

Asset Pricing in Emerging Capital Markets: Stock Returns, Trading Volume, and Returns Volatility

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Contents

List of Tables	iv
Acknowledgements	1
1 Introduction	2
2 Volume- and Size-Related Lead-Lag Effects in Stock Returns and Volatility	8
2.1 Introduction and Literature Review	8
2.2 Trading System, Data, and Methodology	11
2.2.1 Trading System	11
2.2.2 Data	12
2.2.3 Methodology	15
2.3 Empirical Results	18
2.3.1 Lead-Lag Models	18
2.3.2 Dimson Beta Regressions	21
2.4 Conclusions	23
2.5 Tables	25
3 Dynamic Volume-Return Relationship	34
3.1 Introduction	34
3.2 Literature Overview	36
3.3 Data and Methodology	38
3.3.1 Data	38
3.3.2 Methodology	39
3.4 Basic Empirical Results	41
3.4.1 Return-Based Strategies	41
3.4.2 Return- and Volume-Based Strategies	41
3.5 Further Empirical Results	44
3.5.1 Size Effects	44
3.5.2 Additional Effects	46
3.6 Conclusions	47
3.7 Tables	49

4	Institutional Trading and Stock Return Autocorrelation	54
4.1	Introduction	54
4.2	Institutional Traders on the Polish Stock Market and Data	56
4.3	Methodology and Empirical Results	59
4.4	Conclusions	64
4.5	Tables	65
5	Are Financial Spillovers Stable Across Regimes? Evidence from the 1997 Asian Crisis	70
5.1	Introduction	70
5.2	Modeling Financial Spillovers	73
5.2.1	Threshold VAR Model	74
5.2.2	Estimation Procedure	74
5.2.3	Statistical Tests	75
5.3	Data and Empirical Results	78
5.4	Summary and Conclusions	84
5.5	Tables	85
6	Conclusions	89
	Bibliography	91

List of Tables

2.1	Descriptive Statistics for Volume-Size Sorted Portfolios	26
2.2	Descriptive Statistics for Size-Volume Sorted Portfolios	27
2.3	Size-Related Lead-Lag Relationship	28
2.4	Volume-Related Lead-Lag Relationship	30
2.5	Size As Information Transmission Mechanism	32
2.6	Volume As Information Transmission Mechanism	33
3.1	Contrarian Profits Using Return-Based Weights	50
3.2	Summary Statistics: Average Weekly Change in Transaction Level	51
3.3	Contrarian Profits Using Weekly Returns	52
3.4	Contrarian Profits Using Return- and Volume-Based Weights for Three Size-Sorted Portfolios	53
4.1	Institutional Characteristics of Stocks Actively Traded by Pension Funds .	66
4.2	Autocorrelation in Stock Returns in Different Sample Periods	67
4.3	Cross-Sectional Regression Results on the Relationship Between Institu- tional Trading and the Change in Return Autocorrelation	69
5.1	Log-Likelihood Values in the Threshold Models	86
5.2	Tests for Stability of Financial Spillovers	87
5.3	Tests for Granger-Causality Between Markets	88

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Chapter 1

Introduction

The process of information dissemination on capital markets and information assimilation into security prices has long been attracting the attention of academics and practitioners alike. For the latter, the predictability of asset prices and, hence, the possibility to forecast the future development of prices of financial assets establishes a profit opportunity and is therefore of vital importance. From a theoretical point of view, the existence of predictable patterns in financial variables challenges one of the fundamentals of finance, namely the validity of the efficient market hypothesis (EMH). Put forward by Fama (1970) in his seminal paper, the EMH states that, at any point in time, asset prices on an informationally efficient market contain all information relevant for asset valuation. Hence, it is impossible to forecast prices such that this forecast is more accurate than the price observed at present. Important implications of this hypothesis are that, first, prices reflect the true value of any asset and contain all available information relevant for an investment decision and, second, money managers cannot systematically earn abnormal profits. Also, prices are driven by news, and the adjustment to new information is instantaneous.

Due to its implication for the effectiveness of capital assets allocation, both from the point of view of an individual and of the entire economy, the issue of informational efficiency and the predictability of stock returns is one of the central topics in finance. Specifically, it is interesting to analyze how stock prices incorporate new information, and what the determinants of this process are, i.e. how stock markets become informationally efficient. Hence, a study of the joint dynamics of stock returns, volatility, and trading volume, as presented here, sheds additional light on the nature and characteristics of the information dissemination and assimilation processes on the stock markets.

The focus of this study is the emerging capital market of Poland, for several reasons.

First, emerging capital markets attracted increasing attention in the 1990s due to the investment opportunities they offered, since these were characterized by high expected returns and low correlation with developed markets, despite the cost of higher volatility- and liquidity-risk (Bekaert and Harvey (2003)). Second, the countries of Central and Eastern Europe constitute a separate group of emerging markets, since their economies re-emerged from the experience of communism, in contrast to many newly industrialized Asian countries which experienced the industrial revolution only in the last decades of the 20th century. Among the European countries that reintroduced capitalist institutions, including financial markets, Poland has often been cited as an example of successful transformation, an argument which can also be applied to the development of its stock exchange. Last but not least, institutional reforms resulted in a considerable growth of the stock market's importance for the financial system of the country, indicated by the fact that the Polish stock market reached the capitalization level of some medium-size mature European markets. Given the numerous differences in capital market policies as well as in institutional settings of the stock exchanges among the emerging markets, a detailed study of the Polish stock market may give valuable insights into the functioning of a capital market under the conditions of economic transformation. It can also help to assess the appropriateness of a specific regulatory framework for the development of a stock exchange.

Moreover, the finance literature offers a broad spectrum of theoretical and empirical studies on mature capital markets. With a weak interest devoted to emerging markets, there is a risk that the results reported are of relevance only for the mature markets, and that the underlying theories fail to explain stock return behavior if confronted with the "out of sample" data in a broader, international context. To provide a robustness check of whether the previous findings are valid universally, we analyze a market that differs from the mature ones in at least three respects. First, we use price and volume data from both the continuous and the single auction system on the Warsaw Stock Exchange (WSE), which contrasts with earlier studies on US markets that analyzed stocks traded in continuous trading systems. One could expect differences in information assimilation by stock prices and, thus, in price behavior due to the difference in the nature of price setting between these two trading systems (discrete and continuous trading). Second, we intentionally analyze an emerging stock market at an early stage of its development, as it was shown in many studies to be informationally inefficient (e.g., Filer and Hanousek

(1999), Chun (2000), Horsewood and Sutherland (2001), Glimore and McManus (2003)), and thus different from the mature markets analyzed elsewhere. Third, the WSE has institutional and regulatory settings different from stock exchanges previously analyzed. Hence, the replication of studies conducted for mature markets to test for the validity of their results is yet another reason for analyzing the emerging markets.

This thesis consists of four essays, each devoted to one particular aspect of the phenomenon of information dissemination and assimilation on stock markets. In the first essay, entitled "Volume- and Size-Related Lead-Lag Effects in Stock Returns and Volatility," a study of channels and speed of stock return reaction to information is presented. The starting point of the analysis is the finding of Lo and MacKinley (1990), who showed that returns on portfolios consisting of high-capitalization stocks lead returns on portfolios of low-capitalization stocks, but not vice versa. This asymmetric cross-autocorrelation structure has been called "(size-related) lead-lag relationship" and is attributed either to the slower adjustment of small stocks to market-wide news (Brennan, Jegadeesh, and Swaminathan (1993), Badrinath, Kale, and Noe (1995), Brennan, Chordia, and Subrahmanyam (1998), Chordia and Swaminathan (2000)) or to differences in the quality of firm-specific cash-flow information (Yu and Wu (2001)). However, the results of Lo and MacKinley were challenged by several researchers (Conrad, Gultekin, and Kaul (1991), Boudoukh, Richardson, and Whitelaw (1994), and Hameed (1997)) and argued to be a spurious effect of the assets' own autocorrelation. Moreover, additional aspects of the lead-lag relationship have been investigated. First, Chordia and Swaminathan (2000) reported that high-volume portfolio returns lead low-volume portfolio returns, i.e. a volume-related lead-lag relationship, with volume leadership existing independently of size leadership. Second, McQueen, Pinegar, and Thorley (1996) showed that the lead-lag relationship is stronger during up markets (i.e. with positive market return) than during down markets due to the sluggish adjustment of small stocks to positive market-wide news. Finally, Conrad, Gultekin, and Kaul (1991) found volatility shocks to large stocks to lead volatility of small stocks, i.e. size-related lead-lag effects in return volatility.

We analyze the lead-lag structure of portfolio returns and volatility for stocks listed in the single auction system on the WSE during the period January 1996 to October 2000. First, we find that size- and volume-related lead-lag relationships exist and are not spurious effects of the assets' own autocorrelation. Second, size and volume leaderships exist independently from each other. Third, our results indicate slower adjustment of small

(low-volume) portfolios to market-wide information which differs for up and down markets. We also find evidence for volatility spillovers between portfolio returns. Further results indicate that size and trading volume are important, but not exclusive, determinants of information dissemination across the market.

While the above chapter focuses on the role of only one variable, size or volume, for the cross-security differences in the speed of reaction to information, the second essay entitled "Dynamic Volume-Return Relationship" is stimulated by the ongoing discussion in the finance literature on the interaction of stock returns and trading volume. Specifically, we investigate its implications for the speed and extent to which new information is incorporated into security prices. Several theoretical models predict that, first, trading volume might contain valuable information about future stock returns beyond that contained in past returns (Blume, Easley, and O'Hara (1994)), and, second, stock return behavior depends on factors such as the degree of information asymmetry among traders and the intensity of trading among them. For instance, for a market with information distributed symmetrically among traders, Campbell, Grossman, and Wang (1993) show that stock returns following a positive change in trading volume are strongly reverting, whereas this effect is less pronounced after a volume decline. On the other hand, Wang (1994) and Llorente, Michaely, Saar, and Wang (2001) argue that, given information asymmetries among market participants, strong return reversals should be observed after a decrease in trading volume, i.e. for the volume-decreasing stocks, whereas weak reversals or even continuations will characterize stock returns on the volume-increasing stocks.

For the trades conducted on the WSE, we find lagged volume to contain information about future returns beyond that contained in lagged returns, especially for small stocks. Next, we find stock returns on volume-decreasing (volume-increasing) stocks to exhibit positive (negative) autocorrelation, which confirms the predictions of the Campbell, Grossman, and Wang's model. In the spirit of Wang (1994) and Llorente, Michaely, Saar, and Wang (2001), these results indicate that the majority of trades on the WSE, especially in small stocks, is conducted primarily for non-informative purposes, i.e. is driven by liquidity needs of the market participants or portfolio rebalancing due to changes in their risk aversion.

Apart from market capitalization and trading volume, the degree of institutional trading in a security is argued in the literature to constitute yet another determinant of the adjustment speed to information. The overwhelming body of theoretical arguments

and empirical evidence supports the hypothesis that heavy trading by institutions increases stock return autocorrelation, implying slower adjustment to information and the existence of predictable patterns in returns. More specifically, the following arguments are put forward. First, investors tend to break up trades and distribute them over time to lower their price impact (Barclay and Warner (1993)). Second, in conjunction with the models presented above, informed trades by institutions increase stock return autocorrelation. Third, information arriving different groups of investors only sequentially will cause stock prices to move in one direction for a certain period of time, resulting in stock return autocorrelation (Holden and Subrahmanyam (2002)). Finally, an interaction of herding and positive feedback trading by institutional investors may increase stock return autocorrelation (Grinblatt, Titman, and Wermers (1995)).

The Polish capital market offers an interesting and unique environment to investigate the impact of institutional trading on autocorrelation in stock returns. This is due to the pension system reform, which resulted in the emergence of several private pension funds as investors on the WSE in 1999. The existence of this "natural experiment" is utilized and stock return behavior prior to and after the pension funds entered the market is investigated. The finding is that the observed increase in institutional trading resulted in a decrease in return autocorrelation, implying an improvement in informational efficiency. This is in line with the model of Badrinath, Kale, and Noe (1995) showing stocks with higher levels of institutional ownership to experience quicker adjustment to information. Several empirical studies (Lakonishok, Shleifer, and Vishny (1992), Cohen, Gompers, and Vuolteenaho (2002)) also fail to find evidence for herding and feedback trading among institutional investors.

In the fourth essay, the focus shifts from a purely domestic to an international perspective. This analysis is motivated by both a large number of papers and the public debate on the interdependencies between stock markets worldwide, especially in the context of financial crises and so-called financial contagion. We analyze the process of information dissemination across borders, with a special interest in the intertemporal stability of the direction and strength of these information spillovers. For the relationships between the US market and each of eight Asian stock markets, we find strong evidence in favor of time-varying spillover patterns, i.e. differences in spillovers between tranquil and turbulent periods. A novel finding is that, while information originating in the US is incorporated into the security prices in Asia under any condition, the information orig-

inating on the Asian market also has a significant impact on US stock returns, albeit only during the turbulent periods. These periods are characterized by low stock returns and high volatility. By contrast, previous studies assuming the intertemporal stability of information spillover patterns failed to find a causality relationship running from Asia to the US. The findings reported here also constitute evidence of financial contagion, defined as a break in the interdependency structure among capital markets.

Chapter 2

Volume- and Size-Related Lead-Lag Effects in Stock Returns and Volatility

2.1 Introduction and Literature Review

The predictability of asset returns has long drawn the attention of both academics and practitioners. Various forms of predictability have been tested for: cross-sectional return predictability based on equilibrium models such as CAPM or APT, time series return predictability emerging from seasonal patterns in returns, and time series predictability arising from return autocorrelation.¹ In this study, we rely on the findings of the literature addressing autocorrelation in returns in order to establish empirical evidence on the patterns and sources of cross-autocorrelations for stocks listed on the Warsaw Stock Exchange (WSE).

In their seminal paper, Lo and MacKinley (1990) found that returns on large portfolios (consisting of high capitalization stocks) predict future returns on small (low capitalization) portfolios, but not vice versa. This asymmetric cross-autocorrelation structure has been termed a (size-related) lead-lag relationship and attributed either to the slower adjustment of small stocks to market-wide news (Brennan, Jegadeesh, and Swaminathan (1993), Badrinath, Kale, and Noe (1995), Brennan, Chordia, and Subrahmanyam (1998), and Chordia and Swaminathan (2000)) or to differences in the quality of firm specific cash-flow information (Yu and Wu (2001)).

These findings were followed by a debate on the sources and importance of own- vs.

¹See, e.g., Hawawini and Keim (1995) and Kaul (1996) for an overview of the relevant literature.

cross-autocorrelations in returns (Boudoukh, Richardson, and Whitelaw (1994)). On the one hand, it has been argued that the lead-lag effects reported by Lo and MacKinlay are spurious and can be explained in terms of the assets' own autocorrelations (Boudoukh, Richardson, and Whitelaw (1994), Hameed (1997), and Conrad, Gultekin, and Kaul (1991)). On the other hand, the autonomy of cross-autocorrelations has been confirmed, and other dimensions of a lead-lag relationship, beyond size, have been sought. For example, Brennan, Jegadeesh, and Swaminathan (1993) find that the number of investment analysts following a stock increases the speed of adjustment of the stock's price to common news, thereby giving rise to lead-lag patterns in returns between stocks with high and low analyst coverage. Badrinath, Kale, and Noe (1995) find that the level of institutional ownership plays an important role. Namely, returns on stocks held by (informed) institutional traders are found to lead returns on stocks held by (uninformed) non-institutional investors. This effect persists even after controlling for the size leadership effect.

Moreover, various studies find trading volume to be a significant determinant of returns.² Chordia and Swaminathan (2000) find high volume portfolio returns to lead low volume portfolio returns, i.e. volume-related leadership. These authors report that volume and size leadership exist independently from each other (also Richardson and Peterson (1999)). In addition, Desai and Tavakkol (2001) find that the size effect is stronger than the volume effect.

A theoretical model providing an economic rationale for the asymmetry of the aforementioned lead-lag effects is presented by Chordia and Swaminathan (2004). These authors demonstrate that, for investors with information on a limited number of stocks and costly arbitrage, prices on stocks with more informed trading adjust faster to common news, giving rise to a lead-lag relationship. The number of informed investors depends on the costs of becoming informed and the number of liquidity traders. Empirical evidence shows that variables such as size, volume, analyst coverage, institutional holding, and bid-ask spread capture either trading or information-gathering costs, thus being good proxies for informed trading causing the lead-lag patterns.

Furthermore, two additional aspects of the lead-lag relationship are of relevance. First, McQueen, Pinegar, and Thorley (1996) show that the lead-lag relationship is

²Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996) show that expected stock returns are (negatively) affected by liquidity. Datar, Naik, and Radcliffe (1998) and Brennan, Chordia, and Subrahmanyam (1998) report a significant relationship between liquidity and expected returns, even after controlling for other risk factors including market size.

stronger for up (with positive market return) than down (with negative market return) markets due to the sluggish adjustment of small stocks to positive market-wide news. Second, Conrad, Gultekin, and Kaul (1991) find variance shocks to the large stocks to lead the variance of the small stocks, i.e. size-related lead-lag effects in volatility.

In this chapter, we study the nature of own- and cross-autocorrelation in returns and volatility for stocks traded on the Warsaw Stock Exchange (WSE) during the period 1996-2000. We argue that an analysis of an emerging capital market can also be of relevance for those concerned with mature stock exchanges. Previous empirical studies of the correlation structure discussed above focused exclusively on the US market. Hence, there is a risk that these results are of relevance only for the US market, and that the underlying theories fail to explain stock return behavior if confronted with the "out of sample" data in a broader, international context. To provide a robustness check for whether the previous findings are valid universally, we analyze a market that differs from the American one in at least three respects. First, we use price and volume data from the single auction system on the WSE, which is in contrast to the earlier studies on US markets that analyzed stocks traded in continuous trading systems. One could expect differences in information assimilation by stock prices and, hence, in price behavior due to the difference in the nature of price setting between these trading systems: a discrete versus a continuous one. Second, we intentionally analyze an emerging stock market at its early stage of development, as it was shown in many studies to be informationally inefficient (e.g. Filer and Hanousek (1999), Chun (2000), Horsewood and Sutherland (2001), Glimore and McManus (2003)), and thus different from the US market analyzed elsewhere. Third, the WSE has institutional and regulatory settings different from those of the stock exchanges previously analyzed. The possible similarities between the mature and the post-communist emerging Polish capital market might also be of interest in the context of the EU eastward enlargement, as it sheds light on the degree of financial market maturity in one of the new EU members.

We perform an empirical analysis of stocks listed on the WSE. For the size- and volume-related lead-lag relationships, we investigate whether own- and cross-autocorrelations are independent from each other. Moreover, we study the question of whether the volume- and size-related effects are independent. We also control for the possible cross-sectional spillovers in the conditional volatility, as suggested by Conrad, Gultekin, and Kaul (1991), as well as for the differences in lead-lag patterns in up and down markets, as shown by

McQueen, Pinegar, and Thorley (1996). Last, we explore whether the differences in the adjustment speed to market-wide news by securities that differ in size and volume can explain the lead-lag patterns in portfolio returns.

We find that, for stocks listed on the WSE, both return- and volatility-related cross-autocorrelations remain even after controlling for own autocorrelations. We also find evidence for significant volatility spillovers from large to small and high to low volume portfolios, as well as evidence on asymmetric return patterns in up and down markets. Further analysis indicates that both volume- and size-related lead-lag patterns can be partially explained by the slower adjustment of small (low volume) portfolios to common news. Size- and volume-related effects are independent from each other. However, our results suggest that size and volume capture only a fraction of informed trading and that other factors, such as analyst coverage or institutional ownership, might be other important proxies for informed trading, further explaining lead-lag patterns in stock returns.

The remainder of this chapter is organized as follows. In Subsection 2.2., the trading system on the WSE is described, descriptive statistics are presented, and the methodology is discussed. In Subsection 2.3., results from the empirical analysis are presented. Conclusions follow in Subsection 2.4.

2.2 Trading System, Data, and Methodology

2.2.1 Trading System

Trading on the Warsaw Stock Exchange (WSE) was re-established on April 16, 1991. Initially trades of five stocks took place in the single-price auction system once a week. Gradually new stocks were introduced, and trades were extended to five days a week. On July 11, 1996, a continuous trading system was launched, and trading of selected highly liquid stocks took place in both the single-auction and the continuous trading systems. However, the former system remained more liquid. In addition, off-session block trades took place. With the introduction of a new trading system (WARSET) on November 17, 2000, each stock was attributed to one of three trading systems: the continuous trading, the single-price auction with one auction, and the single-price auction with two auctions per day. At the end of 2001, there were 230 companies listed on the WSE, accounting for a market capitalization of approximately USD 25 billion, with total daily turnover of USD 186 million.

2.2.2 Data

To conduct our analysis, we utilize daily data from the WSE, for the period January 1996 - October 2000.³ The main index return, WIG, rose from 7,725 to 15,597 points during this period, achieving a maximal value of 22,868 points on March 27, 2000. Out of 947 daily observations, we recorded 495 positive and 452 negative market returns. The average daily return was 0.00016 (0.01338 for up and -0.01431 for down markets), with a standard deviation of 0.01901 (0.01249/0.01361), minimum value of -0.09775 (0.00002/-0.09775) and maximum of 0.08213 (0.08213/-0.00002). Daily market returns show skewness of -0.24612 (1.72330/-2.16366) and kurtosis of 2.64301 (4.00143/7.49190), with 1-st order autocorrelation of 0.12551 (-0.00368/0.18560). There is no convincing evidence in the literature that crises originating in other emerging markets during this period had a significant long-term impact on the WIG behavior (Galos and Sahay (2001), Krzak (1998), Scheicher (2001)) and thus biased our results.

The analysis is based on the daily prices of shares traded in the single auction system. We form two sets of portfolios. To analyze the size-related lead-lag relationship independently from the volume effects, we form three pairs of portfolios, with each pair containing two portfolios of equal volume but different size, as follows. First, portfolios are formed by ranking companies based on their average trading volume in the previous year and then divided into three portfolios with low, medium, and high volume. Next, within each volume portfolio, two size portfolios (small and large capitalization) are formed by ranking the companies based on their average market capitalization in the previous year.⁴ These portfolios are re-formed each year, including newly listed stocks, and referred to as volume-size sorted portfolios. To analyze the volume-related lead-lag relationship independently from size effects, we form three pairs of portfolios, with each pair containing two portfolios of equal size but different volume, analogously to the way we built the volume-size sorted portfolios. These other portfolios are referred to as size-volume sorted

³The reason for choosing this specific period is that information on shares traded on the WSE in the auction system is available from January 1996. Since November 17, 2000, all shares were listed either in the new continuous system or in one of the auction systems, whereas in the previous period some highly liquid shares could be traded in both systems. Hence, to avoid the impact of the structural break we found in portfolio returns at the time of the introduction of WARSET, we conduct our analysis for the period January 1996 – October 2000.

⁴This sorting procedure is based on Chordia and Swaminathan (2000). The whole-year average capitalization and trading volume are used to account for well-known seasonal patterns in stock prices and trading volume.

portfolios.⁵ We use the turnover ratio (ratio of the number of shares traded to the number of shares outstanding) as a measure of volume.⁶ The number of securities in each portfolio varies from 12 in 1996 to 34 in 2000.

Daily returns of each portfolio are computed as the equally-weighted average of daily stock returns defined as the percentage change in daily price.⁷ To account for the possible risk of spurious autocorrelation of returns resulting from non-synchronous trading, we follow Chordia and Swaminathan (2000) and exclude returns at day t and $t - 1$ of shares that did not trade at day t when computing portfolio returns. Descriptive statistics for two sets of portfolios are presented in Tables 2.1 and 2.2.

[Tables 2.1 and 2.2 about here]

The motivation behind forming two sets of portfolios was to analyze the influence of only one factor (size or volume) on the correlation structure of portfolio returns. For a size-related (volume-related) lead-lag relationship, this requires that within one volume (size) class, two portfolios are of equal volume (size), but differ in size (volume). For instance, portfolios P11 and P12 in Table 2.1 should have equal volume but different size, and portfolios P11 and P12 in Table 2.2 – equal size but different volume. This is exactly what we find for our portfolios, at high significance levels (as indicated by the values of the Z-statistics in the last four columns in Tables 2.1 and 2.2). This feature enables us to analyze the size- and volume-related correlation patterns independently from each other. We proceed with a preliminary analysis in this section and present further results in Section 2.3.

First, earlier studies (e.g. Lo and MacKinley (1990)) found mean portfolio returns to decrease in size. This is what we also find, albeit only if the market return decreases (down market, e.g. mean return on small portfolio P11^{DOWN} is higher than on large portfolio P12^{DOWN} given equal volume - Table 2.1). However, if the market return increases (up

⁵A higher number of portfolios would strengthen the results. However, increasing the number of portfolios would decrease the number of stocks in each portfolio. This would result in portfolio characteristics, such as return correlation, size, and volume, being very vulnerable to outliers and thus unreliable. Building six portfolios seems to be confirmed by the data, since we obtain portfolios of equal volume (size) within each volume (size) class, but of different size (volume), as reported in Table 2.1 (2.2).

⁶For a discussion on turnover ratio see: Datar, Naik, and Radcliffe (1998), Chordia and Swaminathan (2000), Lo and Wang (2000)

⁷Equally - weighted portfolio returns describe the average return of stocks in a given portfolio, and are used, e.g., by Lo and MacKinley (1990) and Chordia and Swaminathan (2000). Size weighting of stock returns would result in portfolio returns biased towards large stocks, and hence would not be a suitable description of the average stock return.

market), returns tend to be higher for larger stocks, given equal volume (e.g. mean return on P31^{UP} and P32^{UP} in Table 2.1). Further, Chordia and Swaminathan (2000) report a negative relationship between trading volume and returns. Again, we find this phenomenon to appear only for down, but not up markets (e.g. mean return on low volume portfolio P11^{DOWN} is higher than on high volume portfolio P12^{DOWN} in Table 2.2). When the market is up, stocks with higher volume have higher returns within each size class. Hence, our preliminary findings fit the existing evidence, but also show differences between up and down markets.

Second, if prices adjust slowly to common news (as suggested, e.g., by Brennan, Jegadeesh, and Swaminathan (1993) and Chordia and Swaminathan (2000)), positive autocorrelation in returns should be expected. Moreover, if size (volume) is a transmission mechanism for common news, one should expect large (high volume) stocks to adjust more rapidly to information than small (low volume) stocks. This would imply lower values of the autocorrelation coefficients for large (high volume) portfolios. For the relationship between size and autocorrelation (Table 2.1), we find autocorrelation in returns to be mostly insignificant in the case of up markets, meaning immediate (within one day) adjustment to positive market-wide news independent of size. For down markets, we find clear patterns only for first-order autocorrelation q_{-1} within each volume class. First-order autocorrelations are significant and higher for smaller portfolios (e.g. 0.188081 for P11 versus 0.152017 for P12), suggesting slower adjustment of small stocks to negative news. This contrasts the findings of McQueen, Pinegar, and Thorley (1996) who found small stocks to adjust slower to information than large stocks when the market is up, but no difference in the speed of adjustment when the market is down. However, the finding of a negative relationship between return autocorrelation and size for up and down markets is in line with the results reported by Chordia and Swaminathan (2000). Our results indicate that, on the WSE, autocorrelation arises from the small stocks' sluggish return reactions to negative news.

For the relationship between trading volume and lagged return autocorrelation (Table 2.2), we also mostly find insignificant return autocorrelation for an up market, suggesting immediate adjustment to positive news independently from volume. For a down market, first-order autocorrelation increases as we move from a low- to a high-volume portfolio within each size class (e.g. from 0.208736 for P11 to 0.261315 for P12). This could indicate a slower adjustment of high volume portfolio returns to common informa-

tion when the market is down. This finding is in contrast to other studies (e.g. Chordia and Swaminathan (2000)) that find return autocorrelation to decrease in trading volume.

2.2.3 Methodology

After a preliminary analysis of descriptive statistics, we follow Brennan, Jegadeesh, and Swaminathan (1993) and Chordia and Swaminathan (2000) and analyze the cross-sectional lead-lag effects as well as estimate the Dimson beta regression models (Dimson (1979)). We also study the volatility spillovers. The methodology employed here is discussed in the context of the lead-lag relationship in the following section.

Testing for lead-lag effects

First, we consider two portfolios, A and B, where returns on B are assumed to lead returns on A, but not vice versa. To account for volatility spillovers between these portfolios, a three-step procedure similar to that of Conrad, Gultekin, and Kaul (1991) is used. The difference is that, in addition to the volatility spillovers from e.g. portfolio B to A, we also control for the possible volatility spillovers from the market portfolio M to portfolio A. Our first step is to generate the shocks in returns on portfolios A and B, $u_{A,t}$ and $u_{B,t}$, as residuals from the regression of each portfolio returns on its own lagged values as well as on lagged returns of another portfolio. Therefore, the following model is estimated for portfolio A and B separately:

$$R_{J,t} = \alpha_0 + \sum_{i=1}^L \alpha_{J,i} R_{J,t-i} + \sum_{i=1}^L \alpha'_{J,i} R_{J,t-i} D^{UP} + \sum_{i=1}^L \beta_{K,i} R_{K,t-i} + \sum_{i=1}^L \beta'_{K,i} R_{K,t-i} D^{UP} + u_{J,t}$$

$$h_{J,t} = \gamma_0 + \gamma_1 u_{J,t-1}^2 + \gamma_2 h_{J,t-1} \quad (2.1)$$

where $R_{J,t-i}$ ($R_{K,t-i}$) indicates the return on portfolio $J = A, B$ ($K = A, B$) at $t - i$, D^{UP} is a dummy variable that takes on the value 1 if the market return is positive (up market) and zero otherwise, and error terms are modelled as a GARCH(1,1) process with $h_{J,t}$ being the conditional variance. Variable $u_{J,t}$ constitutes the return shocks, i.e. the part of return $R_{J,t}$ that is independent of own- and cross-autocorrelation.

Second, we generate the shocks to the market portfolio, $v_{M,t}$, as residuals from the following AR(5)-GARCH(1,1) model for market returns:

$$R_{M,t} = \sum_{i=1}^5 R_{M,t-i} + v_{M,t}, \quad h_{M,t} = \gamma_0 + \gamma_1 v_{M,t-1}^2 + \gamma_2 h_{M,t-1}. \quad (2.2)$$

$v_{M,t}$ constitutes shocks to market-wide returns, i.e. the part of $R_{M,t}$ that is independent of own-autocorrelation.

Third, for each portfolio $J=A,B$ we employ lagged squared shocks to the return on another portfolio $K=A,B$, $u_{K,t-1}^2$, estimated in model (2.1), as well as lagged squared shocks to the market return, $v_{M,t-1}^2$, estimated in model (2.2), as explanatory variables in the conditional variance equation. These squared unexpected returns are proxies for the variance of unexpected returns on portfolio K and the market portfolio M , respectively. Here, we also differentiate between the up and down market in the variance equation. Therefore, the following model for each portfolio $J = A, B$ is estimated:

$$R_{J,t} = \alpha_0 + \sum_{i=1}^L \alpha_{J,i} R_{J,t-i} + \sum_{i=1}^L \alpha'_{J,i} R_{J,t-i} D^{UP} + \sum_{i=1}^L \beta_{K,i} R_{K,t-i} + \sum_{i=1}^L \beta'_{K,i} R_{K,t-i} D^{UP} + u_{J,t}$$

$$h_{J,t} = \gamma_0 + \gamma_1 u_{J,t-1}^2 + \gamma_2 h_{J,t-1} + \gamma_3 u_{K,t-1}^2 + \gamma'_3 u_{K,t-1}^2 D^{UP} +$$

$$\gamma_4 v_{M,t-1}^2 + \gamma'_4 v_{M,t-1}^2 D^{UP} \quad (2.3)$$

Hence, for e.g. $J = A$ and $K = B$, the parameter $\alpha_{A,i}$ measures portfolio A's own-autocorrelation at lag i , $\beta_{B,i}$ - the impact of portfolio B on portfolio A at lag i , and γ_3 - the magnitude of volatility spillovers from portfolio B to portfolio A, all in the case of a down market.⁸

If an asymmetric lead-lag relationship between returns on B and A exists, we would expect lagged returns on B (the large cap/high volume portfolio) to exert significantly larger influence on the current returns on A (the small cap/low volume portfolio) than lagged returns on A do on current returns on B, after controlling for own-autocorrelations. Hence, the null hypothesis of symmetry in the lead-lag patterns is: $\sum_{i=1}^L \beta_{B,i} = \sum_{i=1}^L \beta_{A,i}$ when the market is down, and: $\sum_{i=1}^L (\beta_{B,i} + \beta'_{B,i}) = \sum_{i=1}^L (\beta_{A,i} + \beta'_{A,i})$ when the market is up. The one-sided alternative hypothesis of the lead-lag asymmetry is that the sum of lagged coefficients of the large (high volume) portfolio, B, is larger than the sum of lagged

⁸Employing GARCH models is justified by the existence of (G)ARCH effects in residuals, as indicated by the values of the Ljung-Box statistics (not reported). Also, GARCH models provide a parsimonious specification of volatility dynamics, allow for simultaneous estimation of return and variance equations (Bollerslev (1986), Diebold and Lopez (1995)), and are widely used in the related literature, e.g. Conrad, Gultekin, and Kaul (1991) and McQueen, Pinegar, and Thorley (1996). Alternative specifications ranging from GARCH(1,1) to GARCH(5,5) have also been estimated, but the model used here turned out to have the best fit, measured by the Schwarz information criterion. Results of these alternative specifications were qualitatively the same. Also, defining the up variable as one if weekly (monthly) market return is positive and zero otherwise resulted in an inferior fit of the models, but did not change the results significantly. The same conclusions apply to the Dimson beta models (2.4).

coefficients of the small (low volume) portfolio, A. If the null is rejected and portfolios A and B differ in size (volume) but are of similar volume (size), we will talk about size (volume) leadership. Moreover, if volatility spillovers from portfolio B to portfolio A exist after controlling for volatility autocorrelation and the impact of market volatility, the parameter γ_3 (for down market, and $\gamma_3 + \gamma'_3$ for up market) should be significantly different from zero.

Testing for speed of adjustment to market-wide news

Whereas the above framework makes it possible to measure the speed of adjustment of one portfolio's returns in comparison to another, the Dimson beta regression technique can be employed to assess the speed of adjustment of portfolio returns to market-wide information (Chordia and Swaminathan (2000)). For each pair of portfolios under consideration (A and B), we form a zero net investment portfolio, "zero-portfolio", that is long in the "leading" portfolio B and short in portfolio A. We do it by subtracting returns on A from returns on B. Next, we regress zero-portfolio returns on L leads, L lags, as well as the current value of stock index returns (being a proxy for market portfolio returns containing common news):

$$R_{0,t} = \alpha_0 + \sum_{i=-L}^L \beta_{0,i} R_{M,t+i} + \sum_{i=-L}^L \beta'_{0,i} R_{M,t+i} D^{UP} + u_t,$$

$$h_t = \gamma_0 + \gamma_1 u_{t-1}^2 + \gamma_2 h_{t-1}, \quad (2.4)$$

where $R_{0,t}$ equals the return on the zero-portfolio (return on B minus return on A), $R_{M,t+i}$ is the return on the market portfolio at $t+i$, D^{UP} is defined as above, and error terms follow a GARCH(1,1) process. If portfolio B adjusts to common information at a higher pace than portfolio A, we should observe $\beta_{0,i=0}$ (if the market is down, or $\beta_{0,i=0} + \beta'_{0,i=0}$ if the market is up) to be positive (since we would expect current returns on portfolio B to adjust more rapidly to common news contained in current market returns than portfolio A). Also, the sum of lagged coefficients, $\sum_{i=-L}^{-1} \beta_{0,i}$ (if the market is down, or $\sum_{i=-L}^{-1} (\beta_{0,i} + \beta'_{0,i})$ if the market is up), should be negative (since it takes more time for portfolio A than B to adjust to common news).

2.3 Empirical Results

In this section, we apply the methodology described above to the data on stocks listed on the WSE. We analyze the size- and volume-related lead-lag relationship in returns and volatility in Subsection 2.3.1, and the cross-portfolio differences in the speed of adjustment to market-wide news in Subsection 2.3.2.

2.3.1 Lead-Lag Models

To investigate the importance of own- vs. cross-autocorrelations and the existence of size- and volume-related lead-lag effects in portfolio returns and volatility, we first estimate the lead-lag models (2.3) as described in Subsection 2.2.3. All models are estimated using 5 lags.⁹ To investigate the size-related (volume-related) effects, we use daily data for volume-size (size-volume) sorted portfolios of similar volume (size) and different size (volume), constructed as described in Subsection 2.2.2).

Size-related return effects

In Table 2.3, Panel A, results from the analysis of size-leadership for low-, medium-, and high-volume stocks are presented. For all cases, the parameter α measures own-, whereas β cross-autocorrelation.

[Table 2.3 about here]

For the regressions of small on large portfolio returns (e.g. R11 on R12), in both up and down markets we observe lagged returns on the large portfolio to be an explanatory factor for current small portfolio returns at the 5% significance level, even after controlling for own-autocorrelation of the small portfolio ($\sum_{i=-5}^{-1} \alpha_{J,i}$). This is the case for either short term (measured by $\beta_{K,-1}$ for down and $\beta_{K,-1} + \beta'_{K,-1}$ for up market) or long term causality ($\sum_{i=-5}^{-1} \beta_{K,i}$ for down and $\sum_{i=-5}^{-1} (\beta_{K,i} + \beta'_{K,i})$ for up market) in all three volume groups. However, in the regressions of large on small portfolio returns (e.g. R12 on R11), we find only a weak influence of small on large portfolios for the down markets (high

⁹The number of lags for this analysis of daily returns was chosen following Brennan, Jegadeesh, and Swaminathan (1993), Boudoukh, Richardson, and Whitelaw (1994), and Chordia and Swaminathan (2000), to enable the comparison of results. Moreover, applying 5 lags makes it possible for us to account for the well-known day-of-the-week effects in returns. Additional tests with 1-10 lags have also been conducted, and conclusions were virtually the same.

volume portfolios), but two cases of a significant short-lived impact of a small portfolio on a large one in the case of up market (for medium and high volume portfolios).

The Z-statistics further reveal the size-related lead-lag relationship to be significant for all volume groups in the case of down markets. However, when the market is up, we find no significant lead-lag relationship from large to small stocks. Finally, the goodness of fit (as measured by adjusted R^2) of the large portfolio equations (with returns on large stocks as dependent variables) is lower than the same measure for small portfolio equations (with returns on small stocks as dependent variables). Generally, these results indicate that cross-autocorrelation in lagged large portfolio returns exists independently from own-autocorrelation, and, for the down market, possess higher explanatory power for current small portfolio returns than vice versa. This finding is consistent with the size-related lead-lag hypothesis, but in contrast to McQueen, Pinegar, and Thorley (1996), who attribute lead-lag patterns to the differentiated return behavior in the up market.

Size-related variance effects

In Table 2.3, Panel B, selected parameter values from the variance equation h_t from model (2.3) are presented. The significance of the parameter γ_3 in the small portfolio equation indicates volatility spillovers from the large to the small stocks when the market is down. As can be seen, we find this effect to be present for low and high volume stocks (regressions with R11 and R31 as dependent variables). This is in line with the findings of Conrad, Gultekin, and Kaul (1991). However, for the medium volume portfolios, the opposite is found – shocks to the small portfolios are a significant determinant of the conditional variance of large portfolio's unexpected returns. For the up market, we find only one case of significant volatility spillovers from large to small stocks (given by $\gamma_3 + \gamma'_3$), but two in the opposite direction – from small to large stocks. Therefore, no definite conclusion concerning the direction of volatility spillovers can be made. The volatility spillovers observed here are not caused by the market volatility.

Volume-related return effects

In Table 2.4, Panel A, results from the lead-lag analysis of volume leadership for small, medium, and large stocks are presented.

[Table 2.4 about here]

For the regressions of low on high volume portfolio returns (e.g. R11 on R12), we observe in all but one case, in both up and down markets, returns on the lagged high volume portfolio to be an explanatory factor for current returns on the low volume portfolio, at the 5% significance level and after controlling for own-autocorrelations of the low volume portfolio. This can be seen from the significance of short or long term causality, as measured by the lagged beta or the sum of lagged betas, respectively. On the other hand, in the regressions of high on low volume portfolio returns (e.g. R12 on R11), we find only weak and short-lived significant influence of low on high volume portfolios for the down markets, and a significant impact of low on high volume portfolio returns in the case of up markets (for large portfolios).

In general, the asymmetric volume-related lead-lag relationship in returns is found to be significant for four out of six cases, as shown by the values of the Z-statistic. The goodness of fit of the low-volume portfolio equation (with returns on low volume stocks as dependent variables, e.g. R11) is higher than the same measure for the high-volume portfolio equation (with returns on high-volume stocks as dependent variables, e.g. R12) for each size class, suggesting that lagged high-volume portfolio returns possess higher explanatory power for current low-volume portfolio returns than vice versa. This is in line with the hypothesis that high volume portfolio returns lead low volume portfolio returns. For volume-related lead-lag effects, no systematic difference between up and down markets can be observed.

Volume-related variance effects

In Table 2.4, Panel B, results from the test of volatility linkages between high and low volume portfolios are presented. The significance of parameter γ_3 (in down market, and of $\gamma_3 + \gamma'_3$ in up markets) indicates volatility spillovers for some portfolios, although no general pattern can be observed. These variance spillovers are not driven by the common dependence of portfolios on the variance of market returns.

In sum, for the stocks listed on the WSE we find evidence that portfolio cross-autocorrelation exists independently of own-autocorrelation, and that size- and volume-related leadership effects, although not universally present, are independent from each other. These findings are in line with those of Lo and MacKinley (1990) and Chordia and Swaminathan (2000) and others and are in contrast to the hypothesis of Boudoukh, Richardson, and Whitelaw (1994) stating that cross-autocorrelations are a spurious phe-

nomenon. The size-related effects are more prevalent in down than up markets. However, the fact that we do not find significant lead-lag relationships for all portfolios analyzed suggests, in light of Chordia and Swaminathan's model, that factors such as size and volume are not sufficient proxies for informed trading and are unable to capture a large proportion of informed trading. Moreover, although we find several significant volatility spillovers, there is hardly any systematic pattern to be observed there. Hence, there is only weak evidence for the WSE stocks in favor of asymmetric lead-lag volatility spillovers, as reported in Conrad, Gultekin, and Kaul (1991) for large versus small stocks.

2.3.2 Dimson Beta Regressions

Although we have established some empirical evidence in favor of size- and volume-related lead-lag patterns in portfolio returns, we are unaware of the sources of these phenomena. In this section, we test the hypothesis proposed by Brennan, Jegadeesh, and Swaminathan (1993) that the differences in speed of adjustment to common news between large (high volume) and small (low volume) portfolio returns are the driving factor behind the lead-lag effects observed above. To address the question of the source of lead-lag patterns in portfolio returns, we analyze the responsiveness of portfolio returns to common information using the Dimson beta technique (Dimson (1979)) as discussed in Subsection 2.2.3. Specifically, we analyze size leadership by constructing a zero-beta portfolio, in that we subtract returns on a small portfolio from returns on a large portfolio within each volume class (Table 2.5), and, for volume leadership, returns on a low-volume portfolio from returns on a high-volume portfolio within each size class (Table 2.6). Next, we regress the zero-beta portfolio returns on five leads, five lags, and the current value of the return on the market portfolio, as well as on a set of dummy variables to account for differences in the regression parameters in up and down markets.¹⁰ As an approximation for the market portfolio, we use the stock market index, WIG.¹¹

¹⁰The number of lags has been chosen following Chordia and Swaminathan (2000), to enable comparability of results. Moreover, 5 lags makes it possible to account for the day-of-the-week effects in returns. Tests with 1-10 lags have also been performed additionally, but results were virtually the same.

¹¹WIG is the total return index including all companies listed at the end of the previous quarter on the main market. Weights are calculated based on the market capitalization of the stocks, albeit the individual company's (sector) participation is limited to 10% (30%) of the WIG portfolio.

Size as information transmission mechanism

In Table 2.5, we report results from the regressions of the difference between large and small size portfolio returns on the market returns, i.e. model (2.4) described in Subsection 2.2.3. for volume-size sorted portfolios.

[Table 2.5 about here]

Generally, the results indicate quicker adjustment of large stocks to common news. Specifically, when the market is down, for all volume classes the contemporaneous beta, $\beta_{0,0}$, is positive and significant, and lagged beta, $\beta_{0,-1}$, is negative and significant. These results indicate that large portfolios adjust more rapidly to negative common information than small portfolios of similar volume. The fact that the sum of lagged betas of the market return is insignificant indicates that the speed of lagged adjustment (beyond lag one) to negative common information is equal for small and large portfolios. When the market is up, the contemporaneous beta on all portfolios, $\beta_{0,0} + \beta'_{0,0}$, is positive and significant, meaning quicker immediate adjustment of large portfolios to positive news. For lagged adjustment, we find the first lagged coefficient, $\beta_{0,-1} + \beta'_{0,-1}$, and the sum of lagged betas of the market return to be negative and significant only for high volume stocks. Hence, whereas the difference in adjustment speed is short-lasting for low and medium volume stocks, there are significant long term differences in the adjustment speed between large and small high volume portfolios.

Although we find larger stocks to adjust quicker to common news than small stocks, this fact cannot fully explain the size-related lead-lag patterns, as described in Section 3.1. Hence, we conclude that size-related lead-lag patterns are only partially caused by the differences in the speed of adjustment to common information between large and small stocks, as proposed by, among others, Brennan, Jegadeesh, and Swaminathan (1993), Badrinath, Kale, and Noe (1995), and Brennan, Chordia, and Subrahmanyam (1998). Another important determinant could be the difference in quality of firm-specific news (Yu and Wu (2001)).

Volume as information transmission mechanism

To analyze the role of volume as an information transmission mechanism, we estimate regressions of the difference in returns between high and low volume portfolios on leads

and lags of the market portfolio, i.e. model (2.4) described in Subsection 2.2.3. for size-volume sorted portfolios. Results are displayed in Table 2.6.

[Table 2.6 about here]

The results indicate that the differences in adjustment speed are overall present but rather short-lasting. When the market is down, the contemporaneous beta, $\beta_{0,0}$, is positive and highly significant for all size classes, indicating quicker immediate adjustment of high volume stocks to common news. When the market is up, the differences in the adjustment speed for low and high volume stocks are longer-lasting than for medium volume stocks, as can be seen from the significance of lagged betas. Generally, low volume small stocks tend to adjust slower to both positive and negative market-wide news.

In sum, our results support the findings of Chordia and Swaminathan (2000) and others that that differences in the speed of adjustment to common news are an important, albeit not exclusive, driving force behind the lead-lag patterns in portfolio returns. The differences in quality of firm-specific news (Yu and Wu (2001)) could be another important factor. Moreover, we document significant differences in the adjustment to market-wide news between up and down markets. Namely, the significance of lagged betas for the former indicates slower adjustment of small and low volume stocks to positive than negative market-wide news, as suggested by McQueen, Pinegar, and Thorley (1996).

2.4 Conclusions

In this chapter, we conduct a study on daily return data for the shares traded in the single auction system on the Warsaw Stock Exchange during the period January 1996 – October 2000. The focus of this study is threefold. First, we analyze whether the size-related lead-lag relationship between portfolio returns (cross-autocorrelation) is a real or spurious phenomenon, attributable solely to portfolio own-autocorrelations and contemporaneous cross-autocorrelations in portfolio returns (Lo and MacKinley (1990), Boudoukh, Richardson, and Whitelaw (1994)). Second, we analyze the role of trading volume in explaining cross-autocorrelation patterns in portfolio returns and its independence from size effects. Third, we investigate whether size- and volume-related lead-lag patterns emerge from the differences in the speed of adjustment of small vs. large (low vs. high volume) stocks to common news. In addition, the framework used also enables us to test for the volatility

spillovers from the large (high volume) to small (low volume) portfolios and vice versa, as well as for the differences between up and down markets.

We find that cross-autocorrelation of portfolio returns remains even after controlling for a portfolio's own-autocorrelation. This result implies that lead-lag patterns are not spurious, and that past returns on large (high volume) portfolios contain information about present returns on small (low volume) portfolios beyond that contained in the lagged returns of the latter. Hence, the notion proposed by Boudoukh, Richardson, and Whitelaw (1994) is not an appropriate description of the source of cross-autocorrelations of stocks traded on the WSE. However, the fact that some small (low volume) stocks seem to lead large (high volume) stocks suggests that other factors, not accounted for in this study, such as analyst coverage or institutional ownership, might capture a significant fraction of informed trading determining the lead-lag relationship between portfolio returns. Second, we find that both size and trading volume contain information about the correlation structure independent from each other, and beyond that contained in a portfolio's own autocorrelation. Third, we provide empirical evidence that, for shares traded in the single action system on the WSE, large (high volume) portfolios adjust faster to market-wide news than their small (low volume) counterparts. We also find evidence for asymmetry in predicting volatility from large (high volume) to small (low volume) portfolios. A further important finding is that the lead-lag patterns differ significantly between up and down markets.

Our results are important for three reasons. First, the correlation structure of returns on stocks traded on an inefficient emerging market, the WSE, at its early stage of development, is found to be similar to that found for the mature US market. Moreover, information transmission mechanisms (size and volume) for stocks traded in the auction system on the WSE turn out to be similar to those prevailing in the continuous systems on the US markets analyzed so far in the literature. Hence, similar forces of price determination are at play worldwide, regardless of the institutional and regulatory differences. These results constitute additional evidence in favor of the theoretical predictions that cross-autocorrelations partially result from the differences in the adjustment speed among stocks. Second, we find statistically significant predictability in portfolio returns. However, the fact that these patterns are not arbitrated away might be due to the lack of their economic significance. Nevertheless, as Chordia and Swaminathan (2000) notice, the finding that size and volume play a role in the speed of adjustment to news

yields important insights into the determinants of how of security prices function. Last, Lo and MacKinley (1990) argue that cross-autocorrelations are, beyond overreactions, an important source of contrarian profits. Our findings imply that lead-lag effects should be taken into account when considering the profitability of contrarian investment strategies pursued on the WSE.

2.5 Tables

Table 2.1: Descriptive Statistics for Volume-Size Sorted Portfolios

Portfolio	Market	Return					q_{-1}	$\sum_{i=-10}^{-1} q_i$	Mean Volume x100	Z-test Volume	Mean Size	Z-test Size
		Mean	Median	Stand. dev.	Stand. dev.	Stand. dev.						
P11	DOWN	-.009070	-.006856	.014199	.188081***	.048012	0.132806	170.104.150				
	UP	.008497	.006475	.012411	.098466	.033127	1,37				-69.80***	
P12	DOWN	-.012413	-.008766	.013841	.152017***	-.028195	0.128483	1.693.545.894				
	UP	.011443	.008599	.012219	.201214	.275985						
P21	DOWN	-.009772	-.007040	.014750	.216434***	.146520**	0.310135	59.535.423				
	UP	.009298	.007864	.012466	.101015	.000080	1,59				-63.90***	
P22	DOWN	-.013049	-.009588	.015619	.209423***	.138420***	0.299140	402.269.194				
	UP	.011277	.009028	.013007	.100237	-.073710						
P31	DOWN	-.010821	-.008940	.016680	.304049***	.259510***	0.575547	33.598.336				
	UP	.009863	.007663	.013439	.102217*	-.052230	0,08				-24.51***	
P32	DOWN	-.013463	-.010291	.016006	.241852***	.286800**	0.573854	215.912.807				
	UP	.011921	.009391	.014840	.069775	-.164690						

Note: Data on daily stock prices from the Warsaw Stock Exchange for the period: January1996 – October 2000 has been utilized. Portfolio Pkj refers to the portfolio in k-th volume class (where k=1 indicates the low volume and k=3 the high volume portfolio) and j-th size class within each volume class (with j=1 for small and j=2 for large portfolios). DOWN (UP) refers to the portfolio characteristics in case of decreasing (increasing) market returns. ‘Stand. dev.’ refers to the standard deviation of portfolio returns, q_{-1} refers to the value of the first autocorrelation coefficient of portfolio return, and $\sum_{i=-10}^{-1} q_i$ is the sum of the first ten autocorrelation coefficients. ‘Mean Volume’ refers to the average trading volume of stocks in each portfolio, as measured by the turnover ratio (number of shares traded to number of outstanding shares), and ‘Mean Size’ refers to the average market capitalization of stocks in each portfolio, as measured in Polish Zloty (PLN). ‘Z-test Volume (Size)’ refers to the Z-statistic of the test on equality of average volume (size) within each volume class. Symbols ***, **, * indicate significance at 1%, 5%, and 10% - levels, respectively.

Table 2.2: Descriptive Statistics for Size-Volume Sorted Portfolios

Portfolio	Market	Return					Mean Size	Z-test Size	Mean Volume x100	Z-test Volume
		Mean	Median	Stand. dev.	q_{-1}	$\sum_{i=-10}^{-1} q_i$				
P11	DOWN	-.009205	-.007173	.014638	.208736***	.075422**	29,481,284	0.395941		
	UP	.008487	.006985	.012415	.114837**	.079891			-13.42***	
P12	DOWN	-.011310	-.008711	.016779	.261315***	.128020*	29,319,853	0.668779		
	UP	.010730	.008512	.014558	.103695	.038785				
P21	DOWN	-.010128	-.007769	.014804	.238711***	.315380**	103,139,909	0.193093		
	UP	.009108	.007460	.012112	.041179	-.267230**			-19.20***	
P22	DOWN	-.011376	-.008688	.015500	.246393***	.258280***	102,000,039	0.354170		
	UP	.010051	.007765	.012912	.106200	.065860				
P31	DOWN	-.012315	-.009349	.012768	.099635**	-.067766	1,218,704,660	0.112483		
	UP	.011446	.009081	.015096	.218878	.287854			***	
P32	DOWN	-.014170	-.010025	.015096	.181726***	.125800*	1,194,909,603	0.234215		
	UP	.012752	.009801	.013775	.120263	.002280				

Note: Data on daily stock prices from the Warsaw Stock Exchange for the period: January1996 – October 2000 has been utilized. Portfolio Pk_j refers to the portfolio in k-th size class (where k=1 indicates the smallest and k=3 the largest portfolio) and j-th volume class within each size class (with j=1 for low volume and j=2 for high volume portfolios). DOWN (UP) refers to the portfolio characteristics in case of decreasing (increasing) market returns. ‘Stand. dev.’ refers to the standard deviation of portfolio returns, q_{-1} refers to the value of the first autocorrelation coefficient of portfolio return, and $\sum_{i=-10}^{-1} q_i$ is the sum of the first ten autocorrelations. ‘Mean Size’ refers to the average market capitalization of stocks in each portfolio, as measured in Polish Zloty (PLN), and ‘Mean Volume’ refers to the average trading volume of stocks in each portfolio, as measured by the turnover ratio (number of shares traded to number of outstanding shares). ‘Z-test Size (Volume)’ refers to the Z-statistic of the test on equality of average size (volume) within each size class. Symbols ***, **, * indicate significance at the 1%, 5%, and 10% - levels, respectively.

Table 2.3: Size-Related Lead-Lag Relationship

Portfolio	Low Volume		Medium Volume		High Volume	
Dep.Variable (J)	R11	R12	R21	R22	R31	R32
Indep.Variables (J,K)	R11, R12	R12, R11	R21, R22	R22, R21	R31, R32	R32, R31
Panel A: MEAN EFFECTS						
DOWN MARKET						
Own-autocorrelation						
$\alpha_{J,-1}$.062035 (.415)	.086928 (.235)	.006339 (.932)	.191325** (.013)	.246167*** (.004)	.169189* (.063)
$\sum_{i=-5}^{-1} \alpha_{J,i}$	-.002766 (.986)	.009191 (.953)	-.12631 (.506)	.21633 (.235)	-.09002 (.614)	.50996*** (.009)
Cross-autocorrelation						
$\beta_{K,-1}$.166971*** (.007)	.09042 (.205)	.200221*** (.001)	.005858 (.944)	.05399 (.446)	.10604 (.267)
$\sum_{i=-5}^{-1} \beta_{K,i}$.21374* (.098)	-.08174 (.615)	.23679 (.111)	-.23824 (.226)	.42640* (.080)	-.31641* (.099)
Z-STAT	1.42*		1.92**		2.97***	
UP MARKET						
Own-autocorrelation						
$\alpha_{J,-1} + \alpha'_{J,-1}$	-.01517 (.823)	.13873** (.030)	.07199 (.361)	.00956 (.904)	-.04799 (.556)	-.04242 (.604)
$\sum_{i=-5}^{-1} \alpha_{J,i} + \alpha'_{J,i}$	-.21703 (.137)	.17198 (.165)	.35705* (.057)	-.36279** (.021)	-.02748 (.870)	-.44008** (.033)
Cross-autocorrelation						
$\beta_{K,-1} + \beta'_{K,-1}$.16760*** (.004)	.09309 (.216)	.03156 (.652)	.16048* (.055)	.15378** (.016)	.17803* (.056)
$\sum_{i=-5}^{-1} \beta_{K,i} + \beta'_{K,i}$.22274* (.073)	.12675 (.411)	-.34051** (.028)	.65264*** (.000)	.00783 (.916)	.40115** (.042)
Z-STAT	.49		-4.36		-1.52	
Panel B: VARIANCE EFFECTS						
γ_3	.08615** (.030)	-.01419 (.665)	-.00138 (.907)	.06098** (.046)	.07871** (.012)	.00853 (.802)
$\gamma_3 + \gamma'_3$.14458*** (.000)	.04922 (.842)	-.02120 (.316)	.04956** (.034)	-.02127 (.298)	.11373** (.019)
Adj. R ²	.026437	-.008789	.040032	.009943	.041170	.017245
NOB	952	952	952	952	952	952

Note: In this table, results for the volume-size sorted portfolios are presented. Data on daily stock prices from the Warsaw Stock Exchange for the period: January 1996 – October 2000 has been utilized. ‘Rkj’ refers to the return on the portfolio in k -th volume class (where $k=1$ indicates the low volume and $k=3$ the high volume portfolio) and j -th size class within each volume class (with $j=1$ for small and $j=2$ for large portfolios). For each dependent variable, the following regression has been estimated (Model (2.3)):

$$R_{J,t} = \alpha_0 + \sum_{i=1}^L \alpha_{J,i} R_{J,t-i} + \sum_{i=1}^L \alpha'_{J,i} R_{J,t-i} D^{UP} + \sum_{i=1}^L \beta_{K,i} R_{K,t-i} + \sum_{i=1}^L \beta'_{K,i} R_{K,t-i} D^{UP} + u_{J,t},$$

$h_{J,t} = \gamma_0 + \gamma_1 u_{J,t-1}^2 + \gamma_2 h_{J,t-1} + \gamma_3 u_{K,t-1}^2 + \gamma'_3 u_{K,t-1}^2 D^{UP} + \gamma_4 v_{M,t-1}^2 + \gamma'_4 v_{M,t-1}^2 D^{UP}$, where $R_{J,t-i}$ indicates the return on portfolio J at $t-i$, D^{UP} is a dummy variable that takes on the value 1 if the market is up and zero otherwise, and error terms are modeled as a GARCH process, with conditional variance depending additionally on the squared return shocks to the portfolio K ($u_{K,t-1}^2$) and on the squared shocks to the return on market portfolio M ($v_{M,t-1}^2$). ‘Z-STAT’ refers to the Z-statistic for the cross-equation test with H_0 hypothesis that the sum of lagged coefficients on the large portfolio, B, is equal to the sum of lagged coefficients on the small portfolio, A ($\sum_{i=1}^L \beta_{B,i} = \sum_{i=1}^L \beta_{A,i}$ when the market is

down, and $\sum_{i=1}^L (\beta_{B,i} + \beta'_{B,i}) = \sum_{i=1}^L (\beta_{A,i} + \beta'_{A,i})$ when the market is up), against the one-sided alternative hypothesis that the sum of lagged coefficients on a large portfolio is greater than the sum of lagged coefficients on a small portfolio. ‘Adj. R^2 ’ refers to the value of adjusted R^2 . ‘NOB’ refers to the number of observations. Symbols: ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. P-values of the t-statistics (for a single parameter) and Wald statistics (for the sum of parameters) are in parenthesis.

Table 2.4: Volume-Related Lead-Lag Relationship

Portfolio	Small		Medium Size		Large	
Dep.Variable (J)	R11	R12	R21	R22	R31	R32
Indep.Variables (J,K)	R11, R12	R12, R11	R21, R22	R22, R21	R31, R32	R32, R31
Panel A: MEAN EFFECTS						
DOWN MARKET						
Own-autocorrelation						
$\alpha_{J,-1}$	-.03234 (.695)	.21328*** (.005)	.04651 (.550)	.12812* (.083)	-.00988 (.920)	.09216 (.365)
$\sum_{i=-5}^{-1} \alpha_{J,i}$	-.30002 (.134)	.02535 (.888)	-.18739 (.363)	.21328 (.323)	-.27621 (.176)	.29189 (.161)
Cross-autocorrelation						
$\beta_{K,-1}$.27791*** (.000)	.06426 (.428)	.20738*** (.001)	.17594** (.033)	.16063* (.075)	.07901 (.434)
$\sum_{i=-5}^{-1} \beta_{K,i}$.39376** (.018)	.18193 (.405)	.52063*** (.003)	.10352 (.560)	.37096* (.050)	-.28678 (.209)
Z-STAT	.77		1.51*		2.22**	
UP MARKET						
Own-autocorrelation						
$\alpha_{J,-1} + \alpha'_{J,-1}$	-.03690 (.673)	.04361 (.570)	-.02746 (.731)	.14876* (.060)	.24877*** (.004)	-.03501 (.654)
$\sum_{i=-5}^{-1} \alpha_{J,i} + \alpha'_{J,i}$	-.23532 (.220)	.05410 (.760)	-.36391* (.072)	.27789 (.118)	.50622*** (.007)	-.39672** (.033)
Cross-autocorrelation						
$\beta_{K,-1} + \beta'_{K,-1}$.20224*** (.006)	.08929 (.280)	.13430* (.084)	.00984 (.914)	-.00999 (.904)	.18097** (.034)
$\sum_{i=-5}^{-1} \beta_{K,i} + \beta'_{K,i}$.37456** (.020)	-.01807 (.931)	.18572 (.280)	-.22585 (.274)	-.22727 (.194)	.46591** (.018)
Z-STAT	1.49*		1.53*		-2.63	
Panel B: VARIANCE EFFECTS						
γ_3	.09401*** (.001)	.08581 (.108)	.01916 (.510)	.16985*** (.000)	.17617*** (.000)	.02725 (.699)
$\gamma_3 + \gamma'_3$.08649*** (.005)	-.01065 (.825)	.00721 (.805)	.10219*** (.002)	.18123 (.000)	.04541 (.423)
Adj. R ²	.046336	.019974	.042448	.022555	-.003042	-.00845
NOB	952	952	952	952	952	952

Note: In this table, results for the size-volume sorted portfolios are presented. Data on daily stock prices from the Warsaw Stock Exchange for the period: January 1996 – October 2000 has been utilized. ‘Rkj’ refers to the return on the portfolio in k -th size class (where $k=1$ indicates the smallest and $k=3$ the largest portfolio) and j -th volume class within each size class (with $j=1$ for low volume and $j=2$ for high volume portfolios). For each dependent variable, the following regression has been estimated (Model (2.3)): $R_{J,t} = \alpha_0 + \sum_{i=1}^L \alpha_{J,i} R_{J,t-i} + \sum_{i=1}^L \alpha'_{J,i} R_{J,t-i} D^{UP} + \sum_{i=1}^L \beta_{K,i} R_{K,t-i} + \sum_{i=1}^L \beta'_{K,i} R_{K,t-i} D^{UP} + u_{J,t}$, $h_{J,t} = \gamma_0 + \gamma_1 u_{J,t-1}^2 + \gamma_2 h_{J,t-1} + \gamma_3 u_{K,t-1}^2 + \gamma'_3 u_{K,t-1}^2 D^{UP} + \gamma_4 v_{M,t-1}^2 + \gamma'_4 v_{M,t-1}^2 D^{UP}$, where $R_{J,t-i}$ indicates the return on portfolio J at $t-i$, D^{UP} is a dummy variable that takes on the value 1 if the market is up and zero otherwise, and error terms are modeled as a GARCH process, with conditional variance depending additionally on the squared return shocks to the portfolio K ($u_{K,t-1}^2$) and on the squared shocks to the return on market portfolio M ($v_{M,t-1}^2$). ‘Z-STAT’ refers to the Z-statistic for the cross-equation test with H_0 hypothesis that the sum of lagged coefficients on a high volume portfolio, B, is equal to the sum of lagged coefficients on a low volume portfolio, A ($\sum_{i=1}^L \beta_{B,i} = \sum_{i=1}^L \beta_{A,i}$ when the market is down, and $\sum_{i=1}^L (\beta_{B,i} + \beta'_{B,i}) = \sum_{i=1}^L (\beta_{A,i} + \beta'_{A,i})$ when the market is up), against the alternative one-sided hypothesis that the sum of lagged coefficients on a high volume portfolio is greater than the sum of lagged coefficients on a low volume portfolio. ‘Adj. R²’ refers to the value of adjusted R². ‘NOB’ refers to the number of observations. Symbols: ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. P-values of the t-statistics (for a single parameter) and Wald statistics (for the sum of parameters) are in parenthesis.

Table 2.5: Size As Information Transmission Mechanism

Portfolio	Low Volume	Medium Volume	High Volume
Dependent Variable	R12-R11	R22-R21	R32-R31
DOWN MARKET			
$\sum_{i=+1}^{+5} \beta_{0,i}$.03347	-.02827	.07061
	(.510)	(.559)	(.141)
$\beta_{0,0}$.24809***	.24162***	.17720***
	(.000)	(.000)	(.000)
$\beta_{0,-1}$	-.07560***	-.06127***	-.05265**
	(.002)	(.007)	(.017)
$\sum_{i=-5}^{-1} \beta_{0,i}$	-.07558	-.07571	-.073718
	(.149)	(.148)	(.107)
UP MARKET			
$\sum_{i=+1}^{+5} \beta_{0,i} + \beta'_{0,i}$.01766	-.07855	.04536
	(.768)	(.144)	(.287)
$\beta_{0,0} + \beta'_{0,0}$.32190***	.24650***	.17258***
	(.000)	(.000)	(.000)
$\beta_{0,-1} + \beta'_{0,-1}$	-.02254	-.02658	-.07906***
	(.311)	(.189)	(.000)
$\sum_{i=-5}^{-1} \beta_{0,i} + \beta'_{0,i}$.04806	.07016	-.10068**
	(.387)	(.139)	(.029)
Adj. R ²	.172318	.153843	.074017
NOB	946	946	946

Note: Data on daily stock prices from the Warsaw Stock Exchange for the period January 1996 – October 2000 has been utilized. Results from the regressions of the zero net investment portfolios (long in the large portfolio, short in the small portfolio) on the market portfolio are reported. R_{kj} refers to the return on the portfolio in the k -th volume class (where $k=1$ indicates the lowest and $k=3$ the highest volume portfolio) and j -th size class within each volume class (with $j=1$ for small and $j=2$ for large portfolios).

For each column, the following equation is estimated (Model (2.4)): $R_{0,t} = \alpha_0 + \sum_{i=-L}^L \beta_{0,i} R_{M,t+i} +$

$\sum_{i=-L}^L \beta'_{0,i} R_{M,t+i} D^{UP} + u_t$, $h_t = \gamma_0 + \gamma_1 u_{t-1}^2 + \gamma_2 h_{t-1}$, where $R_{0,t}$ equals the return on a zero net

investment portfolio (long in the large and short in the small portfolio), $R_{M,t+i}$ is the return on the market portfolio at $t+i$, D^{UP} is a dummy variable that takes on value one when the market is up and zero otherwise, and u_t is the error term modeled as a GARCH(1,1) process. The test for significance of the regression coefficient $\beta_{0,i}$ ($\beta'_{0,i}$) is a conventional t-test with $H_0: \beta_{0,i} = 0$ ($\beta'_{0,i} = 0$). The test

for significance of the sum of parameters is a Wald test with $H_0: \sum_{i=-5}^{-1} \beta_i = 0$ for the sum of five lags on

market return in the case of the down market, and analogously for the remaining variables. ‘Adj. R²’ refers to the value of adjusted R². ‘NOB’ refers to the number of observations. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. P-values of the t-statistics (for a single parameter) and Wald statistics (for the sum of parameters) are in parenthesis.

Table 2.6: Volume As Information Transmission Mechanism

Portfolio	Small	Medium Size	Large
Dependent Variable	R12-R11	R22-R21	R32-R31
DOWN MARKET			
$\sum_{i=+1}^{+5} \beta_{0,i}$	-0.07379	.06206	-.04405
	(.155)	(.192)	(.322)
$\beta_{0,0}$.16833***	.09483***	.14315***
	(.000)	(.000)	(.000)
$\beta_{0,-1}$	-.03363	.01282	-.02901
	(.178)	(.608)	(.212)
$\sum_{i=-5}^{-1} \beta_{0,i}$	-.01213	-.05927	-.05762
	(.796)	(.220)	(.163)
UP MARKET			
$\sum_{i=+1}^{+5} \beta_{0,i} + \beta'_{0,i}$	-.03484	.05136	.05382
	(.497)	(.229)	(.157)
$\beta_{0,0} + \beta'_{0,0}$.12903***	.08442**	.14105***
	(.000)	(.001)	(.000)
$\beta_{0,-1} + \beta'_{0,-1}$	-.06411***	-.002022	-.05565***
	(.005)	(.315)	(.001)
$\sum_{i=-5}^{-1} \beta_{0,i} + \beta'_{0,i}$	-.10174**	.02360	-.06298
	(.026)	(.596)	(.132)
Adj. R ²	.083885	.024703	.045606
NOB	946	946	946

Note: Data on daily stock prices from the Warsaw Stock Exchange for the period January 1996 – October 2000 has been utilized. Results from the regressions of the zero net investment portfolios (long in the high volume portfolio, short in the low volume portfolio) on the market portfolio are reported. R_{kj} refers to the return on the portfolio in the *k*-th size class (where *k*=1 indicates the smallest and *k*=3 the largest portfolio) and *j*-th volume class within each size class (with *j*=1 for low volume and *j*=2 for high volume portfolios). For each column, the following equation is estimated (Model (2.4)):

$$R_{0,t} = \alpha_0 + \sum_{i=-L}^L \beta_{0,i} R_{M,t+i} + \sum_{i=-L}^L \beta'_{0,i} R_{M,t+i} D^{UP} + u_t, \quad h_t = \gamma_0 + \gamma_1 u_{t-1}^2 + \gamma_2 h_{t-1},$$

where $R_{0,t}$ equals the return on a zero net investment portfolio long in the high volume and short in the low volume portfolio, $R_{M,t+i}$ is the return on the market portfolio at $t+i$, D^{UP} is a dummy variable that takes on value one when the market is up and zero otherwise, and u_t is the error term modeled as a GARCH(1,1) process. The test for significance of the regression coefficient $\beta_{0,i}$ ($\beta'_{0,i}$) is a conventional t-test with $H_0: \beta_{0,i} = 0$ ($\beta'_{0,i} = 0$). The test for significance of the sum of parameters is a Wald test with $H_0:$

$$\sum_{i=-5}^{-1} \beta_i = 0$$

for the sum of five lags on market return in the case of a down market, and analogously for the remaining variables. ‘Adj. R²’ refers to the value of adjusted R². ‘NOB’ refers to the number of observations. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. P-values of the t-statistics (for a single parameter) and Wald statistics (for the sum of parameters) are in parenthesis.

Chapter 3

Dynamic Volume-Return Relationship

3.1 Introduction

There is growing interest in the economic literature in the relationship between trading volume and stock returns. Blume, Easley, and O'Hara (1994) present a model in which both past returns and past volume are informative, especially for small stocks. For a market with information distributed symmetrically among traders, Campbell, Grossman, and Wang (1993) show that returns following a positive change in trading volume are strongly reverting, whereas this effect is less pronounced after a volume decline. Existence of this dynamic volume-returns relationship is confirmed by Conrad, Hameed, and Niden (1994) for small US stocks. On the other hand, Wang (1994) and Llorente, Michaely, Saar, and Wang (2001) argue that, given information asymmetries among market participants, strong return reversals should be observed after a decrease in trading volume, i.e. for the volume decreasing stocks, whereas weak reversals or even continuations will characterize the returns on the volume increasing stocks (following an increase in trading volume). This is exactly what Cooper (1999) and Llorente et al. (2001) find for large US stocks.

Using the methodology of Conrad, Hameed, and Niden (1994), we analyze the relationship between volume changes and subsequent returns on stocks traded on the Warsaw Stock Exchange (WSE). We find it both important and interesting to analyze an emerging capital market, for several reasons. Namely, most empirical evidence is available for the mature US market. By conducting an analysis of a new market, we are able to test whether the previous results reported in the literature hold only for the stock markets considered so far, or whether the theories under investigation are valid universally and

the underlying theoretical models suit the reality well. In other words, we investigate whether the previous research presents a clinical study of the US market and results reported there are due to the data snooping bias. Hence, this study constitutes an "out-of-sample" robustness check for the models of the volume-return relationship, since we analyze a market that differs from the American one in many respects. For the WSE stocks, prices from the single auction system are utilized, which is in contrast to the US stocks traded continuously. Second, by intentionally covering an early period of the WSE development (1996-2000), we analyze a market shown to be informationally inefficient (e.g. Filer and Hanousek (1999), Chun (2000), Horsewood and Sutherland (2001)), again in contrast to the US stock exchanges. Third, WSE differs also in the institutional and regulatory settings from the markets analyzed so far in the literature. The knowledge of the volume and return dynamics on the emerging markets and of the informativeness of trades is relevant not only for academics interested in the functioning of financial markets, but also for portfolio investors seeking diversification gains from international asset allocation.

In this chapter, we address several issues. First, we test whether past stock returns are (fully) informative, and whether past trading volume can be exploited to obtain additional information about future stocks returns. Second, we investigate whether trades on the WSE are motivated by asymmetric information distribution across investors, or non-informational motives. Lastly, we analyze whether it is the mere fact of the volume change or rather its magnitude that contains relevant information. In line with Blume, Easley, and O'Hara's model, we find lagged volume to contain additional information about future returns beyond that contained in lagged returns, especially for small stocks. Next, we find returns on volume decreasing (volume increasing) stocks to exhibit positive (negative) autocorrelation, which confirms the predictions of Campbell, Grossman, and Wang's model. In the spirit of Wang (1994) and Llorente et al. (2001), these results indicate that trades on the WSE are primarily noninformative, especially for small stocks.

The remainder of the chapter is organized as follows. In Subsection 3.2, the relevant literature is presented. Subsection 3.3 describes the data and the methodology. In Subsections 3.4 and 3.5, the empirical results are outlined, while Subsection 3.6 concludes.

3.2 Literature Overview

The relationship between trading volume and stock price behavior is analyzed by Blume, Easley, and O'Hara (1994). These authors present a model in which aggregate supply is fixed and traders obtain noisy signals of different quality about the assets' fundamental values. Under these conditions it is shown that prices alone are not fully informative. Trading volume contains information about the agents' noisy signals beyond that contained in prices, and the sequence of volume and prices is argued to be informative. Based on their findings, these authors hypothesize that additional profits can be obtained by focusing on past volume statistics, especially for small, thinly traded stocks.

A link between trading volume and prices is further established in the model of Campbell, Grossman, and Wang (1993). Here, risk-averse market makers are assumed to accommodate the buying (selling) pressure of the liquidity traders (hence, there are no information asymmetries and all trades are non-informational). To induce these risk-averse individuals to trade, prices and, hence, expected returns have to change. Under the assumption that changes in the average risk aversion will cause trading volume to increase, whereas arrivals of public information will not, changes in trading volume might indicate the reason for observed price movements: demand for liquidity vs. changing risk aversion. An important implication of this model is that while price changes accompanied by positive volume changes should be expected to reverse (implying negative autocorrelation in returns), price changes accompanied by negative volume changes will be less likely.

Whereas Campbell, Grossman, and Wang (1993) assume information symmetry and investors' heterogeneity only with respect to risk-attitude, in the model of Wang (1994) traders possess heterogeneous investment possibilities, information asymmetry prevails, and trades might be conducted for both informational and non-informational motives. Without information asymmetry, a current price drop (decreasing return) accompanied by high volume leads to an increase in expected future returns and, hence, price reversal (meaning negative autocorrelation in returns). This finding is in line with Campbell, Grossman, and Wang (1993). However, under information asymmetry, price behavior depends on the degree of this asymmetry. The higher the share of informational trades, the higher the autocorrelation in prices. Specifically, when high returns are accompanied by high trading volume, high future returns should be expected and price continuations (i.e. positive return autocorrelation) observed. A model presented by Llorente et al. (2001)

generates similar results.

Empirical results in this area are inconclusive. Campbell, Grossman, and Wang (1993) analyze the relationship between lagged volume and return autocorrelation on stock market indexes as well as on individual stocks, and report negative autocorrelation (price reversals) in returns following high volume days.

Conrad, Hameed, and Niden (1994), using a variant of a contrarian strategy proposed by Lehmann (1990), find strong empirical evidence for a relationship between lagged trading volume and subsequent returns on the NASDAQ stocks. Consistent with the predictions of Blume, Easley, and O'Hara (1994), a strategy designed to incorporate information contained in past volume changes is found to perform better than a purely returns-based contrarian strategy. Moreover, this improvement is more pronounced for small rather than large stocks. These authors also find that volume increasing stocks are characterized by negative autocorrelation in returns (experience price reversals), and the opposite is true for volume decreasing stocks - as predicted by the information symmetry model of Campbell, Grossman, and Wang (1993). Again, these results are stronger for small rather than large stocks. Applying identical methodology for the Chilean stock market, Parisi and Acevedo (2001) validate the volume-return relationships observed by Conrad, Hameed, and Niden (1994) for all but one portfolio.

In a study conducted for large NYSE and AMEX securities, Cooper (1999) finds the profitability of purely returns-based contrarian strategies to depend positively on the magnitude and sustainability of past returns. Lagged volume statistics are reported to contain additional information about future returns, in line with the predictions of Blume, Easley, and O'Hara (1994). However, in contrast to the findings of Campbell, Grossman, and Wang (1993), Cooper finds that returns on volume-decreasing stocks experience strong reversals and on volume-increasing stocks experience weak reversals and even continuations. Hence, profitability of the mixed return- and volume-based contrarian strategy might be increased by focusing on changes in past trading volume in addition to past returns - by holding volume-decreasing stocks. These results support the implications of the information-asymmetry model of Wang (1994). Cooper (1999) interprets the discrepancy between his finding for large stocks and those of Conrad, Hameed, and Niden (1994) for small stocks as evidence for systematic differences in the relationship between lagged volume and current returns: "[...] it may be that in periods of large price movements, high volume for smaller (larger) stocks represents a higher percentage

of liquidity (informed) traders, resulting in greater subsequent reversals (continuations)” (p.921). Llorente et al. (2001) directly examine the relationship between information asymmetry and return behavior and find returns on stocks associated with a high (low) degree of informational trading to exhibit continuations (reversals).

3.3 Data and Methodology

3.3.1 Data

Trading on the WSE was launched on April 16, 1991. At the beginning, five stocks were traded in the single-price auction system once a week. Gradually new stocks were introduced, and trades were extended to five days a week. On July 11, 1996, selected highly liquid stocks started trading in both the single-auction and the continuous trading systems. In the auction system, orders were placed between 8:00 a.m. and 11:00 a.m., followed by the price determination by a specialist and eventual post-auction trading to balance the market. Trades in the continuous system started at 1:00 p.m. with the opening price being determined by the orders received between 8:00 a.m. and 1:00 p.m., and continued till 4:00 p.m. In addition, off-session block trades took place. With the introduction of a new trading system WARSET on November 17, 2000, each stock was attributed to one trading system: the continuous trading or the single-price auction with two auctions per day. Also, the time schedule for orders and trading was changed. At the end of 2001, there were 230 companies listed on the WSE, accounting for a market capitalization of approximately USD 25 billion, with total daily turnover of USD 186 million (WSE (2002)).

The data were supplied by the WSE. Given the focus of this study on an early stage of capital market development, and due to the changes in the trading system and structural breaks resulting therefrom, we conduct our analysis for the period from January 1996 to October 2000. During this period, the WIG index return increased from 7,725 to 15,597 points, achieving the maximal value of 22,868 points on March 27, 2000. Out of 947 daily market returns, we recorded 495 positive and 452 negative values. The average daily return was 0.00016, with standard deviation of 0.01901, minimum value of -0.09775 and maximum of 0.08213. Daily market returns show skewness of -0.24612 and kurtosis of 2.64301, with 1-st order autocorrelation of 0.12551. There is no convincing evidence in the literature that crises originating in other emerging markets during this period had

significant long-term impact on the WIG behavior (Galos and Sahay (2001), Krzak (1998), Scheicher (2001)) and, hence, that our results are driven by infrequent exogenous shocks.

We utilize the data on closing prices from the single-auction system and on trading volume from the single auction system, continuous trading, and block trades. To account for the impact of trading volume on the auction system closing price at time 't', we sum volume statistics from all three trading systems: trading volume from the auction system from day 't' and from the two remaining systems from day 't-1'. Thereafter, we compute weekly Wednesday-close to Wednesday-close price and volume statistics, in line with short-horizon investment literature. As a transaction measure, we follow Campbell, Grossman, and Wang (1993) and Cooper (1999) and employ turnover ratio (the number of shares traded to the number of shares outstanding). In addition to enabling comparison with these studies, applying this approach has the advantage of disentangling the effect of firm size and trading volume (Chordia and Swaminathan (2000)),¹ and has strong theoretical backgrounds (Lee and Swaminathan (2000)).

3.3.2 Methodology

To analyze the relationship between changes in trading volume and subsequent return behavior, as well as the informational content of volume, we first consider gains from the contrarian strategy as proposed by Conrad, Hameed, and Niden (1994). This approach focuses on past returns, and allows for attributing profits from a contrarian strategy exclusively to the autocorrelation in stock returns.² The weight given to a security 'i' at time 't' is:

$$w_{pit} = R_{it-1} / \sum_{i=1}^{N_p} R_{it-1} \quad (3.1)$$

where R_{it-1} is the weekly return on security 'i' at time 't-1' and N_p is the number of securities in the winner (p=W) or loser (p=L) portfolio. If not stated otherwise, the winner portfolio consists of shares with $R_{it-1} > 0$ and the loser portfolio of shares with $R_{it-1} < 0$. Since both the numerator and the denominator of the winner (loser) portfolio are always

¹The correlation between turnover ratio and firm size in our sample is -0.1155 (p-value=0.0740). However, we find the correlation between the number of shares traded and firm size to be 0.5270 (p-value=0) and between the value of shares traded and firm size to be 0.6540 (p-value=0).

²For the contrarian strategy proposed by Lehmann (1990), Lo and MacKinley (1990) showed that about 50% of profits result from cross-autocorrelation between securities' returns rather than from own-autocorrelation. Since our focus is on autocorrelation in returns, we use the modified version of portfolio weights as proposed by Conrad, Hameed, and Niden (1994).

positive (negative), weights are positive and sum to one for each portfolio. Hence, the construction of a zero net investment portfolio, T , is possible simply by buying losers and shorting winners. As in Lehmann's strategy, larger weights are placed on extreme losers and winners.

Having established a benchmark strategy based on past stock returns, we now follow Conrad, Hameed, and Niden (1994) and consider a strategy designed to incorporate both returns and changes in trading volume into the portfolio construction procedure. A comparison of the performance of this return-volume-based strategy with the pure return-based strategy will allow us to assess the importance of trading activities on subsequent returns, as hypothesized by Blume, Easley, and O'Hara (1994), Campbell, Grossman, and Wang (1993), and Wang (1994), among others.

We use the following measure of abnormal trading activity:

$$u_{it} = (T_{it} - T_{it-1})/T_{it-1} \quad (3.2)$$

where T_{it} is the turnover ratio for security 'i' in week 't'. This approach ensures that the behavior of u_{it} is attributable only to the behavior of T_{it} for each stock, making it immune to potential time-series patterns in portfolio behavior and to cross-sectional effects. For an increase (decrease) in trading activity, u_{it} will be positive (negative), implying a positive (negative) trading shock in security 'i'. We label this security a high volume (low volume) security.³

On the basis of the previous week's return and volume, we form four portfolios of winners/losers and high/low volume stocks, with each security's weight computed as:

$$w_{pit}^* = (R_{it-1}(1 + u_{it-1})) / \sum_{i=1}^{N_p} (R_{it-1}(1 + u_{it-1})) \quad (3.3)$$

with N_p being the number of securities in each portfolio. As in the first case, weights are always positive and sum to one for each portfolio, allowing for the construction of zero net investment portfolios (TL for low volume and TH for high volume stocks) simple by buying losers and shorting winners.

³In Subsection 3.5, we redefine the criteria for being a winner (loser) and high volume (low volume) stock.

3.4 Basic Empirical Results

3.4.1 Return-Based Strategies

In Table 3.1, we present the average weekly returns for loser (L) and winner (W) portfolios, as well as for a combined strategy of buying losers and shorting winners (T). Each portfolio's weights are given by equation (3.1).

[Table 3.1 about here]

Since these figures are for positive investment, reversals in losers (winners) will appear as positive (negative) returns. We find the returns on loser portfolio to be reverting, albeit not significant, which is in line with the findings of Conrad, Hameed, and Niden (1994). Also Cooper (1999) and Parisi and Acevedo (2001) report negative (although significant) loser returns. For the winner portfolio, a negative number indicates reversals in returns. However, this number is not significant, either. Conrad, Hameed, and Niden (1994) and Parisi and Acevedo (2001) report positive and insignificant winners' returns, whereas Cooper (1999) finds returns on moderate winners to be positive and significant, but returns on extreme winners to be negative and not significant. A common feature in all the studies is an apparent asymmetry between the magnitude of returns on winner and loser portfolios. Namely, the absolute return on losers is higher than the absolute return on winners. Cooper (1999) notes that this fact is in line with the literature on short-term contrarian strategies, as well as with the conventional wisdom that short positions are less profitable than long positions. Lastly, we do not find the contrarian strategy to be highly profitable - returns from the combined strategy turn out to be positive but significant only at the 10% significance level. This is consistent with the results reported in the previous studies for more developed markets.

3.4.2 Return- and Volume-Based Strategies

After having established the performance of our benchmark, purely return-based, strategy, we now address the issue of the informativeness of trading volume. Specifically, if the hypothesis of Blume, Easley, and O'Hara (1994) holds, we would expect the strategy focusing on volume (in addition to return) to outperform any pure return-based strategy. Moreover, the winner-loser approach applied here allows us to track the performance of both components of the contrarian portfolio, winners and losers, as well as to observe the

return reactions to volume shocks - as suggested by Campbell, Grossman, and Wang (1993) and Wang (1994).

The first approach is to utilize volume data only for the sorting procedure, but not for portfolio weighting. Here, we first divide stocks into losers and winners based on their past return. Next, we use the weekly change in turnover ratio, u_{it} defined in equation (3.2), as a criterion for labelling each stock as a high volume (low volume) one. In this way, we obtain four portfolios: high and low volume losers (LH and LL) as well as high and low volume winners (WH and WL), with weights given by equation (3.1). Table 3.2 presents descriptive statistics of the volume-change variable.

[Table 3.2 about here]

In Panel A, the overall sample average is presented: the average weekly change in transaction level amounts to 29% and is highly significant. As compared to Conrad, Hameed, and Niden's results, figures for the WSE stocks show higher mean value, but also higher dispersion of u_{it} . As should be expected, considerable differences in u_{it-1} (trading volume in portfolio formation week) between high and low transaction portfolios are found (Panel B). High volume winners (WH) and losers (LH) experience much higher levels of trading shocks than low volume winners (WL) and losers (LL), and are also more volatile. However, as shown in Panel C, in the week thereafter (portfolio performance assessment week) transaction shocks of high volume portfolios are lower than those experienced by low volume portfolios, and less volatile. Altogether, the high volume stocks tend to experience positive volume shocks in the following week, whereas the low volume stocks tend to recover from the previous week's negative volume shock and record an increase in trading activities. These findings are in line with evidence presented by Conrad, Hameed, and Niden (1994) for the NASDAQ stocks.

In Table 3.3, Panel A, returns on portfolios with return-based weights given by equation (3.1) and sorted by volume changes are presented.

[Table 3.3 about here]

For low volume portfolios, our results suggest continuations for winners ($WL > 0$) and reversals for losers ($LL > 0$). Returns from the combined strategy in low volume stocks turn out to be negative and significantly lower than returns on the combined portfolio 'T' (reported in Table 3.1), indicating continuations following negative volume shocks. For

high volume winners and losers, we observe price reversals, albeit not significant. The combined strategy delivers average weekly return $TH=0.9375\%$, which is statistically significant and significantly higher than return on the combined portfolio 'T'. This result implies return reversals (negative autocorrelation) following positive volume shocks. As compared with the results presented in Table 3.1, grouping stocks by volume significantly increases the profitability of the contrarian strategy applied for high volume stocks, as suggested by Blume, Easley, and O'Hara (1994). These results are in line with findings of Conrad, Hameed, and Niden (1994) who report positive (negative) profits from the high volume (low volume) contrarian strategy, as well as superior performance of high-volume portfolios vis-a-vis the basic return-based strategy described in Subsection 3.4.1. In contrast, Parisi and Acevedo (2001) find returns on both TL and TH to be negative, implying the dominance of continuations in both high and low volume portfolios, as well as a decrease in returns by focusing separately on high and low volume stocks. Our finding of return reversals following positive volume shocks also support the theoretical predictions of the model proposed by Campbell, Grossman, and Wang (1993), and can be interpreted in light of the models by Wang (1994) and Llorente et al. (2001) as an indicator for the prevalence of non-informative trades at the WSE.

To further explore the question of whether the magnitude of autocorrelation in returns is related to the magnitude in the previous week's change in trading volume, in addition to volume-based sorting procedure we employ the weighting strategy as given by equation (3.3). In this approach, both past returns and past trading volume are taken into account. The results are presented in Table 3.3, Panel B. We find returns on high volume portfolios to be reverting and weakly significant, resulting in positive and highly significant returns from the combined contrarian strategy ($TH=1,2979\%$, t -statistic=2.89). For low volume portfolios, positive returns on winners indicate price-continuations, and are of higher magnitude than positive returns on losers (implying reversals), resulting in negative profits from the low volume contrarian strategy. However, these numbers are not significant. Patterns observed here support the hypothesis of Campbell, Grossman, and Wang (1993) that high volume stocks experience strong price reversals, whereas their low volume counterparts do so to a lesser degree, or even record continuations in returns. Moreover, incorporating a measure of change in trading activity into portfolio weights, as done in equation (3.3), and attributing larger weights to stocks with extreme volume shocks, causes the profits from investment in high volume (low volume) stocks to in-

crease significantly (decrease) vis-a-vis the profits from a purely return-weighted strategy presented in Table 3.3, Panel A. The last finding is consistent with the hypothesis that trading volume contains information about future prices beyond that extractable from past prices - as suggested by Blume, Easley, and O'Hara (1994).

Another issue discussed in the literature is whether it is the sign or the magnitude of volume shocks that provides information about subsequent return behavior. If the magnitude is relevant, one should obtain higher profits from the strategy with return- and volume-based weights (as given by equation (3.3)) than from a strategy based on dividing stocks into high and low volume portfolios and attributing pure return-based weights to them (as given by equation (3.1)). The fact that profits from the former strategy (shown in Table 3.3, Panel B) surpass profits from the latter strategy (reported in Table 3.3, Panel A) might indicate that both the sign and the magnitude of volume shocks reveal information about subsequent returns. However, Conrad, Hameed, and Niden (1994) conclude for results similar to ours that it is more likely the sign rather than the magnitude that contains information about future returns. To clarify this issue, we investigate it in more detail in Subsection 3.5.

Overall, our results are in line with those of Conrad, Hameed, and Niden (1994) and Parisi and Acevedo (2001): high volume stocks tend to experience negative autocorrelation in returns, which is less pronounced for low-volume stocks. These findings indicate that for stocks traded on the WSE, trading volume contains information about future returns beyond that contained in current returns. Moreover, these patterns indicate that most of the trades are conducted for non-informative motives. However, Cooper (1999) finds opposite effects for the large US stocks. In addition to the company size, this author discusses other effects relevant to the volume-return relationship. We analyze these issues in the next section.

3.5 Further Empirical Results

3.5.1 Size Effects

The impact of size on stock returns is a well documented phenomenon. In context of the volume-return relationship discussed here, Blume, Easley, and O'Hara (1994) argue that the informativeness of past trading activities for the stock prices is more pronounced for small rather than large stocks. Conrad, Hameed, and Niden (1994) show that, as

size decreases, price reversals (continuations) of high volume (low volume) stocks become stronger, resulting in an increase (decrease) in profits from the contrarian strategy.

To assess the importance of size for the volume-return relationship, each year we divide stocks into three size-groups, based on the average market capitalization in December of the previous year, and regroup them annually. Next, we calculate returns on winners/losers high/low volume portfolios (WH, WL, LH and LL) with portfolio weights given by equation (3.3). Results are presented in Table 3.4.

[Table 3.4 about here]

Returns on size-sorted portfolios can be seen to be differentiated, with small stocks generating the highest returns from the contrarian strategy - as predicted by the volume informativeness hypothesis of Blume, Easley, and O'Hara (1994) and found in an empirical study of the NASDAQ market by Conrad, Hameed, and Niden (1994). For small stocks, both winners and losers are reported to experience price reversals, although significantly positive returns are found only for the high volume loser portfolio. As a result, only the high volume contrarian strategy results in significant and positive returns. As size increases, profits on both high and low volume combined portfolios decrease, remaining positive but insignificant for large stocks. Returns on the large (small) high-volume portfolio are significantly lower (higher) than those on combined high volume portfolio reported in Table 3.3, Panel B, and returns on low volume portfolios for all three size groups are significantly higher.⁴ These findings differ from those of Conrad, Hameed, and Niden (1994). These authors report price continuations for all low volume portfolios, generating negative profits from a contrarian strategy, whereas we find returns on all low volume loser portfolios to exhibit negative autocorrelation and a low volume strategy to yield positive profits. However, in general we find evidence in favor of Campbell, Grossman, and Wang's theory that volume increasing stocks experience strong price reversals, whereas this is less true for volume decreasing stocks (the same was also found by Conrad, Hameed, and Niden (1994)). Moreover, trading volume is found to be most informative for returns on small stocks, in line with Blume, Easley, and O'Hara (1994) and Conrad, Hameed, and Niden (1994).

⁴Due to the fact that we re-balance portfolios once a year, stocks introduced within a year are not included into the analysis until the beginning of the next year. The absence of some stocks can be a partial explanation of the phenomenon that all low-volume combined portfolios yield positive returns, whereas the returns on the TL-portfolio reported earlier (Table 3.3) are negative.

3.5.2 Additional Effects

We also conduct additional tests to assess the relevance of the length of the portfolio formation period and of the extreme price and volume changes on the volume-return relationship. We discuss the results briefly in this section.⁵

First, none of the theoretical studies mentioned above specifies the length of the period sufficient for returns or volume changes to exert significant influence on future stock prices. Weekly frequency is used to allow for comparability with existing literature on medium term over- and underreactions. However, if it takes e.g. two weeks for prices to revert, allowing for longer stock selection periods would better capture this effect and could improve results from contrarian strategies discussed here. Hence, to assess the impact of the selection-period length on the return behavior, we follow Cooper (1999) and analyze price behavior of stocks that experienced two instead of one week of positive (winners) or negative (losers) returns. We find that price reversals are strongest for small (rather than large) and for volume-increasing stocks, as in the basic case. However, the magnitude of profits from the contrarian strategies is generally lower than that for the one-week case, which is in contrast to Cooper (1999) who reports losers to be more likely to exhibit price reversals after two weeks of consecutive decrease in prices. This finding can indicate that the prices of WSE stocks recover quickly from short-term price decreases, but need longer to recover from long-term (longer than one week) price decreases.

In addition, we also analyze portfolios consisting of stocks which recorded a decrease (increase) in trading volume for two instead of one consecutive week. The logic behind this step is analogous to that presented above. We form portfolios and label a stock a high (low) volume one if trading volume increased (decreased) for two consecutive weeks. Similar to our earlier findings, the magnitude of price reversals is highest for small and high volume stocks. Stocks generally tend to experience price reversals, although most returns are not significant. However, most profits from contrarian portfolios are lower than those from the one-week strategy. This indicates that no additional information can be extracted from the persistence of volume shocks, only their appearance is informative.

Second, Cooper (1999) argues that focusing only on extreme changes in returns instead of analyzing all winners and losers boosts the "signal-to-noise" ratio of contrarian investment strategy by incorporating only truly overreacting stocks, and, hence, improves

⁵Results not reported.

profits. We analyze the importance of the magnitude in past returns for price reversals or continuations. To do so, we redefine winner (loser) stocks as those for which the level of past returns is higher (lower) than its median value for each size group and past return group (e.g. small stock is attributed to the winner portfolio if its past return is lower than the median for small losers equal to -0.0417). As compared with the basic case (Table 3.4), we find reversals in small and large high volume stocks to be more pronounced (significantly higher returns from combined contrarian strategies), indicating stronger tendency of stocks experiencing positive volume shocks to reverse. For example, applying the contrarian strategy to small high volume stocks with extreme past returns yields weekly return of 1.7153%, versus 1.4140% from the contrarian portfolio with all small high volume stocks. However, all except one remaining portfolios record an significant increase in return autocorrelations (weaker reversals), so that we cannot fully confirm Cooper's predictions for low volume stocks for the WSE. Nevertheless, in general our analysis shows that the magnitude of past returns might matter for subsequent price behavior, especially for high volume stocks.

Additionally, we assess the importance of the magnitude of volume changes in the analogous way. For large stocks, we find autocorrelation in returns to increase after an extreme positive volume shock and to decrease after an extreme negative volume shock (and no significant effects for small and medium-size stocks). These figures are in line with our findings reported in the earlier sections, and support the theory of Campbell, Grossman, and Wang (1993). In the light of Wang (1994), this would indicate that the majority of trades on the WSE are noninformative. Our results can also be used to comment upon the issue raised by Conrad, Hameed, and Niden (1994) of whether it is the sign or the magnitude of volume shocks that is informative for subsequent price changes. Since we find returns on only one portfolio to increase significantly after focusing on extreme volume shocks (and returns on remaining portfolios to decrease), we would argue that the sign rather than the magnitude of volume changes is a more relevant information transmission vehicle.

3.6 Conclusions

Theoretical researchers (e.g. Blume, Easley, and O'Hara (1994)) note that past trading volume data can contain information about future returns beyond that contained

in past returns. Moreover, stocks experiencing positive (negative) changes in trading volume were argued to experience return reversals (continuations), due to the prevalence of informed (uninformed) traders on the market (Campbell, Grossman, and Wang (1993), Wang (1994), Llorente, Michaely, Saar, and Wang (2001)). Using an approach developed by Conrad, Hameed, and Niden (1994) and the refinements proposed by Cooper (1999), we conduct an empirical analysis of the volume-return relationship for stocks traded in the single auction system on the Warsaw Stock Exchange at an early stage of its development.

We find lagged trading volume to contain additional information about future returns beyond that contained in past returns, in line with Blume, Easley, and O'Hara's theory and empirical results for the US (Conrad, Hameed, and Niden (1994), Cooper (1999)) and Chilean (Parisi and Acevedo (2001)) stock market. Moreover, in accordance with previous studies, these effects are most pronounced for small stocks. Stocks traded on the WSE are found to experience price reversals after positive volume shocks, and price continuations after negative volume shocks. These effects are strongest for small stocks and indicate, in light of the models of Wang (1994) and Llorente et al. (2001), the prevalence of uninformed traders on the Polish capital market. Trading in large US stocks is found by Cooper (1999) to be dominated by informed traders, whereas results similar to ours are reported by Conrad, Hameed, and Niden (1994) for the NASDAQ and Parisi and Acevedo (2001) for Chilean stocks. Rather than for information-related motives, most traders on the WSE seem to act due to the changes in their liquidity needs or preferences.

However, in contrast to Cooper (1999), focusing on longer portfolio formation periods does not improve our results. Including only extreme values of weighting criteria (past return or changes in trading volume) generally does not strengthen price trends, either (with the exception of some high volume portfolios), in contrast to what has been shown by Cooper (1999). On the basis of our empirical findings we also conclude that, for the WSE stocks, the sign of volume change is more informative than the magnitude of change in transaction activity, as observed by Conrad, Hameed, and Niden (1994).

Our results further show that models of the dynamic volume-return relationship, shown in previous studies to explain the behavior of the investors on the US markets well, can also be applied to other markets - with different trading system, institutional and regulatory settings, being at different stage of development and even shown to be

informationally inefficient. This finding presents an additional evidence supporting the notion that theoretical predictions concerning the informativeness of trading volume are valid universally and are not restricted to the US market.

3.7 Tables

Table 3.1: Contrarian Profits Using Return-Based Weights

Portfolio	mean [in%]	t-stat.	s.d.	min.	max.
W	-0.110597	-0.338213	0.051080	-0.320170	-0.163710
L	0.444366	1.331920	0.043788	-0.166720	0.184000
T	0.554963	1.772930	0.048896	-0.131660	-0.353190

Note: We use data on weekly Wednesday-close-to-Wednesday-close stock prices on the Warsaw Stock Exchange for the period January 1996 - October 2000. 'W' refers to the winner portfolio, 'L' to the loser portfolio, and 'T' to the combined zero net investment portfolio. The winner portfolio 'W' (loser portfolio 'L') consists of shares with positive (negative) returns in week t-1, with weights given by equation (3.1). The combined portfolio 'T' is long in losers and short in winners. 'Mean' is the average weekly portfolio return in percent and 's.d.' is the sample standard deviation of the average weekly portfolio return (not corrected for autocorrelation and heteroscedasticity). We use the GMM-methodology (Hansen (1982)) allowing for computation of autocorrelation- and heteroscedasticity robust standard errors. The t-statistic for returns, 't-stat.', is calculated using the corrected standard errors. 'Min.' and 'max.' refer to the minimal and maximal return recorded. The sample consists of 243 weeks.

Table 3.2: Summary Statistics: Average Weekly Change in Transaction Level

Portfolio	mean	s.d.	min.	max.	t-stat.
Panel A: Cross-sectional statistics					
all shares	0,2901	0,7403	-0,6281	4,0239	12,2
Panel B: Change in Week t-1 by Portfolio					
WH	1.0321	0.5317	0.0000	3.8484	
WL	-0.3202	0.0824	-0.5923	-0.0326	
LH	0.8082	0.5245	0.0000	4.0239	
LL	-0.3622	0.0828	-0.6281	-0.1256	
Panel C: Change in Week t by Portfolio					
WH	0.0439	0.3587	-0.5203	2.2755	
WL	0.4540	0.6030	-0.6019	3.0353	
LH	0.1233	0.4734	-0.6199	3.2756	
LL	0.4979	0.5709	-0.6014	2.9839	

Note: We use data on weekly Wednesday-close-to-Wednesday-close turnover ratios on the Warsaw Stock Exchange for the period January 1996 - October 2000. Turnover ratio is computed as the ratio of the number of shares traded to the number of shares outstanding. Average weekly change in the transaction level is measured as:

$$u_{it} = (T_{it} - T_{it-1})/T_{it-1},$$

with T_{it} being the turnover ratio at time 't'. 'Mean' is the average weekly change in turnover ratio and 's.d.' refers to the sample standard deviation of the average weekly change in turnover ratio (not corrected for autocorrelation and heteroscedasticity). 'Min.' and 'max.' refer to the minimal and maximal change in turnover ratio. We use the GMM-methodology (Hansen (1982)) allowing for computation of autocorrelation- and heteroscedasticity robust standard errors. The t-statistic for the mean, 't-stat.', is calculated using the corrected standard errors. The sample consists of 243 weeks.

'WH' ('WL') refers to the volume increasing (volume decreasing) winner portfolio, 'LH' ('LL') to the volume-increasing (volume decreasing) loser portfolio. 'WH' ('WL') consists of shares with positive returns in week t-1 and positive (negative) change in transaction level in week t-1, with weights given by equation 3.1. Portfolio 'LH' ('LL') consists of shares with negative returns in week t-1 and positive (negative) change in transaction level in week t-1, with weights given by equation 3.1.

Table 3.3: Contrarian Profits Using Weekly Returns

Portfolio	mean [in%]	t-stat.	s.d.	min.	max.
Panel A: Return-Based Weights					
WH	-0.358163	-1.022830	0.054698	-0.357260	0.159600
WL	0.601735	1.268030	0.056622	-0.220660	0.415330
LH	0.550447	0.106084	0.053460	-0.183860	0.363150
LL	0.290029	0.862566	0.042064	-0.170230	0.118070
TH	0.937471	2.272050	0.064452	-0.203540	0.388440
TL	-0.311705	-0.971402	0.050124	-0.412650	0.252980
Panel B: Return- and Volume-Based Weights					
WH	-0.644392	-1.774090	0.056738	-0.365790	0.117260
WL	0.613053	1.199050	0.061110	-0.260510	0.505820
LH	0.653463	1.740950	0.058632	-0.172920	0.436270
LL	0.330798	1.014160	0.043325	-0.172550	0.128500
TH	1.297900	2.885150	0.070268	-0.214750	0.441580
TL	-0.275955	-0.764757	0.056365	-0.505800	0.308500

Note: We use data on weekly Wednesday-close-to-Wednesday-close stock prices on the Warsaw Stock Exchange for the period January 1996 - October 2000. 'WH' ('WL') refers to the volume increasing (volume decreasing) winner portfolio, 'LH' ('LL') to the volume increasing (volume decreasing) loser portfolio, and 'T' to the combined zero net investment portfolio. 'Mean' is the average weekly portfolio return in percent and 's.d.' refers to the standard deviation of the average weekly portfolio return (not corrected for autocorrelation and heteroscedasticity). We use the GMM-methodology (Hansen (1982)) allowing for computation of autocorrelation- and heteroscedasticity robust standard errors. The t-statistic for returns, 't-stat.', is calculated using the corrected standard errors. 'Min.' and 'max.' refer to the minimal and maximal return recorded. The sample consists of 243 weeks.

In Panel A, portfolio 'WH' ('WL') consists of shares with positive returns in week t-1 and positive (negative) change in transaction level in week t-1, with return-based weights given by equation 3.1. The portfolio 'LH' ('LL') consists of shares with negative returns in week t-1 and positive (negative) change in transaction level in week t-1, with return-based weights given by equation 3.1. The combined portfolio 'T' is long in losers and short in winners.

In Panel B, portfolio 'WH' ('WL') consists of shares with positive returns in week t-1 and positive (negative) change in transaction level in week t-1, with return- and volume-based weights given by equation 3.3. The portfolio 'LH' ('LL') consists of shares with negative returns in week t-1 and positive (negative) change in transaction level in week t-1, with return- and volume-based weights given by equation 3.3. The combined portfolio 'T' is long in losers and short in winners.

Table 3.4: Contrarian Profits Using Return- and Volume-Based Weights for Three Size-Sorted Portfolios

Portfolio	mean [in%]	t-stat.	s.d.	min.	max.
Panel A: Large Firms					
WH	-0.167795	-0.482153	0.054362	-0.155260	0.168710
WL	0.123981	0.374798	0.049763	-0.222360	0.186560
LH	0.250091	0.623405	0.059193	-0.238330	0.224830
LL	0.395111	1.093170	0.053151	-0.162840	0.283190
TH	0.417886	1.003580	0.065043	-0.222480	0.241360
TL	0.271130	1.057610	0.051901	-0.137310	0.234060
Panel B: Medium-Size Firms					
WH	-0.303946	-0.814867	0.058265	-0.276890	0.181450
WL	0.154634	0.357275	0.048481	-0.146900	0.170420
LH	1.056300	2.062120	0.080015	-0.149100	0.681820
LL	0.488631	1.456220	0.052415	-0.162770	0.358650
TH	1.360200	2.365020	0.089843	-0.184590	0.681820
TL	0.333997	0.964089	0.054116	-0.186200	0.390240
Panel C: Small Firms					
WH	-0.618045	-1.483100	0.065095	-0.252920	0.335570
WL	-0.796821	-0.208739	0.059629	-0.158160	0.269120
LH	0.795979	2.070810	0.060043	-0.255610	0.216550
LL	0.385578	1.145480	0.052580	-0.231150	0.215730
TH	1.414000	2.913710	0.075807	0.257730	0.305510
TL	0.465261	1.302600	0.057145	-0.302430	0.207800

Note: We use data on weekly Wednesday-close-to-Wednesday-close stock prices on the Warsaw Stock Exchange for the period January 1996 - October 2000. 'WH' ('WL') refers to the volume increasing (volume decreasing) winner portfolio, 'LH' ('LL') to the volume increasing (volume decreasing) loser portfolio, and 'T' to the combined zero net investment portfolio. 'Mean' is the average weekly portfolio return in percent and 's.d.' refers to the sample standard deviation of the average weekly portfolio return (not corrected for autocorrelation and heteroscedasticity). We use the GMM-methodology (Hansen (1982)) allowing for computation of autocorrelation- and heteroscedasticity robust standard errors. The t-statistic for returns, 't-stat.', is calculated using the corrected standard errors. 'Min.' and 'max.' refer to the minimal and maximal return recorded. The sample consists of 243 weeks.

Portfolio 'WH' ('WL') consists of shares with positive returns in week t-1 and positive (negative) change in transaction level in week t-1, with return-based weights as given by equation 3.3. The portfolio 'LH' ('LL') consists of shares with negative returns in week t-1 and positive (negative) change in transaction level in week t-1, with return- and volume-based weights as given by equation 3.3. The combined portfolio 'T' is long in losers and short in winners.

Chapter 4

Institutional Trading and Stock Return Autocorrelation

4.1 Introduction

In the late 1980s, capital markets world-wide experienced an unprecedented increase in the number of stocks traded by institutional investors which increased the interest of researchers into the impact of institutional trading on stock prices. In particular, due to the specific trading behavior of institutions, numerous theoretical and empirical investigations put forward arguments in favor of their impact on autocorrelation in stock returns. First, Barclay and Warner (1993) argue that informed investors will break up their trades and distribute them over time to lower their price impact. This will induce an increase in autocorrelation of stock returns. As far as trades are cross-sectionally correlated, simultaneous actions of informed institutional traders will induce positive return autocorrelation. Chan and Lakonishok (1995) also find empirical evidence for order-splitting by institutional traders.

A second argument for positive return autocorrelation can be derived from the model put forward by Wang (1994). It relies on the information asymmetry between traders and on the impact of informed trading on the behavior of uninformed investors. The main finding is that as the share of informed traders increases, autocorrelation in returns also increases. Cooper (1999) finds that for stocks with high information asymmetry autocorrelation in returns becomes positive. If institutional investors are assumed to be informed (e.g. Arbel and Strebel (1983), Sias and Starks (1997), Sias, Starks, and Titman (2001)), institutional ownership increases return autocorrelation.

Third, it can be argued that sequential information arrival induces increases in re-

turn autocorrelation. As the best informed traders receive price-relevant information and trade on it, prices move in one direction. As the second-best informed traders later receive the same information, they also trade on it, moving the prices even further.¹ This sequential trading causes the price to move in one direction for a certain period of time, inducing positive autocorrelation. Findings of Sias and Starks (1997) that autocorrelation in stock returns depends positively on the fraction of (best informed) institutional traders, and that this autocorrelation is positive, provide us with empirical evidence in favor of this postulate. Holden and Subrahmanyam (2002) also show that returns are positively autocorrelated under the condition of sequential information acquisition.

Fourth, positive feedback trading and herding by institutional investors may increase return autocorrelation. Results reported by Sias and Starks (1997) and Nofsinger and Sias (1999) are in line with this hypothesis. From their analysis of mutual funds, Grinblatt, Titman, and Wermers (1995) conclude that there is evidence of momentum trading by these investors. Lakonishok, Shleifer, and Vishny (1992), however, find only weak evidence that pension funds engage in positive feedback trading and herding. Furthermore, their findings support the positive feedback trading and herding hypothesis only for small stocks. McQueen, Pinegar, and Thorley (1996) note that momentum trading and herding are more pronounced in the case of up markets than down markets. Badrinath and Wahal (2002) analyze the behavior of various institutions at different stages of the investment process and find only modest evidence for momentum trading. This is due to the fact that institutions act as momentum traders when they initiate a new position in a stock, but follow a contrarian approach when they re-balance portfolios or terminate their position in a stock. Evidence of momentum trading for pension funds is especially weak.

In contrast to the large body of empirical evidence finding an increase in autocorrelation in stock returns due to institutional trading, the argument that increasing institutional ownership lowers autocorrelation in stock returns finds only weak support in the literature. Badrinath, Kale, and Noe (1995) argue that, due to the differential information set-up costs and legal restrictions, institutional investors will acquire information on (and purchase) only a subset of traded firms. This will cause a shift in stock

¹The first trader might be unwilling to fully exploit his information due to the price impact considerations of his action and the information revelation of his trades. Moreover, the degree of uncertainty about the quality of the private signal might be an explanation: as more and more traders obtain private information, it becomes less uncertain and agents are more willing to trade on it (Holden and Subrahmanyam (2002)).

prices. The remaining stocks traded by less informed investors will adjust to the market-wide information contained in these trades with a lag. One prediction of their model is that stocks with a higher (lower) level of institutional ownership will experience quicker (slower) adjustment to information and, hence, lower (higher) autocorrelation in returns. Empirical results presented by the authors are in line with these predictions.

This brief review of the literature shows that the available empirical findings mainly provide evidence in favor of positive stock return autocorrelation and that the investigations concentrate, without exception, on the US stock market. In contrast, by exploiting a unique institutional characteristic of the Polish stock market, our empirical findings do not support the hypothesis of positive return autocorrelation due to institutional investors' trading. The special feature arises from the pension reform in Poland in 1999 when privately managed pension funds were established and started to invest on the domestic capital market. We focus on the return behavior of stocks listed on the Warsaw Stock Exchange (WSE) prior to and after the first transfer of money to the pension funds on May 19, 1999. The appearance of large institutional traders and the resulting increase in institutional ownership makes it possible for us to investigate the impact on return autocorrelation. Specifically, relying on both a standard and a non-linear autoregression-cum-GARCH framework, we test whether autocorrelation coefficients in the return time series of stocks actively traded by pension funds increase after the increase in institutional holdings, as often found in the finance literature. Moreover, we investigate the relationship between the change in return autocorrelation and the increase in institutional trading after the appearance of pension funds in the cross-section of our sample.

The remainder of this chapter is organized as follows. In Subsection 4.2, the pension reform in Poland, its consequences for the capital market, and the data are described. We present the time series methodology, the cross-sectional approach, and empirical results in Subsection 4.3, while Subsection 4.4 concludes.

4.2 Institutional Traders on the Polish Stock Market and Data

Trading on the Polish stock market exclusively takes place on the WSE. Re-established in 1991, the WSE was designed as an order-driven call market. Continuous trading was launched in 1996 and the most liquid stocks were gradually introduced into

this system. The WSE is the most liquid stock market in Central Eastern Europe. The total turnover in stocks in 2001 was more than ten billion euro and was thus roughly twice as high as the turnover on the Budapest Stock Exchange, the second most important stock market of the region. The free float is estimated in newspaper reports to be roughly 30%.² Due to its success, the WSE has attracted considerable interest from foreign investors. Nevertheless, the majority of traders have been small, private investors.³

A major change in the investor structure took place after the Polish pension reform. In 1999, the public pension system was enriched by a private component. Younger citizens were forced to invest part of their income in privately managed open-end pension funds, the so-called "Otwarte Fundusze Emerytalne" (OFEs).⁴ A significant share of the workforce chose the new system and a large amount of money was transferred to the OFEs by the Polish Social Security Institution, the so-called "Zakład Ubezpieczeń Społecznych" (ZUS). The ZUS is responsible for collecting the savings of all employees and transferring them to the OFEs. The first transfer of money to the OFEs took place on May 19, 1999. By the end of 1999, Polish OFEs had 2.3 billion Polish zlotys at their disposal, and by the end of 2001, their holdings amounted to 18.5 billion Polish zlotys.

OFEs are obliged to publish their total holdings annually and all positions that exceed 1% of their entire portfolio semi-annually. We combined the data from the publications of all pension funds to construct a hand-collected data set of pension fund holdings in Poland. These publications show that the number of OFEs active on the market varies over time due to the liquidation of old and the emergence of new funds, but it is relatively stable between 15 and 20. The four largest OFEs account for 70% of all pension fund holdings.⁵

Common stocks are an important component of OFEs portfolios. The share of stocks constantly amounted to more than 20% of total funds invested and gradually increased over time. Thus, OFEs became important players on the Polish stock market. The appearance of OFEs makes it possible for us to compare the period before May 19, 1999, that is mainly characterized by non-institutional trading with the period after that date, where OFEs account for a considerable share of market volume.

²Data on the free float of individual stocks are not available on the WSE, therefore we are not able to include this measure in the analysis.

³For a detailed description of the trading systems and the investor structure see WSE (2002).

⁴Older citizens had the choice of investing in OFEs or exclusively relying on the public pension system.

⁵Data on the portfolio structures of all Polish OFE are available on request from the author.

From the OFE publications, we are able to identify those stocks that they traded actively. We select the thirty stocks most actively traded by OFEs on the Polish stock market. By focusing on the stocks that were subject to institutional trading, we can test the influence of institutional traders on stock return autocorrelation. As a measure of OFE trading activity in stock i , we choose the monetary value of the OFE holdings of stock i at the end of 2000 divided by total turnover of stock i during the same period:

$$INST_i = \frac{\text{monetary value of the OFE holdings of stock } i}{\text{total turnover of stock } i}. \quad (4.1)$$

This variable measures the cumulative net purchases of all pension funds in our sample as a percentage of the stock's overall trading volume.⁶ Data on trading volume and stock prices were provided by the WSE. We prefer a relative measure over the absolute value of OFE holdings as the theory outlined in Subsection 4.1 predicts that the impact of institutional trading is higher the larger the share of these players in the market. As a robustness check, however, we selected the thirty stocks with the largest absolute values of OFE holdings. Several of these stocks were identical to the stocks selected using a relative measure and the overall results did not vary significantly from those reported here. Additional information on the stocks used in our study are presented in Table 4.1.

[Table 4.1 around here]

The table shows that OFE holdings of the thirty stocks comprise more than 6% of the overall trading volume for each stock. For the five stocks with the highest percentage share of institutional trading, the ratio of OFEs holdings to total volume is larger than one third. Thus, trading of pension funds accounts for a large percentage share of overall trading volume.

To check the robustness of the results and to investigate whether possible changes in autocorrelation are related to the appearance of pension fund investors or are a market-wide phenomenon, we additionally use a sample of control stocks in our empirical investigation. This control sample consists of 30 stocks, which were randomly selected from the remaining stocks listed on the WSE. We are not able to construct a control sample

⁶Since we only have data on the OFE holdings and not on OFE trading volume, the true share of OFE trading volume may even be higher. This would be the case if some funds bought additional shares during the investigation period and sold them before the reporting day. Since OFEs are long-term investors and had to invest large amounts of money in a relatively short period of time, it is likely that the number of sells is rather low and that our indicator consistently mirrors OFE trading behavior.

of stocks matched to the stocks in Table 4.1 with respect to market capitalization and trading volume because all large and frequently traded stocks are in the OFE portfolios. Thus, there are no stocks with comparable size and volume remaining on the market.

The descriptive statistics in Table 4.1 indicate that our sample is well-suited for the investigation of institutional trading on stock return autocorrelation. We will now turn to the econometric techniques used and the results of our empirical analysis.

4.3 Methodology and Empirical Results

First, we conduct an empirical investigation of institutional traders' influence on return autocorrelation by estimating the following model for daily returns

$$R_{it} = \alpha_{i0} + \alpha_{i1}R_{it-1} + \alpha_{i2}D_tR_{it-1} + \varepsilon_{it} \quad (4.2)$$

and

$$h_{it} = \beta_{i0} + \beta_{i1}\varepsilon_{it-1}^2 + \beta_{i2}h_{it-1}. \quad (4.3)$$

The return on stock i is defined as the logarithmic difference in prices, $R_{it} = \ln P_{it} - \ln P_{it-1}$, where P_{it} denotes the stock price. $\varepsilon_{it} \sim N(0, h_{it})$ is the unpredictable component of the returns. The dummy variable, D_t , in equation (4.2) is zero before May 19, 1999, and one afterwards. Note that before May 19, 1999, the expected return is $E(R_{it}) = \alpha_{i0} + \alpha_{i1}E(R_{it-1})$, while in the period after the entrance of institutional traders in the Polish stock market it is $E(R_{it}) = \alpha_{i0} + (\alpha_{i1} + \alpha_{i2})E(R_{it-1})$. Consistent with our discussion on the influence of institutional traders on stock returns, the α_{i2} parameter is expected to be positive and statistically significant resulting in a positive sum $(\alpha_{i1} + \alpha_{i2})$. With the GARCH(1,1) model (4.3) we take into account the well-known conditional heteroscedasticity characteristics of many financial time series.⁷

Table 4.2 reports the test results of the impact of institutional traders on the autocorrelation structure of the Polish stocks discussed in Subsection 4.2. Equations (4.2) and (4.3) are jointly estimated for three different periods, namely January 2, 1999 - December 30, 1999; July 1, 1998 - June 30, 2000; and January 2, 1998 - December 30, 2000, to provide a check of robustness. As can be seen from Table 4.2, in the minority of all cases

⁷In addition to the standard GARCH(1,1) model we estimated a modified GARCH specification in line with Glosten, Jaganathan, and Runkle (1993) to take into account asymmetry in individual stock returns' volatility. In only six out of 90 regressions we found evidence in favor of asymmetries (results are not reported but are available on request). Hence, we rely on the standard GARCH(1,1) model.

we observe statistically significant α_{i1} and α_{i2} coefficients. Although the α_{i2} parameters are positive for a substantial number of stocks only six of them are positive and statistically significant at the conventional levels. With respect to the sum of coefficients, in the majority of cases ($\alpha_{i1} + \alpha_{i2}$) is negative. The values of the remaining positive sums are relatively low and result from statistically insignificant α_{i1} and α_{i2} parameters. Only for three stocks (Stalprodukt, BSK, and PBK), the empirical results are in line with the theoretical prediction that institutional trading generates positive autocorrelation in individual stock returns. However, for these three stocks the empirical evidence is not robust with respect to the selection of the sample. In all other cases the findings are not consistent with this hypothesis.

[Table 4.2 around here]

To check the robustness of our results, we estimate the model given by equations (4.2) and (4.3) for a control sample of 30 stocks as described in Subsection 4.2 for the three periods under investigation. The results (not reported) are similar to those reported in Table 4.2, i.e., the parameter $\hat{\alpha}_{i2}$ is insignificant in the majority of cases and does not provide evidence in favor of positive return autocorrelation.

Second, we analyze whether the lack of significant changes in the autocorrelation structure is due to a misspecification of the model for daily returns. Substantial empirical evidence (LeBaron (1992), Booth and Koutmos (1998a), (1998b), Watanabe (2002)) shows that the autocorrelation pattern of stock returns exhibits complexity that cannot be captured completely by the simple first-order autocorrelation coefficient in equation (4.2). In particular, an inverse relationship between first-order return autocorrelation and volatility has been found for some markets. To account for this effect, we model stock returns as conditionally heteroscedastic processes with time-dependent autocorrelation, in line with LeBaron (1992), in the following way

$$R_{it} = \gamma_{i01} + \gamma_{i02}D_t + f(h_{it})R_{it-1} + f'(h_{it})R_{it-1}D_t + \varepsilon_{it}, \quad (4.4)$$

where

$$f(h_{it}) = \gamma_{i11} + \gamma_{i21} \exp(-h_{it}/\sigma_i^2), \quad (4.5)$$

and

$$f'(h_{it}) = \gamma_{i12} + \gamma_{i22} \exp(-h_{it}/\sigma_i^2). \quad (4.6)$$

In addition, the simple GARCH(1,1) process may be misspecified because the volatility process contains a structural break after May 19, 1999. A general model specification for the conditional volatility is given by

$$h_{it} = \beta_{i01} + \beta_{i02}D_t + \beta_{i11}\varepsilon_{it-1}^2 + \beta_{i12}\varepsilon_{it-1}^2D_t + \beta_{i21}h_{it-1} + \beta_{i22}h_{it-1}D_t. \quad (4.7)$$

The notation is known from the discussion above. σ_i^2 is the sample variance of the return time series of stock i . Before May 19, 1999, the expected return equals $E(R_{it}) = \gamma_{i01} + \gamma_{i11}E(R_{it-1})$ during high volatility periods, and $E(R_{it}) = \gamma_{i01} + (\gamma_{i11} + \gamma_{i21})E(R_{it-1})$ during low volatility periods. In the period after the entrance of institutional traders into the Polish stock market the expected return is equal to $E(R_{it}) = (\gamma_{i01} + \gamma_{i02}) + (\gamma_{i11} + \gamma_{i12})E(R_{it-1})$ when the conditional volatility is high and $E(R_{it}) = (\gamma_{i01} + \gamma_{i02}) + (\gamma_{i11} + \gamma_{i21} + \gamma_{i12} + \gamma_{i22})E(R_{it-1})$ when the conditional volatility is low. Hence, the change in the autocorrelation coefficient resulting from the entrance of pension fund investors is given by γ_{i12} for the high volatility regime, and by $(\gamma_{i12} + \gamma_{i22})$ for the low volatility regime. Consistent with our discussion of the influence of institutional traders on stock returns, the parameters γ_{i12} and $(\gamma_{i12} + \gamma_{i22})$ are expected to be positive and statistically significant resulting in positive sums $(\gamma_{i11} + \gamma_{i12})$ and $(\gamma_{i11} + \gamma_{i21} + \gamma_{i12} + \gamma_{i22})$.

Results of the estimation of equations (4.4) to (4.7) for our three estimation periods (not reported but available upon request) clearly show that for both low and high volatility regimes only a few of the parameters of interest are statistically significant. Focusing on the significant ones, no definite conclusion can be made about the prevailing sign of stock return autocorrelation. This statement is valid for both the period before and after the entrance of pension fund investors on the Polish stock market. In sum, we have found little empirical evidence for Polish stocks that would support the hypothesis that institutional trading induces positive return autocorrelation. Only in a few cases are the estimated coefficients statistically significant and consistent with the hypothesized positive return autocorrelation, while in the majority of cases the parameters are insignificant or their values contradict the hypothesis under study.

The pension funds probably entered the Polish stock market only gradually. Hence, shortly after the first transfer from the ZUS on May 19, 1999, it may be unlikely to find evidence in favor of the pension funds' influence on stock returns. Therefore, we omitted a period of three as well as of six months after May 19, 1999, to provide evidence on a potential bias in the results presented above against finding an impact of pension

funds' trading on stock returns. Our empirical findings (not reported but available on request) support our main conclusion. Omitting three and six months after May 19, 1999, respectively, does not change the finding that in the overwhelming majority of cases the appearance of pension fund investors do not induce positive return autocorrelation.

Finally, we investigate the relationship between stock return autocorrelation and institutional trading in the cross-section of our sample. In order to have a sufficient number of observations, we include all stocks in the cross-sectional regressions that were traded by Polish pension funds. We obtain 53 stocks which we include in the analysis. We aim to investigate whether there is a systematic relationship between the increase in institutional trading and the change in return autocorrelation after the appearance of pension fund investors on the market.

To answer this question, we first estimate equation (4.2) for all 53 stocks and obtain estimates of $\hat{\alpha}_{2i}$. This parameter measures the increase in return autocorrelation of stock i after the appearance of pension funds. We then regress the estimated coefficient $\hat{\alpha}_2$ on the change in institutional trading. Institutional trading in stock i is captured by our relative measure of pension fund activity defined in equation (4.1), $INST_i$,

$$\hat{\alpha}_{2i} = \beta_0 + \beta_1 INST_i + \varepsilon_i. \quad (4.8)$$

If there is a positive relationship between the amount of institutional trading in stock i , $INST_i$, and the change in autocorrelation, $\hat{\alpha}_{2i}$, as suggested by the theory, we will observe positive and significant values of β_1 .⁸

The appearance of institutional investors on the market also increases the trading volume of stocks. Since it is well known that higher volume decreases autocorrelation (see Boudoukh et al. (1994)), we disentangle the impact of institutional trading from trading volume on return autocorrelation and run a second regression with the relative institutional trading measure and the change in trading volume as the explanatory variables. The change in trading volume of stock i , ΔVOL_i , is defined as the logarithm of the ratio between average trading volume of the stock in the post-event and pre-event period, where pre- and post-event periods are separated by the event day May 19, 1999. The extended regression model has the form

$$\hat{\alpha}_{2i} = \beta_0 + \beta_1 INST_i + \beta_2 \Delta VOL_i + \varepsilon_i. \quad (4.9)$$

⁸As $\hat{\alpha}_{2i}$ is obtained as a ML estimate, it may be measured with error. Since this parameter is the dependent variable in regression (4.8), however, it does not lead to biased parameter estimates. Any potential measurement error is captured by the error term ε_i . See Judge et al. (1988) for more details.

In Table 4.2, we have reported coefficient estimates of $\hat{\alpha}_{2i}$ for three different sub-periods. We therefore calculate regressions (4.8) and (4.9) for all three estimates of $\hat{\alpha}_{2i}$ separately and obtain six individual regression equations. The results are presented in Table 4.3.

[Table 4.3 around here]

The table reports estimates of $\hat{\alpha}_{2i}$ over three different time periods. Standard errors are heteroscedasticity-consistent using the White (1980) correction. Moreover, we checked the regression for possible multicollinearity between the relative institutional trading measure and the change in trading volume. Since the absolute value of the correlation coefficients between the institutional trading measure and the change in volume varied between 0.15 and 0.29 in the three estimation periods, multicollinearity does not seem to be present in the data.

The results reported in Table 4.3 indicate a negative relationship between changes in autocorrelation and the amount of institutional trading in our sample. All estimated β_1 coefficients are significant at the 1% level. Volume has a positive impact on autocorrelation, but the estimates of β_2 are only significant at the 10% level for the period January 2, 1998 to December 31, 2000 and insignificant for the periods July 1, 1998 to June 30, 2000 and the shortest period covering the year 1999. The explanatory power of the regressions measured by R^2 coefficients is higher for the periods covering the year 2000 with values between 0.187 and 0.280. Overall, the findings indicate a robust negative relationship between the amount of institutional trading and the change in autocorrelation across our sample.

This finding contradicts the majority of empirical studies on the impact of institutional trading on return autocorrelation as outlined in Subsection 4.1. The negative relationship between autocorrelation and institutional trading can result from increased information flow due to the trades of pension funds as outlined in Badrinath et al. (1995). If pension fund managers are better informed than other investors about the fundamental values of the stocks they trade, their trading may cause a faster adjustment of stock prices to fundamentals and, correspondingly, a decrease in return autocorrelation.

A variable likely to affect autocorrelation is bid-ask bounce. Since stocks are traded at their bid and ask prices, quoted prices fluctuate around the quote midpoint, which introduces negative autocorrelation into the return series. The larger the spread, the larger the degree of autocorrelation (see, e.g., Roll (1984)). Thus, if bid-ask spreads change over

time so may autocorrelation.

Unfortunately, spread data are not available on the WSE for the time under investigation. However, a market-wide change in bid-ask spreads does not affect our main results obtained from estimation of equations (4.8) and (4.9). If autocorrelation coefficients of all stocks are affected by changes in bid-ask spreads identically, this effect will be observable in the intercept term β_0 in both regressions but will not have any effect on the regression coefficient β_1 .

Changes in bid-ask spreads only have an impact if they are correlated with the measure of institutional trading. This can happen in two ways: First, stocks with a higher degree of institutional trading become more liquid, which causes spreads to narrow and autocorrelation to increase. This contradicts our finding in Table 4.3 which implies a stable negative relationship between the measure of institutional trading and changes in autocorrelation. Moreover, liquidity changes are captured by the control variable ΔVOL_i in equation (4.9). The coefficient β_1 , however, remains significantly negative even after controlling for changes in liquidity.

Second, bid-ask spreads are correlated with the measure of institutional trading if the institutional investors are better informed investors and, thus, small investors lose money when they trade with them. In this case, a higher degree of institutional trading causes adverse selection components of spreads to increase since the probability of informed trading is higher, and autocorrelation decreases with the degree of institutional trading. This negative relationship between the degree of institutional trading and changes in autocorrelation is reported in Table 4.3. Again, this finding lends support to our view that the appearance of institutional investors on the Polish stock market ensures a better flow of information, which leads to a decrease in stock return autocorrelation.

4.4 Conclusions

In this study, we provide additional empirical evidence on the impact of institutional investors on stock return autocorrelation. The reform of the Polish pension system in 1999 is used as an institutional peculiarity to perform a variant of the event study methodology for individual stock returns traded by pension fund investors. Furthermore, to the best of our knowledge, all studies investigating the impact of institutional investors on stock prices rely on US data and no study is publicly available for an emerging capital market. The

implementation of a standard and a non-linear autoregression-cum-GARCH framework allows us to answer the question of whether the increase in institutional ownership after the first appearance of Polish pension funds on May 19, 1999, resulted in increasing and positive return autocorrelation as suggested in a substance number of theoretical and empirical studies. Cross-sectional regressions on the relationship between the change in return autocorrelation and the increase in institutional trading provide further insight into the importance of pension fund trading for return autocorrelation.

Our empirical findings for the 30 stocks most actively traded by Polish pension funds show that in the vast majority of cases the increase in institutional ownership does not have an impact on the return autocorrelation structure of the individual stocks. This empirical finding is fairly robust with respect to different model specifications and sample periods. Furthermore, our findings from the cross-sectional analysis show that the level of pension funds' trading in a stock is negatively related to its return autocorrelation. These results are in contrast to theoretical arguments in favor of positive return autocorrelation due to institutional ownership. However, the findings are consistent with the empirical results in Lakonishok et al. (1992) as well as Badrinath and Wahal (2002) who also find only weak evidence in favor of positive feedback trading or momentum trading and herding by pension fund investors. Our findings are in line with the hypothesis that institutional traders encourage information flows and accelerate the adjustment of stock prices to their fundamental levels, thereby increasing efficiency of the stock market (Lakonishok et al. (1992), Badrinath et al. (1995)).

4.5 Tables

Table 4.1: Institutional Characteristics of Stocks Actively Traded by Pension Funds

Company	Sector	OFE holdings / total turnover	OFE holdings (million zlotys)
Inter Groclin	Other Industry	0.485	6.73
Petrobank	Bank	0.466	12.19
Echo	Construction	0.431	48.32
Permedia	Chemicals	0.382	4.01
Instal	Construction	0.346	4.02
NFI 03	Investment fund	0.210	49.65
Ropczyce	Chemicals	0.201	3.38
Strzelec	Food	0.189	5.26
Lentex	Building materials	0.173	21.35
NFI 04	Investment fund	0.165	10.42
Kety	Metals	0.162	46.01
Bauma	Building materials	0.150	1.92
Stomil Olsztyn	Chemicals	0.118	69.35
Swiecie	Wood and paper	0.116	55.76
Viscoplast	Light Industry	0.104	2.32
Grajewo	Wood and paper	0.102	7.60
Stalprodukt	Metals	0.094	5.46
WBK	Bank	0.094	69.44
Pekao S.A.	Bank	0.092	239.29
NFI10	Investment fund	0.088	6.70
BPH	Bank	0.086	50.54
Poligrafia	Other services	0.084	1.92
PGF	Wholesale & Retails	0.077	13.45
Kable	Electronics	0.072	1.87
Budimex	Construction	0.071	30.10
Impexmetal	Metals	0.071	8.17
PBK	Bank	0.069	120.25
BSK	Bank	0.068	64.14
Pia Piasecki	Construction	0.066	3.17
Yawal	Building materials	0.062	2.94

Note: The table presents the thirty stocks most actively traded by Polish pension funds and their corresponding sectors. Column three displays our measure of institutional trading activity. It is defined as the absolute holdings of pension funds at the end of the year 2000 divided by absolute trading volume over the period May 19, 1999 to the end of the year 2000.

Table 4.2: Autocorrelation in Stock Returns in Different Sample Periods

Stock	99-01-02		99-12-31		98-07-01		00-06-30		98-01-02		00-12-31	
	α_{i1}	α_{i2}	$\alpha_{i1} + \alpha_{i2}$	α_{i1}	α_{i2}	$\alpha_{i1} + \alpha_{i2}$	α_{i1}	α_{i2}	$\alpha_{i1} + \alpha_{i2}$	α_{i1}	α_{i2}	$\alpha_{i1} + \alpha_{i2}$
Inter Groclin	-0.11	0.04	-0.07	-	-	-	-	-	-	-	-	-
Petrobank	0.07	0.01	0.08	0.04	-0.01	0.03	0.00	-0.03	-0.03	0.00	-0.03	-0.03
Echo Invest	-0.00	-0.12	-0.12	0.17	-0.31**	-0.14	0.15**	-0.26***	-0.11	0.15**	-0.26***	-0.11
Permedia	-0.19**	-0.10	-0.29	0.19	-0.40	-0.21	-	-	-	-	-	-
Instal	0.05	-0.12	-0.07	0.04	-0.03	0.01	-	-	-	-	-	-
NFI03	0.03	0.04	0.07	0.10	-0.02	0.08	0.03	-0.01	0.03	0.03	-0.01	0.03
Ropczyce	-0.04	0.00	-0.04	-0.13	0.11	-0.02	-0.05	0.01	-0.05	-0.05	0.01	-0.05
Strzelec	-0.14	0.09	-0.05	0.00	-0.09	-0.09	0.03	-0.12*	-0.09	0.03	-0.12*	-0.09
Lentex	-0.15**	0.06	-0.09	-0.01	-0.06	-0.07	-0.05	-0.01	-0.06	-0.05	-0.01	-0.06
NFI04	0.08	-0.11	-0.03	0.06	-0.11	-0.05	0.05	-0.10	-0.05	0.05	-0.10	-0.05
Kety	-0.19*	0.15	-0.04	-0.12*	0.02	-0.10	-0.13**	0.07	-0.06	-0.13**	0.07	-0.06
Bauma	-0.24**	-0.01	-0.25	-0.07	-0.12	-0.19	-0.01	-0.15*	-0.16	-0.01	-0.15*	-0.16
Stomil Olsztyn	-0.14	0.18	0.04	-0.14	0.17	0.03	-0.09	0.12	0.03	-0.09	0.12	0.03
Swiecie	0.21	-0.18	0.03	-0.00	0.02	0.02	-0.02	0.01	-0.01	-0.02	0.01	-0.01
Viscoplast	0.34***	-0.44***	-0.10	0.16**	-0.33***	-0.17	0.19***	-0.32***	-0.13	0.19***	-0.32***	-0.13
Grajewo	0.00	-0.13	-0.13	-0.09	0.08	-0.01	-0.02	-0.10	-0.12	-0.02	-0.10	-0.12
Stalprodukt	-0.01	0.24*	0.23	0.15**	0.02	0.17	-0.01	0.24*	0.23	-0.01	0.24*	0.23
WBK	-0.22	0.19	-0.03	-0.25***	0.18*	-0.07	-0.18***	0.12	-0.06	-0.18***	0.12	-0.06
Pekao S.A.	-0.08	0.12	0.04	-0.04	0.03	-0.01	-	-	-	-	-	-
NFI10	-0.04	0.03	-0.01	0.07	-0.05	0.02	0.04	0.02	0.06	0.04	0.02	0.06
BPH	-0.00	-0.03	-0.03	0.01	-0.07	-0.06	-0.01	-0.08	-0.09	-0.01	-0.08	-0.09
Poligrafia	-0.33***	0.24**	-0.09	-0.11	0.05	-0.06	-0.02	-0.03	-0.05	-0.02	-0.03	-0.05
PGF	-0.20**	0.18	-0.02	0.10	-0.11	-0.01	-	-	-	-	-	-
Kable	-0.09	0.03	-0.06	-0.08	0.07	-0.01	-0.08	0.09	0.01	-0.08	0.09	0.01
Budimex	-0.20*	0.16	-0.04	-0.11*	0.12	0.01	-0.12**	0.10	-0.02	-0.12**	0.10	-0.02

Table 2 (continued)

Stock	99-01-02		99-12-31		98-07-01		00-06-30		98-01-02		00-12-31	
	α_{i1}	α_{i2}	$\alpha_{i1} + \alpha_{i2}$	α_{i2}	α_{i1}	α_{i2}	$\alpha_{i1} + \alpha_{i2}$	α_{i2}	α_{i1}	α_{i2}	$\alpha_{i1} + \alpha_{i2}$	$\alpha_{i1} + \alpha_{i2}$
Impxmetal	-0.07	0.05	-0.02	-0.06	0.06	-0.06	0.00	-0.06	0.09	-0.23**	-0.14	-
PBK	0.01	0.17	0.18	0.10	0.01	0.10	0.11	0.10	-0.04	0.15*	0.11	-
BSK	-0.21*	0.37**	0.16	-0.02	0.11	-0.02	0.09	-0.02	0.04	0.01	0.05	-
Pia Piasecki	-0.03	0.06	0.03	-0.02	0.04	-0.02	0.02	-0.02	-	-	-	-
Yawal	-0.12	0.05	-0.07	-0.09	0.11	-0.09	0.02	-0.09	-	-	-	-

Note: The estimation results rely on the model given by equations (4.2) and (4.3). *, **, and *** denote significance at the 10%, 5%, and 1% level of significance, respectively.

Table 4.3: Cross-Sectional Regression Results on the Relationship Between Institutional Trading and the Change in Return Autocorrelation

Dependent variable: $\hat{\alpha}_{2i}$				
Period	Intercept	$INST_i$	ΔVOL_i	Adj. R^2
99-01-02 to 99-12-31	0.107***	-0.410***		0.086
	0.107***	-0.383***	0.017	0.072
98-07-01 to 00-06-30	0.081***	-0.667***		0.261
	0.067***	-0.624***	0.038	0.280
98-01-02 to 00-12-31	0.066***	-0.538***		0.187
	0.063***	-0.498***	0.037*	0.215

Note: The table presents regression results of the change in autocorrelation of stock i , $\hat{\alpha}_{2i}$, on the relative institutional trading measure, $INST_i$, and the change in trading volume of stock i , ΔVOL_i , as described in equations (4.8) and (4.9). Standard errors are heteroscedasticity-consistent using the White (1980) correction. *** and * denote significance at the 1% and 10% level, respectively.

Chapter 5

Are Financial Spillovers Stable Across Regimes? Evidence from the 1997 Asian Crisis

5.1 Introduction

Cross-border spillovers occupy an important place in international finance literature. Interdependencies between capital markets play a significant role for asset pricing and cost of capital calculation, and determine the gains and risks of international portfolio diversification. Macroeconomic policy makers and investors are not only concerned about the existence of the inter-market linkages but even more about sudden breaks in these linkages, for example the breaks caused by currency crises. Such breaks could affect the economy through a change in capital flows or in real linkages between markets, such as trade. They may lower diversification benefits from international investing and change investors' behavior after the break (Ang and Bekaert (2002), Forbes and Rigobon (2002), Rigobon (2003)).

In contrast to the contemporaneous interdependencies between markets, as measured by correlation coefficients, focusing on the time structure of spillovers sheds new light on the assimilation of shocks and time-varying patterns of cross-country return causality. Measuring causality provides insight on the speed of information and capital flows between markets. As price-relevant information emerges on one market, it not only generates trades in domestic assets, but can also be relevant for the valuation of foreign assets, hence inducing trades and price movements abroad. However, for information to travel across borders, transmission channels must exist. Real economic linkages between countries,

financial markets, and financial institutions, as well as the existence of common lenders have been established in the literature as channels of information flow (Kaminsky and Reinhart (2000), Kodres and Pritsker (2002), and Pritsker (2001), among others).

Empirical studies on the causal relationship between capital markets traditionally focused on the return spillovers between mature markets (Chen, Chiang, and So (2003), Eun and Shim (1989), Karolyi (1995), Malliaris and Urrutia (1992), Peiró, Quesada, and Uriel (1998)), between mature and emerging markets (Hu, Kholdy, and Sohrabian (2000), Masih and Masih (2001), Ng (2000)), and across emerging capital markets (Galos and Sahay (2001), Scheicher (2001)). The overwhelming evidence is that, first, US market returns lead both developed and emerging markets around the world. Second, these studies also find other highly capitalized stock exchanges to exert non-negligible international influence, e.g. the Japanese market leads Asian emerging markets. Third, causal relationships between emerging stock markets, albeit weak, also exist. Moreover, the bulk of existing studies shows spillovers to be unidirectional, with newly emerged capital markets found to be lagging behind their mature counterparts, and being themselves not a source of spillovers to the developed markets.

However, the assumption of inter-temporal stability and the unidirectional character of financial spillovers, common in previous studies, can be considered inappropriate in the context of return causality. Given the number of financial crises which occurred repeatedly in the past decade around the world, one would expect causation patterns to differ between calm and crisis periods. Changes in the patterns of causality may take the form of temporal strengthening or weakening of spillovers, or even as a reversal in causality between markets. Increases in the contemporaneous linkages during financial crises have already been reported in the empirical literature, e.g. in the US in the context of the 1987 crisis, and during the Asian crisis of 1997 (Bekaert, Harvey, and Ng (2005), King and Wadhvani (1990), Rigobon (2003)).

Furthermore, the relative importance of spillover channels is argued to be time-varying, with some channels being more active in crisis periods. According to Pritsker (2001), channels between financial markets can exist due to 1) real economic linkages, 2) actions of banks operating internationally, and 3) financial market effects. The latter can be driven by common macroeconomic news (King and Wadhvani (1990)), cross-border portfolio rebalancing due to liquidity shock in one country (Calvo (1999)), to hedging of macroeconomic risks (Kodres and Pritsker (2002)), or to wealth changes induced by

changing stock prices (Kyle and Xiong (2001)). A wide use of trading strategies such as feedback trading, herding, and application of risk management rules (Schinasi and Smith (1999)), mostly by portfolio investors like mutual funds (Kaminsky, Lyons, and Schmukler (2001)), will magnify these cross-border spillovers. Theoretical arguments and empirical evidence suggest that the channels discussed above allow initially domestic shocks to spill across borders, inducing reactions of markets abroad. Hence, a change in the interdependence between markets arises. This establishes an economic rationale for the hypothesis investigated in this study that spillover patterns differ across regimes.

In this study, we extend the existing literature by analyzing changes in spillover patterns between the US market and emerging stock markets in South-East Asia in the period when the latter markets undergo a financial crisis. Specifically, we focus on the severe financial crisis of 1997 that could have reversed spillover patterns between markets, e.g. due to contagion effects. We expect, first, shifts in cross-border causality patterns, and, second, stronger causation effects from the Asian markets to the US market in a crisis regime and much weaker effects in a stable one, due to the notion that specific shock transmission channels are more active during crises. The regime-change hypothesis is often discussed in empirical literature supposing South-East Asia as the source of the 1997 crisis (e.g. Climent and Meneu (2003), Forbes and Rigobon (2002), Kaminsky and Schmukler (1999), Rigobon (2003), Sander and Kleimeier (2003)).

We employ a novel methodology in the context of financial spillovers, namely threshold vector autoregressive (TVAR) models, with estimation and testing procedures developed by Tsay (1998) and Hansen and Seo (2002). Being in general more flexible and avoiding the construction of arbitrary spillover structures and mechanisms, this approach overcomes the severe shortcomings of the previous studies. We discuss this issue in more detail in the next section. Moreover, using the tests for Granger-causality, we explicitly investigate whether the direction and strength of spillovers change significantly as markets move from one regime to another.

We find strong evidence in favor of breaks in causality patterns across regimes, with the US market being a significant source of causality in both regimes. Spillovers from Asia to the US are observable almost exclusively in the crisis regimes, i.e. following large (negative) return or volatility shocks. These findings are generally in line with results reported by Chen, Chiang, and So (2003), Climent and Meneu (2003), Rigobon (2003), and others using different data samples and methodologies.

The remainder of this chapter is organized as follows: Subsection 5.2 provides a description of the methodology applied, Subsection 5.3 presents data and discusses empirical results as well as their interpretation, and Subsection 5.4 summarizes and concludes.

5.2 Modeling Financial Spillovers

Few approaches have been proposed to model changes in the cross-border return spillovers resulting from switching between tranquil and turbulent regimes. Previous literature uses models with shifts being captured by dummy variables or by arbitrary sample splitting. These studies document significant increases in spillovers during crisis periods (Climent and Meneu (2003), Malliaris and Urrutia (1992), Theodossiou, Kahya, Koutmos, and Christofi (1997)). More recently, Chen, Chiang, and So (2003) model regime changes within the double-threshold autoregressive GARCH model. The advantage of this method is that the crisis window is not set arbitrarily on the basis of ex-post information, which would give rise to possible data mining (Billio and Pelizzon (2003)), but is estimated from the data. The disadvantage is that one cannot identify where the crisis originates since both countries change regimes simultaneously.

The methodology employed in this study, threshold VAR models, overcomes several shortcomings common in the empirical literature. First, it does not impose any arbitrary relationship between daily index returns, but allow them to depend on lagged values of the second market returns as well as on autoregressive terms, hence capturing the intertemporal dynamic structure of spillovers. Our framework allows all variables representing stock index returns on the markets to be explained by the model. In this way we avoid the estimation bias resulting from overlooking the bi-directional spillovers between the US and Asian markets (Billio and Pelizzon (2003), Forbes and Rigobon (2002)). Second, we estimate regime changes endogenously and explicitly test for the difference between parameter values in two regimes. We utilize approaches of Tsay (1998) and Hansen and Seo (2002) to compute sample estimates and test statistics as they offer an easy-to-handle treatment to this problem, in contrast to the method of Chen, Chiang, and So (2003) consisting of several steps and lacking the simplicity of asymptotic solution.

We first construct the models of financial spillovers between the US market and an emerging East Asian market. Next, we describe the technique to estimate the models and to test for differences in spillovers between markets in calm and crisis regimes.

5.2.1 Threshold VAR Model

We assume that stock index returns on the emerging market, x_t , depend on their past history and on lagged returns from the US market, y_t . We also allow for feedback spillovers from the Asian to the US market because omitting the bilateral dependencies has been argued to bias the results on spillovers between financial markets (Billio and Pelizzon (2003), Forbes and Rigobon (2002)).

Under the null hypothesis, the patterns of linkages between the markets are assumed to be constant across regimes. Hence, the vector autoregressive process generating returns in both countries is given by:

$$z_t = A_0 + \sum_{k=1}^m A_k z_{t-k} + \varepsilon_t, \quad (5.1)$$

where $z_t \equiv [x_t \ y_t]'$, A_0 is a vector of constant terms, A_k is the matrix of coefficients corresponding to lagged stock index returns z_{t-k} , and ε_t is the vector of unobserved innovations on both markets.

Under the alternative hypothesis, the model is the threshold vector autoregression that accounts for possible shifts in causation patterns between the markets due to regime changes:

$$z_t = I(w_{t-d} \geq q) \left(A_0 + \sum_{k=1}^m A_k z_{t-k} \right) + I(w_{t-d} < q) \left(B_0 + \sum_{k=1}^m B_k z_{t-k} \right) + \varepsilon_t \quad , \quad (5.2)$$

where $I(\cdot)$ is an indicator function equal to one if its argument is logically true and zero otherwise. A_k and B_k are the coefficient matrices in the two different regimes of tranquility and crisis, respectively, and A_0 and B_0 are the corresponding vectors of constant terms. w_{t-d} is the threshold variable, lagged by d periods. It is interpreted as a crisis indicator, which determines the current regime of the model. The stock index returns in z_t are generated by the linear vector autoregressive processes $A_0 + \sum_{k=1}^m A_k z_{t-k} + \varepsilon_t$ or $B_0 + \sum_{k=1}^m B_k z_{t-k} + \varepsilon_t$ depending on whether the variable w_{t-d} is above or below the threshold value q , respectively.

5.2.2 Estimation Procedure

An important step in the analysis is the estimation of both VAR models. We apply the algorithm proposed by Hansen and Seo (2002) to estimate parameters of the threshold

VAR model. In the matrix notation the linear VAR model (5.1) can be formulated as:

$$z_t = AX_t + \varepsilon_t, \quad (5.3)$$

where $A \equiv [A_0 \ A_1 \ \dots \ A_k]$ and $X_t \equiv [1 \ (z_{t-1})' \ \dots \ (z_{t-k})']'$. For the two-regime model, let A denote the matrix of the first-regime coefficients and $B \equiv [B_0 \ B_1 \ \dots \ B_k]$ denote the matrix of the second-regime coefficients. Now the threshold VAR model (5.2) takes the form:

$$z_t = CX_t(q) + \varepsilon_t, \quad (5.4)$$

where $C \equiv [A \ B]$, $X_t(q) \equiv [(X_t)'I(w_{t-d} > q) \ (X_t)'I(w_{t-d} \leq q)]'$. When the parameters d and q are known, model (5.4) becomes linear in relation to the parameters in C , and A and B can be estimated using the ordinary least squares (OLS) method.

Hansen and Seo (2002) propose a quasi-Maximum Likelihood (ML) procedure to estimate parameters of the threshold VAR model, when d and q are unknown (see also Hansen (2000)). Since the likelihood function is not smooth in the threshold model (5.4), these authors use a grid search to find estimates of d and q , where $d \in \{1, \dots, m\}$, with m being the lag length in model (5.4), and $q \in G$. G is the set of all observation values of w_{t-d} in the sample, constrained by deleting 10% of the highest and 10% of the lowest observation values, as suggested by Andrews (1993) and Hansen and Seo (2002). For each combination of d and q (denoted as \hat{d} and \hat{q}) selected from the grid, the OLS estimates of A and B , namely \hat{A} and \hat{B} , are computed. The estimates $\{\hat{d}, \hat{q}, \hat{A}, \hat{B}\}$ from the combination that maximizes the concentrated log-likelihood function:

$$L(d, q) = -\frac{n}{2} \log \left| \hat{\Sigma}(d, q) \right| - n \quad (5.5)$$

are the ML estimators. $\hat{\Sigma}(d, q)$ is the estimate of the covariance matrix of ε_t in model (5.4) and n is the number of observations.

5.2.3 Statistical Tests

Our econometric approach to investigate the stability of spillovers between capital markets during financial crises relies on two testing procedures for the threshold VAR models. Under the null hypothesis, H_0 , the process generating z_t is well described by the linear VAR model (5.1). Alternatively, the hypothesis H_1 states that the correct specification is a more general threshold VAR model (5.2). H_0 is nested in H_1 , because the threshold model (5.2) satisfying constraint $A = B$ becomes the linear model (5.1).

If the value of the threshold parameter q were known, one could use the conventional likelihood ratio (LR), Lagrange multiplier (LM), or Wald (W) statistics to test the hypothesis $H_0: A = B$. However, the parameter q is in general not known and it is not identified under the null hypothesis. In this case the statistics LR , LM , and W do not have their asymptotic standard chi-square distributions under H_0 and their true distributions have yet to be derived. Hansen and Seo (2002) consider the $SupLM$ statistic, as in Davies (1987):

$$SupLM = \sup_{qmin \leq q \leq qmax} LM(q), \quad (5.6)$$

where $LM(q)$ is the Lagrange multiplier statistic conditional on the value of q , computed for the estimated models (5.1) and (5.2). $qmin$ and $qmax$ are the lowest and the highest values in the set G , respectively. To calculate a valid first-order approximation of the asymptotic null distribution of $SupLM$, Hansen and Seo employ the fixed-regressor bootstrap technique, similarly to Hansen (1996) and Hansen (2000). They define the new vector of dependent variables $z_t^* \equiv \tilde{\varepsilon}_t u_t$, where $\tilde{\varepsilon}_t$ are residuals from the estimated model (5.1) and the values of u_t are drawn randomly from the $N(0,1)$ distribution.

The statistic $SupLM^*$ is calculated from the estimates of the models (5.1) and (5.2), where z_t^* instead of z_t is set as the vector of dependent variables. The computations of $SupLM^*$ are repeated many times using different draws of u_t from the $N(0,1)$ distribution. Then, the percentage of the calculated $SupLM^*$ statistics exceeding $SupLM$ approximates the asymptotic p -value of the $SupLM$ statistic under the null hypothesis. In our investigation we derive the $SupLM$ and $SupLM^*$ statistics using formula (5.6) from the $LM(q)$ statistic that is adjusted for possible heteroscedasticity of residuals, as explained in detail by Hansen and Seo (2002):

$$LM(q) = vec(\hat{A}' - \hat{B}')'(V_1(q) + V_2(q))^{-1}vec(\hat{A}' - \hat{B}'), \quad (5.7)$$

where

$$V_1(q) = [I_2 \otimes X_1(q)'X_1(q)]^{-1}[\xi_1(q)'\xi_1(q)][I_2 \otimes X_1(q)'X_1(q)]^{-1}, \quad (5.8)$$

$$V_2(q) = [I_2 \otimes X_2(q)'X_2(q)]^{-1}[\xi_2(q)'\xi_2(q)][I_2 \otimes X_2(q)'X_2(q)]^{-1}, \quad (5.9)$$

and I_2 is the identity matrix of order two, \otimes denotes the Kronecker product, $X_1(q)$ and $X_2(q)$ are the matrices of stacked rows $X_t I(w_{t-d} > q)$ and $X_t I(w_{t-d} \leq q)$, respectively. $\xi_1(q)$ and $\xi_2(q)$ are the matrices of stacked rows $\tilde{\varepsilon}_t \otimes [X_t I(w_{t-d} > q)]$ and $\tilde{\varepsilon}_t \otimes [X_t I(w_{t-d} \leq q)]$, respectively.

Tsay (1998) proposes an alternative test for the hypothesis $H_0 : A = B$, which is based on predictive residuals and the recursive least squares method. Consider the set $G^* = \{w_{1-d}, \dots, w_{n-d}\}$ of all n observations of the threshold variable w_{t-d} in the sample. Let $w_{(i)}$ be the i -th smallest element of G^* and $t(i)$ denote the time index of $w_{(i)}$. Arrange the observations in the VAR model (5.1) in the increasing order of the threshold variable w_{t-d} :

$$z_{t(i)+d} = AX_{t(i)+d} + \varepsilon_{t(i)+d}, \quad i = 1, \dots, n. \quad (5.10)$$

Let \hat{A}_l be the estimate of A in the model (5.10) based on the first l observations from the arranged sample, where $l < n$. The predictive residual $\hat{\varepsilon}_{t(l+1)+d}$ and the standardized predictive residual $\hat{\eta}_{t(l+1)+d}$ are then defined as:

$$\hat{\varepsilon}_{t(l+1)+d} = z_{t(l+1)+d} - \hat{A}_l X_{t(l+1)+d}, \quad (5.11)$$

$$\hat{\eta}_{t(l+1)+d} = \hat{\varepsilon}_{t(l+1)+d} / [1 + (X_{t(l+1)+d})' V_l (X_{t(l+1)+d})]^{0.5}, \quad (5.12)$$

where $V_l = [\sum_{i=1}^l (X_{t(i)+d})(X_{t(i)+d})']^{-1}$. Consider the standardized predictive residuals in the regression:

$$\hat{\eta}_{t(l+1)+d} = \Psi X_{t(l+1)+d} + v_{t(l+1)+d}, \quad (5.13)$$

where $l = l_0, \dots, n-1$ and l_0 is the starting point of the recursive least squares estimation. The appropriate statistic proposed by Tsay (1998) for testing the null hypothesis that the model is linear can be formulated as:

$$C(d) = [n - l_0 - (2m + 1)][\ln |S_0| - \ln |S_1|], \quad (5.14)$$

where:

$$S_0 = \frac{1}{n - l_0} \sum_{l=l_0}^{n-1} (\hat{\eta}_{t(l+1)+d})(\hat{\eta}_{t(l+1)+d})', \quad S_1 = \frac{1}{n - l_0} \sum_{l=l_0}^{n-1} (\hat{v}_{t(l+1)+d})(\hat{v}_{t(l+1)+d})', \quad (5.15)$$

and $\hat{v}_{t(l+1)+d}$ are the least squares residuals of regression (5.13). This statistic has an asymptotic chi-square distribution with $2(2m + 1)$ degrees of freedom under the null hypothesis.

We use both tests instead of choosing one for several reasons. First, Tsay's testing statistic has a standard asymptotic chi-square distribution in contrast to the test of Hansen and Seo, where the distribution of the *SupLM* statistic needs to be approximated using a bootstrap technique. However, the latter test is robust against heteroscedasticity of

disturbances, which is important when analyzing financial data. Second, Tsay's statistic is a test of a linear VAR model against a more general nonlinear alternative model, e.g. a Markov switching VAR model, a smooth transition VAR model, or our threshold model. Hansen and Seo provide the statistic that is designed to test directly for the existence of the threshold effect in the VAR model and has higher power in comparison to the test of Tsay (Hansen and Seo (2002)).

5.3 Data and Empirical Results

In our empirical investigation, we analyze the stability of financial spillovers in tranquil and turmoil regimes by modeling the dependency between the US market and eight emerging capital markets in South-East Asia before and during the Asian crisis of 1997. The turbulent period in Asia started with devaluation and a stock market plunge in Thailand in July 1997. It was followed by Malaysian and Indonesian market declines in July and August, respectively, and the Hong Kong crash in mid-October. Subsequently, the Korean market experienced a downslide starting in mid-December and ending in January 1998. Between mid-August 1997 and mid-January 1998, the majority of Asian stock market indices declined by more than 30 percent, with Hong Kong losing almost 48 percent. The crisis spread to other markets in the region and worldwide.

The sample consists of daily observations of stock index returns from the US market (S&P 500), Hong Kong (HSI), Indonesia (JCI), Malaysia (KLSI), Philippines (PSE), Singapore (STI), South Korea (KOSPI), Thailand (SET), and Taiwan (TWII). These Asian markets suffered most from the financial crisis (Corsetti, Pesenti, and Roubini (1999)). In order to avoid the possible influence of other international crises (Mexico in 1994 and Russia in 1998), our sample covers the period from June 1, 1995 to May 31, 1998.¹

We start our investigation by testing for the presence of cointegration (long-run relationship) between stock indices on different markets. If the US stock index were cointegrated with an index from an Asian market, we would have to include an appropriate error correction term in model (5.2). However, using tests of Engle and Granger (1987) and Johansen (Johansen (1991), Johansen (1995)), we find no reliable evidence of bi-variate cointegration between the US index and any investigated Asian stock index. Therefore,

¹Data for the Philippines is only available from November 15, 1996.

we use stationary VAR and TVAR models in our study.²

Employing the data for national stock indices, we model dependencies between the markets and allow for shifts in spillovers during turmoil periods. We test for the existence of those shifts using the tests described in Subsection 5.2. To capture the sluggish adjustment of stock returns to news as well as the day-of-the-week effect, we employ five lags in model (5.2), i.e. $m=5$. Next, we analyze the causality patterns between the markets by conducting Granger-causality tests.

An important part of the analysis is the choice of the threshold variable, which depends on the definition of the calm and crisis regimes. Crisis regimes are usually characterized by low returns and high volatility. This definition of the crisis regime is a controversial issue in the literature, with some authors arguing that asset returns are superior crisis indicators, e.g. Chen, Chiang, and So (2003), Mishkin and White (2003), and others highlighting the importance of changes in volatility between regimes, e.g. Ang and Bekaert (2002), Fong (2003), Rigobon (2003), and Sola, Spagnolo, and Spagnolo (2002). Therefore, we estimate various threshold vector autoregressive models which employ lagged stock index returns or lagged squared returns from the US and respective Asian market as crisis indicator variables. Then, we choose those threshold variables that maximize the respective likelihood functions.³

The results presented in Table 5.1 show that the stock index returns or variance from the US market are superior crisis indicators in seven out of eight models. These optimal threshold variables are used in the further analysis. The fact that the US variables best indicate regime change during the turbulent period in Asia can be explained by the fact that the US market, characterized by higher capitalization and trading volume, is more informationally efficient than its Asian counterparts. Consequently, it incorporates information concerning the latter quicker than it is being done on each of the Asian markets. Hence, the US variables might predict the switch to a turbulent regime for the US-Asian relationship, even if this is the Asian market that becomes the source of spillovers in a crisis regime. For instance, when crisis hits an Asian market, then returns on this market drop significantly but investors still absorb information from the US market and the regime does not yet change. However, when investors in the US notice the crisis,

²Toda and Phillips (1994) describe tests of causality in the presence of cointegration.

³Since the number of observations and parameters does not change for different threshold variables, the maximum likelihood criterion is equivalent to Akaike and Schwarz criteria.

they react with extreme (low) returns and then start to follow information (and returns) from said Asian market. Thus, extreme returns on the US market become direct indicators of regime change.

Moreover, the change in spillover patterns might be induced by a change in trading strategy by US-based portfolio investors, implementing a new strategy first on the home (US) market and subsequently abroad. Also, it is possible that Asian investors react to a change in investment strategy by US investors with a similar change on their home markets, as they interpret the behavior of US investors as a reaction to unobservable shocks influencing both US and Asian markets.

[Table 5.1 about here]

Furthermore, we perform the tests of Hansen and Seo (2002) and Tsay (1998) to investigate possible breaks in financial spillovers between markets. The results are presented in Table 5.2. The results of Tsay's tests are generally in favor of the regime-switching hypothesis. This can be seen in Table 5.2 where six out of eight Tsay statistics reject the linear VAR model at the 5% level of significance, in favor of the regime-switching hypothesis. However, as noted in Subsection 5.2, this test approach can suffer from several weaknesses. Therefore, to obtain additional and more reliable evidence, we further conduct a test by Hansen and Seo which is robust to heteroscedastic errors and has higher power. As in the previous case, Hansen and Seo's test clearly indicates that the null hypothesis of inter-temporal stability in cross-border causation patterns between returns can be rejected at high significance levels, as indicated by high values of the test statistics. This shows that all spillover models are non-linear.

[Table 5.2 about here]

This finding suggests that spillover patterns change between crisis and tranquil regimes in the majority of linkages investigated. Only the outcome for Taiwan (TWII) is mixed, but at least one test rejects the null hypothesis of stability in the spillover patterns. The estimated threshold parameters indicate that markets enter the crisis regime after the returns on the selected (generally US) market fall below some negative threshold value (e.g. -0.8036 for the pair US-Hong Kong (HSI)), or the return volatility, estimated by squared returns, increases beyond some high threshold value, e.g. 1.4971 for the pair US-Thailand (SET). These high absolute values of threshold variables suggest that crisis

regimes are infrequent in the sample, since it is hard for the respective market to surpass the threshold. Indeed, only exceptionally low returns or highly volatile returns on one of the markets lead into a crisis regime. This fact is mirrored by both the high percentage of observations in the calm regime, as well as the short duration of crisis regimes in comparison to turbulent ones. More specifically, in all but one (two) models, over 69 (85) percent of observations are in a calm regime (Table 5.2).

Furthermore, the estimated average length of a crisis regime is usually shorter than two days while tranquil regimes last on average more than seven days for all but two models. A distinctive exception is the relationship between Philippines (PSE) and the US, where a more volatile regime dominates in the sample. Generally, the results on the frequency of regime changes and the duration of regimes indicate that regime changes are not of the structural break type. Markets are characterized by multiple and random swings into crisis and rapid jumps back to a calm regime rather than by a single regime change and long regime duration.

In order to investigate the changes in causality patterns, we conduct tests of Granger-causality for the relationship between the US and Asian markets for each market and regime separately. From the results displayed in Table 5.2, it is reasonable to assume that two regimes are present and that threshold parameters are estimated precisely in each analyzed relationship. Therefore, we can employ the Wald statistics which are robust toward a general form of heteroscedasticity to test whether lagged returns from one market provide important information for modeling current returns on the other market. As a robustness check, we also employ the standard F and the likelihood ratio (LR) tests in models where autoregressive conditional heteroscedasticity (ARCH) is explicitly accounted for.⁴ In order to control for ARCH effects in residuals, we estimate GARCH, EGARCH, and TARARCH models of Bollerslev (1986), Nelson (1991), as well as Glosten, Jaganathan, and Runkle (1993) and Zakoian (1994), respectively, as suggested by Cheung and Fujii (2003). We select the optimal models using the Schwarz information criterion. Results from Granger-causality analysis are presented in Table 5.3.

[Table 5.3 about here]

In accordance with the hypothesis presented in the introduction, spillovers between

⁴The adjustment for the ARCH effects is justified by the presence of conditional heteroscedasticity in residuals in model (5.2): results not reported here. As Cheung and Fujii (2003) show, F and LR tests lack power if the ARCH effects are not explicitly accounted for.

capital markets are found to be unstable and to change across regimes, as reported in Panel A of Table 5.3. The US market leads six Asian markets in a calm regime (Hong Kong, Indonesia, Malaysia, the Philippines, Singapore, and Thailand), as indicated by the significant test statistics. Moreover, we observe additional causation effects to South Korea and Taiwan in a crisis regime. However, the difference between causality from the US market in crisis and calm regimes is modest. The results obtained by Chen, Chiang, and So (2003), Climent and Meneu (2003), and Malliaris and Urrutia (1992) also suggest stronger spillovers from the US market to other markets in turmoil periods. Last, the shocks originating on the US market are found to spill over to the Asian markets in all but one (KOSPI) case, regardless of the regime.

The weak causality for the pair US-Korea deserves additional attention. We believe that this effect is due to the regulations of Korean market, specifically to restrictions on capital flows, asset ownership, as well as governmental interference with the security pricing process, which weakened Korean linkages with the world market (also found e.g. by Baig and Goldfajn (1999), Climent and Meneu (2003), and Kaminsky and Reinhart (2000)). The special position of industrial agglomerates, cheabols, probably also contributed to this outcome.⁵

We now proceed with the novel finding emerging from the results presented in Table 5.3, Panel A. As expected, past returns on the Asian markets are of little importance for the current development of US index returns in a tranquil regime. Only limited causality from Asian markets to the US market is found in the sample. However, in a crisis regime the causation effects from Asian markets to the US market are stronger and statistically significant in five out of eight cases. This result suggests that information from less developed markets is transmitted to the US market, albeit mostly in turbulent periods. These periods are relatively short, as presented in Table 5.2, which in turn explains the lack of causation from emerging markets to the US market detected in some earlier studies (e.g. Chau-Lau and Ivaschenko (2003), Hu, Kholdy, and Sohrabian (2000), Masih and Masih (2001)).

To highlight the importance of our finding of regime-dependent causality between markets, we also estimate linear VAR models and present the results in Panel B of Table

⁵For the chronology of economic and political events in Korea and other countries, see an excellent database by Geert Bekaert and Campbell R. Harvey: <http://www-1.gsb.columbia.edu/faculty/gbekaert/other.html>

5.3. As can be seen, the VAR methodology is unable to differentiate between regimes. As a result, the hypothesis of causality running from Asia to the US is rejected in all but one case. This is in contrast to the results from the TVAR analysis as presented in Panel A, where significant spillovers from Asian markets to the US market are detected in a crisis regime. This outcome can be explained by the short duration of the turbulent regime, and constitutes a justification of the employment of the threshold VAR models that allow for regime changes.

In general, our results from the threshold models suggest that there is evidence of significant spillovers from Asian markets to the US market during the Asian crisis in 1997. In contrast to the results from linear VAR models, the two-regime threshold VAR models are able to detect significant spillovers from Asian markets at least in one regime in seven out of eight cases. Moreover, both regimes are significant in all cases, which suggests that linear models describing dependencies between markets during the Asian crisis may be misspecified.

If a turmoil regime is primarily characterized by the "contagious" financial crisis in South-East Asia, then our results provide important insight into the direction and speed of spillovers from the crisis region to the US market. This finding well fits two definitions of financial contagion widely used in the literature. First, financial spillovers from one market to another can be defined as contagion, as in Claessens, Dornbusch, and Park (2001) and Pritsker (2001), among others. We find evidence in favor of such spillovers from the US to Asia and in the opposite direction during crisis regimes. Second, contagion can be understood as a break in the interdependency structure between countries, a definition introduced by King and Wadhvani (1990) and favored by e.g. Edwards (2000) and Rigobon (2003), among others. In our study, we find a significant difference in spillover patterns between regimes. Hence, our results support both definitions of financial contagion as presented above. Obviously, some information transmission mechanisms are at work mainly during turbulent periods, e.g. actions of bank lenders (Allen and Gale (2000), Kaminsky and Reinhart (2000)) or hedge and mutual funds (Schinasi and Smith (1999), Kaminsky, Lyons, and Schmukler (2001)) responding to macroeconomic, liquidity, or wealth shocks, as discussed in the introduction. This induces changes in spillover patterns between markets.

The economic rationale for spillovers between US and Asian markets might be discussed in the framework of Pritsker's (2001) contagion channels. First, in the presence

of real economic linkages, be it via trade or foreign direct investment, values of companies in one country will react to changes in comparative advantages of companies in the other country induced by changes in interest rates, currency value, taxes and other contributions, property rights protection, etc. Second, involvement of US banks in Asia might establish a channel for spillovers. For instance, in case of shocks deteriorating the profitability of their Asian customers, US banks will at the beginning suffer directly from unpaid and delayed loans and then will try to maintain their liquidity by tightening their credit policy (e.g. reducing credit provision) at home. Third, portfolio rebalancing by US investors as a response to macroeconomic, liquidity, or wealth shocks, will exert impact on stock prices in many countries, an effect magnified by asymmetric information by feedback trading, herding, and use of certain risk techniques by portfolio investors worldwide. In sum, there are several channels through which Asian markets can influence the US one, and vice versa, especially following a shock originating in one country and spilling abroad in turbulent periods.

5.4 Summary and Conclusions

Earlier studies in international finance assumed the stability of cross-border causation patterns or focused on breaks in instantaneous interdependencies between financial markets without analyzing the direction of information flows during turmoil periods. In this study, we extend the existing literature by employing a novel methodology to answer the questions of causation stability as well as the nature and directions of spillovers between US and Asian stock markets.

The results from our analysis suggest that causal relationships between the US and eight Asian markets are not stable and change significantly across regimes. Returns and squared returns from the US market are usually better crisis indicator variables, and dominate as optimal threshold variables. Capital markets seldom enter a crisis regime and leave it after only one or two days. Spillovers from the US market to Asia exist in both regimes and become more intensive in turmoil. On the other hand, causation from Asian capital markets is decent in a calm regime but strong in a crisis regime. These results are in accordance with the literature finding some transmission channels to be more active during crisis than tranquil regimes, a result of changing behavior of bank lenders and portfolio investors. These breaks in spillover patterns may be interpreted as

evidence of financial contagion.

From an economic perspective, we learned that the US market was influenced by Asian markets performance when these emerging markets were hit by financial crisis. All other times, information from the emerging markets played a minor role in the behavior of US stock index returns. On the other hand, the US market is an important determinant of Asian stock returns in both regimes.

International investors can use the knowledge regarding the driving forces behind changes in causality patterns for more accurate return forecasting rather than rebalancing their portfolios. This is due to the short duration of the crisis regimes found by applying the methodology of Hansen and Seo (2002). For instance, the policy of reallocating capital during a two-day turmoil period would imply high portfolio turnover and, hence, extraordinary costs of asset management. Similarly, from the policymakers' perspective, the regime changes were too frequent and crisis periods too short to adjust policy each time they emerge. Short-term changes in macroeconomic policy would be costly, ineffective, and increase market uncertainty. Nevertheless, the results presented in this chapter show that modeling spillovers in a double regime framework provides an approach for better understanding and forecasting information and capital flows between capital markets during crisis periods.

5.5 Tables

Table 5.1: Log-Likelihood Values in the Threshold Models

Country Index	HSI	KOSPI	TWII	STI	SET	JCI	KLCI	PSE
Threshold variable w_{t-d}								
x_{t-1}	-903.76*	-1099.35	-904.77*	-736.85*	-1035.59	-994.45	-1036.04	-525.00
x_{t-2}	-918.33	-1119.49	-930.55	-767.69	-1026.93	-1008.52	-1025.15*	-539.98
x_{t-3}	-926.35	-1113.76	-928.93	-765.88	-1040.27	-1010.12	-1045.17	-536.50
x_{t-4}	-922.40	-1118.85	-926.88	-760.48	-1025.61	-1009.65	-1037.53	-520.94
x_{t-5}	-934.17	-1104.28	-937.57	-742.91	-1022.56	-1027.88	-1050.98	-517.14*
y_{t-1}	-911.99	-1125.07	-923.60	-768.09	-1026.04	-1022.31	-1036.89	-536.24
y_{t-2}	-929.06	-1104.07	-934.65	-752.85	-1029.54	-1007.72	-1049.33	-535.61
y_{t-3}	-924.48	-1107.98	-921.37	-750.57	-1030.08	-1015.21	-1040.24	-538.54
y_{t-4}	-905.38	-1117.50	-934.51	-759.67	-1050.24	-994.13*	-1046.05	-539.38
y_{t-5}	-928.87	-1112.38	-937.24	-758.26	-1029.94	-1024.55	-1048.21	-541.49
x_{t-1}^2	-913.79	-1121.03	-940.66	-764.26	-1042.14	-1017.18	-1037.89	-527.75
x_{t-2}^2	-938.57	-1110.03	-939.12	-742.72	-1028.92	-1013.75	-1051.27	-541.51
x_{t-3}^2	-954.81	-1118.95	-931.13	-774.64	-1040.51	-1022.58	-1050.29	-541.03
x_{t-4}^2	-908.83	-1124.14	-939.57	-768.42	-1020.74*	-1013.94	-1048.39	-528.51
x_{t-5}^2	-938.21	-1093.39*	-937.52	-764.91	-1044.43	-1016.54	-1044.74	-525.10
y_{t-1}^2	-922.59	-1106.08	-931.11	-781.79	-1025.75	-1018.10	-1047.77	-546.85
y_{t-2}^2	-917.96	-1114.42	-921.78	-757.50	-1028.22	-1013.05	-1051.56	-536.99
y_{t-3}^2	-912.24	-1117.17	-935.22	-745.19	-1035.59	-996.58	-1046.54	-542.90
y_{t-4}^2	-914.92	-1106.01	-934.20	-752.06	-1044.72	-1025.48	-1040.58	-531.62
y_{t-5}^2	-939.04	-1123.77	-937.39	-746.59	-1023.80	-1017.85	-1052.36	-546.20

Note: The highest log-likelihood values are marked with *. x_{t-k} denotes stock index returns on the US market at time $t-k$ and y_{t-k} denotes stock index returns on the respective Asian market at time $t-k$.

Table 5.2: Tests for Stability of Financial Spillovers

Country Index	HSI	KOSPI	TWII	STI	SET	JCI	KLCI	PSE
Statistic of Tsay	40.2116*	61.8050**	16.1517	60.9487**	36.4349*	44.1894**	35.7576*	25.2134
	(0.010)	(0.000)	(0.808)	(0.000)	(0.027)	(0.003)	(0.032)	(0.287)
Statistic of Hansen and Seo	37.6420**	29.7121**	27.1726**	31.4391**	33.4605**	36.3683**	44.2809**	30.3096**
	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Estimated threshold parameter	-0.8036	1.4168	-0.8036	-0.8006	1.4971	-1.1901	-0.2582	1.2033
Threshold variable	x_{t-1}	x_{t-5}^2	x_{t-1}	x_{t-1}	x_{t-4}^2	y_{t-4}	x_{t-2}	x_{t-5}
Percentage of observations in the calm regime	89.17	86.02	89.14	89.18	86.02	85.14	69.82	11.51
Average duration of the crisis regime [in days]	1.25	1.23	1.22	1.21	1.27	1.48	1.56	8.97
Average duration of the calm regime [in days]	10.17	7.52	9.89	9.85	7.81	8.38	3.61	1.16

Note: *, ** denote significance at the 5% and 1% levels, respectively. P-values are presented in parentheses. For both tests, the H_0 hypothesis is that there is no difference in the causality patterns across regimes, against H_1 of structural break in causality patterns due to regime change. x_{t-k} denotes stock index returns on the US market at time $t - k$ and y_{t-k} denotes stock index returns on the respective Asian market at time $t - k$.

Table 5.3: Tests for Granger-Causality Between Markets

Country Index/ Null hypothesis	Test	HSI	KOSPI	TWII	STI	SET	JCI	KLCI	PSE
Panel A: Results from the TVAR models									
S&P 500 does not cause <i>y</i> in crisis regime	W	53.013***	6.018	16.315***	19.491***	10.229*	38.642***	26.570***	24.510***
	F	16.517***	2.637**	2.249**	1.863*	10.896***	0.000	3.016**	
	LR	32.867***	4.997	6.439	13.319**	7.023	37.421***	4.581	28.367***
S&P 500 does not cause <i>y</i> in calm regime	W	44.052***	5.974	5.501	19.138***	12.534**	18.131***	12.089**	23.851***
	F	19.880***	0.378	1.583	5.706***	2.652**	2.209*	1.706	3.263***
	LR	99.122***	7.964	3.972	33.385***	16.046***	26.909***	19.296***	10.546*
S&P 500 does not cause <i>y</i> in any regime	W	97.066***	11.992	21.816**	38.629***	22.763**	56.773***	38.659***	48.361***
	F	16.921***	1.237	2.007**	3.902***	2.090**	6.584***	0.841	3.140***
	LR	122.603***	12.784	9.851	.326***	21.880**	66.819***	23.076**	39.546***
<i>y</i> does not cause S&P 500 in crisis regime	W	35.170***	7.805	10.632*	18.181***	11.214**	7.228	6.667	2.771
	F	11.538***	5.096***	7.119***	4.636***	2.803**	0.272	0.000	0.237
	LR	46.029***	32.217***	27.948***	17.419***	8.593	4.034	2.197	3.028
<i>y</i> does not cause S&P 500 in calm regime	W	9.173	7.397	4.672	2.48	5.161	6.708	2.162	8.784
	F	1.783	0.154	0.502	0.436	0.612	1.134	1.229	7.501***
	LR	11.300**	7.596	2.587	2.631	3.826	11.413**	7.627	25.182***
<i>y</i> does not cause S&P 500 in any regime	W	44.343***	15.202	15.304	20.661**	16.375*	13.936	8.829	11.555
	F	6.737***	2.487***	3.792***	2.533***	1.716*	0.764	0.348	3.733***
	LR	53.538***	40.492***	30.021***	19.865**	12.299	14.917	9.698	29.706***
Panel B: Results from the VAR models									
S&P 500 does not cause <i>y</i> in any regime	W	58.074***	6.885	22.482***	29.607***	12.111**	29.678***	11.941**	22.251***
	F	33.161***	0.877	6.134***	12.189***	2.771**	8.204***	3.467***	4.113***
	LR	166.269***	5.375	20.305***	58.698***	17.538***	49.991***	33.333***	29.664***
<i>y</i> does not cause S&P 500 in any regime	W	14.681**	3.521	3.26	4.848	8.932	13.936	4.300	0.851
	F	8.847***	0.000	0.776	1.168	1.871*	1.226	0.894	0.000
	LR	21.323***	7.480	3.422	4.158	6.968	8.069	6.550	1.545

Note: W is the heteroscedasticity-adjusted Wald statistic, F and LR are the ARCH-adjusted F and likelihood ratio statistics, respectively. P-values are presented in parentheses. **, *, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively. It is possible that some values of the F statistic in ARCH models are negative – in this case we enter 0.000 in the table.

Chapter 6

Conclusions

The aim of this thesis was to analyze the various aspects of the process of information dissemination across securities and markets, and to study the information assimilation into security prices. The investigation concentrated on the emerging capital market of Poland. Knowledge about the development and functioning of an emerging market is valuable for practical and theoretical reasons alike. First, because emerging markets attract a considerable amount of foreign capital due to their higher returns and lower correlation with the developed markets, which allows investors to earn higher profits and to decrease total portfolio risk. Second, the legal and regulatory environment differs from that usually found in developed countries. This offers a "natural experiment", which is an unique opportunity to test the hypotheses concerning the functioning of the capital markets.

In the first essay, the focus was on market capitalization and trading volume as two information transmission mechanisms. The analysis was conducted for stocks traded in the single auction system on the Warsaw Stock Exchange during its early stages of development. It has been shown that securities with higher capitalization and higher trading volume tend to adjust to information faster than the low-capitalization, low-volume ones. This asymmetric lead-lag effect is more pronounced for stock returns than for return volatility, and its latitude differs for bullish and bearish markets. All in all, we can conclude that market capitalization and trading volume are important, but not exclusive, determinants of the speed of adjustment of stock returns and volatilities to information.

The interaction between stock returns and trading volume as a determinant of the information assimilation process was investigated in the second essay. Based on the theo-

retical models that predict a link between return behavior and trading volume, we conduct a number of empirical tests in order to assess the role of trading volume in the process of information assimilation by stock prices. The results clearly indicate that trading volume is an important determinant of stock return behavior. Specifically, the finding that returns on volume-decreasing (volume-increasing) stocks exhibit positive (negative) autocorrelation can be interpreted, in the light of the theoretical models, as evidence for the dominance of non-informed trading on the Polish stock exchange.

This latter finding notwithstanding, there is a group of stock market participants who are generally assumed to have superior information about the security value, i.e. the institutional investors. Utilizing a unique institutional characteristic of the Polish capital market emerging from the 1999 pension system reform and the subsequent arrival of private pension funds in the market, we investigate the impact of increased institutional trading on stock returns. Specifically, in the third essay of this thesis, we investigated the change in return autocorrelation as a measure of informational efficiency and, hence, of the speed of information assimilation by stock prices. The empirical results show a significant decrease in stock return autocorrelation due to the increased trading by pension funds. This effect can be seen as evidence for the hypothesis that trades conducted by these institutions are driven by their superior information endowment, and that these transactions increase both the speed of information assimilation by stock returns and the amount of asset-relevant information being reflected in asset prices at any time.

In the final part of this thesis, the focus shifts from a purely domestic to an international perspective. To investigate the flow of information across borders, and in particular to answer the question of how quickly and to what extent information originating abroad is incorporated into the domestic security prices, financial spillovers between eight Asian markets and the US stock market are analyzed. In this study, the emphasis is on the intertemporal stability of these interdependencies among markets. Empirical results from the tests conducted reveal a time-varying nature of cross-border information spillovers. In contrast to the majority of previous studies, we find information originating on the Asian markets to impact the prices of stocks listed in the US significantly, albeit only during the turbulent periods. These periods are short-lived, infrequent, and characterized by low returns or high variance on the US market.

Bibliography

- ALLEN, F., AND D. GALE (2000): “Finacial Contagion,” *Journal of Political Economy*, 108, 1–33.
- AMIHUD, Y., AND H. MENDELSON (1986): “Asset pricing and the bid-ask spread,” *Journal of Financial Economics*, 17, 223–249.
- ANDREWS, D. W. K. (1993): “Tests for parameter instability and structural change with unknown change point,” *Econometrica*, 61, 821–856.
- ANG, A., AND G. BEKAERT (2002): “International asset allocation with regime shifts,” *Review of Financial Studies*, 15, 1137–1187.
- ARBEL, A., AND P. STREBEL (1983): “Pay attention to neglected firms,” *Journal of Portfolio Management*, 9, 37–42.
- BADRINATH, S. G., J. R. KALE, AND T. H. NOE (1995): “On Shepherds, Sheep, and the Cross-Autocorrelations in Equity Returns,” *Review of Financial Studies*, 8, 401–430.
- BADRINATH, S. G., AND S. WAHAL (2002): “Momentum Trading by Institutions,” *Journal of Finance*, 57, 2449–2478.
- BAIG, T., AND I. GOLDFAJN (1999): “Financial market contagion in the Asian crisis,” *IMF Staff Papers*, 46.
- BARCLAY, M. J., AND J. B. WARNER (1993): “Stealth trading and volatility. Which trades move prices?,” *Journal of Financial Economics*, 34, 281–305.
- BEKAERT, G., AND C. R. HARVEY (2003): “Emerging markets finance,” *Journal of Empirical Finance*, 10, 3–55.
- BEKAERT, G., C. R. HARVEY, AND A. NG (2005): “Market integration and contagion,” *Journal of Business*, 78, 39–70.
- BILLIO, M., AND L. PELIZZON (2003): “Contagion and interdependence in stock markets: Have they been misdiagnosed?,” *Journal of Economics and Business*, 55, 405–426.
- BLUME, L., D. EASLEY, AND M. O’HARA (1994): “Market Statistics and Technical Analysis: The Role of Volume,” *Journal of Finance*, 49, 153–181.
- BOLLERSLEV, T. (1986): “Generalized Autoregressive Conditional Heteroscedasticity,” *Journal of Econometrics*, 31, 307–327.

- BOOTH, G. G., AND G. KOUTMOS (1998a): "Interaction of volatility and autocorrelation in foreign stock returns," *Applied Economic Letters*, 5, 715–717.
- (1998b): "Volatility and autocorrelation in major European stock markets," *European Journal of Finance*, 4, 61–74.
- BOUDOUGH, J., M. P. RICHARDSON, AND R. F. WHITELAW (1994): "A Tale of Three Schools: Insights on Autocorrelations of Short-Horizon Stock Returns," *Review of Financial Studies*, 7, 539–573.
- BRENNAN, M. J., T. CHORDIA, AND A. SUBRAHMANYAM (1998): "Alternative factor specifications, security characteristics, and the cross-section of expected stock returns," *Journal of Financial Economics*, 49, 345–373.
- BRENNAN, M. J., N. JEGADEESH, AND B. SWAMINATHAN (1993): "Investment analysis and the adjustment of stock prices to common information," *Review of Financial Studies*, 6, 799–824.
- BRENNAN, M. J., AND A. SUBRAHMANYAM (1996): "Market microstructure and asset pricing: On the compensation for illiquidity in stock returns," *Journal of Financial Economics*, 41, 341–364.
- CALVO, G. A. (1999): "Contagion in emerging markets: When Wall Street is a carrier," *manuscript, University of Maryland*.
- CAMPBELL, J. Y., S. J. GROSSMAN, AND J. WANG (1993): "Trading Volume and Serial Correlation in Stock Returns," *Quarterly Journal of Economics*, 108, 905–939.
- CHAN, L. K. C., AND J. LAKONISHOK (1995): "The Behavior of Stock Prices Around Institutional Trades," *Journal of Finance*, 50, 1147–1174.
- CHAU-LAU, J. A., AND I. IVASCHENKO (2003): "Asian Flu or Wall Street virus? Tech and non-tech spillovers in the United States and Asia," *Journal of Multinational Financial Management*, 13, 303–322.
- CHEN, C. W. S., T. C. CHIANG, AND M. K. P. SO (2003): "Asymmetrical reaction to US stock-return news: Evidence from major stock markets based on a double-threshold model," *Journal of Economics and Business*, 55, 487–502.
- CHEUNG, Y., AND E. FUJII (2003): "A note on the power of money-output causality tests," *Oxford Bulletin of Economics and Statistics*, 63, 247–261.
- CHORDIA, T., AND B. SWAMINATHAN (2000): "Trading Volume and Cross-Autocorrelations in Stock Returns," *Journal of Finance*, 55, 913–935.
- CHORDIA, T., AND B. SWAMINATHAN (2004): "Incomplete information, trading costs and cross-correlations in stock returns," *Economic Notes*, 34, 145–181.
- CHUN, R. (2000): "Compensation vouchers and equity markets: Evidence from Hungary," *Journal of Banking and Finance*, 24, 1155–1178.
- CLAESSENS, S., R. DORNBUSCH, AND Y.-C. PARK (2001): "Contagion: why crises spread and how this can be stopped," in *International financial contagion*, ed. by S. Claessens, and K. J. Forbes, pp. 20–41. Kluwer Academic Publishers.

- CLIMENT, F. J., AND V. MENEU (2003): “Has 1997 Asian crisis increased information flows between international markets?,” *International Review of Economics and Finance*, 12, 111–143.
- COHEN, R. B., P. A. GOMPERS, AND T. VUOLTEENAHO (2002): “Who Underreacts to Cash-Flow News? Evidence from Trading between Individuals and Institutions,” *Journal of Financial Economics*, 66, 409–462.
- CONRAD, J., M. GULTEKIN, AND G. KAUL (1991): “Asymmetric predictability of conditional variances,” *Review of Financial Studies*, 3, 597–622.
- CONRAD, J., A. HAMEED, AND C. NIDEN (1994): “Volume and Autocovariances in Short-Horizon Individual Security Returns,” *Journal of Finance*, 49, 1305–1329.
- COOPER, M. (1999): “Filter Rules Based on Price and Volume in Individual Security Overreaction,” *Review of Financial Studies*, 12, 901–935.
- CORSETTI, G., P. PESENTI, AND N. ROUBINI (1999): “What caused the Asian currency and financial crisis?,” *Japan and the World Economy*, 11, 305–373.
- DATAR, V. T., N. Y. NAIK, AND R. RADCLIFFE (1998): “Liquidity and stock returns: An alternative test,” *Journal of Financial Markets*, 1, 203–219.
- DAVIES, R. B. (1987): “Hypothesis testing when a nuisance parameter is present only under the alternative,” *Biometrika*, 74, 33–43.
- DESAI, A. S., AND A. TAVAKKOL (2001): “The effect of size and turnover volume on cross-autocorrelation of equity returns,” *Working Paper, Kansas State University*.
- DIEBOLD, F. X., AND J. A. LOPEZ (1995): “Modeling volatility dynamics,” *Federal Reserve Bank of New York Research Paper 9522*.
- DIMSON, E. (1979): “Risk measurement when shares are subject to infrequent trading,” *Journal of Financial Economics*, 7, 197–226.
- EDWARDS, E. (2000): “Contagion,” *The World Economy*, 23, 873–900.
- ENGLE, R. F., AND C. GRANGER (1987): “Co-integration and error correction: Representation, estimation and testing,” *Econometrica*, 55, 251–276.
- EUN, C. S., AND S. SHIM (1989): “International transmission of stock market movements,” *Journal of Financial and Quantitative Analysis*, 24, 241–256.
- FAMA, E. F. (1970): “Efficient Capital Markets: A Review of Theory and Empirical Work,” *Journal of Finance*, 25, 383–423.
- FILER, R. K., AND J. HANOUSEK (1999): “The Extent of Efficiency in Central European Equity Markets,” in *Capital Markets in Central and Eastern Europe*, ed. by C. Helmenstein, pp. 392–416. Edward Elgar.
- FONG, W.-M. (2003): “Correlation jumps,” *Journal of Applied Finance*, 13, 29–45.
- FORBES, K. J., AND R. RIGOBON (2002): “No contagion, only interdependence: Measuring stock market co-movements,” *Journal of Finance*, 57, 2223–2261.

- GALOS, G., AND R. SAHAY (2001): "Financial Market Spillovers: How Different are the Transition Economies," in *International Financial Contagion*, ed. by S. Claessens, and K. J. Forbes, pp. 329–366. Kluwer Academic Publishers.
- GLIMORE, C. G., AND G. M. MCMANUS (2003): "Random-walk and efficiency tests of Central European equity markets," *Managerial Finance*, 29, 42–61.
- GLOSTEN, L., R. JAGANATHAN, AND D. RUNKLE (1993): "On the relationship between the expected value and the volatility of the nominal excess return on stocks," *Journal of Finance*, 48, 1779–1801.
- GRINBLATT, M., S. TITMAN, AND R. WERMERS (1995): "Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior," *American Economic Review*, 85, 1088–1105.
- HAMEED, A. (1997): "Time-Varying Factors and Cross-Autocorrelations in Short-Horizon Stock Returns," *Journal of Financial Research*, 20, 435–458.
- HANSEN, B. E. (1996): "Inference when a nuisance parameter is not identified under the null hypothesis," *Econometrica*, 64, 413–430.
- (2000): "Sample splitting and threshold estimation," *Econometrica*, 68, 575–603.
- HANSEN, B. E., AND B. SEO (2002): "Testing for two-regime threshold cointegration in vector error-correction models," *Journal of Econometrics*, 110, 293–318.
- HANSEN, L. (1982): "Large Samples Properties of Generalized Method of Moments Estimators," *Econometrica*, 50, 1029–1054.
- HAWAWINI, G., AND D. B. KEIM (1995): "On the predictability of common stock returns: World-wide evidence," in *Handbooks in OR and MS, Vol. 9.*, ed. by R. Jarrow, V. Maksimovic, and W. T. Ziemba, pp. 497–544. Elsevier Science.
- HOLDEN, C. W., AND A. SUBRAHMANYAM (2002): "New Events, Information Acquisition, and Serial Correlation," *Journal of Business*, 75, 1–32.
- HORSEWOOD, N., AND D. SUTHERLAND (2001): "Market efficiency in transition economies: equity markets and EU accession," in *Financial and monetary integration in the new Europe: convergence between the EU and Central and Eastern Europe*, ed. by D. G. Dickinson, and A. W. Mullineux, pp. 372–394. Edward Elgar.
- HU, F.-N., S. KHOLDY, AND A. SOHRABIAN (2000): "International transmission of stock market movements: Evidence from the Asian financial crisis," *Rivista Internazionale di Scienze Economiche e Commerciali*, 47, 603–618.
- JOHANSEN, S. (1991): "Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models," *Econometrica*, 59, 1551–1580.
- (1995): "Identifying Restrictions of Linear Equations with Application to Simultaneous Equations and Cointegration," *Journal of Econometrics*, 25, 309–342.
- JUDGE, G. G., R. C. HILL, W. E. GRIFFITH, H. LUETKEPOHL, AND T.-C. LEE (1988): *Introduction to the Theory and Practice of Econometrics*. John Wiley & Sons, Inc.

- KAMINSKY, G. L., R. K. LYONS, AND S. L. SCHMUKLER (2001): "Mutual fund investment in emerging markets: An overview," *World Bank Economic Review*, 15, 315–340.
- KAMINSKY, G. L., AND C. M. REINHART (2000): "On crises, contagion, and confusion," *Journal of International Economics*, 51, 145–168.
- KAMINSKY, G. L., AND S. L. SCHMUKLER (1999): "What triggers market jitters?," *Journal of International Money and Finance*, 18, 537–560.
- KAROLYI, G. A. (1995): "A multivariate GARCH model of international transmission of stock returns and volatility: The case of the United States and Canada," *Journal of Business and Economic Statistics*, 13, 11–25.
- KAUL, G. (1996): "Predictable components in stock returns," in *Handbook of Statistics, Vol. 14.*, ed. by G. Mandallla, and C. Rao, pp. 269–296. Elsevier Science.
- KING, M. A., AND S. WADHWANI (1990): "Transmission of volatility between stock markets," *Review of Financial Studies*, 3, 5–33.
- KODRES, L. E., AND M. PRITSKER (2002): "A rational expectations model of financial contagion," *Journal of Finance*, 57, 769–799.
- KRZAK, M. (1998): "Contagion Effects of the Russian Financial Crisis on Central and Eastern Europe: The Case of Poland," *Oesterreichische Nationalbank, Focus on Transition*, 2, 22–37.
- KYLE, A. S., AND W. XIONG (2001): "Contagion as a wealth effect," *Journal of Finance*, 56, 1401–1440.
- LAKONISHOK, J., A. SHLEIFER, AND R. W. VISHNY (1992): "The Impact of Institutional Trading on Stock Prices," *Journal of Financial Economics*, 32, 23–43.
- LEBARON, B. (1992): "Some Relations between Volatility and Serial Correlations in Stock Market Returns," *Journal of Business*, 65, 199–219.
- LEE, C., AND B. SWAMINATHAN (2000): "Price Momentum and Trading Volume," *Journal of Finance*, 55, 2017–2069.
- LEHMANN, B. (1990): "Fads, Martingales, and Market Efficiency," *Quarterly Journal of Economics*, 105, 1–28.
- LLORENTE, G., R. MICHAELY, G. SAAR, AND J. WANG (2001): "Dynamic Volume-Return Relation of Individual Stocks," *Review of Financial Studies*, 15, 1005–1047.
- LO, A., AND C. MACKINLEY (1990): "When Are Contrarian Profits Due to Stock Market Overreaction," *Review of Financial Studies*, 3, 175–205.
- LO, A., AND J. WANG (2000): "Trading volume: Definitions, analysis, and implications of portfolio theory," *Review of Financial Studies*, 13, 257–300.
- MALLIARIS, A. G., AND J. L. URRUTIA (1992): "The international crash of October 1987: Causality tests," *Journal of Financial and Quantitative Analysis*, 27, 353–364.

- MASIH, A. M. M., AND R. MASIH (2001): “Long and short-term dynamic causal transmission amongst international stock markets,” *Journal of International Money and Finance*, 20, 563–587.
- MCQUEEN, G., M. PINEGAR, AND S. THORLEY (1996): “Delayed Reaction to Good News and the Cross-Autocorrelation of Portfolio Returns,” *Journal of Finance*, 51, 889–919.
- MISHKIN, F., AND E. N. WHITE (2003): “U.S. stock market crashes and their aftermath: Implications for monetary policy,” in *Asset price bubbles: The implications for monetary, regulatory, and international policies*, ed. by W. C. Hunter, G. G. Kaufmann, and M. Pomerleano, pp. 53–79. MIT Press.
- NELSON, D. (1991): “Conditional Heteroscedasticity in Asset Returns: A New Approach,” *Econometrica*, 59, 347–370.
- NG, A. (2000): “Volatility spillover effects from Japan and the US to the Pacific-Basin,” *Journal of International Money and Finance*, 19, 207–233.
- NOFSINGER, J. R., AND R. W. SIAS (1999): “Herding and Feedback Trading by Institutional and Individual Investors,” *Journal of Finance*, 54, 2263–2295.
- PARISI, F., AND C. ACEVEDO (2001): “Volume and autocovariance in short-horizon stock return. Evidence from 1992 to 1998 in Chile,” *International Review of Financial Analysis*, 10, 275–285.
- PEIRÓ, A., J. QUESADA, AND E. URIEL (1998): “Transmission of movements in stock markets,” *The European Journal of Finance*, 4, 331–343.
- PRITSKER, M. (2001): “The Channels for Financial Contagion,” in *International Financial Contagion*, ed. by S. Claessens, and K. J. Forbes, pp. 67–95. Kluwer Academic Publishers.
- RICHARDSON, T., AND D. R. PETERSON (1999): “The cross-autocorrelation of size-based portfolio returns is not an artifact of portfolio autocorrelation,” *Journal of Financial Research*, 22, 1–13.
- RIGOBON, R. (2003): “On the measurement of the international propagation of shocks: Is the transmission stable?,” *Journal of International Economics*, 61, 261–283.
- ROLL, R. (1984): “A simple explicit measure of the effective bid-ask spread in an efficient market,” *Journal of Finance*, 39, 1127–1139.
- SANDER, H., AND S. KLEIMEIER (2003): “Contagion and causality: An empirical investigation of four Asian crisis episodes,” *Journal of International Financial Markets, Institutions and Money*, 13, 85–112.
- SCHEICHER, M. (2001): “The Comovements of Stock Markets in Hungary, Poland and the Czech Republic,” *International Journal of Finance and Economics*, 6, 27–39.
- SCHINASI, G. J., AND R. T. SMITH (1999): “Portfolio diversification, leverage, and financial contagion,” *IMF working paper*, 99/136.

- SIAS, R. W., AND L. T. STARKS (1997): "Return autocorrelation and institutional investors," *Journal of Financial Economics*, 46, 103–131.
- SIAS, R. W., L. T. STARKS, AND S. TITMAN (2001): "The Price Impact of Institutional Trading," *Working paper, Washington State University and University of Texas at Austin*.
- SOLA, M., F. SPAGNOLO, AND N. SPAGNOLO (2002): "A test for volatility spillovers," *Economics Letters*, 76, 77–84.
- THEODOSSIOU, P., E. KAHYA, G. KOUTMOS, AND A. CHRISTOFI (1997): "Volatility reversion and correlation structure of returns in major international stock markets," *Financial Review*, 32, 205–224.
- TODA, H., AND P. PHILLIPS (1994): "Vector autoregression and causality: A theoretical overview and simulation study," *Econometric Reviews*, 13, 259–285.
- TSAY, R. S. (1998): "Testing and modeling multivariate threshold models," *Journal of the American Statistical Association*, 93, 1188–1202.
- WANG, J. (1994): "A Model of Competitive Stock Trading Volume," *Journal of Political Economy*, 102, 127–168.
- WATANABE, T. (2002): "Margin requirements, positive feedback trading, and stock return autocorrelations: The case of Japan," *Applied Financial Economics*, 12, 395–403.
- WHITE, H. (1980): "A Heteroscedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity," *Econometrica*, 48, 817–838.
- WSE (2002): *Factbook 2001*.
- YU, C.-H., AND C. WU (2001): "Economic sources of asymmetric cross-correlation among stock returns," *International Review of Economics and Finance*, pp. 19–40.
- ZAKOIAN, J. M. (1994): "Threshold Heteroscedastic Models," *Journal of Economic Dynamics and Control*, 18, 931–944.

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