -values denote results of cross-sectional t -tests. % positive and % significant report the percentage of stocks for which the estimated coefficient is positive and significant, respectively, while the p-value of % positive is the p-value of a test with the null hypothesis that positive and negative coefficients are equally likely across the sample. ^a and ^b denote significance at the 1% and 5% level, respectively.

6 Conclusion

This thesis contains four papers on microstructure topics of the WSE. While these papers address issues that may be of interest to local investors, there is also some academic benefit of these analyses of the WSE.

The first paper shows that there is evidence in favor of the mixture-of-distributions hypothesis (MDH) on the WSE. This hypothesis is the most popular attempt to explain GARCH effects in return time series. Indeed, when including trading volume in the conditional variance equations of our GARCH models, for the majority of stocks we see disappearing GARCH effects as predicted by this hypothesis. However, we can identify a number of stocks, for which the inclusion of trading volume has no or only a moderate effect on the GARCH behavior of the return series. Therefore, we conclude that the MDH can only partly explain volatility behavior on the WSE.

The second paper contributes to the discussion of the benefits of different trading systems. Based on evidence from Israel and France, continuous trading has been shown to improve liquidity and price efficiency of stocks compared to a call auction. The results of the paper included in this thesis question whether this finding can be generalized to all markets. On the WSE, there was obviously no benefit from the introduction of continuous trading. In a separate section, potential differences between these findings and those for the other markets are discussed.

One difference between Poland and France / Israel is the dominance of small, private local investors on the WSE. The third paper explores whether a change in the investor structure of the WSE constitutes a necessary condition for the success of continuous trading. Indeed, the findings show that those (and only those) stocks that are subject to pension fund trading display a more frequent use of continuous trading and improved liquidity. The findings shed light on the importance of institutional traders in continuous trading systems.

Finally, we investigate the price limit regulation of the call auction system of the WSE. Call auctions on the one hand and price limits on the other hand are both a widely used feature of stock markets. We are the first to use

the combination of these two aspects and investigate its benefits and costs. The findings show that the price limits in the call auction system impose severe costs on investors, while we do not see any obvious benefits. These findings may be of interests to regulators who consider the introduction of price limits in similar market settings on different exchanges.

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