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Relation between past stock market returns and trading volume in Europe

Finance

Master's thesis

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Abstract of master's thesis

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BACKGROUND AND OBJECTIVES

The high observed trading volume can be explained by the matter that investors are overconfident about their ability to value and trade stocks. The increasing returns make investors overestimate their trading skills and thus increase their trading. In contrary, decreasing returns make investors decrease their trading. Thus the observed trading volume varies with the level of investor overconfidence. In this thesis, I study whether the investor overconfidence hypothesis holds in the European stock market in the 2000s and which factors have affected the trading volumes of the European national stock exchanges. This study follows the previous research of Statman, Thorley, and Vorkink (2006).

DATA AND METHODOLOGY

The data set used in the study consists of the stock turnover and daily index value data of fourteen European stock indexes from June 2001 to December 2014. The turnover is calculated by dividing the amount of stocks traded in each index by the total amount of stocks underlying each index. The daily data is used on the monthly and weekly level in the study, and the indexes are studied both separately and as a single pooled data set. The full period is also divided into two subsamples to observe the differences between pre- and post-crisis periods around the year 2008. I use the vector autoregression methodology to observe how lagged returns are affecting the current turnover but the methodology also gives results to other combinations of these two variables. In addition, I run impulse response functions for each time period and index to observe how a shock of one standard deviation in return affects the contemporaneous turnover and how many months the turnover is affected by this shock.

FINDINGS

The results of the study indicate that for the full period from 2001 to 2014 the support for the overconfidence hypothesis is weak. However, by dividing the full period into two subsamples to represent the periods before and after the financial crisis of 2008, I find that from 2001 to 2008 the stock turnover is positively related to lagged returns for many months but this relation does not hold during the period after the crisis. Due to this observation, I will also review how the stock market conditions have changed in Europe after the crisis. The two main reasons for the trading to decrease in national stock exchanges despite the market catching up after the crisis are the market regulation and fragmentation.

Keywords Overconfidence, European stock exchanges, trading volume, stock turnover, past returns, financial crisis, market fragmentation, vector autoregression, impulse response function

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TAUSTA JA TAVOITTEET

Markkinoiden korkeat kaupankäyntivolyymit johtuvat osittain siitä, että sijoittajat yliarvioivat kykynsä arvostaa ja vaihtaa osakkeita. Kurssinousut saavat sijoittajat yliarvioimaan kaupankäyntitaitojaan ja täten käymään enemmän kauppaa. Toisaalta kurssilaskut saavat sijoittajat vähentämään kaupankäyntiä. Täten markkinoilla nähtävät kaupankäyntimäärät ovat riippuvaisia sijoittajien yli-itsevarmuudesta. Tutkielmassani selvitän, pitääkö yli-itsevarmuushypoteesi paikkansa Euroopan osakemarkkinoilla 2000-luvulla, ja mitkä tekijät ovat vaikuttaneet kaupankäyntivolyymeihin Euroopan kansallisissa pörsseissä. Tutkielmani metodit seuraavat aiempaa Statmanin, Thorleyn ja Vorkinkin (2006) tekemää tutkimusta yli-itsevarmuudesta osakemarkkinoilla.

DATA JA METODOLOGIA

Tutkielmassani käytän dataa neljäntoista eurooppalaisen kansallisen pörssi-indeksin vaihdetuista osakemääristä sekä indeksien arvoista aikavälillä 1.6.2001–31.12.2014. Kaupankäynnin volyymin mittarina käytän arvoa, joka on laskettu jakamalla indeksissä vaihdetut osakkeet indeksin yritysten osakkeiden kokonaismäärällä. Päivittäisiä havaintoja käytän tutkielmassa sekä viikko- että kuukausitasolla, ja indeksejä tarkastellaan sekä erikseen että yhdeksi sarjaksi koottuna. Jaan tarkastelujakson myös kahteen osaotokseen vuoden 2008 ja 2009 välillä katkaisten, jotta voin verrata kriisiä edeltänyttä ja seurannutta markkinatilannetta. Tutkimuksessa käytän vektoriautoregressio-metodia selvittääkseni, kuinka menneet tuotot vaikuttavat tämän hetkiseen kaupankäynnin aktiivisuuteen. Sama metodi antaa vastaavat tulokset myös muille muuttujien yhdistelmille. Lisäksi käytän impulssivastefunktiota kaikille tarkastelujaksoille ja indekseille selvittämään kuinka yhden keskihajonnan shokki esimerkiksi tuotossa vaikuttaa kaupankäyntiaktiivisuuteen ja kuinka kauan tämä vaikutus kestää.

TULOKSET

Tutkielman tulokset osoittavat, että aikavälillä 2001–2014 hypoteesi sijoittajien yli-itsevarmuudesta pitää paikkansa ainoastaan heikosti. Kun koko tarkastelujakso jaetaan kahteen osaotokseen vuoden 2008 kriisin ympärillä, huomataan, että osakemarkkinoiden kaupankäyntiaktiivisuus on positiivisesti yhteydessä menneisiin tuottoihin usean kuukauden ajan ennen kriisiä. Kriisinjälkeisellä jaksolla tämä yhteys ei kuitenkaan enää päde. Tämän havainnon vuoksi käyn myös läpi markkinaolosuhteiden muutoksia Euroopassa kriisin jälkeen. Kaksi pääsyytä kansallisten osakepörssien kaupankäynnin laskuun markkinoiden noususta huolimatta ovat markkinoiden sääntely sekä hajautuminen.

Avainsanat Yli-itsevarmuus, Euroopan osakepörssit, kaupankäyntivolyymi, osakevaihto, menneet tuotot, finanssikriisi, markkinoiden hajautuminen, vektoriautoregressio, impulssivastefunktio

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1. Introduction

Active trading in the market has received a great deal of attention among financial economists since investors seem to trade more that can be explained by rational market models. From the empirical determinants of trading volume, the overconfident investor behaviour is one of the behavioural biases that academia has modelled and tested to explain the irrationally high trading activity in the market. In the light of the recent financial instability in the European market and consequential financial regulatory changes, the changes in the trading activity of market participants is a current topic that may reveal information about changed market environment and investor overconfidence. These changes are not interesting solely from the empirical but also from the institutional point of view, but these determinants of the trading activity might be challenging to distinguish from each other in the empirical analysis. This thesis focuses on explaining the lead-lag relation between lagged returns and current trading activity and gives an overview of trading volume determinants in the European stock market in the 2000s.

1.1. Motivation and background

Odean (1999) states that research lacks models to determine what the equilibrium trading volume on the market is and agrees that the rational empirical determinants such as hedging needs and portfolio rebalancing are not sufficient to explain the excessive trading in the market. He tests the models in which overconfident investors trade more, and finds that those who trade most lose the most. Also the overconfidence models of Odean (1998a) and Gervais and Odean (2001) predict that overconfident investors increase their trading in the market after observing increased returns. This behaviour is due to the investors’ tight error bounds around return forecasts that causes investors to erroneously attribute high market returns to their ability to pick stocks. On the contrary, decreasing market returns make investors less confident and consequently make them decrease their trading activity. Based on these previous models, the overconfident trading behaviour is the central hypothesis analysed in this study. In addition to this hypothesis, there are also other empirical determinants that might explain the changes in the trading volume over time, and these are also presented briefly in the study.

The models of Odean (1998a) and Daniel, Hirshleifer, and Subrahmanyam (1998) provide testable hypotheses of the investor overconfidence including two general assumptions: investors overweight the precision of their private information in investment decisions and the level of overconfidence varies with the observed market performance. The overconfident behaviour in investment decisions is related to the trading beliefs and market in general, rather than the attitude towards specific stocks or personal holdings (Statman, Thorley, and Vorkink (2006)). This supports the idea to study the overconfidence hypothesis merely with aggregated market-wide data instead of individual investors and their holdings data. So far, empirical research has not given much focus on the overconfidence, due to the lack of testable implications.

In addition to the empirical determinants including different behavioural aspects, the trading volume is also affected by many institutional factors which may switch the trading activity between different trading venues and asset classes, and change the total trading volume in the market as well. Lately, the regulatory changes in the European financial markets have made market environment more transparent and fragmented, and this has affected the trading in traditional stock exchanges that are in the main focus of this study. Mainly the MiFID regulation and fast technical development of the trading venues have caused order flow fragmentation and a new type of competitive setup on the financial markets. The market fragmentation has also caused the trading activity to spread to not only new channels besides the traditional stock exchanges but also to alternative asset classes. The empirical results of this study are also related to these institutional effects and thus these effects are separately commented on.

In this thesis, I focus on the lagged returns explaining the current trading activity in the European stock market and follow the study of Statman, Thorley, and Vorkink (2006) who study the potential support for the overconfidence hypothesis in the U.S. stock market from 1962 to 2001. They find that trading volume is strongly dependent on the past returns for many months, and this finding is supporting the overconfident trading behaviour. My study is also time-series oriented and based on the daily observations of fourteen European national stock exchanges from June 2001 to December 2014. I apply the same methodology to the data on the monthly and weekly level, with the monthly level results as the base case in the study. I use the vector autoregression methodology and impulse response functions to obtain the relationship between lagged stock market returns and stock turnover. The indexes are mainly studied as a one panel but at some points they are also separately analysed and commented on. In addition, I divide the full observation period into two subsamples, from June 2001 to December 2008 and from January 2009 to December 2014, and these subsamples present pre- and post-crisis periods around the financial crisis occurred in 2008.

1.2. Contribution

My contribution to the existing literature is to study the most recent relation between the past returns and the current trading activity in the European national stock exchanges. As mentioned, this is a way to study the overconfident trading behaviour in the market. The fresh data also enables me to take a closer look at this lead-lag relation before and after the financial crisis in 2008, and compare if the past returns explain the current trading activity differently during these periods. According to my knowledge this is the first study to statistically analyse the post-crisis trading activity broadly in the European traditional stock exchanges. Due to the recent regulatory events and market fragmentation in Europe, this study also gives unique viewpoint to the trading activity response to these events. For example, the market fragmentation caused by tightened regulation and new trading venues is still a new topic on the field and thus deserves more attention.

The majority of the previous trading volume research is conducted in the U.S. market (e.g. Ajinkya and Jain (1989), Campbell, Grossman, and Wang (1992), Atkins and Dyl (1997), and Statman, Thorley, and Vorkink (2006)), and the regulatory differences and later observed fragmentation in the European market create differences in the market environment. I will not go into more detail in comparing the market environment in the U.S. and Europe but rather focus on collecting information and describing the changes obtained recently in the European stock market from the viewpoint of the traditional stock exchanges. Notably, the data covers widely the whole Europe and thus gives a comprehensive overview of the trading activity in the European national stock exchanges.

1.3. Findings and limitations

The main finding of this study indicates that overconfidence hypothesis also holds in Europe but not as strongly as in the U.S. shown in the previous study of Statman, Thorley, and Vorkink (2006). The second finding of this study shows that the overconfidence hypothesis has the strongest long-term empirical support in the traditional stock exchanges during the pre-crisis period from June 2001 to December 2008. The subsample covering the post-crisis period from January 2009 to December 2014 reveals contrary long-term results over years, as trading activity has constantly decreased despite the fact that the market returns have increased after the crisis. Despite these long-term differences in the subsample results, the weekly level study reveals that for couple of weeks, the trading activity actually follows the increasing returns during all periods, but the focus is still kept on the long-term results on the monthly level. To find the explanation for these contrary long-term findings between the subsamples, I will describe the factors that have affected trading activity in the European traditional exchanges: market regulation including increasing market transparency and market fragmentation including new alternative trading venues and electronic trading in the European stock market. Due to the lack of academic research of the very recent market fragmentation in Europe, I will collect and analyse the post-crisis media insights concerning the decreasing stock trading volume. Also the effect of investor sentiment on the trading activity is separately studied.

I acknowledge that there might be alternative explanations for these empirical results, which are interpreted here as a support of the overconfidence hypothesis, but following the previous literature and methodologies closely and finding the similar results gives additional support for the hypothesis. In addition, the clear difference between lagged returns and trading volume relation during the full, pre-crisis, and post-crisis periods make the topic interesting from the viewpoint of the prevailing market conditions. The post-crisis market confidence has been widely discussed in media and only lately the decreases in traditional stock exchange trading volumes have been traced to be caused by shifting trading volume instead of decrease in confidence. The limitation of this study is related to the time period that is affected heavily by the crisis period, and thus the longer term effects might not be witnessed in the results, and short-term results might be distorted. Furthermore, a larger amount of stock indexes covering also non-traditional exchange venues could give a more comprehensive view of the European stock market trading activity, since the market fragmentation effect might be diluted from the study.

The paper is organised as follows. In Section 2, I will review the literature related to empirical determinants of the trading activity in the financial markets with the main focus on the overconfidence theory. Moreover, I will give a brief introduction to the institutional factors affecting the stock trading volume especially after the recent financial crisis. In Section 3, I will describe the data and methodology used in the analysis. The section reviews the vector autoregression methodology and impulse response functions, as well as the details considered in the calculations. Section 4 presents the empirical results of the methodologies applied, first on the monthly level for the pooled market-wide level followed by a more detailed analysis on the stock index level. Also a weekly level study and investor sentiment effects on trading activity are presented. In Section 5, I present a qualitative study concerning the post-crisis market environment in the European stock market. The conclusions and suggestions for the future research are stated in the last section.

2. Literature review and hypothesis

In this section I will present the previous literature related to the empirical and institutional determinants of the stock trading volume. First, the focus is on the empirical models and findings covering the overconfidence hypothesis that is testable with the lagged return effects on the current trading activity. Second, the institutional part gives attention to the stock market regulation and the recent market fragmentation in Europe. These changes have affected the trading especially in the traditional and domestic stock exchanges that are also in the focus of this study.

2.1. Empirical determinants of trading volume

Why do investors participate in active trading? In a perfectly rational world, there would not be any trading, but the noise caused by non-rational traders keeps the markets busy. Many studies suggest that private information drives different parties to trade, and under these conditions, rational traders are not willing to trade, since the traders with superior information would be the ones dominating the market. The first exit from the zero trading equilibrium was offered by Black (1986), as he was the first who argued that noise traders can overcome this equilibrium out of perfectly rational models. He argues that noise is created by expectations which make it difficult to form theories about the ways markets are working. More recently, Odean (1998a) and Gervais and Odean (2001) develop a model assessing noise trading and find that overconfident traders increase their trading in bull market, since they falsely attribute the value increase to their trading skills. In addition to the overconfident trading, Statman, Thorley, and Vorkink (2006) present alternative empirical motivations for active trading.

2.1.1. Overconfidence hypothesis

Odean (1999) studies a group of discount brokerage account customers and concludes that investors do trade too much and this is due to overconfidence. The study refers to Benos (1998) and Odean (1998a) who also state that overconfident investors trade more than would be optimal for them in a fully rational world and that this behaviour increases expected trading volume. They relate the overconfidence to overweighting the precision of their own information, as do also Daniel, Hirshleifer, and Subrahmanyam (1998). The latter developed a model to describe over- and underreaction in the stock market. The overconfidence is studied to be related to one’s biased self-attribution including tight error bounds and return forecasts. In their study, they summarise psychological cognitive evidence about individuals overestimating their own abilities. They also add that overconfident behaviour is only triggered by signals received personally, not by signals publicly received by all investors. Odean (1998a) also gives a comprehensive overview to previous work related to the overconfidence hypothesis. In this study, I follow closely the methodology of Statman, Thorley, and Vorkink (2006) who find that lagged returns are able to explain current trading volume for many months. They study the relation on the index and security level and find that the relationship holds for both.

With Finnish stock trading data, Grinblatt and Keloharju (2009) study overconfidence and sensation seeking trading behaviour. They find that these characteristics in addition to other behavioural attributes contribute to higher trading volumes, but they do not specifically find a relation between overconfidence and stock turnover. They state that "*overconfidence is the tendency to place an irrationally excessive degree of confidence in one's abilities and beliefs*". Behind this definition lie actually two separate interpretations, which are presented by Glaser and Weber (2004), who also found that market returns affect trading volumes. First, the miscalibration interpretation arises from tight error bounds around return forecasts, and the second interpretation is an idea that investors think their skills are better than average. This effect causes an investor to shift the perceived mean irrationally and for example De Long et al. (1991), Kyle and Wang (1997), and Benos (1998) conclude that these kind of investors may earn higher profits due to the aggressive trading with the first-mover advantage. The difference between these two types of overconfidence cannot be distinguished in this study, and Statman, Thorley, and Vorkink (2006) do not distinguish these in their tests either.

But is overconfidence persistent or is it possible to learn to be less overconfident? Gervais and Odean (2001) note that overconfident investing behaviour decreases with time, but there are always new overconfident traders entering the market. They describe that overconfident behaviour does not lead to higher profits but greater profits lead to overconfidence. It is actually widely recognised that the more you trade the more you lose (e.g. Odean (1999)). Gervais and Odean (2001) show that greater overconfidence increases trading volume and that trading volume is higher (lower) after increased (decreased) market returns. However, these previous studies do not state any findings related to specific lead-lag relations between returns and volumes. There are also dissenting views about how overconfidence changes and persists over time, for example Griffin and Tversky (1992) state that experts are actually more overconfident than novices in a certain market environment.

Related to the findings of Gervais and Odean (2001), I will test if increasing market returns lead to higher trading activity over time. The theory of overconfident investors increasing and decreasing their trading with past returns supports the hypothesis, but also the alternative explanations for this relation are presented briefly in the subsequent paragraphs.

2.1.2. Other determinants of trading volume

It is widely recognised that rational motivations are not able to fully explain the trading volume and that some of the volume is clearly driven by behavioural motivations. There are also other behavioural aspects than overconfidence that have been modelled to explain the changes in trading volume. For example Shefrin and Statman (1985) present the disposition effect, which can also explain the changes in the trading volumes as investors are increasing their trading after realising paper gains. However, Statman, Thorley, and Vorkink (2006) note that this effect explains only the motivation for the one side of the trade, and if large amount of trades is disposition related, pricing equilibrium might be distorted and new information is reflected slowly to the prices. In contrast, overconfident stock-picking is able to explain both sides of a transaction due to the differences in opinion and tight error bounds, and thus the transaction does not have to involve other liquidity traders or rational traders.

The disposition effect is generally attached to investor's beliefs towards a specific stock in his portfolio rather than the market as a whole. Nevertheless, an overconfident investor is likely to maintain his belief about stocks in general rather than an individual security he is currently holding. The difference between overconfident behaviour and disposition effect is nonetheless indistinguishable in the market-wide tests, since the high trading activity followed by high market returns can be a result from either of these two behavioural biases. In their study, Statman, Thorley, and Vorkink (2006) separate between these two by studying the stock-level trading volumes, and they also argue that market-wide aggregate data contain the best chance to find evidence of the overconfident investor behaviour. They state that if investors overestimate their ability to gain with active trading, they are likely to have this bias towards stocks in general. Partly due to this argument and the large number of different stock indexes included, I will not go into the stock level analysis in this study but rather focus on the index level analysis.

Statman, Thorley, and Vorkink (2006) are the first to document a positive lead-lag relationship between returns and trading volume, and they also place other alternative explanations on explaining the changes in trading activity. Portfolio rebalancing, liquidity, tax-driven, and speculative trading derived from rational expectations model compared to models based on differences in opinion. These explanations are presented by Harris and Raviv (1993), and they believe that traders do have differences in opinion, even though they would have the same information. For example, economists usually have access to the exactly same data and still giving dissenting statements. This behavioural bias is also related to overconfidence theory described previously, in which investor with biased self-attribution overweighs his own information. Due to the focus on the investor overconfidence, these alternative explanations mentioned are not studied any further in this paper.

2.2. Other studies between returns and trading volume

There are only few studies concerning lagged returns effect on the current trading activity, the subject of this study. The asset market literature has been more focused on explaining asset prices rather than volumes and has only recently started to produce results related to trading volumes (Harris and Raviv (1993)). Gallant, Rossi, and Tauchen (1992) studied stock price, volatility, and volume co-movement and find that price changes lead to movements in volume and that the effect is almost symmetric for both price increases and decreases. However, the paper does not relate the observed effect to the overconfidence hypothesis. Chordia and Swaminathan (2000) examine the pace of pricing the new information and short-term interaction between volumes and return and find that trading volume is a significant determinant when the lead-lag autocorrelations in stock returns are observed. They conclude that trading volume plays a major role in reflecting new information to prices.

In a few papers the subject of this thesis is studied contrariwise so that historical turnover effects on contemporaneous returns are observed. Gervais, Kaniel, and Mingelgrin (2001) study the short term high-volume return premium that is related to the visibility of the stock after a shock in trading volume (trader interest) and find that this premium holds. Cooper (1999) examines overreaction on individual securities and finds that historical volume is related to the direction of price trends. Chordia and Swaminathan (2000), Lee and Swaminathan (2000), and Llorente et al. (2002) have also contributed to the research of the volume and return relation, but most of the studies are not market aggregated but executed on the security level. In addition, a large amount of empirical research is related to contemporaneous turnover and return without considering the lagged effects, for example Karpoff (1987), Bessembinder and Seguin (1993), Bessembinder, Chan, and Seguin (1996), Chordia, Roll, and Subrahmanyam (2000), and Lo and Wang (2000). Karpoff (1987) contributes to the research between price changes and trading volume and proposes one of the first models for studying the price-volume relation. The results in his study imply that this relation is the strongest at times when the information flow is most volatile.

Considerable amount of studies relate volume to contemporaneous return volatility, such as Karpoff (1987), Gallant, Rossi, and Tauchen (1992), Harris and Raviv (1993), Bessembinder and Seguin (1993), and Shalen (1993). The findings of positive correlation in these studies support to include contemporaneous and lagged observations of return volatility to the vector autoregression models executed in this study to control the analysis.

2.3. Institutional aspects of trading volume

The previous empirical trading volume studies are mostly focused on the U.S. stock markets (see e.g. Ajinkya and Jain (1989), Campbell, Grossman, and Wang (1992), Atkins and Dyl (1997), and Statman, Thorley, and Vorkink (2006)). The U.S. stock market has already experienced similar changes that have recently also become reality in the European markets and thus the comparison is relevant. The biggest market changes I will describe next are market regulation and fragmentation, which, in fact, are closely related to each other since the recent high speed of the market fragmentation is partly due to the new regulatory environment in the European market. The changed market environment is a rather new phenomenon and thus it is still lacking broader academic research. With this study, I contribute to this recent topic by collecting the information available about these changes from the viewpoint of the European national stock exchanges. The traditional stock exchanges are losing foothold in being the main market operators in domestic stock trading as new alternative trading venues appear to the market enabling the pan-European trading.

2.3.1. European stock market regulation

This study is based on the data of the European national stock exchanges, which are also considered as the traditional stock market operators on the field. Thus the trading activities of different national exchanges are heavily affected by the changed regulation in the European financial markets during the observation period from June 2001 to December 2014 (presented in more detail later in the data section). In June 2009, the Committee of European Securities Regulators (CESR) published the report analysing the impact of MiFID (Markets in Financial Instruments Directive) on the European equity markets. The time period in the analysis is only 18 months after the MiFID came into effect on the 1st of November 2007, and thus all the longer term effects might not be obtained on the report.

Prior to the MiFID introduction, the national stock exchanges in Europe enjoyed good positions in the stock trading. The intention of the introduction of the new regulation was to increase transparency and accessibility in the market. The report agrees that the introduction of MiFID has changed the secondary markets widely in Europe, but there might be also other drivers affecting the market than this introduction. For example, the market volatility on the observation period was extremely high and the financial crisis caused many defaults for counterparties. The original objective of MiFID was to increase competition among different trading venues, reduce trading costs, and increase the transparency on the market while supporting investor protection and market efficiency. This study also reviews how these goals are reached and which effects were not originally considered.

2.3.2. Market fragmentation

As a consequence to the tightened regulation in the European stock market, the new trading opportunities have risen for investors, and order flow competition between trading venues has increased. The national exchanges have been faced with several challenges after the introduction of the new MiFID regulation in 2007, but nonetheless the changes have caused mainly positive liquidity implications (e.g. Chlistalla and Lutat (2011) and He, Jarnecic, and Liu (2015)). According to the CESR report, MiFID classifies the trading venues explicitly into three groups: Regulated markets (in this study generally the national stock exchanges), multilateral trading facilities (MTFs) and systematic internalisers (SIs). The latter and all other types of venues are classified as OTCs (over-the-counter). The largest impact on the regulated markets trading have been caused by new multilateral trading facilities, which have attracted trading by having competitive fees, fast electronic trading venues, and enabling pan-European stock trading. MTFs have steadily increased their market share in all markets and the speed of growth has accelerated with the launches of new MTFs. However, it is important to notice that the majority of European stock trading still remains on the regulated markets rather than MTFs, even though the market share of the national stock exchanges has decreased after the implementation of MiFID. This is due to the limited trading between national stock exchanges and the shares that have been admitted to trading only to these specific exchanges.

The CESR report also indicates that MiFID has indeed increased the competition among trading venues on the secondary stock market and increased the options for market participants to execute their orders. The fragmentation of the European equity trading has been acknowledged and studied by e.g. Chlistalla and Lutat (2011), Gomber et al. (2011), O'Hara and Ye (2011), and Menkveld (2013). At the same time, the trading fees have dramatically decreased and alternative markets have enabled the availability of narrower spreads (better prices) in the stock market. Trade sizes have decreased and number of trades have increased, which, however, is most likely due to the algorithmic trading and market fragmentation rather than the MiFID regulation itself.

According to the CESR report, the drawback of the MiFID introduction has been a decrease in overall market transparency and market data quality that has been observed also by Preece and Rosov (2014). IT costs have increased because regulated market players enhance their IT systems to reduce order latency and improve connectivity to compete with the flexible newcomers in the market. Also the overall trading costs have increased due to the decreases in average order sizes and increases in average execution amounts, even though the trading costs have dramatically decreased. Menkveld (2013) presents a new trader type, high-frequency trader, who also contributes to ever fragmenting equity market. This trader type is also created by electronic and high-speed securities market, and thus the market operators having effective IT systems are able to attract high-frequency traders.

In addition to the alternative trading venues mentioned, a part of the trading has also gone to the dark trading venues, in which the pre-trade transparency is limited (Preece and Rosov (2014)). Kwan, Masulis, and McInish (2015) study the market fragmentation in the U.S. and the competition between regulated markets and dark trading venues. They find that market fragmentation is speeded up by the difference in regulatory treatment since dark pools do not face similar constraints in stock spreads as traditional stock exchanges. It is also interesting how different investor types have divided their trading in different venues. For example, Zhu (2014) builds a model predicting that regulated traditional exchanges are more attractive for informed traders, and uninformed traders are more likely to trade in dark trading venues. However, this study does not take into account the separation between different investor types.

Two years after CESR publications, in June 2011, the CFA Institute published a report (Preece, 2011) examining the European equity market and the regulation related to different trading venue types. The report suggests considerations for the MiFID policy and collects the observations since the introduction of new regulation. According to CFA, European equity trading is split in half between the OTC trading and trading in regulated markets or MTFs and that there has been no trend in this splitting from January 2008 to October 2010. The report also suggests that transaction sizes are getting smaller. This might be due to the increasing trade amounts as the trades are more often done electronically and also algorithmic trading contributes to decreasing trade sizes and increasing trade amounts. The CFA report concludes that, in all, the increased market transparency has been beneficial for stock investors.

3. Data and methodology

In this section I will present the European market-wide stock index data and the methodology used in the study. Following Statman, Thorley, and Vorkink (2006), I use the vector autoregression method and impulse response functions to obtain the lagged return effects on the trading activity and find support for the overconfidence hypothesis.

3.1. Data description

The study is executed on the stock index level and it contains fourteen European national stock indexes. These indexes and their details are presented in Table 1. The sample covers the indexes from the following European countries: Austria, Belgium, Denmark, Finland, France, Sweden, Greece, Ireland, United Kingdom, Germany, Hungary, Switzerland, Poland, and Spain, and thus represents broadly the European stock market. In the data collection, also other European national stock exchange indexes were discovered, but they were dropped from the study due to the limited historical data available. Some of the potential exchanges had also been established after the beginning of the time series in this study (i.e. after June 2001) and thus are excluded. All the indexes included are established in the exchanges during the early 90s or before, and these market places can thus be seen as traditional stock exchanges that have long enjoyed their market shares on the domestic stock trading.

Table 1. Stock index details.

Detailed information of the European national stock indexes included in the study. The increased member count is taken into account in trading volume calculations by measuring trading volume as a turnover ratio. The indexes are selected according to the price and volume data availability. The ticker names are used in retrieving data from the Bloomberg Terminal.

			Member count			
Ticker	Name	Country	14-Jan-02	30-Dec-14	Currency	Start date
ASE Index	Athens Stock Exchange	Greece	60	60	EUR	1987-01-02
ATX Index	Vienna Stock Exchange	Austria	20	20	EUR	1986-01-08
BEL20 Index	Brussels Stock Exchange	Belgium	20	20	EUR	1990-12-31
BUX Index	Budapest Stock Exchange	Hungary	17	13	HUF	1991-01-02
CAC Index	Paris Stock Exchange	France	40	40	EUR	1987-07-09
DAX Index	Frankfurt Stock Exchange	Germany	30	30	EUR	1959-10-01
HEX Index	Helsinki Stock Exchange	Finland	122	130	EUR	1987-01-02
ISEQ Index	Irish Stock Exchange	Ireland	63	47	EUR	1983-01-05
KFX Index	Copenhagen Stock Exchange	Denmark	20	20	DKK	1989-12-04
MADX Index	Madrid Stock Exchange	Spain	113	107	EUR	1988-12-30
OMX Index	Stockholm Stock Exchange	Sweden	30	30	SEK	1986-12-18
SMI Index	Swiss Stock Exchange	Switzerland	27	20	CHF	1988-07-01
UKX Index	London Stock Exchange	U.K.	101	102	GBP	1983-12-31
WIG Index	Warsaw Stock Exchange	Poland	112	382	PLN	1991-04-16
Total			775	1021		

First in processing the data, I collected the observations of the daily index closing values (Bloomberg ticker: PX_LAST) to calculate the logarithmic daily returns. I collected separately the dividend yields and added them to the daily returns, which are used in calculating volatility on monthly and weekly levels. Second, I collected daily stock amounts traded in each exchange (Bloomberg ticker: PX_VOLUME) and the total amounts of stocks outstanding in each index (manually collected from the index Member Weightings, MEMB). The daily observations of stocks traded and returns are summed and used on the monthly level in the base case study. The data covers the period from June 1st, 2001 to December 31st, 2014, and I retrieved it from the Bloomberg Terminal provided by Bloomberg L.P. The historical data time series is limited due to the stock volume data available (limited PX_VOLUME and MEMB data). The base case study is carried out on a monthly level, but weekly analysis is also executed and its results are presented and commented separately but not fully reported. Statman, Thorley, and Vorkink (2006) also focus on the monthly analysis, since the changes of investor overconfidence are likely to be more evident over long time periods.

When examining the long-term trading activity, it must be noted that the number of outstanding shares of stock indexes has increased significantly. As Statman, Thorley, and Vorkink (2006) do, I also follow Lo and Wang (2000) and measure trading activity with turnover (shares traded divided by shares outstanding). I collected the data of daily stock amount traded, and the total stock amount traded in each index. The latter data was limited and it was not automatically available on daily basis. Thus the total amount of stocks is collected manually and adjusted on yearly basis so that the last value of each year represents the total shares outstanding every month during a year in question. The values of outstanding shares are adjusted for stock splits over time. The daily stock turnover is then calculated by dividing the daily amount of stocks traded by the total amount of stocks in the index. For monthly and weekly observations, the numerator is the sum of the daily stocks traded during each month or week.

Figure 1 presents monthly index turnovers from the observation period for all fourteen indexes. Turnover level varies among the indexes across Europe and the growing long-term trend before 2001 is not observable in these graphs. However, it is still visible that the turnover series are nonstationary, and this leads to bias in the coefficient standard errors of the vector autoregression methodology used in this study. Even though the turnover is a relative measure, it has a trend over time. Turnover is always a non-negative measure and thus log transformation helps to eliminate the visual correlation between the turnover trend level and volatility around it. With a log transformation, I am able to remove nonlinear trends from the data and reject the null hypothesis of a unit root using the Phillips and Perron (1988) test[1].

Despite the fact that the unit root was not found and thus the data could be used in the analysis without detrending, I will follow the methods and the following data modifications used by Statman, Thorley, and Vorkink (2006) to maximise the comparative potential of the studies. Thus I further modify the time series by using Hodrick and Prescott (1997) algorithm to detrend the turnover series[2]. Also simpler linear time-trend methods could be used in detrending, but they are not flexible enough in finding trends of various turnover patterns of equity indexes I examine. Figure 1 contains the dotted line that is a trend calculated from the log turnover series. The detrended time series used in this study is the monthly difference between log turnover and its trend. Detrending the turnover series might create a bias against finding the results supporting overconfidence hypothesis, since the realised returns may actually cause long-term trends in trading volumes. The VAR results of nondetrended turnover analysis are also observed, and partly reported and commented in the following sections.

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[1] The Phillips and Perron (1988) test statistic for 14 indexes varies from -2.95 to -7.41 for log market turnover and from -7.00 to -12.51 for detrended log market turnover. The critical value of 5% for the test statistic is -2.89.

[2] The Hodrick-Prescott (1997) algorithm minimises the variance of the raw series *y* around the trend to create the trend series *s*. The second difference of the trend penalises variations in the growth rate of the trend component. The filter chooses S_t to minimise $\sum_{t=1}^{T}(y_t - s_t)^2 + \lambda \sum_{t=2}^{T-1}[(s_{t+1} - s_t) - (s_t - s_{t-1})]^2$. The λ is the penalty parameter and trend becomes smoother when λ increases. I follow the common practice of setting λ=14,000 in monthly, and λ=270,400 in weekly analysis. Since the purpose of using the HP filter is to detrend the series and not forecast the trend, I allow the trending method to be two-sided, i.e. to use the data before and after time *t* in smoothing.

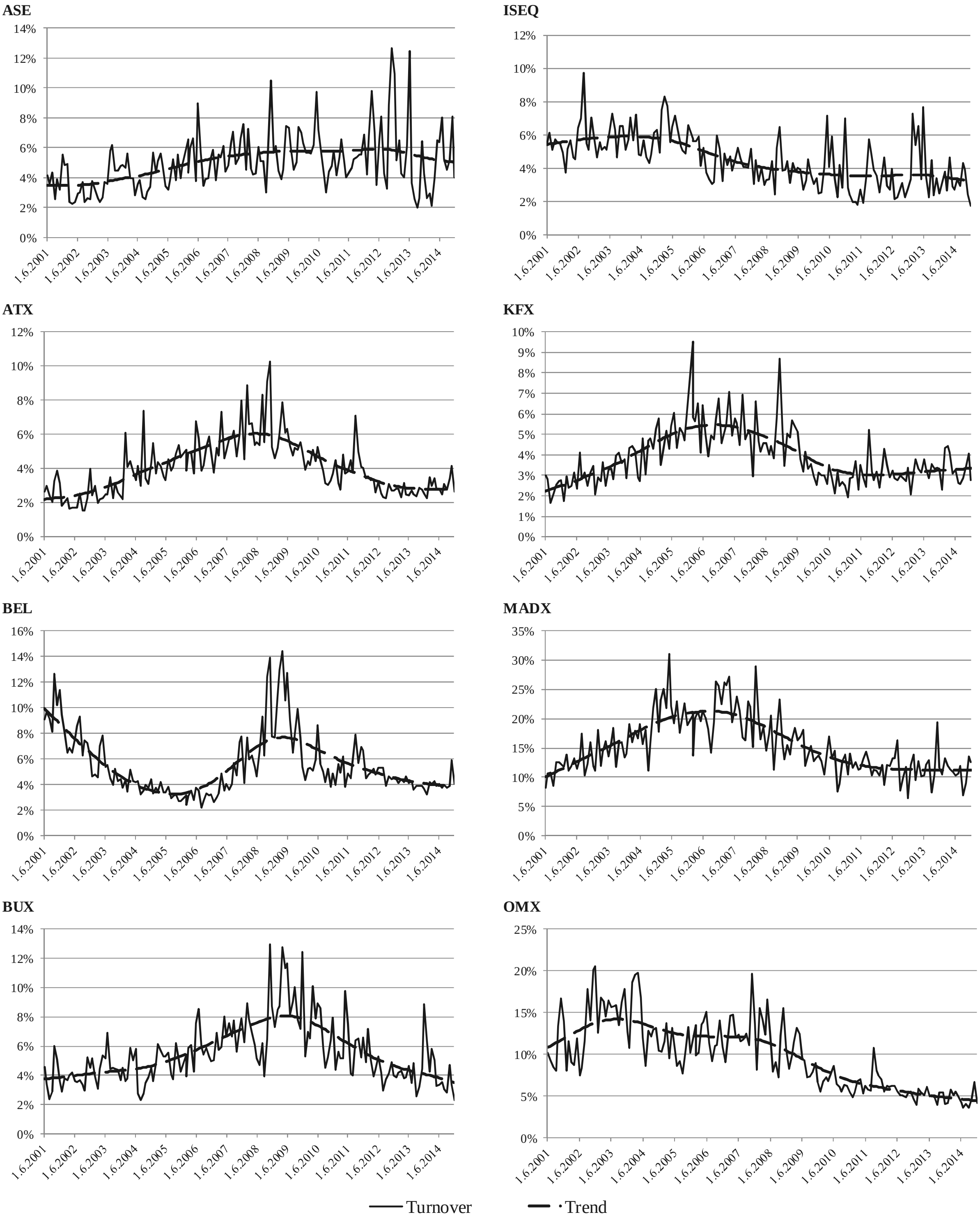


Fig. 1. Monthly turnover for 14 European stock indexes with trend line.
This figure presents the monthly stock turnover for the 14 stock indexed included to the study. The turnover ratio is calculated by dividing the amount of stocks traded monthly by the total amount of stocks included in the index. The time period is the full observation period from June 2001 to December 2014. The index ticker names are presented in Table 1. The dotted trend line is calculated by using the Hodrick-Prescott (1997) algorithm.

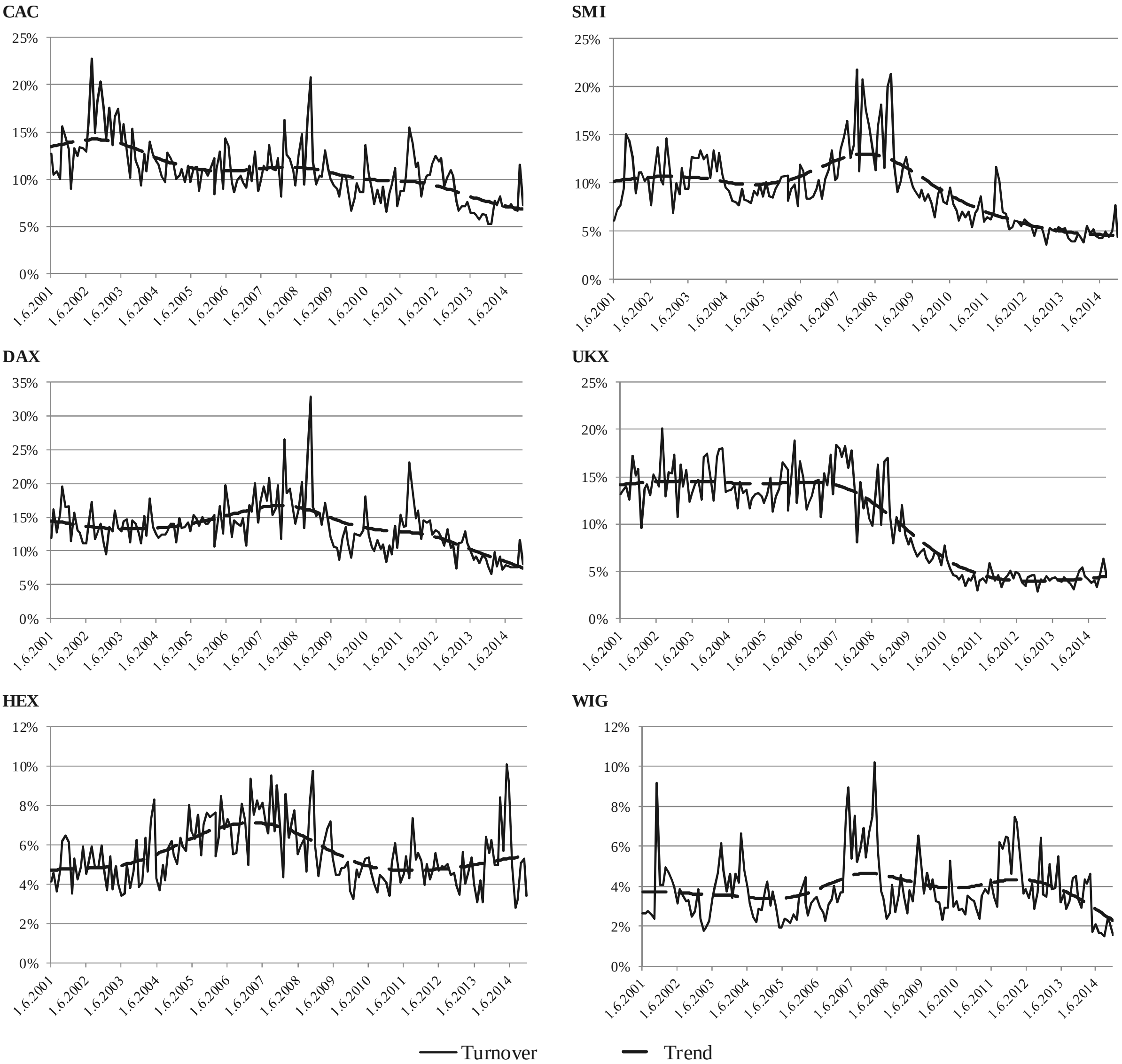


Fig. 1 (continued)

Table 2 presents summary statistics of the monthly market-wide turnover and returns in addition to the control variable, market volatility, for the full period sample from June 2001 to December 2014. The second part of the table also presents the subsample summary statistics for the two non-overlapping time series that are later used in examining the difference of results before and after the financial crisis in 2008 (pre- and post-crisis periods). The means and standard deviations (SD) of subsample turnovers are not very different from each other and this supports the rejection of the unit root in the series. However, I still also obtain the detrended log turnover for the time series, and their means and standard deviations also indicate stationary time series.

Table 2. Market descriptive statistics.

This table reports the detailed statistics on the stock indexes included in the study. All values are reported in percentage points. Turnover is the monthly turnover calculated by shares traded during a month divided by outstanding shares at that time. Detrended log turnover (*turn*) is log transformed and detrending is done by using the Hodrick-Prescott (1997) algorithm. Return (*ret*) is the monthly index return calculated as natural logarithmic change from the first and last observation each month. Volatility (*volatility*) is the French, Schwert, and Stambaugh (1987) volatility measure based on daily observations and their standard deviations during a month. The first part of the table reports the full period from June 2001 to December 2014 and two other parts report the pre- and post-crisis subsamples, from June 2001 to December 2008, and from January 2009 to December 2014, respectively. The index ticker names are presented in Table 1.

	Full period
Period	6/2001-12/2014
Monthly obs.	163
from weekly obs.	709
from daily obs.	3480

	ASE	ATX	BEL	BUX	CAC	DAX	HEX	ISEQ	KFX	MADX	OMX	SMI	UKX	WIG
Turnover														
Mean	5.01	4.01	5.48	5.49	10.85	13.44	5.56	4.50	3.86	15.31	9.82	9.23	10.22	3.85
SD	1.90	1.62	2.45	2.11	3.08	3.72	1.53	1.54	1.33	4.85	4.17	3.62	4.98	1.54
Minimum	2.00	1.51	2.20	2.32	5.24	6.62	2.83	1.78	1.64	6.47	3.53	3.60	2.90	1.51
Maximum	12.64	10.28	14.42	12.96	22.82	32.91	10.10	9.71	9.51	31.03	20.47	21.83	20.05	10.20
Detrended log turnover (*turn*)														
Mean	-2.19	-1.25	-1.64	-1.43	-0.93	-0.88	-1.12	-1.66	-1.02	-0.80	-1.09	-1.10	-0.79	-2.70
SD	13.70	9.63	9.54	10.69	8.37	8.13	9.38	11.64	8.80	8.06	9.10	8.62	7.37	13.85
Minimum	-43.51	-22.67	-23.32	-29.40	-19.09	-21.79	-27.67	-29.26	-23.78	-24.28	-23.52	-22.54	-21.40	-30.79
Maximum	34.9	28.3	27.3	33.5	27.1	31.3	28.0	32.9	27.7	23.6	24.2	24.4	18.5	39.2
Return (*ret*)														
Mean	-0.47	0.62	0.44	0.72	0.26	0.68	0.30	0.23	0.82	0.52	0.67	0.45	0.47	1.03
SD	9.04	6.82	5.56	6.81	5.69	6.65	7.26	6.33	5.56	6.06	5.64	4.46	4.50	6.63
Minimum	-31.07	-29.74	-21.67	-29.63	-18.20	-22.84	-22.33	-20.97	-18.98	-18.54	-16.37	-15.92	-14.38	-27.94
Maximum	22.55	19.11	12.62	19.99	13.42	19.95	25.93	16.92	19.55	16.90	14.62	12.41	11.87	21.92
Volatility (*volatility*)														
Mean	7.78	6.09	5.24	6.39	5.66	6.03	6.71	5.81	5.29	5.90	5.84	4.75	4.45	5.61
SD	4.06	4.13	3.60	3.89	3.59	3.71	3.64	3.81	3.18	3.38	3.42	3.26	3.05	2.89
Minimum	2.29	1.68	0.72	1.63	0.43	1.64	0.76	1.24	1.42	1.42	1.23	1.04	0.34	1.28
Maximum	28.25	34.49	25.52	37.30	22.46	23.21	19.27	31.13	26.58	25.05	22.60	23.20	21.76	21.69

The two subsamples from June 2001 to December 2008 and from January 2009 to December 2014 are formed to test the effects of the recent financial crisis on the analysis. I also included a crisis dummy for the period of the highest return volatility during the crisis, that is to say, from October 2008 to December 2008. This dummy is not included in the base case study, since the results were not highly affected by the added variable. In Figure 1 there is not a large market-wide temporary change in turnover during the crisis, but it seems that after the crisis the turnover has constantly decreased in all countries included in the study. Nevertheless, this effect is contrary to the overconfidence hypothesis when compared to the market performance that has done quite well after the crisis (See Appendix A for the performance of fourteen stock indexes and their monthly return volatility (*volatility*) during the observation period). This post-crisis phenomenon is the main reason to use the two subsamples in studying the main hypothesis of overconfidence pre- and post-crisis.

Table 2 (continued)

	Pre-crisis subsample
Period	6/2001-12/2008
Monthly obs.	91
from weekly obs.	396
from daily obs.	1943

	ASE	ATX	BEL	BUX	CAC	DAX	HEX	ISEQ	KFX	MADX	OMX	SMI	UKX	WIG
Turnover														
Mean	4.51	4.23	5.41	5.18	12.34	14.93	6.03	5.23	4.31	17.65	12.61	11.28	14.21	3.90
SD	1.51	1.85	2.55	1.72	2.87	3.51	1.56	1.29	1.48	4.92	3.23	3.24	2.35	1.69
Minimum	2.22	1.51	2.20	2.32	8.17	9.54	3.40	2.43	1.64	8.18	7.23	6.06	8.08	1.77
Maximum	10.49	10.28	13.89	12.96	22.82	32.91	9.73	9.71	9.51	31.03	20.47	21.83	20.05	10.20
Detrended log turnover (*turn*)														
Mean	-1.48	-1.05	-2.25	-1.79	-0.29	0.07	-0.40	-0.94	-0.63	-0.50	-0.94	-0.26	0.06	-2.54
SD	11.54	10.84	9.23	10.22	8.05	7.65	8.59	8.68	8.97	7.85	10.17	9.40	7.37	14.88
Minimum	-27.63	-22.67	-23.32	-29.40	-19.09	-17.18	-19.45	-21.10	-23.78	-22.51	-23.52	-22.5	-21.40	-30.79
Maximum	26.46	28.32	26.88	21.55	27.06	31.33	19.52	22.76	27.71	18.68	21.79	23.45	18.48	39.24
Return (*ret*)														
Mean	-0.33	0.56	-0.18	0.83	-0.42	-0.16	-0.50	-0.69	0.00	0.22	-0.23	-0.15	-0.12	0.78
SD	7.72	7.00	6.08	6.98	5.72	7.00	7.99	6.76	6.01	5.49	6.18	4.62	4.36	7.20
Minimum	-28.62	-29.74	-21.67	-29.63	-18.20	-22.84	-22.33	-20.97	-18.98	-18.54	-16.37	-15.92	-14.38	-27.94
Maximum	15.68	12.03	12.62	19.20	13.17	19.95	25.93	13.62	13.61	15.27	14.62	8.94	9.01	20.41
Volatility (*volatility*)														
Mean	5.93	5.38	5.32	6.38	5.62	6.21	7.27	5.75	5.28	4.96	6.29	5.13	4.49	5.88
SD	3.54	4.52	4.20	4.35	3.95	4.12	4.02	4.41	3.54	3.30	3.63	3.77	3.45	2.72
Minimum	2.29	1.68	1.42	1.81	0.62	1.94	2.08	1.24	1.80	1.42	1.82	1.04	1.05	2.05
Maximum	28.25	34.49	25.52	37.30	22.46	23.21	19.27	31.13	26.58	25.05	22.60	23.20	21.76	21.69

	Post-crisis subsample
Period	1/2009-12/2014
Monthly obs.	72
from weekly obs.	313
from daily obs.	1537

	ASE	ATX	BEL	BUX	CAC	DAX	HEX	ISEQ	KFX	MADX	OMX	SMI	UKX	WIG
Turnover														
Mean	5.63	3.75	5.58	5.90	8.98	11.55	4.97	3.58	3.29	12.34	6.29	6.65	5.16	3.79
SD	2.15	1.23	2.33	2.47	2.19	3.08	1.29	1.34	0.79	2.64	1.97	2.12	1.81	1.35
Minimum	2.00	2.25	3.26	2.32	5.24	6.62	2.83	1.78	1.92	6.47	3.53	3.60	2.90	1.51
Maximum	12.64	7.87	14.42	12.74	15.45	23.14	10.10	7.69	5.66	19.36	13.17	12.70	11.95	7.49
Detrended log turnover (*turn*)														
Mean	-3.09	-1.51	-0.88	-0.97	-1.75	-2.09	-2.02	-2.57	-1.52	-1.18	-1.28	-2.16	-1.87	-2.90
SD	16.06	7.91	9.94	11.32	8.75	8.60	10.28	14.57	8.62	8.36	7.60	7.44	7.29	12.51
Minimum	-43.51	-17.22	-22.35	-22.17	-18.96	-21.79	-27.67	-29.26	-20.98	-24.28	-17.35	-18.0	-20.14	-23.64
Maximum	34.86	27.99	27.32	33.55	22.61	25.75	28.00	32.86	23.81	23.58	24.23	24.40	15.63	23.67
Return (*ret*)														
Mean	-0.66	0.64	1.17	0.67	0.80	1.40	0.93	1.15	1.62	0.68	1.51	0.95	1.00	1.23
SD	10.53	6.63	4.77	6.63	5.62	6.11	6.17	5.61	4.83	6.74	4.74	4.20	4.64	5.88
Minimum	-31.07	-18.87	-14.13	-16.14	-13.09	-19.01	-16.75	-15.81	-14.24	-15.67	-13.93	-15.01	-11.46	-16.82
Maximum	22.55	19.11	11.94	19.99	13.42	17.41	24.49	16.92	19.55	16.90	13.97	12.41	11.87	21.92
Volatility (*volatility*)														
Mean	10.12	6.99	5.14	6.39	5.71	5.80	6.01	5.88	5.31	7.10	5.28	4.26	4.41	5.27
SD	3.44	3.39	2.68	3.25	3.11	3.12	2.98	2.92	2.68	3.12	3.08	2.40	2.48	3.07
Minimum	2.96	2.41	0.72	1.63	0.43	1.64	0.76	2.41	1.42	1.59	1.23	1.58	0.34	1.28
Maximum	19.76	16.94	13.33	15.20	15.93	17.09	16.00	17.26	14.02	16.01	14.10	15.06	13.24	16.92

In the study I follow Statman, Thorley, and Vorkink (2006) methodology in which I explain the previously described detrended log turnover, *turn*, and daily market return, *ret*, with lagged daily returns and turnovers, and control the process with the volatility of the index, *volatility*, following the volatility measure of French, Schwert, and Stambaugh (1986). Statman, Thorley, and Vorkink (2006) follow this same way of measuring volatility, but they also include another control variable, cross-sectional dispersion, calculated from stock level information. Since I will not observe the stock level data in my study, and there is not any direct volatility indexes fitting the data, I will leave the dispersion control variable out from the analysis. If used, the dispersion would control the potential trading activity associated with portfolio rebalancing which might be caused by large differences in the individual stock returns. The unreported analysis shows that the spreads have been rather stable during the fourteen year analysis period, only slightly increasing during crisis periods in 2001 and 2008. I will also include different sets of dummy variables into the analysis. In the monthly and weekly level study there is a dummy for each month during the observation period (163 dummies) and a dummy for each country (14 dummies) to capture the month-, week- and country-specific fixed effects. Nonetheless, these dummies are left out from the final result tables due to the large amount of data.

The stock turnover, *turn*, is used as a trading activity measure, and it is the detrended log turnover which is calculated based on the share amount traded in each index monthly. Market return, *ret*, is the monthly return including dividends paid on the stocks. Indexes are value-weighted portfolios and all underlying stocks in indexes are included at all times. The subsample standard deviations for *ret* are stable and thus indicate stationary time series. The subsample means for *ret* are differing more, most likely due to the crisis that is included in the end of the first subsample. Only by dropping couple of last observations of 2008 from the mean calculation, the mean return increases to the levels of the post-crisis period mean. The turnover and return variables for all fourteen indexes are visualised on monthly basis in Appendix B. The trading activity measure varies evenly around zero and thus indicates that the detrending of the series has been executed properly.

The reported control variable in this study, *volatility*, is the monthly volatility calculated from the daily returns each month, measured in percentage points. The use of volatility control measure is based on Karpoff (1987), who studied the relationship of contemporaneous volume and volatility. The volatility measure is similar to the one used in Statman, Thorley, and Vorkink (2006) and it is based on French, Schwarz, and Stambaugh (1987)[3]. The control variable is correcting for realised autocorrelation, which is caused by non-synchronous trading of stocks. The return volatility increased temporarily during the crisis time, but has been rather stable at other times during the observation period.

Statman, Thorley, and Vorkink (2006) use only a single large U.S stock index (NYSE/AMEX) in their study. Since I use data of fourteen separate smaller European indexes, my main study mainly observes the results of the panel data that pools all the indexes together. The monthly and weekly panels include 2,282 and 9,926 observations, respectively, and the sequential panel variable is defining the different indexes in the pooled analysis. After obtaining the results of the pooled data, I present the analysis of the separate indexes.

3.2. Empirical methodology

I will follow the vector autoregression and impulse response functions methodology used in the study by Statman, Thorley, and Vorkink (2006) to observe the lagged return effects on the stock turnover. Statistical analysis of the study is executed by using Stata 12 software.

3.2.1. Vector autoregression model

The general form of the vector autoregression (VAR) model is

$$Y_t = \propto + \sum_{k=1}^{K} A_k Y_{t-k} + \sum_{l=0}^{L} B_l X_{t-1} + e_t \tag{1}$$

where Y_t is n x 1 vector of period t observations of endogenous variable, 2 x 1 vector of turnover and return in this model. X_t is a period t observations of the volatility, the exogenous control variable, and e is a n x 1 residual vector, 2 x 1 vector of turnover and return residuals in this model. A_k and B_l are the regression coefficients which estimate the relationship between turnover, return, and volatility. L and K specify the amount of lagged observations used in the model. In the VAR methodology, the contemporaneous correlation between endogenous variables, *turn* and *ret*, is captured since the residual vector e has a covariance structure.

The amount of lags in the VAR model is the same than used in Statman, Thorley, and Vorkink (2006), that is to say, K = 10 and L = 2. These are determined by their data and the

[3] Month t volatility is calculated as $volatility_t^2 = \sum_{\tau=1}^{T} r_\tau^2 + 2\sum_{\tau=1}^{T} r_\tau r_{\tau-1}$, where r_τ is day τ's return and T is the number of trading days in month t.

Schwartz Information Criteria (SIC). The selection is based on a log likelihood function that is adjusted by a penalty for the number of parameters. L = 2 indicates that contemporaneous and two lags of volatility variable, *volatility*, is used to explain and predict the endogenous variables. Notably, the lagged endogenous variables (K = 10) are starting with the first monthly lag, since naturally the current value is not taken into account. For comparison purposes, the same lag lengths are used when analysing the panel data and the data of separate indexes, even though SIC might suggest some variation for the optimal lengths. The weekly study that is not fully reported, but only partly commented on here, includes the values of K = 24 and L = 8, since the main focus of the weekly analysis is to take a closer look at the first six months of the monthly analysis.

3.2.2. Impulse response functions

Based on the VAR model, I also execute impulse response functions (IRF) to visually illustrate how a shock in a residual e_t affects the current value of the dependent variable, *turn* or *ret*. The impulse response function traces the effect of a one standard deviation shock in one endogenous variable residual to current and future values of the endogenous variables. The complete equation of the bivariate VAR model illustrates the components of the model including the endogenous variables, stock turnover and index return, and the exogenous variable, stock index volatility:

$$\begin{bmatrix} turn_t \\ ret_t \end{bmatrix} = \begin{bmatrix} \propto_{turn} \\ \propto_{ret} \end{bmatrix} + \sum_{k=1}^{K} A_k \begin{bmatrix} turn_{t-k} \\ ret_{t-k} \end{bmatrix} + \sum_{l=0}^{L} B_l \, volatility_{t-1} + \begin{bmatrix} e_{turn,t} \\ e_{ret,t} \end{bmatrix} \tag{2}$$

In the impulse response function, the shock in a residual e will change the current value of the dependent variable, turnover or return. The shock will also have an effect on the future values of the dependent variables, since the lagged variables are also used as explanatory variables in the model. The main purpose of this study is to obtain the relation between current turnover and lagged returns. To test this hypothesis I use the impulse response functions and shock the market return residual, $e_{ret,t}$, by one standard deviation. Also the response of future turnover values to the shock in the current turnover is observed to study the turnover autocorrelation. Using the respective VAR model executed first, the impulse regression function output is a simple graph of how the endogenous variables are related after the shock.

4. Results

In this section I will present the results of the vector autoregression analysis and the impulse response functions. The both methods are conducted for the pooled data of all indexes as well as for the single indexes, and the results are reported and commented on separately. The base case results are on the monthly level but also weekly results are examined.

4.1. Vector autoregression results

The vector autoregression is first executed to the pooled data including all fourteen stock indexes combined, followed by the more detailed analysis for the separate indexes. For the full period, the results indicate light support for the overconfidence hypothesis, and the subsample analysis reveals the difference in the relation between lagged returns and turnover when pre- and post-crisis periods are compared.

4.1.1. Panel data analysis

Table 3 summarises the results of the pooled bivariate vector autoregression between detrended log turnover, *turn*, and return, *ret*. The results are shown for the full period from June 2001 to December 2014 and for the two subsamples. The table is organised by three six-column sets for the endogenous variables (*turn* and *ret*) and by rows for lagged endogenous and exogenous variable coefficients. For each coefficient, I report the estimated value (Coeff.), standard error (SE), and the *p*-value (*p*-val.). For clear table presentation, the significance levels are not shown on the table and all values are rounded to two digits. I generally refer to coefficients with *p*-values of 0.05 or less as significant, and coefficients with *p*-values of 0.01 or less as highly significant.

For all observed periods, Table 3 shows that lagged turnover is explaining the current turnover, that is to say, that *turn* is autocorrelated with a highly significant first lagged coefficients of 0.37, 0.40, and 0.31 respectively for the full period and the two subsamples (with low standard errors of 0.02, 0.03, and 0.03). Hereinafter, the full period and the subsamples from 2001 to 2008 (pre-crisis) and from 2009 to 2014 (post-crisis) are referred to in respective order in this study. The turnover coefficients of the second and higher lags are rapidly declining in magnitude right after the first lag, and thus the strong autocorrelation of turnover persists only for a short period of time. The weekly analysis reveals that the autocorrelation is extremely strong only with the first weekly lag and diminishes drastically already on the second lag observations for all periods. Figure 2 visualises the autocorrelation of the pooled data on the monthly level.

To study the overconfidence hypothesis, the particular attention is paid to how the current turnover is dependent on the lagged returns in different observation periods. For the full period, the first lagged return has a significant positive effect on turnover, with the coefficient of 0.09 (with standard error of 0.04). Also for the both subsamples, the first lag of *ret* is positive, but these coefficients are not significant in the long-term analysis, and thus I separately analyse this effect on the weekly level later. However, both of the subsamples have significant second lag coefficients of 0.15 and -0.20. Moreover, other significant coefficients are positive and negative within the subsamples, respectively, meaning that before the crisis turnover increased with lagged returns, but this relation does not hold after the crisis. The positive and significant association between the turnover and lagged returns of the full period

Table 3. Vector autoregression (VAR) estimation results, panel data, all periods.

This table reports Coefficients, their standard errors (SE), and *t*-statistic significance levels (*p*-val.) of a VAR of detrended logged market turnover (*turn*) and return (*ret*), with 10 lags, for the full period sample as well as for the two subsamples, that are summarised in Table 2. The VAR also includes contemporaneous and two lags of the exogenous variable return volatility (*volatility*), as described in Table 2.

	Full period						Pre-crisis subsample						Post-crisis subsample					
	$turn_t$			ret_t			$turn_t$			ret_t			$turn_t$			ret_t		
	Coeff.	SE	*p*-val.	Coeff.	SE	*p*-val.	Coeff.	SE	*p*-val.	Coeff.	SE	*p*-val.	Coeff.	SE	*p*-val.	Coeff.	SE	*p*-val.
ret_{t-1}	0.09	0.04	0.05	-0.03	0.02	0.18	0.10	0.06	0.12	-0.05	0.03	0.08	0.08	0.08	0.32	-0.03	0.03	0.36
ret_{t-2}	-0.02	0.04	0.69	0.00	0.02	0.96	0.15	0.06	0.02	-0.02	0.03	0.61	-0.20	0.08	0.02	-0.08	0.03	0.02
ret_{t-3}	0.00	0.04	0.97	0.02	0.02	0.29	0.05	0.06	0.44	-0.07	0.03	0.02	-0.05	0.08	0.53	0.07	0.03	0.04
ret_{t-4}	-0.09	0.04	0.04	-0.01	0.02	0.55	-0.10	0.06	0.11	-0.02	0.03	0.54	-0.16	0.08	0.04	-0.04	0.03	0.19
ret_{t-5}	0.02	0.04	0.67	0.00	0.02	0.88	0.19	0.06	0.00	-0.03	0.03	0.34	-0.12	0.08	0.13	-0.02	0.03	0.47
ret_{t-6}	-0.07	0.04	0.10	-0.02	0.02	0.29	-0.09	0.06	0.14	-0.05	0.03	0.07	-0.03	0.08	0.73	0.03	0.03	0.35
ret_{t-7}	0.11	0.04	0.01	-0.03	0.02	0.10	0.11	0.06	0.07	0.00	0.03	1.00	0.13	0.08	0.09	-0.08	0.03	0.01
ret_{t-8}	0.01	0.04	0.85	0.01	0.02	0.67	-0.01	0.06	0.90	0.01	0.03	0.85	0.04	0.08	0.58	0.01	0.03	0.73
ret_{t-9}	-0.01	0.04	0.73	0.01	0.02	0.62	-0.01	0.06	0.82	0.04	0.03	0.17	0.05	0.08	0.50	-0.03	0.03	0.29
ret_{t-10}	-0.05	0.04	0.23	0.02	0.02	0.45	0.00	0.06	0.93	0.01	0.03	0.82	-0.05	0.08	0.51	0.05	0.03	0.14
$turn_{t-1}$	0.37	0.02	0.00	0.00	0.01	0.83	0.40	0.03	0.00	0.02	0.01	0.17	0.31	0.03	0.00	-0.01	0.01	0.61
$turn_{t-2}$	0.02	0.02	0.28	-0.02	0.01	0.13	0.02	0.03	0.49	0.00	0.02	0.76	0.01	0.04	0.72	-0.02	0.01	0.18
$turn_{t-3}$	0.08	0.02	0.00	0.01	0.01	0.58	0.08	0.03	0.01	0.00	0.02	0.79	0.06	0.04	0.09	-0.01	0.01	0.42
$turn_{t-4}$	-0.05	0.02	0.03	-0.03	0.01	0.01	-0.04	0.03	0.23	-0.04	0.02	0.01	-0.06	0.04	0.07	-0.01	0.01	0.38
$turn_{t-5}$	0.05	0.02	0.03	0.01	0.01	0.25	0.01	0.03	0.68	0.03	0.01	0.05	0.07	0.04	0.07	-0.01	0.01	0.40
$turn_{t-6}$	0.06	0.02	0.00	0.01	0.01	0.42	0.12	0.03	0.00	0.01	0.01	0.57	0.03	0.04	0.46	0.01	0.01	0.45
$turn_{t-7}$	-0.01	0.02	0.51	0.01	0.01	0.37	-0.06	0.03	0.03	0.01	0.01	0.58	0.02	0.04	0.59	0.02	0.01	0.15
$turn_{t-8}$	-0.08	0.02	0.00	-0.01	0.01	0.16	-0.06	0.03	0.05	-0.05	0.01	0.00	-0.10	0.04	0.01	0.02	0.01	0.14
$turn_{t-9}$	-0.03	0.02	0.13	0.00	0.01	0.89	-0.01	0.03	0.78	0.01	0.01	0.51	-0.06	0.04	0.09	0.00	0.01	0.95
$turn_{t-10}$	-0.07	0.02	0.00	-0.01	0.01	0.62	-0.05	0.03	0.07	0.00	0.01	0.86	-0.08	0.04	0.02	-0.01	0.01	0.42
cons	-0.10	0.02	0.00	0.04	0.01	0.00	-0.10	0.03	0.00	-0.06	0.02	0.00	-0.10	0.02	0.00	0.03	0.01	0.00
$volatility_t$	1.15	0.09	0.00	-0.33	0.04	0.00	1.01	0.12	0.00	-0.53	0.06	0.00	0.95	0.31	0.00	-0.74	0.13	0.00
$volatility_{t-1}$	-0.45	0.10	0.00	0.07	0.05	0.17	-0.27	0.13	0.04	0.09	0.06	0.16	-0.46	0.31	0.13	0.00	0.13	0.98
$volatility_{t-2}$	-0.36	0.10	0.00	0.00	0.05	1.00	-0.20	0.13	0.12	-0.01	0.06	0.89	-0.94	0.32	0.00	-0.22	0.13	0.10

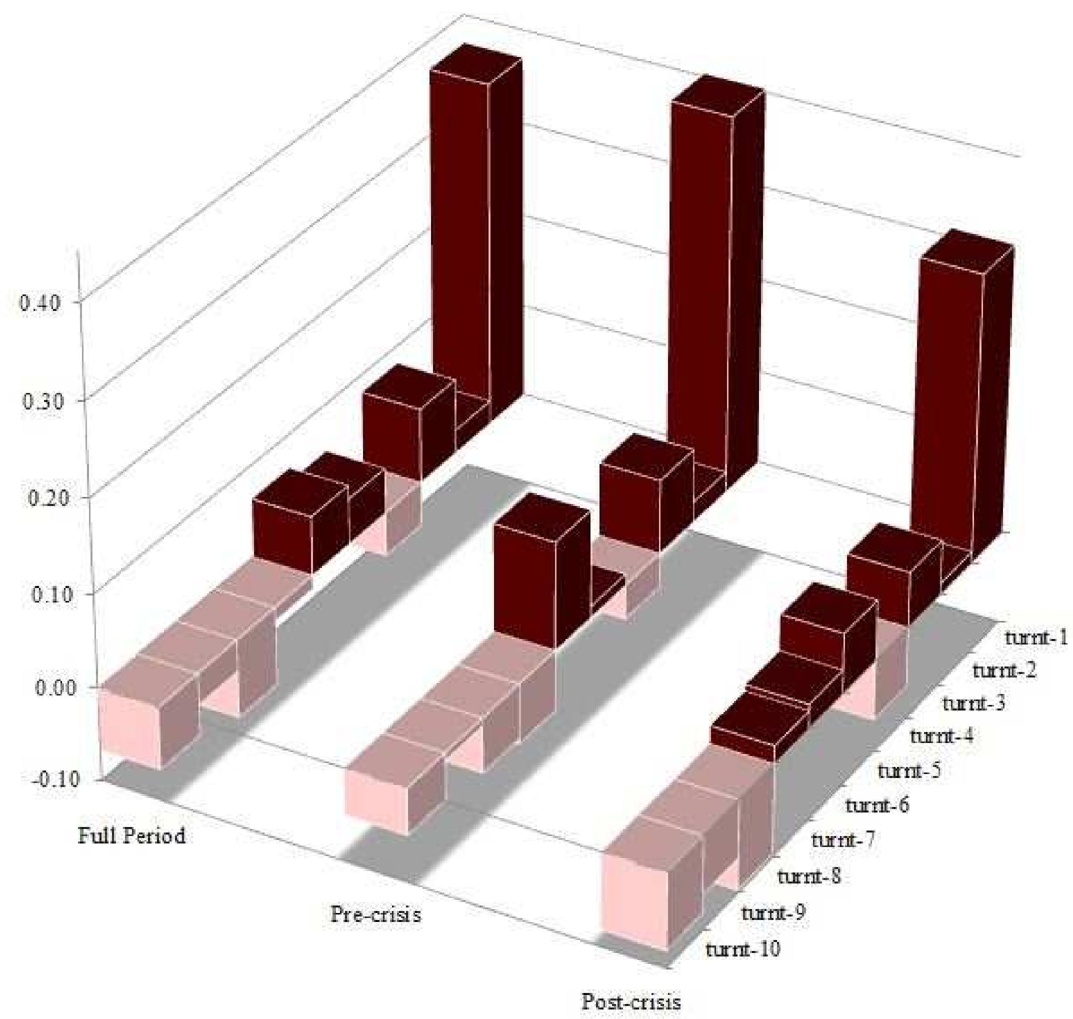


Fig. 2. Coefficients, lagged turnover explaining turnover, panel data, all periods.
This figure compares the coefficients between different lags of monthly turnover and samples in this study. The coefficients measure the effect of lagged turnover on the current turnover. Darker columns represent positive coefficients and lighter columns represent negative coefficients.

and the first subsample supports the overconfidence hypothesis and are similar to the findings of Statman, Thorley, and Vorkink (2006). The second lagged return coefficient of the pre-crisis subsample is significant and highly negative and it is followed by other negative coefficients. This reversed post-crisis effect is discussed in more detail later on the section including the separate post-crisis analysis.

The coefficients of the lagged returns explaining the turnover on the monthly level are summarised in Figure 3, and they present the key finding of this study. The X (category) axis is presenting the observed time period. The leftmost columns show the coefficients for the full period from June 2001 to December 2014, the middle columns for the pre-crisis period from June 2001 to December 2008, and the rightmost columns for the post-crisis period from January 2009 to December 2014. The Y (value) axis is the coefficient magnitude and the Z

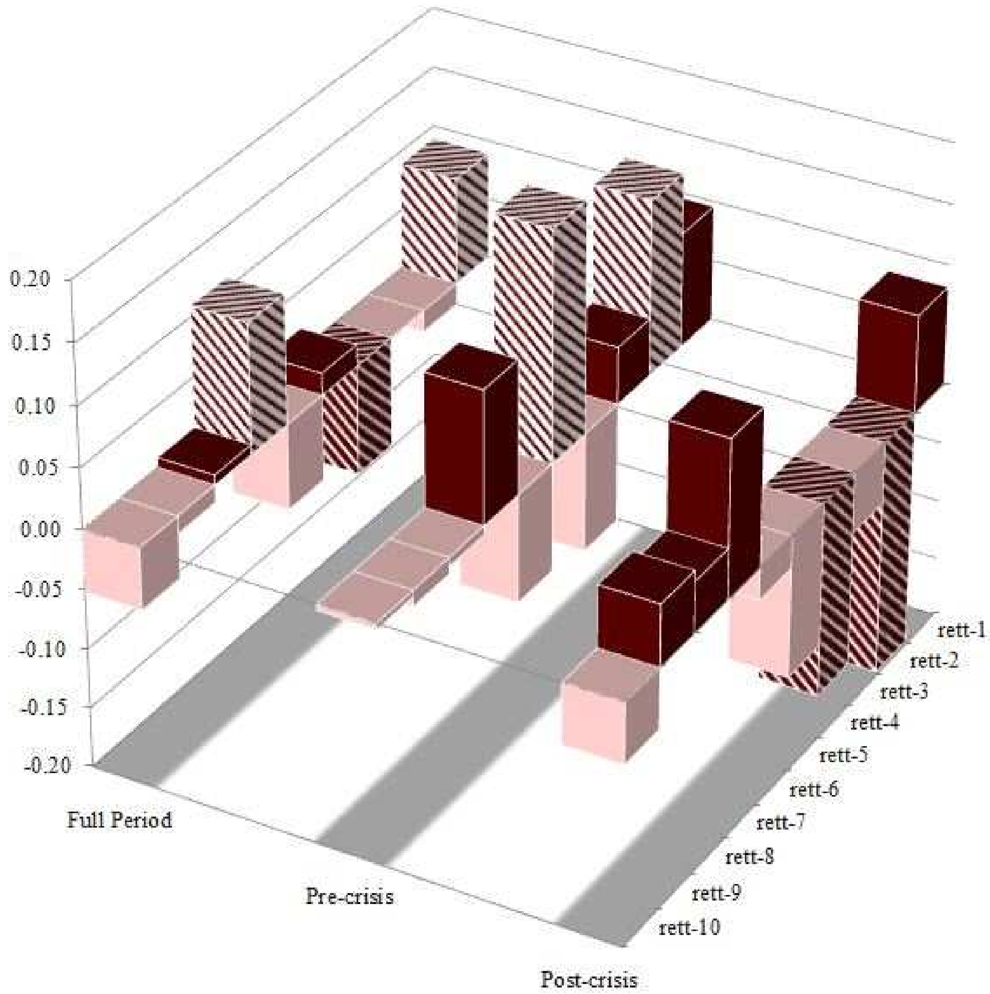


Fig. 3. Coefficients, lagged return explaining turnover, panel data, all periods, monthly.
This figure compares the coefficients between different lags of monthly return and samples in this study. The coefficients measure the effect of lagged returns on the current turnover. Darker columns represent positive coefficients, lighter columns represent negative coefficients, and all striped columns represent the coefficients that are significant at 5% level or less.

(series) axis marks the monthly lags from the current value. The dark columns represent positive and the light columns negative coefficients, and all striped columns represent the coefficients that are significant at 5% level or less. The overconfidence hypothesis is supported by the significantly positive striped columns in the full and pre-crisis periods. However, there is a clear change in the relation of return and turnover when the financial crisis has passed, even though the first lagged return coefficient seems to be positive for all periods and this observation is analysed next.

The first lag coefficients in Figure 3 for each period are positive and thus I observe the first four monthly lags also on a weekly level to see how these observations are formed. Figure 4 has the same chart area properties than Figure 3, but the lags presented on the Z axis are weekly lags instead of monthly lags. The weekly level analysis shows that there is a

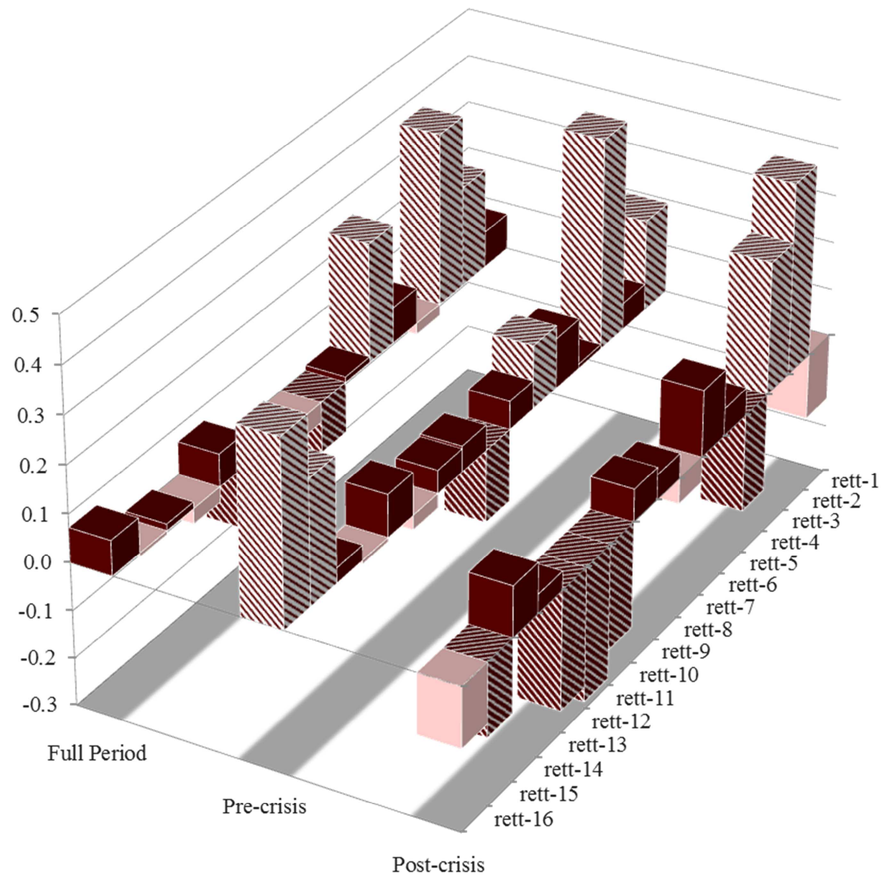


Fig. 4. Coefficients, lagged return explaining turnover, panel data, all periods, weekly.
This figure compares the coefficients between different lags of weekly return and samples in this study. The coefficients measure the effect of lagged returns on the current turnover. Darker columns represent positive coefficients, lighter columns represent negative coefficients, and all striped columns represent the coefficients that are significant at 5% level or less.

significant positive relation on all periods between lagged returns and trading activity, and this relation last over a month until the difference obtained already in monthly analysis starts to show. This finding is supporting Statman, Thorley, Vorkink (2006) findings, though for the shorter period of time than they observed, and this finding shows significant support for an immediate increase in trading after the market returns increase. This finding supports short-term overconfidence, and holds for all observation periods in the study. Approximately six weeks of lagged returns have a positive effect on the turnover during the full observation period.

As in Karpoff (1987), Table 3 reveals the contemporaneous volatility to have a large and positive significant effect on the turnover that has coefficients of 1.15, 1.01, and 0.95. Lagged values of the exogenous variable must be interpreted with caution since the autocorrelation in volatility is widely recognised. Coefficient estimates are very sensitive to the number of lags included in the exogenous control variable, and here I follow the Statman, Thorley, and Vorkink (2006) and add the contemporaneous observation and two monthly lags. In the weekly study, the number of lags used is eight weeks.

As is consistent with weak-form market efficiency, the dependent variable *ret* in Table 3 shows that lagged returns or turnovers are not able to predict the contemporaneous return, and only a few small significant coefficients are observed in the results. For example, the first lagged turnover coefficients explaining return are not significant and very small 0.00, 0.02, and -0.01 (with standard errors of 0.01, 0.03, and 0.01). The similar non-significant coefficients explaining the subsequent returns are found in weekly study as well as in the study with raw nondetrended turnover. To keep the scope of the study in the main hypothesis, I focus on the results related to the lagged returns affecting turnover in the subsequent sections.

I followed Statman, Thorley, and Vorkink (2006) by including the calendar month dummies for the full period panel data from January to December to the analysis. The results indicate that the trading activity is higher in the first trading months of a year and slightly drops during the summer months. These findings are not reported here or included in the base case study, since the inclusion does not affect any of the key findings.

4.1.2. Single index analysis

To get more detailed information about how the results presented in the panel data section are actually formed, Figures 5, 6, and 7 visualise the VAR coefficients on the index level for the full period and the two subsamples, respectively. The figures contain the coefficients of the fourteen separate stock indexes and the panel data (visualised previously in Figure 3) for *turn* as endogenous variable with monthly lags of *ret* up to ten months. The Y (value) axis is the coefficient value and, for the comparison purposes, these axes are scaled to have the same minimum and maximum values for each observation period. The X (category) axis presents the index in question, and the rightmost category represents the pooled data including all indexes. The Z (series) axis marks the monthly lags, and the first month is located in the back and the lags are increasing to the front, since the first lag is assumed to have the highest impact (largest coefficient) on the current value. The dark columns mark again the positive coefficients and the lighter columns the negative coefficients. The striped columns mark each coefficient that is significant at 5% level or less. To keep the scope, the single index results for the current return as a dependent variable are not reported here, but the results are similar to findings of Statman, Thorley, and Vorkink (2006), supporting the weak-form market efficiency. There are no large differences between different time periods or indexes.

To observe the results related to the overconfidence hypothesis, Figures 5, 6, and 7 visualise how the current turnover is affected by monthly lagged returns. In the full period graph, Figure 5, there are only a few significant coefficients, and all of the coefficients are smaller than 0.40. Only a half of the significant coefficients are positive. This graph hardly gives any support for the overconfidence hypothesis, not even an individual country shows any strong effect of turnover following the monthly returns. For the CAC, ISEQ, MADX, and UKX there are no significant coefficients, and the significant first lags are in ASE, DAX, KFX, and WIG indexes. The separate VAR analyses for the two subsamples reveal the difference between the pre- and post-crisis time that actually causes the larger significant effects for the full period to offset.

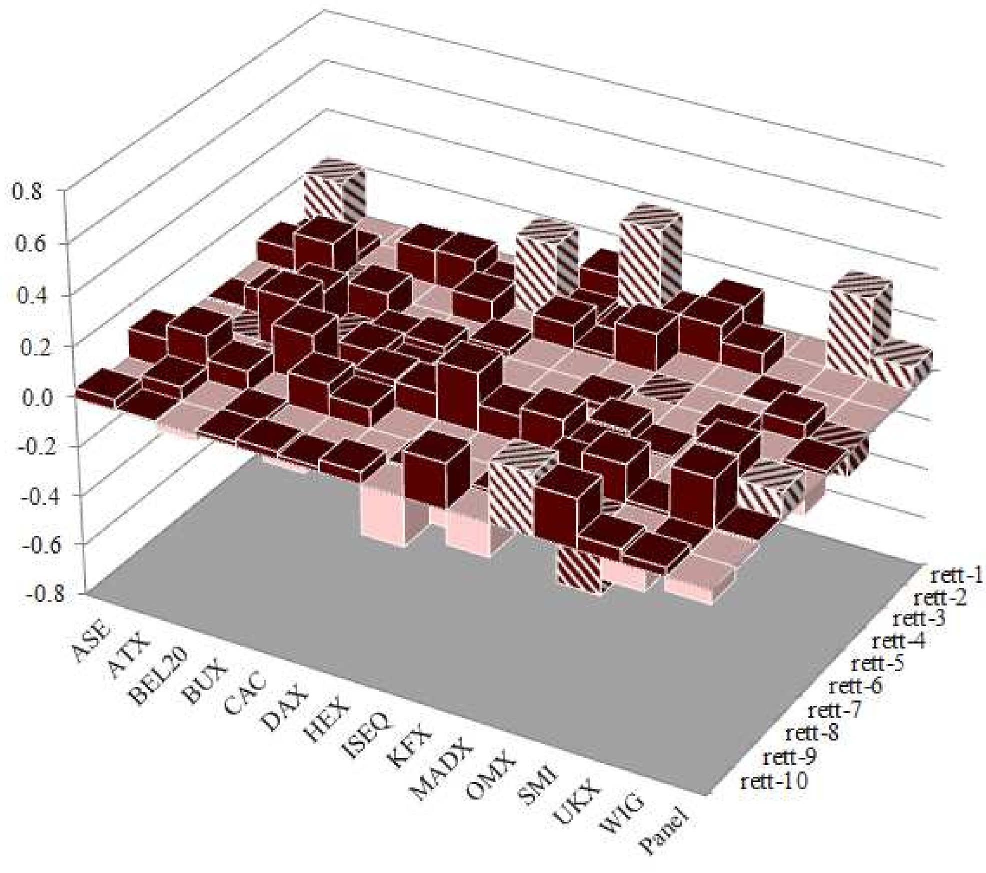


Fig. 5. Coefficients, lagged return explaining turnover, single indexes, full period.
This figure compares the coefficients between different lags of monthly return and indexes in the full period from June 2001 to December 2014. The coefficients measure the effect of lagged returns on the current turnover. Darker columns represent positive coefficients, lighter columns represent negative coefficients, and all striped columns represent the coefficients that are significant at 5% level or less. The index ticker names are presented in Table 1.

In Figure 6 representing the pre-crisis stock market from June 2001 to December 2008, there are many significant coefficients and the vast majority of them are large and positive. Twelve of the significant coefficients are larger than the 0.40 that is the upper limit for the full period coefficients. However, the first lags do not seem to have substantially larger effect to the contemporaneous turnover than the later lags. Nonetheless, this finding supports the overconfidence hypothesis, as the current turnover is followed by increased lagged monthly returns. The ASE index shows the strongest support for the overconfidence hypothesis with three highly significant first lags. HEX, KFX, SMI, and UKX do not have any significant coefficients and thus the support for overconfidence or against it is not found.

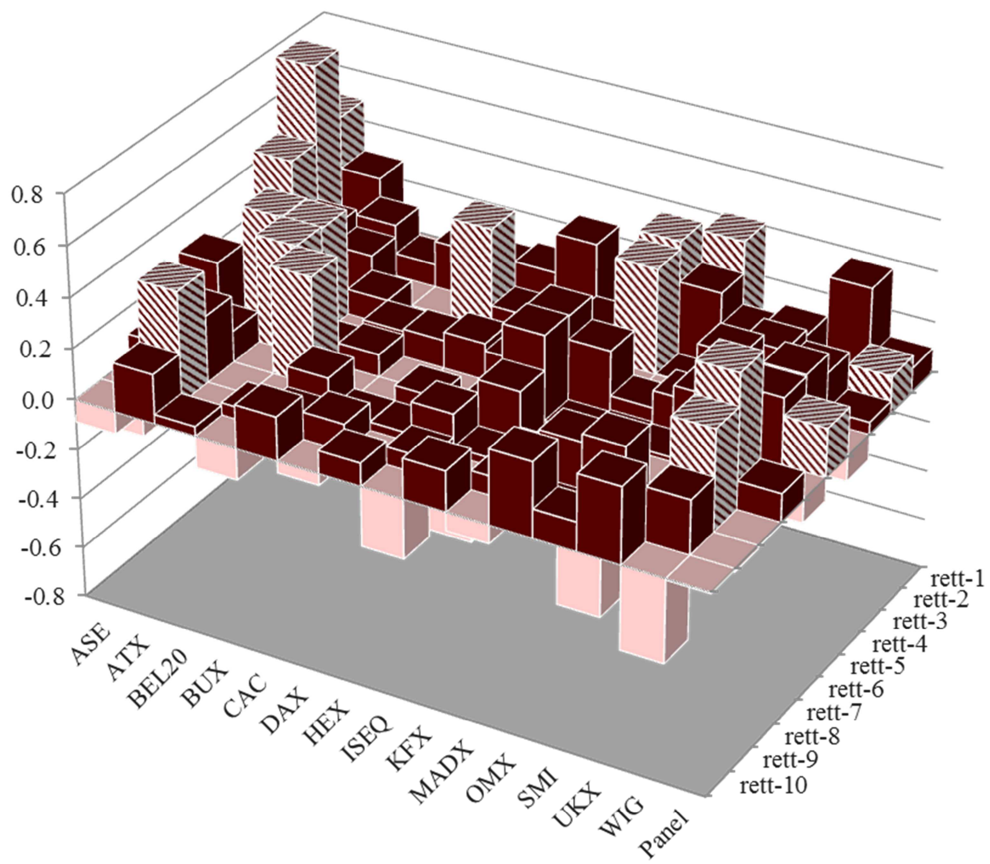


Fig. 6. Coefficients, lagged return explaining turnover, single indexes, pre-crisis.
This figure compares the coefficients between different lags of monthly return and indexes in the pre-crisis period from June 2001 to December 2008. The coefficients measure the effect of lagged returns on the current turnover. Darker columns represent positive coefficients, lighter columns represent negative coefficients, and all striped columns represent the coefficients that are significant at 5% level or less. The index ticker names are presented in Table 1.

In Figure 7, the second subsample representing the post-crisis stock market from 2009 to 2014, the coefficients look completely different. The vast majority of the significant coefficients are actually negative, indicating reversed relationship between lagged returns and contemporaneous turnover compared to Figure 6. These negative values are observable in Appendix C with other index-specific coefficients and *p*-values since the 3D graphs show them only partially. The post-crisis finding of a large amount of negative coefficients goes against the overconfidence hypothesis, but this does not imply that there would not be any overconfidence in the market after crisis. Potential explanations for this post-crisis finding and decreasing trading volume are presented later. Notably, despite the large amount of negative significant coefficients, there are still six positive first lag coefficients, even though they are not significant. ASE index that previously showed strong support for overconfident trading during the pre-crisis period does not have any significant coefficient in the post-crisis analysis, and most of its coefficients are negative. BEL20 and OMX indexes show the strongest support against the overconfidence hypothesis, having four significantly negative coefficients during the post-crisis period.

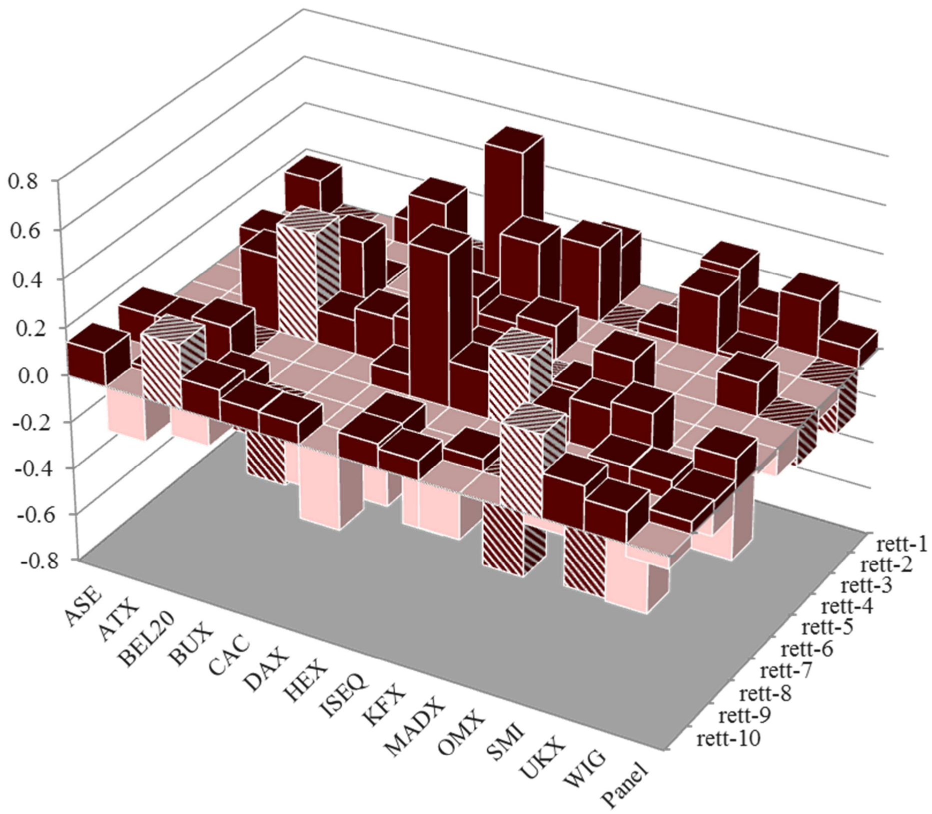


Fig. 7. Coefficients, lagged return explaining turnover, single indexes, post-crisis.
This figure compares the coefficients between different lags of monthly return and indexes in the post-crisis period from January 2009 to December 2014. The coefficients measure the effect of lagged returns on the current turnover. Darker columns represent positive coefficients, lighter columns represent negative coefficients, and all striped columns represent the coefficients that are significant at 5% level or less. The index ticker names are presented in Table 1.

4.2. Impulse response function results

As explained in the methodology section, Table 3 showing the VAR coefficients does not tell the complete truth about the impact of exogenous variable observations. All of the VAR coefficient estimates are used in the impulse response functions (IRF) to trace the impact of the shock in residual, which has a magnitude of one standard deviation. This way it is possible to trace the impact of each endogenous variable shock to each other, that is to say, how return shocks affect returns and turnovers, and turnover shocks affect returns and turnovers. Even though the VAR analysis output contains results between all variables and many impulse response functions could be obtained, only the effects of return shocks are presented thoroughly here.

4.2.1. Panel data impulse response functions

Figure 8 presents the impulse response function of a turnover shock affecting the current turnover for the following months, and Figures 9 and 10 present the impulse response functions of a return shock affecting the current turnover on the monthly and weekly level, respectively. All impulse response functions are executed after the panel VAR analysis, in which all the indexes are combined. The figures also show 95% confidence boundaries for each function. Figure 8 shows the effect of one standard deviation shock in turnover on the following months' turnover values. The previously recognised autocorrelation is again visible, and the positive relation seems to last many months after the shock. The confidence interval of the function is very narrow and thus the size of the effect is known quite precisely. This relation is shown only for the full period and on the monthly level, since the findings are very similar with the two subsamples and on the weekly level. Due to the log transformation of the *turn* variable, the vertical axis of each IRF figure shows the percentage change in monthly or weekly turnover relative to the non-shocked value. For example in Figure 8, I observe similar results than Statman, Thorley, and Vorkink (2006), as the turnover shock results approximately 3.0% increase in the following month's turnover, and the cumulative increase during the following six months is 11.0%. The consistent results in turnover impulse response function imply that the sequential turnover patterns and behaviour are similar in the U.S. and Europe. Notably, the detrended turnover series forces impulse response functions to zero over time. The non-detrended and weekly level results are unreported, but indicate mainly positive and declining values for all 24 months before the effect dilutes.

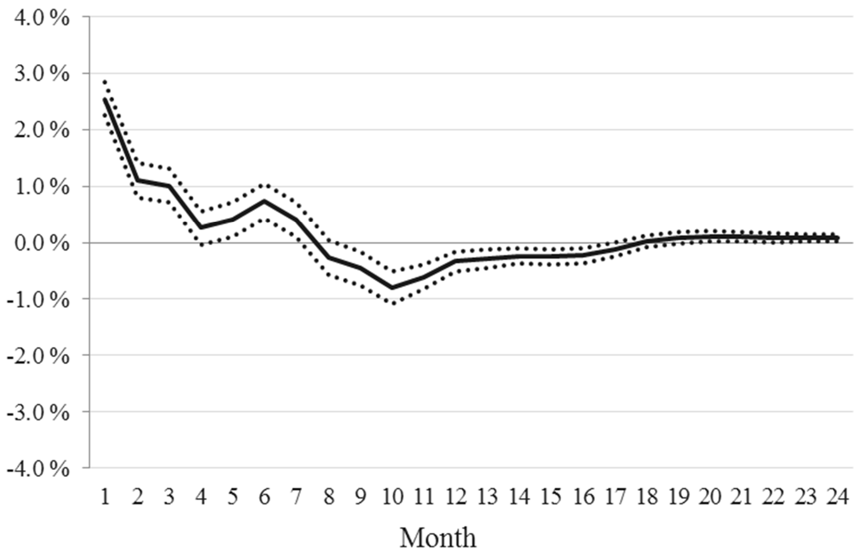
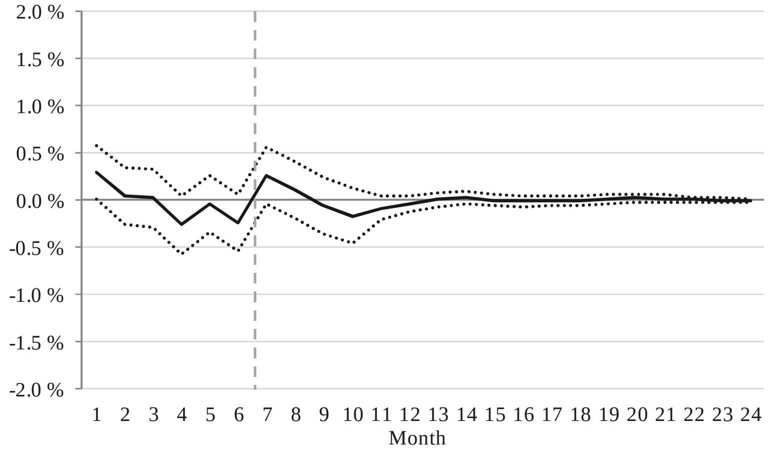
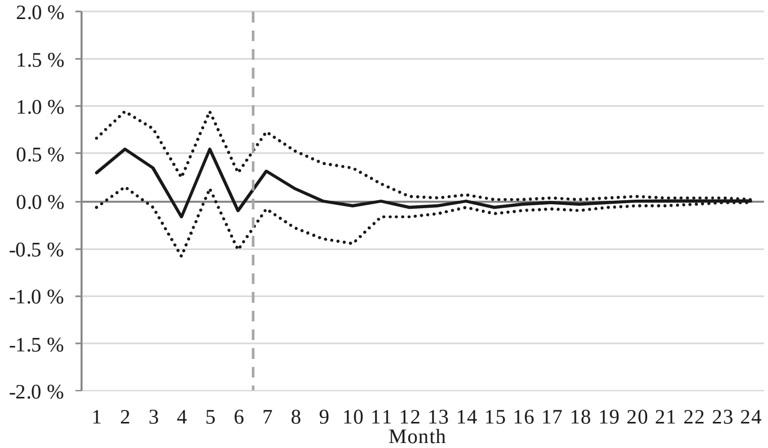


Fig. 8. Impulse response function, turnover response to turnover shock, full period.
Impulse response functions with 95% confidence intervals. This figure shows turnover response to a turnover shock on the monthly level for the full period from June 2001 to December 2014. The shock to the residual e_{turn} has a magnitude of one standard deviation.

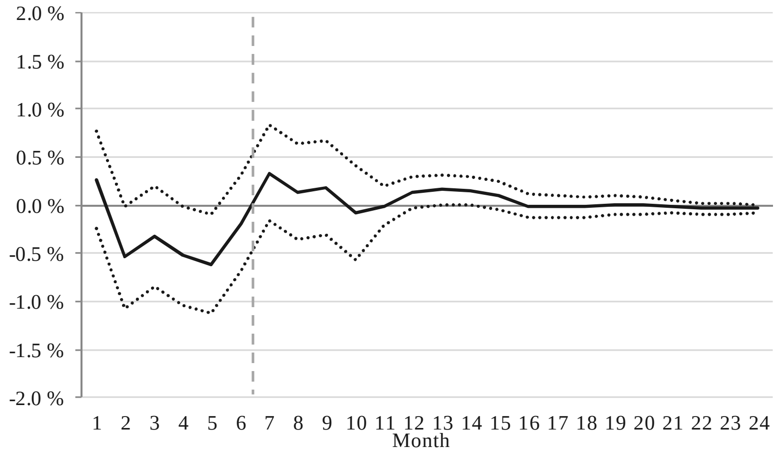
Figure 9, Panels A, B, and C, shows the impulse response function graphs for the full period and the subsamples in the case of the return shock impulse affecting the contemporaneous turnover. The function is executed on the monthly level, and the first six months separated with a dashed line are shown on the weekly level in Figure 10. The function results are observed after the panel data VAR analysis for each time period. Statman, Thorley, and Vorkink (2006) find evidence for the overconfidence hypothesis from this analysis, and the findings here reveal similar results but with smaller effects. In Figure 9 the shock has a very small positive, less than 0.5% effect during the following month in all observation periods, and especially mild response over months for the full period (Panel A), since the cumulative six months effect is 0%. The pre-crisis period responses are clearly more positive in Panel B, supporting the overconfidence hypothesis with cumulative six months effect of 1.5%. The responses on the post-crisis period (Panel C) reveal contrary effects, as the cumulative six months response is -1.9%. This supports the previous finding that the overconfidence hypothesis does not hold strongly within European national stock exchanges in the full observation period, and that the pre-crisis period reveals more support for the overconfident investing behaviour than the post-crisis period. Later I will discuss possible explanations to this finding compared to Statman, Thorley, and Vorkink (2006), who find very high accumulated turnover response to a return shock over the first six months.



Panel A: Turnover response to return shock, full period



Panel B: Turnover response to return shock, pre-crisis 2001-2008

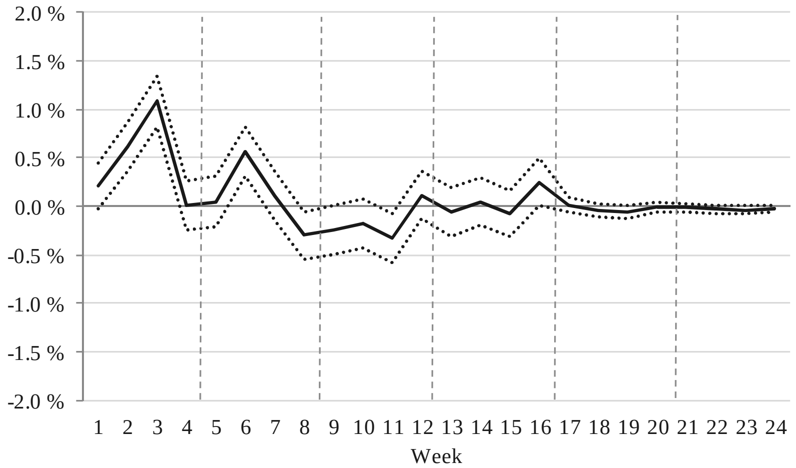


Panel C: Turnover response to return shock, post-crisis 2009-2014

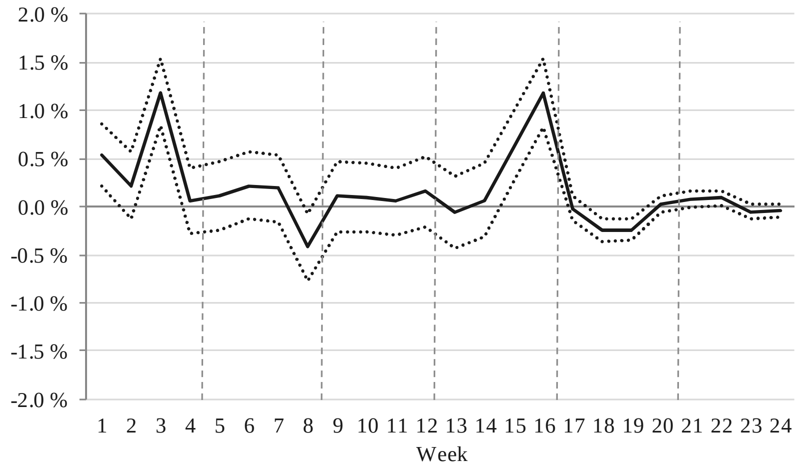
Fig. 9. Impulse response function, turnover response to return shock, monthly.
Impulse response functions with 95% confidence intervals. This figure shows monthly turnover response to a return shock on the monthly level for the full period from June 2001 to December 2014 (Panel A), the pre-crisis period from June 2001 to December 2008 (Panel B), and the post-crisis subsample from January 2009 to December 2014 (Panel C). The shock to the residual e_{ret} has a magnitude of one standard deviation. The dashed line separates the first 6 months observations, and this period is shown on the weekly level in Figure 10.

On the weekly level impulse response functions I analyse the return shock affecting the weekly turnover during the first six months, that is to say, 24 weeks. It should be noted that months are generally longer than four weeks and thus the 24 week period does not exactly match the six month period. Figure 10 shows how the turnover is affected on a weekly basis during each observation period. Interestingly, eight weeks from the shock the impulse response functions give very similar results for all observation periods. The cumulative effects of the shock on the weekly turnover are 2.35%, 2.10%, and 1.42% for the full, pre-crisis, and post-crisis periods, respectively. The largest change in responses is shown from the week 9 to 16, as the respective cumulative effects on the weekly turnover are 0.00%, 2.22%, and -2.16%. These results are not directly comparable to the monthly impulse response function results, but the direction of the effects are the same from third week onwards, that is to say, positive response during the-pre crisis period and negative response during the post-crisis period.

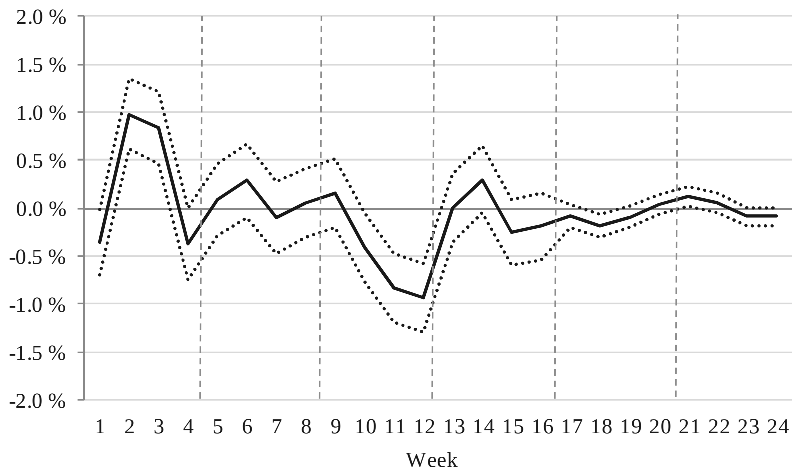
Due to the scope of the study I do not present the impulse response function graphs for the response of the return to a one standard deviation shock in *turn* and *ret*. In these cases, the measured change is the difference in return compared to the average return. The overall results of all observation periods are not significantly different from zero, and the finding is consistent with weak-form market efficiency as in the VAR analysis where the current return is not explained by lagged return on lagged turnover. This finding is similar to the findings of Statman, Thorley, and Vorkink (2006).



Panel A: Turnover response to return shock, full period



Panel B: Turnover response to return shock, pre-crisis 2001-2008



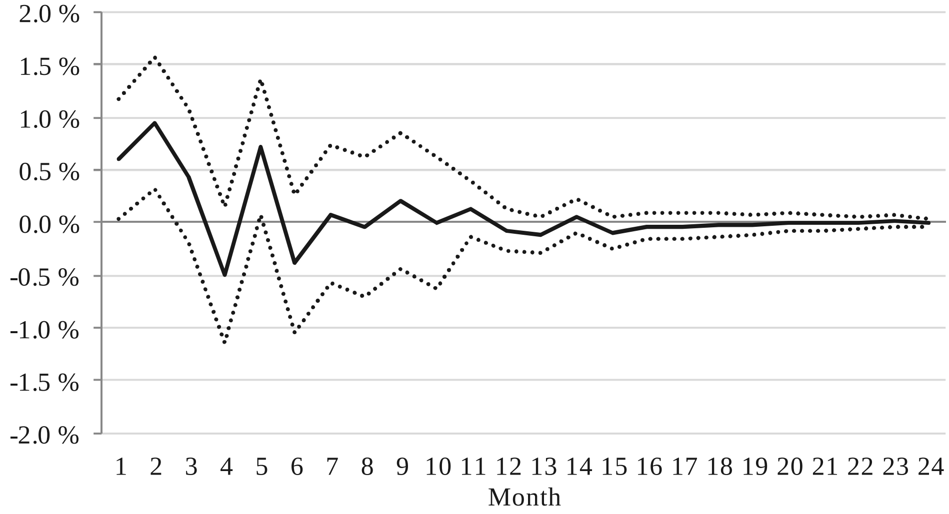
Panel B: Turnover response to return shock, post-crisis 2009-2014

Fig. 10. Impulse response function, turnover response to return shock, weekly.
Impulse response functions with 95% confidence intervals. This figure shows weekly turnover response to a return shock on the weekly level for the full period from June 2001 to December 2014 (Panel A), the pre-crisis period from June 2001 to December 2008 (Panel B), and the post-crisis subsample from January 2009 to December 2014 (Panel C). The shock to the residual e_{ret} has a magnitude of one standard deviation. The dashed lines separate the 4 week periods' observations from each other.

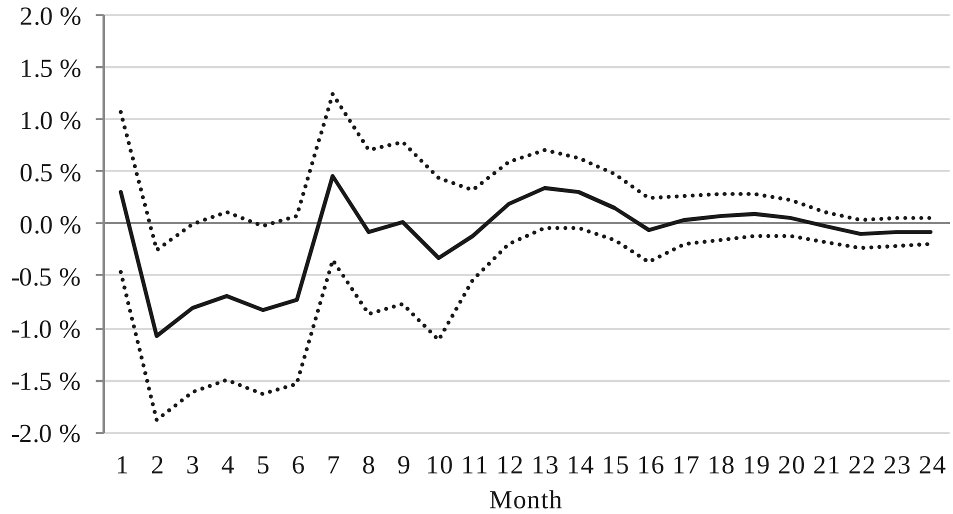
4.2.2. Pre- and post-crisis impulse response functions comparison

Due to the large amount of indexes in the study, there is also a possibility to test response magnitudes with different index combinations. To visualise the pre- and post-crisis difference more clearly, I collected a separate subsample of indexes that have a positive first-lag effect on turnover after a return shock during the first subsample period in the monthly level analysis. Appendix D shows the pre-crisis impulse response functions for the single indexes, and due to the large amount of indexes, the single index impulse response functions for the full period or the post-crisis data are not reported in this study separately. In other words, I study separately the countries having the strongest first monthly lag implications of overconfidence before the crisis and see how the effect changes post-crisis. The indexes in the sample are ASE (Greece), ATX (Austria), ISEQ (Ireland), KFX (Denmark), MADX (Spain), OMX (Sweden), and WIG (Poland). The impulse response function results of the pooled data of this rebuilt index list are shown in Figure 11. The figure shows how one standard deviation shock in return affects the monthly turnover before and after the financial crisis in 2008.

Comparison of Panels A and B of Figure 11 confirms the difference in monthly turnover responses after a return shock during the pre- and post-crisis periods witnessed already in Figure 9. The cumulative positive effect during the first six months of the pre-crisis period is 1.8% and over 5% with the upper 95% confidence bound. The values for the post-crisis period are -3.8% and -8.6% with the lower 95% confidence bound. This finding gives additional support for the results of the VAR analysis and impulse response functions executed for the sample including all fourteen indexes. The pre-crisis findings are interpreted as a support for the overconfidence hypothesis, and it is similar to previous findings of Odean (1998a), Gervais and Odean (2001), and Statman, Thorley, and Vorkink (2006) who find that overconfident traders increase their trading after observing increasing returns. The results of the post-crisis period are not giving implications of the overconfidence, and this effect is discussed in Section 5.



Panel A: Turnover response to return shock in the panel of selected indexes, pre-crisis 2001-2008



Panel B: Turnover response to return shock in the panel of selected indexes, post-crisis 2009-2014

Fig. 11. Impulse response function, turnover response to return shock, subsamples.
Impulse response functions with 95% confidence intervals. This figure shows turnover response to a return shock for the pre-crisis period from June 2001 to December 2008 (Panel A), and the post-crisis subsample from January 2009 to December 2014 (Panel B). The shock to the residual factor e_{ret} has a magnitude of one standard deviation. The both panels include the stock indexes ASE, ATX, ISEQ, KFX, MADX, OMX, and WIG. These indexes are selected based on the positive first lagged return coefficient explaining turnover. The coefficients are observed in the impulse response functions executed for the separate indexes for the pre-crisis period (2001-2008), and these functions are shown in Appendix D.

4.3. Investor sentiment and trading volume

There is only a limited amount of research conducted on the relation of investor sentiment and trading volume, but in their working paper Lei, So, and Zou (2012) find a positive relationship between these two. They state that noise traders should affect the market as they trade, and thus the trading volume should have a relationship with the noise. They use the volatility index VIX to measure the sentiment in the market, to assess the impact of noise traders participating in trading. Due to these previous findings I will also study separately how adding the investor sentiment to the original VAR analysis affects the results obtained. If the level of general investor sentiment gives additional information about the relation of lagged stock returns and trading activity, then adding the investor sentiment to the analysis should decrease the coefficients of lagged returns explaining the current turnover.

Due to the lack of comprehensive European volatility index, I will use The Economic Sentiment Indicator as an indicator for the investor sentiment. The index is calculated from the European Commission's Business and Consumer surveys and contains weightings for industrial confidence, service confidence, consumer confidence, construction confidence, and retail trade confidence. Figure 12 visualises the investor sentiment in Europe during the

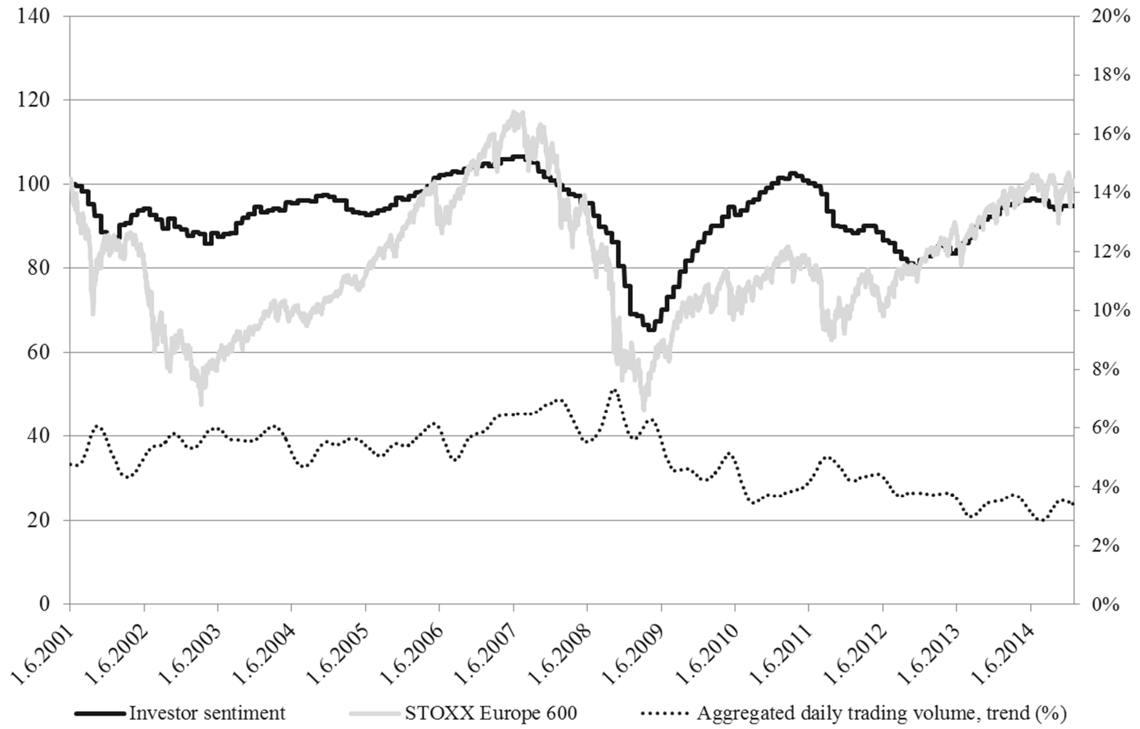


Fig. 12. Investor sentiment, stock market performance, and trading volume.
Daily investor sentiment (EUESEMU Index) retrieved from Bloomberg: "*The Economic Sentiment Indicator is calculated from the European Commission's Business and Consumer Surveys. It is constructed from the following indicators: the industrial confidence indicator (40%), the service confidence indicator (30%), the consumer confidence indicator (20%), the construction confidence indicator (5%), and the retail trade confidence indicator (5%).*" For the comparison, figure shows the STOXX Europe 600 performance (SXXP Index). SXXP and EUESEMU Indexes are scaled 1.6.2001=100. Trading volume is aggregated from the daily turnovers of the 14 indexes by summing the *equally weighted* daily index turnovers. The turnover trend in the Figure is calculated from these values by using the Hodrick-Prescott (1997) algorithm (with the penalty parameter λ=270,400).

observation period of the study. For the comparison, I also added the values of the STOXX Europe 600 index value, of which shape is close to the separate national exchange indexes included in the VAR analysis (shown in Appendix A). The values for the two indexes are retrieved from Bloomberg. The investor sentiment seems to follow the market performance very closely, and thus it might not provide any additional value to the analysis, since the change in market return with several lags is already considered in the main results.

I executed the monthly VAR analysis for the separate indexes as previously but added the current monthly change in the investor sentiment index to the analysis with two lags, similar to the return volatility control variable in the base case model. Figure 13 shows the pattern of changes in the investor sentiment during the observation period. The changes in the investor sentiment also follow the return change pattern, and the same pattern is visible especially before and after the financial crisis in 2008 (see Appendix B for monthly returns). Notably, the average of the changes in the investor sentiment is very close to zero, meaning that the sentiment changes offset each other over time, since the investor sentiment cannot increase persistently. During the pre-crisis subsample from 2001 to 2008, the investor sentiment decreased 29 percentage points and during the post-crisis subsample from 2009 to 2014, increased 24 percentage points, returning to the levels of 2004.

For the full period and both subperiods, the VAR R^2 values remain almost the same, and the coefficients of the change in sentiment are not significant. The VAR results are not heavily affected by the introduction of the new variable, which implies that the market return itself is already including similar information about the sentiment in the stock market. This finding is supported for example by Brown and Cliff (2004) who find that past market returns are an important determinant of the investor sentiment and thus the sentiment is highly correlated with contemporaneous market returns.

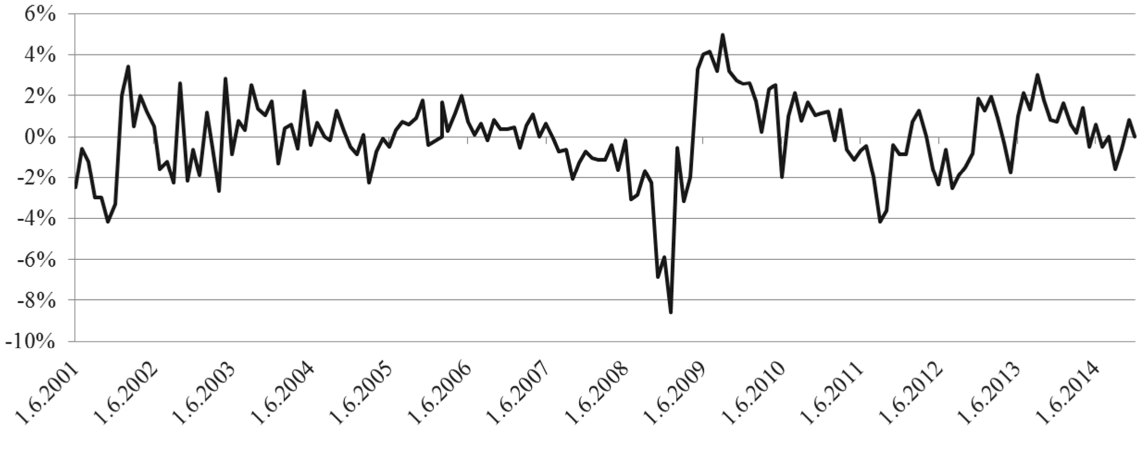


Fig. 13. Monthly changes in investor sentiment.
Figure shows the monthly changes of the investor sentiment (EUESEMU Index) for the full observation period.

5. Post-crisis analysis

In the light of the results presented for the full observation period and the two subsamples before and after the financial crisis, in this section I will take a closer look to the events after the financial crisis in 2008. Directly by comparing the previously presented Figure 1 turnover graphs with Appendix A index performances, one can see that after the financial crisis the trading volumes have drastically decreased in the traditional stock exchanges, even though these indexes have enjoyed market-wide increases in returns since 2009. Due to the changed market environment in the last decade, the continuous trading activity decreasing in national exchanges cannot blindly be blamed on the vanished overconfidence in the market, but rather on the changed market environment Thus as an additional part of the study, I will discuss briefly other drivers of the decreasing stock trading in the European national exchanges.

The post-crisis downhill in the stock turnover is a rather recent phenomenon, and thus there are only a few authors to contribute academically on the issue. However, the topic is widely dealt with in media, and these media insights are analysed in more detail in this section. To understand the idea, in 2011, the Wall Street Journal wrote that multilateral trading facilities (MTFs) offering pan-European stock trading are shaking the positions of the national European stock exchanges. MTFs offer faster trading and lower costs and this has consequently made the incumbent market players to decrease their trading fees and upgrade their trading system technologies. In addition, the Financial Times wrote in 2013 that money on the European markets is allocated merely to cash and fixed income rather than stocks, the drought of mergers and acquisitions causes low volumes, and that low interest rates still favours the debt market over equity capital. Still in 2014, Reuters wrote about decreasing post-crisis trading volumes and revenues.

5.1. Decreasing and shifting trading volume

There are two possible explanations for the decreasing stock turnover that is seen in Figure 1. The first reasoning concerns the market as a whole and refers to the effects of the crisis on the stock turnover, and the second reasoning concerns the decrease especially in the traditional exchanges, due to the alternative trading venues appearing to the market. The detailed interrelation between the crisis, regulation, emergence of alternative trading venues, and trading volume is not analysed in more detail in this study, but I observe bilateral relations between some of these variables.

The increased regulation is a clear consequence of the crisis itself, and the alternative trading venues have increased their market share, as the new regulatory environment has placed new rules for trade transparency, and this has been done partly at the cost of the traditional trading venues. Figure 14 presents the annual value of share trading in the selected European stock exchanges before and after the crisis. The data include fourteen European regulated stock exchanges and it is collected from the World Federation of Exchanges (WFE) (It should be noted that the indexes are not the same than in the base case analysis of this study). The figure implies that the turnover in the National Exchanges has drastically decreased after 2008. However, when the trading in BATS Chi-X Europe is added to the total trading value of the traditional exchanges, the trading seems to climb back to its original levels. BATS Chi-X Europe is the first multilateral trading facility in Europe that received a status of Recognised Investment Exchange (RIE) in 2013[4]. With these facts one can argue that actually the outlier may not be the decreasing trading volume we have witnessed post-crisis, but rather the pre-crisis increase caused by the development of electronic trading systems.

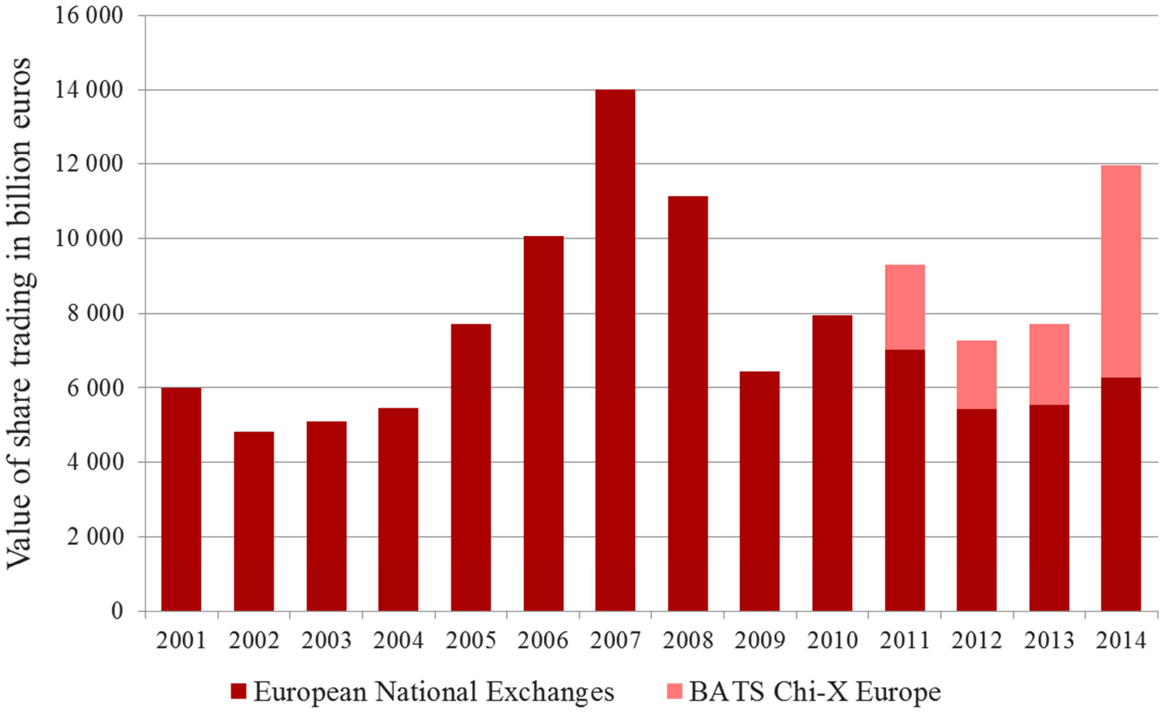


Fig. 14. Annual stock trading value, full period.
Summary of the value of shares traded in 14 European regulated stock exchanges in addition to the BATS Chi-X Europe, which is, since 2011, included in the data after BATS acquired Chi-X Europe. The data is collected from the World Federation of Exchanges (WFE) Annual Query Tool and includes all the European indices that are WFE member exchanges and have data available during the observation period. Notably, for this reason, the indexes are not exactly the same than in this study. The non-euro values in the original data are converted to euros using the annual average of each exchange rate retrieved from Bloomberg. Data source: www.world-exchanges.org.

[4] www.batstrading.co.uk

The Federation of European Securities Exchanges (FESE) has been the first to publish the European Equity Market Report since 2008, after the introduction of the MiFID regulation. The report gathers data from all Regulated Market operators and Multilateral Trading Facilities which are recognised as FESE members in the European equity market. The report enables accurate comparison between trading venues in the terms of turnover on monthly basis from January 2009 to January 2015. On the report, turnover values are grouped according to the market type, Regulated Market (including traditional stock exchanges) or Multilateral Trading Facility. It should be noted that the largest decreases in trading happened already before the FESE data starts. Figure 15 presents the post-crisis development of European equity market reported by FESE, and the data is shown on a monthly level. Note that the BATS Chi-X Europe is categorised as MTF in the figure, even though it became a regulated market operator in 2013.

The implication of Figures 13 and 14 is that the trading volumes tumbled due to the financial crisis and the total stock market volume despite of the exchange type. However, the recovery of the overall stock trading has not been seen in the traditional exchanges but rather in the alternative trading venues that have entered the market and increased their market share recently. Only in 2012, almost five years after the crisis, it seems that also the continuous decrease in the traditional exchanges has stopped.

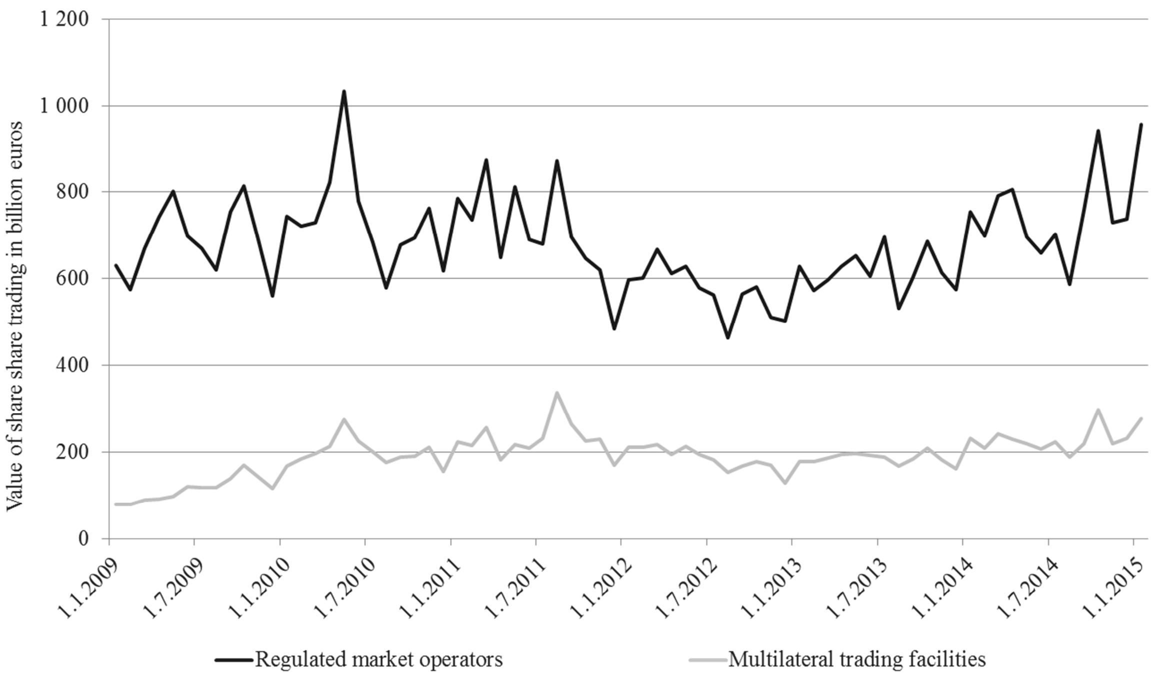


Fig. 15. Monthly stock trading value by market operator types, post-crisis.
This figure shows the division of share trading value between regulated market operators and multilateral trading facilities in Europe. The data is collected from the Federation of European Securities Exchanges (FESE). Note that as of 20th May 2013, BATS Chi-X Europe has become a Recognised Investment Exchange (Regulated market), but here it is included to MTF category for the whole period, since it does not represent the traditional stock exchanges in this study. Data source: www.fese.eu.

5.2. Media insights of decreasing trading volume

Table 4 summarises chronologically the topics discussed in media about causes of decreasing trading volume after the financial crisis in 2008. The exact measures and definitions of trading volume in the texts are unknown, but it is assumed that the overall volume in traditional exchanges has decreased in all general volume measures and thus the results are comparable. I do not take into account here that some of the causes are closely related to each other, but the causes are picked only according to the wording used in the text. The texts are collected from the web pages of the publishers mentioned in the table, and the full reference list of the articles is shown in Appendix E.

The table shows that the topics discussed over years after the crisis have regularly changed in the media. The majority of the topics appeared well after the crisis started, in 2012, when the media started to raise up the topics concerning lack of investor confidence and shifting to other asset classes from equities. Also unstable economic conditions appeared to the media after the long-standing European debt crisis. After 2012 the stricter regulation has not been a hot topic, but rather its consequence, off-exchange trading.

"*Traders are sitting on their hands*" is a widely used phrase in the post-crisis media in all of its forms. The stricter regulation is appearing in many forms, for example, tighter capital requirements of Solvency II and Basel III are seen as a global response to the financial crisis. Credit Suisse report from 2012 is dividing the turnover affecting factors to seasonal and structural. The seasonal factors including equity allocation, active turnover, hedge fund leverage, and corporate activity are driving the volumes down even though structural factors such as high-frequency and algorithmic trading made possible by new technologies are increasing it. However, in the U.S., the structural factors are not able to increase the total trade amount. The huge shift from equities is explained by increased trading of equity futures and options, ETFs, and bonds, but large bond redemptions and lowering coupon payments are seen as a good thing for equity volumes. The decreasing volumes of traditional exchanges are blamed to the off-exchange operations, but also their volumes were slowing down after the crisis. The traditional exchange trading is maintained due to the fact that still many operations such as IPOs, secondary offerings and a range of derivatives trading are operated via them.

Table 4. Media insights of decreasing trading volume, post-crisis.

Table shows in chronological order the topics discussed in media concerning the decreasing stock trading volume after the financial crisis. The texts are collected via Google Search (www.google.com). See the full list of reference in Appendix E.

		Causes of the low stock trading volume after the crisis						
Date	**Publisher**	**Stricter regulation**	**Lack of investor confidence**	**Shifting to other asset classes**	**Off-exchange trading**	**Unstable economic conditions**	**Taxation issues**	**Low M&A and IPO levels**
07/2007	Bloomberg	x		x	x			
10/2008	Traders Magazine	x			x			
05/2011	Traders Magazine	x			x			
06/2011	BlackRock	x			x			
10/2011	The Wall Street Journal	x			x			
01/2012	Bloomberg	x	x	x		x		
04/2012	CNBC	x	x	x				
05/2012	Reuters	x	x			x	x	
08/2012	Credit Suisse	x		x		x		x
07/2012	The Wall Street Journal		x			x		
06/2012	The New York Times		x	x	x	x		
09/2012	Pricemetrix					x		
01/2013	Financial Times		x	x		x		x
02/2013	Business Insider			x				
05/2013	The Economist		x	x	x	x		x
10/2013	Reuters	x			x	x		
07/2014	MarketWatch		x	x	x			
11/2014	Thomson Reuters	x			x			

6. Discussion and conclusion

Academia has widely agreed that the trading volume witnessed in the markets cannot be justified by rational motives such as portfolio rebalancing or hedging needs. The trading activity changes not only with different rational and behavioural empirical factors but also with institutional determinants. The one part of the empirical research has tried to find a relation between market performance and trading activity. The formalised theories of investor overconfidence have recently tried to explain overconfident investor behaviour associated with market performance. Research has created a proposition that investors become overconfident after increasing market returns and increase their trading activity. This behaviour is due to the investors associating the higher returns to their abilities to pick stocks. Contrarily, decreasing market returns make investors less confident and consequently make them decrease trading. So far, empirical research has not presented a lot of testable implications to the overconfidence hypothesis, and thus there is only little empirical research about the topic. The overconfidence models have been presented for example by Odean (1998a), Daniel, Hirshleifer, and Subrahmanyam (1998), and Gervais and Odean (2001). The overconfidence hypothesis is tested for example in Odean (1999) and Statman, Thorley, and Vorkink (2006).

This study contributes to the previous research by testing the overconfidence hypothesis in Europe with the most recent data available. The study follows closely Statman, Thorley, and Vorkink (2006) who test the overconfidence hypothesis in the U.S. stock market. Also other volume studies are mostly focused on the U.S. market (see e.g. Ajinkya and Jain (1989), Campbell, Grossman, and Wang (1992), and Atkins and Dyl (1997)), and thus I contribute to the existing literature by studying how the hypothesis holds on the European stock market that has experienced great changes during the observation period from June 2001 to December 2014. The full observation period is analysed in the study, but I also divide it into two subsamples to obtain the difference in the market before and after the financial crisis in 2008. The data set includes market returns and trading turnovers of fourteen European national stock exchange indexes. The overconfidence hypothesis is tested in this study by using the vector autoregression (VAR) method and impulse response functions (IRF), which require the VAR method conducted beforehand. The pooled data set of all fourteen indexes is analysed separately, and more detailed analysis for separate indexes is also done in both parts of the methodology.

The main finding of this study is that the overconfidence hypothesis holds in the European stock market, that is to say, the investors increase (decrease) their trading after observing higher (lower) market returns. However, this relation holds only during the pre-crisis period, from 2001 to 2008, and the support for the hypothesis is not found in the post-crisis subsample from 2009 to 2014. As a matter of fact, the trading volume has drastically decreased in traditional stock exchanges included in the study after the financial crisis, although the market performance has recovered after the crisis. The post-crisis volume decrease has slowed down only for couple of years now. The weekly level study reveals that on the short-term, approximately six weeks, the positive relation holds for all observation periods. The long-term support for the overconfidence during the pre-crisis period is similar to the findings of Statman, Thorley, and Vorkink (2006) and the findings also confirm the models of Odean (1998a) and Gervais and Odean (2001) who find that overconfident traders increase their trading after observing increased returns.

Due to the recency of these post-crisis market events and the scope of the study, I do not empirically test the causes of the decreasing trading volume after the crisis, but I present recent statistics and media insights related to the European stock trading during the post-crisis period. The two main explanations for the decreasing trading volume in the traditional stock exchanges are market regulation and market fragmentation. The MiFID regulation has enabled the market fragmentation by increasingly allocating the order flow to alternative trading venues, the so called multilateral trading facilities that have enabled pan-European stock trading with fast electronic trading solutions. Recently, the media has highlighted that the decreasing trading volume is also caused by switching the asset classes away from direct stocks to e.g. bonds, ETFs, and equity derivatives.

Although this study is motivated by the theories of overconfidence, there is clear empirical evidence supporting these theories that should be acknowledged. There might also be other factors explaining trading activity following the past returns in the stock market, and the distinction between these explanations might be subjective. The findings of this study suggest that further development and empirical research may be allocated to study the regulation and market fragmentation effects on the trading activity. The market fragmentation effect might also be diluted if the sample in the analysis included also trading data of alternative trading venues. Moreover, it would be interesting to investigate which investor types are most affected by the new market environment, i.e. who is most likely to switch trading away from the traditional trading venues.

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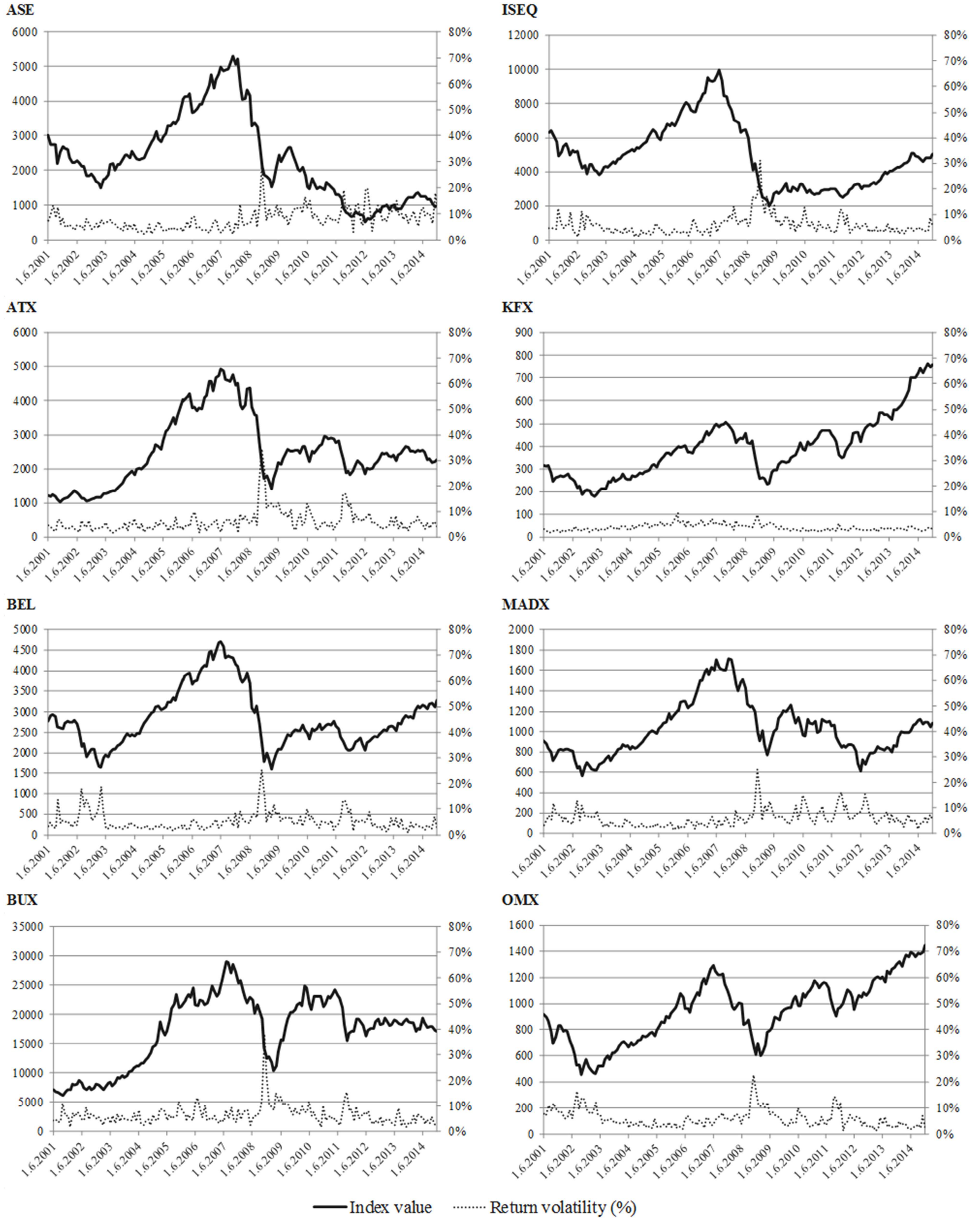
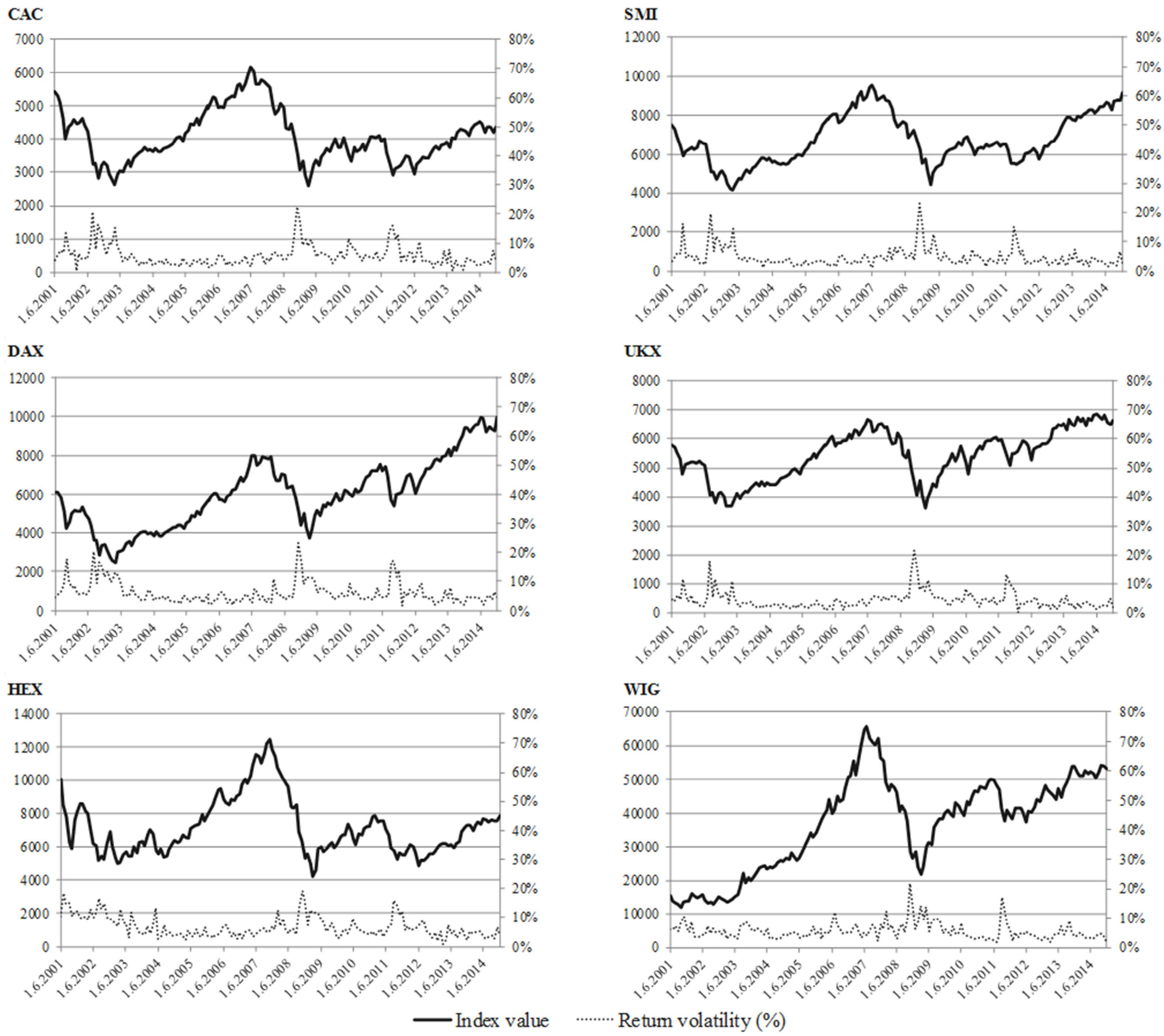
Appendix A. Index performance and return volatility



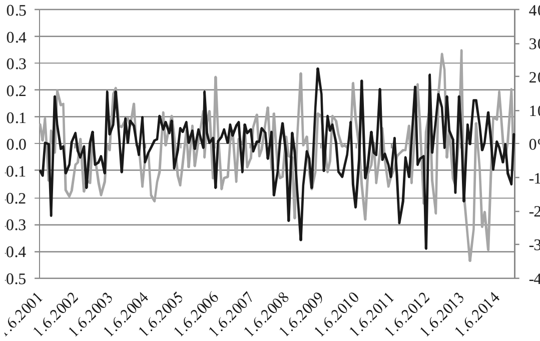
Performance of 14 European stock indexes with monthly return volatility calculated from daily returns.



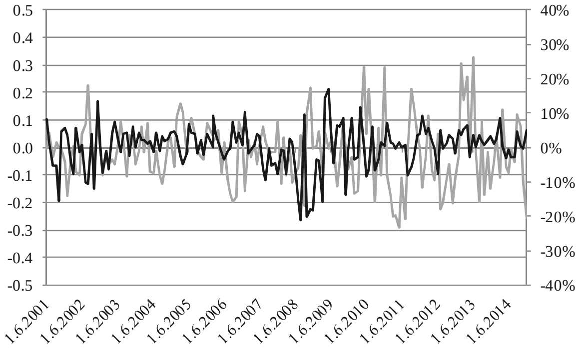
Appendix A continued

Appendix B. Monthly detrended log turnover and index return

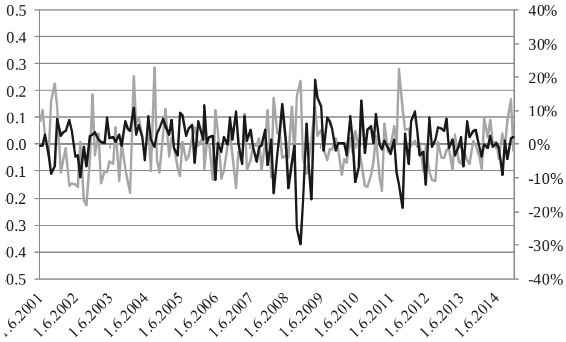
ASE



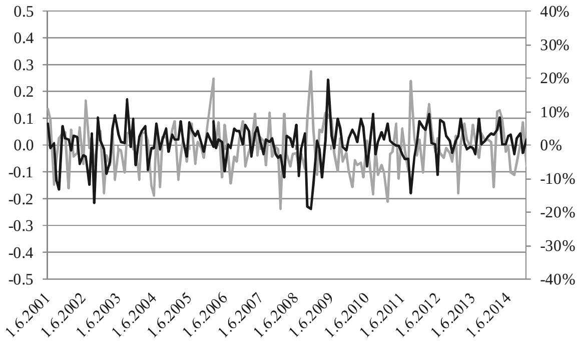
ISEQ



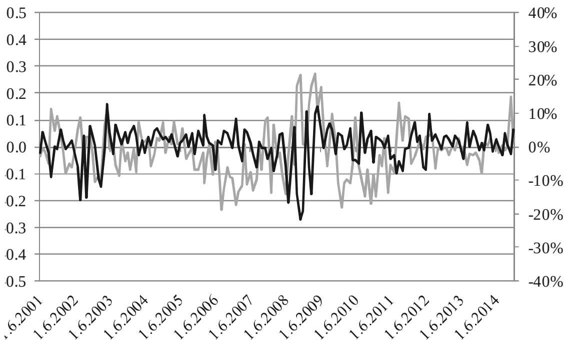
ATX



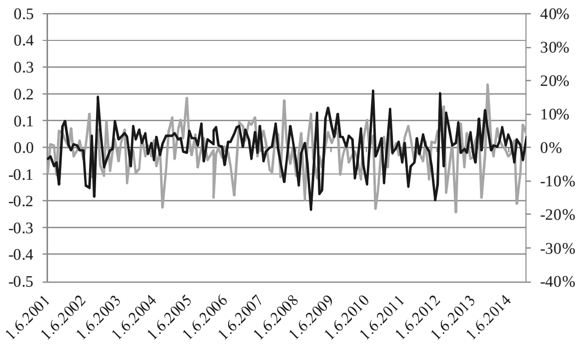
KFX



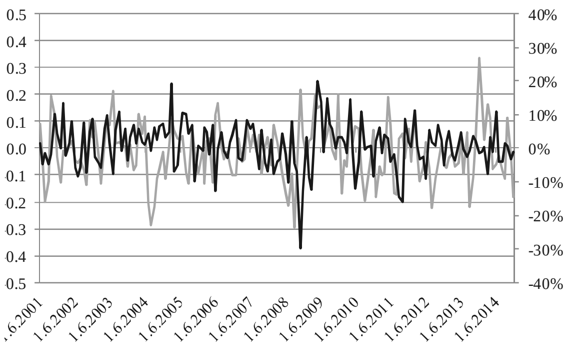
BEL



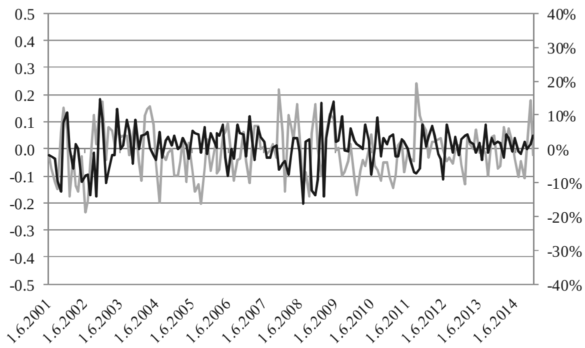
MADX



BUX

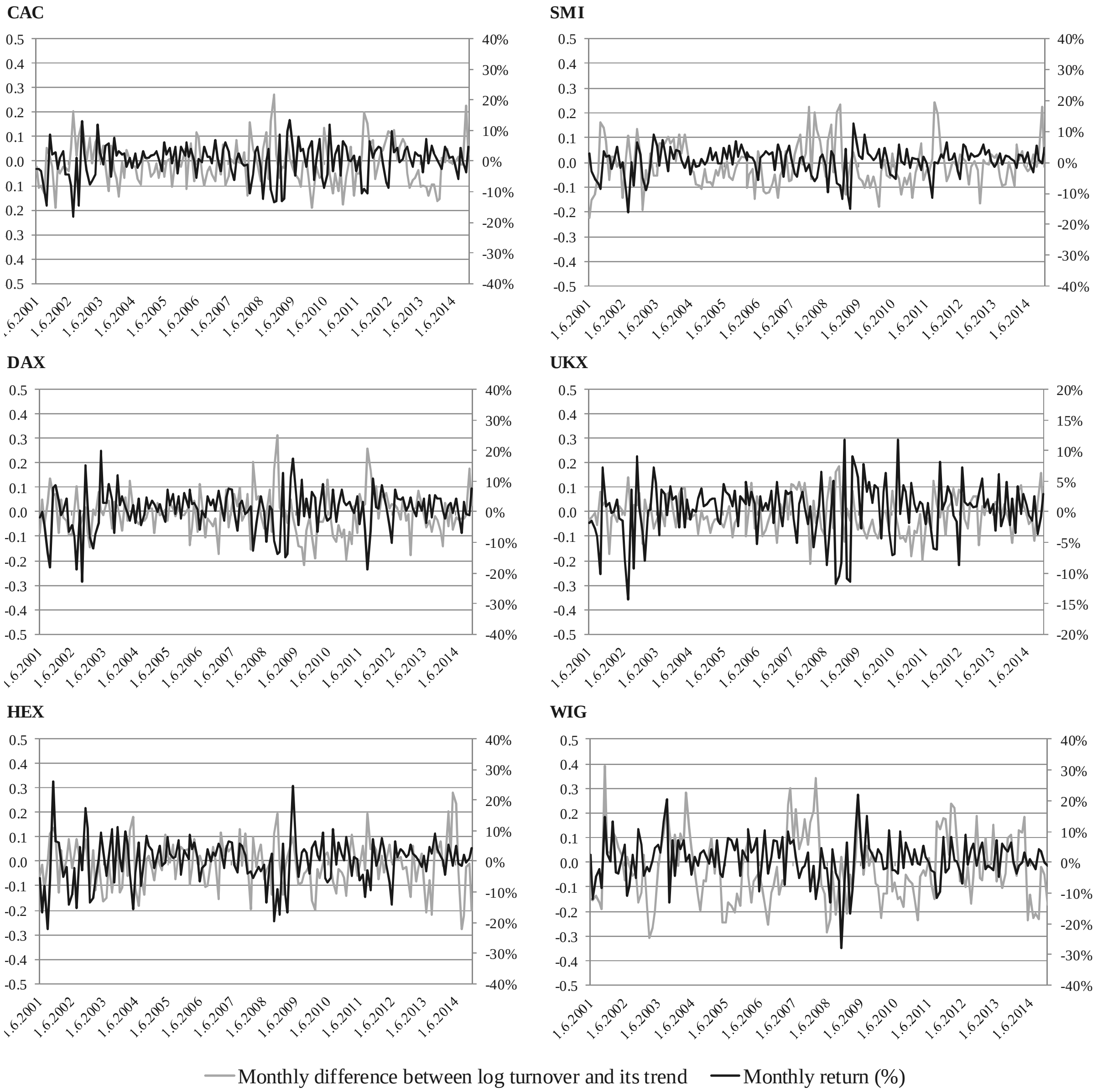


OMX



Monthly difference between log turnover and its trend — Monthly return (%)

Variables *turn* and *ret* visualised for all 14 indexes included in the VAR analysis of single indexes.



Appendix B continued

Appendix C. VAR results for separate indexes

Lagged return, full period

turn$_t$		ret$_{t-1}$	ret$_{t-2}$	ret$_{t-3}$	ret$_{t-4}$	ret$_{t-5}$	ret$_{t-6}$	ret$_{t-7}$	ret$_{t-8}$	ret$_{t-9}$	ret$_{t-10}$
ASE	Coeff.	0.21	0.03	0.09	-0.08	0.01	-0.14	-0.03	0.12	-0.04	0.04
	p-val.	0.04	0.80	0.37	0.44	0.93	0.12	0.73	0.22	0.69	0.66
ATX	Coeff.	-0.07	0.04	0.16	-0.17	0.09	-0.23	-0.02	0.17	0.06	0.00
	p-val.	0.59	0.75	0.15	0.11	0.38	0.03	0.82	0.10	0.60	0.97
BEL20	Coeff.	-0.18	-0.06	-0.34	-0.18	0.16	0.20	-0.28	0.08	-0.08	-0.03
	p-val.	0.16	0.63	0.01	0.14	0.17	0.07	0.01	0.46	0.48	0.79
BUX	Coeff.	0.04	0.14	-0.02	0.12	-0.30	0.00	0.19	-0.05	0.02	0.02
	p-val.	0.72	0.23	0.89	0.27	0.01	0.99	0.09	0.65	0.87	0.87
CAC	Coeff.	-0.16	0.14	-0.16	-0.14	0.06	0.09	-0.03	0.13	-0.14	0.03
	p-val.	0.15	0.20	0.15	0.20	0.58	0.36	0.79	0.17	0.13	0.75
DAX	Coeff.	-0.20	0.07	0.10	-0.12	0.08	0.05	0.11	0.08	-0.07	0.02
	p-val.	0.04	0.46	0.27	0.21	0.38	0.55	0.18	0.33	0.38	0.82
HEX	Coeff.	-0.13	0.29	-0.07	0.03	-0.03	0.00	0.10	-0.04	-0.07	0.05
	p-val.	0.25	0.01	0.51	0.76	0.79	0.98	0.27	0.68	0.46	0.59
ISEQ	Coeff.	0.13	0.05	0.10	-0.28	-0.02	-0.08	0.23	-0.02	0.01	-0.19
	p-val.	0.46	0.79	0.56	0.09	0.90	0.59	0.13	0.87	0.96	0.20
KFX	Coeff.	0.36	0.02	0.02	-0.09	-0.06	-0.09	0.11	-0.02	-0.18	0.18
	p-val.	0.01	0.87	0.88	0.43	0.63	0.45	0.35	0.85	0.11	0.11
MADX	Coeff.	0.05	-0.02	0.15	-0.03	0.03	-0.03	0.14	-0.08	0.01	-0.13
	p-val.	0.67	0.88	0.15	0.80	0.77	0.74	0.14	0.41	0.88	0.17
OMX	Coeff.	0.14	0.15	-0.06	-0.30	-0.11	0.07	0.06	0.08	-0.12	0.24
	p-val.	0.27	0.20	0.61	0.01	0.36	0.55	0.61	0.47	0.29	0.03
SMI	Coeff.	-0.09	0.09	-0.04	-0.06	-0.01	0.01	-0.03	0.15	-0.27	0.19
	p-val.	0.55	0.53	0.75	0.63	0.93	0.92	0.82	0.21	0.03	0.11
UKX	Coeff.	-0.16	-0.15	0.01	-0.15	0.06	-0.01	-0.08	0.02	-0.20	0.05
	p-val.	0.24	0.28	0.97	0.25	0.64	0.96	0.50	0.88	0.08	0.65
WIG	Coeff.	0.31	-0.09	-0.03	0.07	-0.10	-0.20	0.21	0.20	0.00	0.03
	p-val.	0.03	0.54	0.84	0.60	0.45	0.12	0.11	0.12	0.99	0.78

Lagged return, pre-crisis period

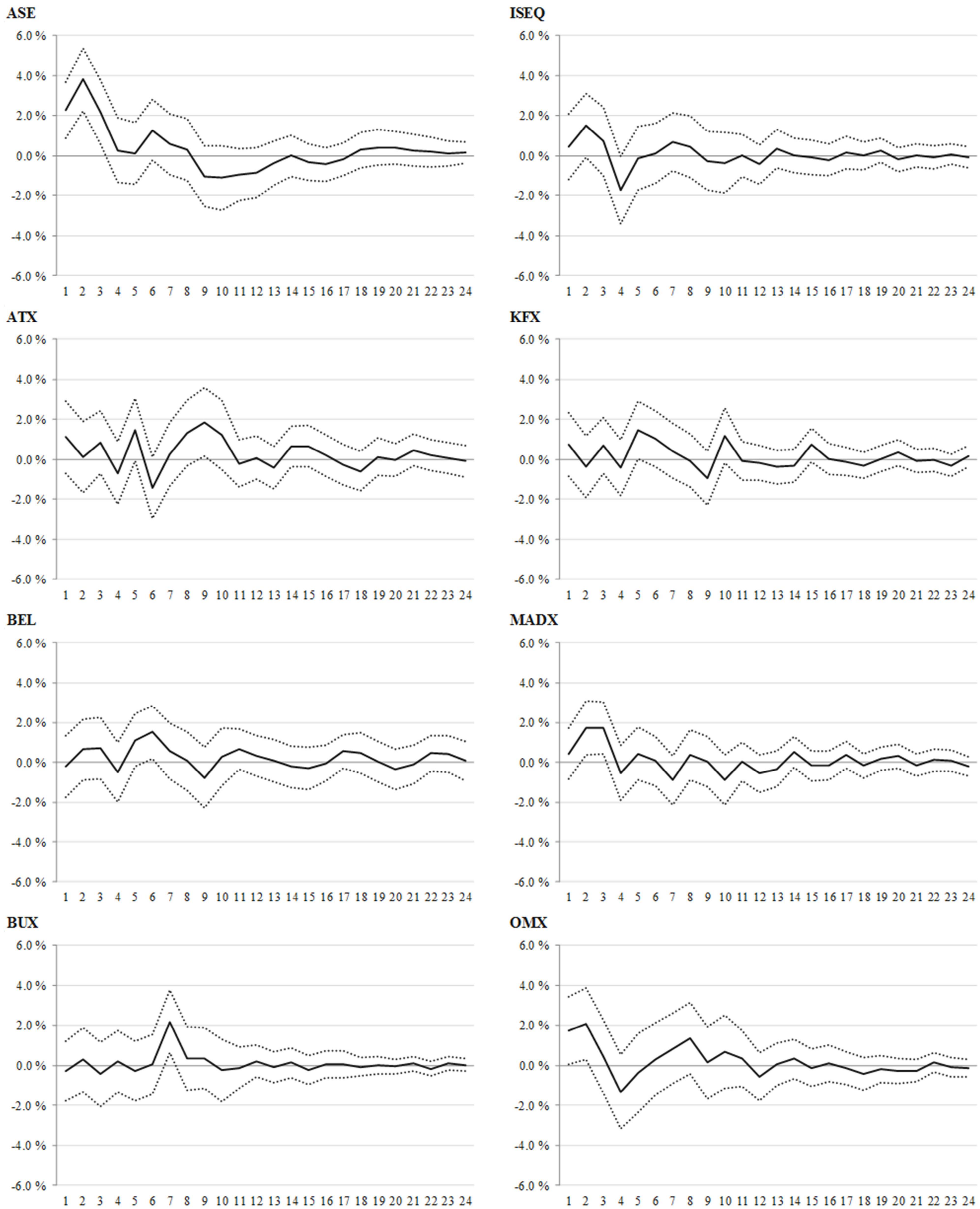
turn$_t$		ret$_{t-1}$	ret$_{t-2}$	ret$_{t-3}$	ret$_{t-4}$	ret$_{t-5}$	ret$_{t-6}$	ret$_{t-7}$	ret$_{t-8}$	ret$_{t-9}$	ret$_{t-10}$
ASE	Coeff.	0.48	0.76	0.45	0.11	0.06	0.27	0.09	0.10	-0.18	-0.09
	p-val.	0.00	0.00	0.01	0.52	0.73	0.06	0.53	0.50	0.20	0.51
ATX	Coeff.	0.28	-0.03	0.23	-0.20	0.42	-0.46	0.12	0.26	0.44	0.19
	p-val.	0.23	0.89	0.24	0.30	0.03	0.02	0.55	0.20	0.04	0.37
BEL20	Coeff.	-0.06	0.20	0.16	-0.21	0.42	0.43	-0.05	-0.01	-0.04	0.04
	p-val.	0.79	0.34	0.44	0.32	0.03	0.02	0.80	0.96	0.84	0.83
BUX	Coeff.	-0.06	0.09	-0.13	0.10	-0.10	0.07	0.43	-0.12	0.05	-0.12
	p-val.	0.72	0.55	0.38	0.49	0.50	0.64	0.00	0.41	0.73	0.39
CAC	Coeff.	-0.24	0.18	-0.07	-0.44	0.10	0.09	-0.17	0.16	0.08	0.17
	p-val.	0.14	0.22	0.64	0.00	0.48	0.51	0.17	0.22	0.55	0.15
DAX	Coeff.	-0.28	0.17	0.40	-0.24	0.11	-0.06	-0.09	0.03	0.11	-0.05
	p-val.	0.02	0.17	0.00	0.06	0.38	0.57	0.36	0.73	0.28	0.63
HEX	Coeff.	-0.07	0.19	0.09	-0.08	0.14	-0.08	0.09	0.03	-0.02	0.09
	p-val.	0.62	0.16	0.49	0.55	0.22	0.52	0.39	0.76	0.86	0.40
ISEQ	Coeff.	0.11	0.35	0.08	-0.46	0.11	0.02	0.05	0.16	0.07	-0.23
	p-val.	0.59	0.07	0.68	0.02	0.54	0.92	0.79	0.37	0.69	0.18
KFX	Coeff.	0.19	-0.04	0.14	-0.04	0.34	0.35	0.21	0.03	-0.21	0.16
	p-val.	0.36	0.85	0.46	0.82	0.08	0.06	0.23	0.85	0.23	0.38
MADX	Coeff.	0.12	0.45	0.42	-0.12	0.25	0.02	-0.15	0.08	0.08	-0.07
	p-val.	0.50	0.01	0.02	0.54	0.15	0.92	0.32	0.63	0.65	0.65
OMX	Coeff.	0.41	0.29	0.00	-0.31	0.08	0.02	0.08	0.20	0.02	0.29
	p-val.	0.04	0.13	0.99	0.09	0.67	0.89	0.62	0.25	0.93	0.08
SMI	Coeff.	-0.36	0.17	0.02	-0.29	0.15	0.02	-0.26	0.23	-0.35	0.11
	p-val.	0.12	0.48	0.93	0.17	0.52	0.94	0.21	0.27	0.10	0.55
UKX	Coeff.	-0.22	0.21	0.23	-0.41	0.38	0.30	-0.32	-0.28	-0.04	0.30
	p-val.	0.37	0.40	0.25	0.06	0.07	0.10	0.07	0.13	0.84	0.09
WIG	Coeff.	0.36	-0.20	0.19	0.27	0.26	-0.07	0.52	0.39	0.21	-0.33
	p-val.	0.09	0.36	0.34	0.18	0.19	0.73	0.00	0.03	0.23	0.07

Lagged return, post-crisis period

turn$_t$		ret$_{t-1}$	ret$_{t-2}$	ret$_{t-3}$	ret$_{t-4}$	ret$_{t-5}$	ret$_{t-6}$	ret$_{t-7}$	ret$_{t-8}$	ret$_{t-9}$	ret$_{t-10}$
ASE	Coeff.	0.17	-0.13	0.09	-0.19	-0.07	-0.22	-0.01	0.13	-0.05	0.14
	p-val.	0.29	0.43	0.57	0.20	0.59	0.10	0.93	0.33	0.71	0.30
ATX	Coeff.	-0.38	-0.05	0.05	-0.18	-0.13	-0.07	-0.07	0.14	0.02	-0.19
	p-val.	0.03	0.76	0.75	0.22	0.39	0.62	0.59	0.23	0.86	0.12
BEL20	Coeff.	-0.31	-0.13	-0.79	-0.31	-0.61	0.31	-0.37	0.18	-0.24	0.27
	p-val.	0.09	0.51	0.00	0.17	0.00	0.06	0.02	0.24	0.08	0.05
BUX	Coeff.	0.11	-0.04	0.02	0.27	-0.74	0.45	-0.02	-0.04	0.08	0.13
	p-val.	0.64	0.86	0.94	0.20	0.00	0.04	0.93	0.86	0.68	0.50
CAC	Coeff.	-0.38	0.32	-0.33	0.00	-0.27	0.14	-0.14	-0.03	-0.31	0.09
	p-val.	0.05	0.12	0.10	1.00	0.19	0.45	0.33	0.84	0.02	0.48
DAX	Coeff.	-0.09	0.07	-0.39	-0.15	-0.37	0.19	0.00	-0.05	-0.29	0.09
	p-val.	0.69	0.76	0.09	0.54	0.12	0.35	1.00	0.77	0.06	0.51
HEX	Coeff.	-0.02	0.62	-0.26	0.17	-0.29	0.21	0.09	-0.38	0.00	-0.31
	p-val.	0.94	0.05	0.43	0.60	0.33	0.37	0.69	0.09	0.99	0.09
ISEQ	Coeff.	-0.07	-0.19	0.36	0.10	0.05	-0.37	0.63	-0.08	0.10	0.10
	p-val.	0.88	0.66	0.38	0.81	0.91	0.36	0.09	0.83	0.78	0.76
KFX	Coeff.	0.23	0.31	-0.16	0.14	-0.45	-0.24	0.19	-0.15	-0.31	0.08
	p-val.	0.29	0.16	0.48	0.52	0.04	0.24	0.32	0.43	0.09	0.64
MADX	Coeff.	-0.03	-0.39	-0.03	-0.09	-0.20	0.04	0.30	-0.18	0.05	-0.19
	p-val.	0.87	0.02	0.88	0.59	0.22	0.79	0.03	0.18	0.70	0.15
OMX	Coeff.	-0.55	0.05	-0.36	-0.46	-0.65	0.13	0.11	-0.26	-0.38	0.00
	p-val.	0.01	0.83	0.09	0.03	0.00	0.50	0.55	0.10	0.02	0.99
SMI	Coeff.	0.28	0.24	-0.36	-0.09	-0.42	0.30	0.18	-0.16	-0.16	0.33
	p-val.	0.20	0.27	0.09	0.65	0.03	0.15	0.32	0.31	0.28	0.02
UKX	Coeff.	0.13	0.02	-0.32	-0.11	-0.19	-0.06	0.22	0.08	-0.37	0.18
	p-val.	0.55	0.93	0.16	0.60	0.37	0.75	0.21	0.62	0.02	0.25
WIG	Coeff.	0.24	-0.34	-0.18	0.14	-0.52	-0.33	-0.05	0.08	-0.38	0.13
	p-val.	0.51	0.33	0.56	0.64	0.07	0.21	0.85	0.75	0.12	0.61

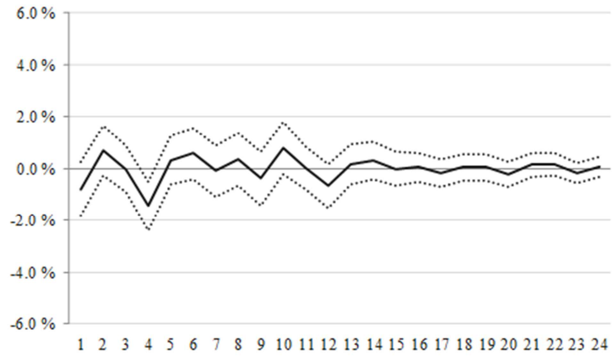
VAR coefficients and p-values of single indexes, all periods.

Appendix D. Pre-crisis impulse response functions for single indexes

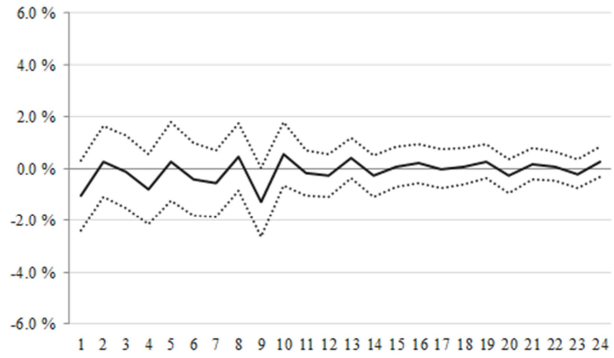


Impulse response functions with 95% confidence interval, turnover response to return shock, pre-crisis subsample from June 2001 to December 2008.

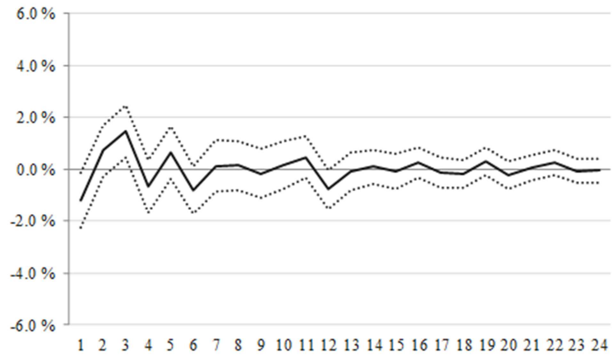
CAC



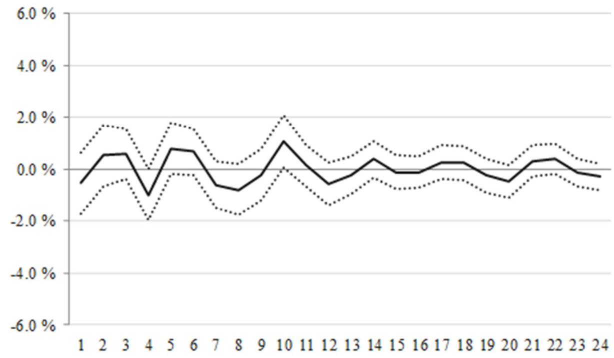
SMI



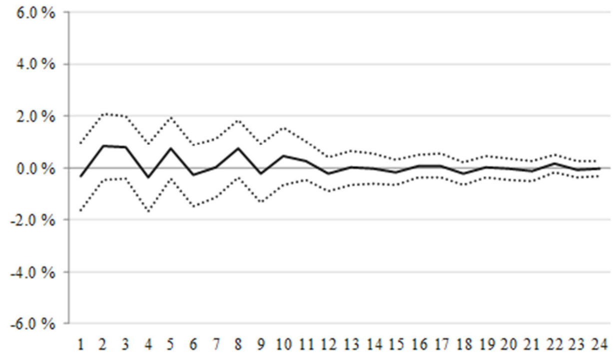
DAX



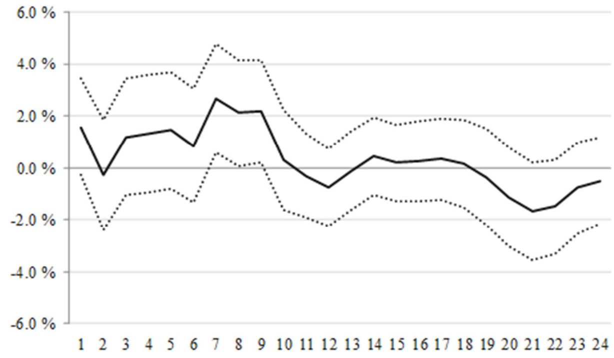
UKX



HEX



WIG



Appendix D continued

Appendix E. Table of media insights

Year	Publisher	Writer	Title	Retrieved from
2011	BlackRock	-	Equity Market Trading in Europe: The Case for Refinement Over Revolution	www.blackrock.com
2007	Bloomberg	Scott, M.	Online Trading Blooms in Europe	www.bloomberg.com
2012	Bloomberg	Wang, L., Nagi, C., and Baker, N.	Stock Trading Lowest in U.S. since 2008 Amid Fund Withdrawals	www.bloomberg.com
2013	Business Insider	Boesler, M.	GOLDMAN: Here's Where all the S&P 500 Trading Volume Went	www.businessinsider.com
2012	CNBC	Melloy, J.	Where has all the Trading Gone? Volume Hits 4-Year Low	www.cnbc.com
2012	Credit Suisse	Mackintosh, P. and Casciano, S.	Where has all the Trading Gone?	www.credit-suisse.com
2013	Financial Times	Stevenson, A.	European Stocks Trade Volumes Slump	www.ft.com
2014	MarketWatch	Reklaitis, V. and Mahmudova, A.	Why Trading Volume is Tumbling, Explained in 5 Charts	www.marketwatch.com
2012	Pricemetrix	-	Decreasing Year-Over-Year Trade Volume - Fact Or Fantasy	www.pricemetrix.com
2012	Reuters	-	Share Volume to Stay Low as Euro Crisis Hits Industry	www.wallstreetandtech.com
2013	Reuters	Cruise, S. and Jessop, S.	Dark Pool Stock Trading Picks Up as Europe Debates New Curbs	www.reuters.com
2013	The Economist	-	Going Broke in Stocks	www.economist.com
2012	The New York Times	Popper, N.	Stock Trading is Still Falling After '08 Crisis	www.nytimes.com
2011	The Wall Street Journal	Dunkley, E.	Pan-Europe Vs. the Nationals	www.wsj.com
2012	The Wall Street Journal	Phillips, M. and Cheng, J.	Traders Tune Out Noise from Europe	www.wsj.com
2014	Thomson Reuters	Laurent, L.	Europe Stock-Trading Revenue Likely to Fall in 2014-Report	www.reuters.com
2008	Traders Magazine	Chapman, P.	Gunning for the Old Guard	www.tradersmagazine.com
2011	Traders Magazine	Ramage, J.	No Changes to Dark Pools: Buyside	www.tradersmagazine.com

Reference list for the media insights, alphabetical order by the publisher.