Uncovering Hidden Information and Relations in Time Series Data with Wavelet analysis: Three Case Studies in Finance

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ABSTRACT

This thesis aims to provide new insights into the importance of decomposing aggregate time series data using the Maximum Overlap Discrete Wavelet Transform. In particular, the analysis throughout this thesis involves decomposing aggregate financial time series data at hand into approximation (low-frequency) and detail (high-frequency) components. Following this, information and hidden relations can be extracted for different investment horizons, as matched with the detail components. The first study examines the ability of different GARCH models to forecast stock return volatility in eight international stock markets. The results demonstrate that de-noising the returns improves the accuracy of volatility forecasts regardless of the statistical test employed. After de-noising, the asymmetric GARCH approach tends to be preferred, although that result is not universal. Furthermore, wavelet de-noising is found to be more important at the key 99% Value-at-Risk level compared to the 95% level. The second study examines the impact of fourteen macroeconomic news announcements on the stock and bond return dynamic correlation in the U.S. from the day of the announcement up to sixteen days afterwards. Results conducted over the full sample offer very little evidence that macroeconomic news announcements affect the stock-bond return dynamic correlation. However, after controlling for the financial crisis of 2007-2008 several announcements become significant both on the announcement day and afterwards. Furthermore, the study observes that news released early in the day, i.e. before 12 pm, and in the first half of the month, exhibit a slower effect on the dynamic correlation than those released later in the month or later in the day. While several announcements exhibit significance in the 2008 crisis period, only CPI and Housing Starts show significant and consistent effects on the correlation outside the 2001, 2008 and 2011 crises periods. The final study investigates whether recent returns and the time-scaled return can predict the subsequent trading in ten stock markets. The study finds little evidence that recent returns do predict the subsequent trading, though this predictability is observed more over the long-run horizon. The study also finds a statistical relation between trading and return over the long-time investment horizons of [8-16] and [16-32] day periods. Yet, this relation is mostly a negative one, only being positive for developing countries. It also tends to be economically stronger during bull-periods.

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CHAPTER ONE

Introduction

"*The key lesson in synthesizing the wavelet transforms is to facilitate and develop the theoretical insight into the interdependence of economic and financial variables. New tools are most likely to generate new ways of looking at the data and new insights into the operation of the finance–real interaction*". Gallegati and Semmler (2014, p.x)

1.1 Research Motivation

Most econometric methods have, at least initially, been developed to deal with aggregate data. This, however, hinders the ability of learning from the data at hand, especially when there is a need for a deep understanding about how economic or financial relations vary continuously. An example of this dynamic relation can be how an investor behaves in financial markets by making decisions over different investment horizons. Behaviour might change over time depending upon his needs, political, economic and psychological factors that drive the investment away from being in the same position over time.

Yet, methods that consider only frequency domains have been widely used to examine statistical relations without referring to timescale. One of these approaches is the basic Fourier transform, which has many applications in diverse disciplines, including finance. The Fourier transform relies mainly on the combination of sine and co-sine functions, and it works on the frequency basis, but in isolation of any time frame. The basic Fourier has very limited effectiveness in detecting the low-frequency parts of the time series, such as the seasonality and the cyclical components. Apart from this issue, the basic Fourier transform assumes that the time series data is stationary, while in the real world, the stationary assumption cannot be guaranteed for the financial or economic data.

Gabor (1946) introduced a new filter called short–time Fourier Transform (STFT) to partially solve the problems arising from using the basic Fourier. The fundamental assumption of the STFT is applying the filtering process on the short-time blocks.

On the other hand, to accentuate the importance of time-scaling in economics, for example, Gallegati and Semmler (2014, p.ix) argue that:

"*The existence of time scales, or "planning horizons", is an essential aspect of economic analysis… A corollary of this assumption is that different planning horizons are likely to affect the structure of the relationships themselves, so that they might vary over different time horizons* *or hold at certain time scales, but not at others. Economic relationship might also show negative relationship over some time horizon, but a positive one over others. These different time scales of variation in the data may be expected to match the economic relationships more precisely than a single time scale using aggregated data. Hence, a more realistic assumption should be to separate out different time scales of variation in the data and analyze the relationships among variables at each scale level, not at the aggregate level*".

Therefore, examining the relations over different time horizons is essential to learn from the data. For this reason, the methodology known as wavelet analysis has been introduced. More specifically, it has attracted much attention in finance and economics over the last twenty years, due to it is ability to simultaneously examine the relations over the time and scales domains, which makes the wavelet analysis capable of overcoming the aforementioned shortcomings of the standard pre-processing filters.

Contrary to the basic Fourier transform, and by definition, wavelet represents a small wave with a finite length. It begins at some point of time and dies out quickly afterward. Wavelet transform employs two types of filters to extract more features from the data. The first filter focuses on the low-frequency components and is called the father wavelet. The second, the mother wavelet, complements the father by convolving over time series data, to detect the high-frequency components. More specifically, the mother wavelet utilises a combination of the translation and stretching functions in a flexible process and both of these functions work to capture the elements of the time series in time and frequency domains. This distinct feature of wavelet facilitates the understanding of the varying characteristics of real-world time series, without any necessity to assume that the time series itself is stationary.

Given such promising features, wavelet analysis started to be introduced into finance literature in the late 1990s. Also, surveys prepared recently (see, for example, In and Kim, 2013; Gallegati and Semmler, 2014) have highlighted the importance of using wavelet in finance and economics. The results of the case studies considered in these surveys are interesting, on the grounds they detect relations which could not be empirically observed using the aggregate data, proving it to be a promising research area. Studies in the literature generally consider two applications for wavelet, namely, de-noising and time scale analysis to examine the dynamic relations between variables. For the purpose of de-noising, wavelet method extracts the high-frequency components from the raw data first, before removing the noise from the high-frequency components. In order to decide on the noisy part of data, the process must set the statistical threshold limit on each time scale depending on the variance of the data at that scale. This process of de-noising is useful when it comes to analysing return in financial markets. For example, in a month of trading in the market, informed investors who enter the market today will trade based on their private information, as well as the public information. At that time, the uninformed investors will more likely compete with the informed investors making the market more volatile. As the time goes approaching the end of the month, both types of information must be embedded into the price, and the volatility level might then decrease. At that late time, the private information that the informed investors previously acquired will also be revealed to the traders, (Ko and Huang, 2007).

More volatility in the markets, however, would need to be accurately forecast in a way which benefits all participants in the markets, including investors themselves and risk managers. In risk management, for example, using the clean return data is of highly importance to obtain more accurate risk estimation. To do that, a given approach is required to extract the latent volatility by analysing the return series over time. Accordingly, both the existence of noise and the dynamic relations in data requires further examination over the time horizons. For this reason, the wavelet methods have been applied in finance and economics. Wavelet analysis is important in managing the time-varying features of financial data. This thesis significantly complements the studies in finance that employs wavelet for time-scale analysis and de-noising.

Yet, to date very little research has been done to examine the appropriateness of removing the noise before forecasting the volatility, (e.g. Capobianco 2002, among others). On the other hand, more research has applied the time scale property of wavelet to examine the dynamic relations in finance covering, for example, the issue of financial markets interaction (see, for example, Kiviaho et al., 2014; Bekiros et al., 2016; Ftiti et al., 2015). Although, it is still required to understand how macroeconomic factors also affect co-movements over the investment intervals. Such analysis in this area must consider the behaviour of the investor during the financial crises, the time when factors, such as investor sentiment, are assumed to impact the financial markets (e.g., Kontonikas et al., 2013). To my knowledge, there is no research which has succeeded in combining all these areas (i.e. financial markets interaction, financial crises and the planning horizons).

Other strands of research have analysed the dynamic relation between the trading volume and stock market returns, Karpoff 1987, is an early example. Theories introduced within this area, e.g. Investor overconfidence, have linked the trading activity today to investors' psychological beliefs in the past. However, very little has been said about the role of recent return or the subsequent return in explaining subsequent trading activity, either due to methodological difficulties or other reasons.[1] The impulse response function (IRF), for instance, tells researchers how much today's variation in the depended variable can be explained by shocks in the

[1] Throughout this thesis, the recent return means today's return. Also, the subsequent returns and trading are respectively the decomposed detailed return and trading volume series at the time-scales from 1 to 6.

explanatory variables. Yet, IRF does not directly consider the subsequent changes in the dependent variable from the beginning prior to the analysis. From this point of view, decomposing the trading volume on different time intervals a head into the future and trying to statistically explain it further using the return series must benefit the stock market participants.

This thesis, in three studies, aims to begin filling these above-mentioned gaps; volatility de-noising, financial markets macroeconomic level interaction and return-trading volume interplay. Before proceeding to the empirical chapters, a review of the wavelet theory and the most commonly used wavelet approaches in finance will also be presented.

1.2 Organisation of the thesis and its main findings

Following this introductory chapter, the remaining chapters, are as follows. **Chapter two** reviews the theoretical and empirical sides of the literature concerning the application of wavelet to the financial markets. It starts by offering a comparison between the wavelet analysis and other Fourier transforms. Also described is the decomposition approach via two of the most commonly used wavelet methods, the maximum overlap discrete wavelet (MODWT) and the discrete wavelet transforms (DWT), including the key differences of these two wavelet methods.

Chapter two also summarises the relevant empirical literature on volatility forecasting using the autoregressive conditional heteroscedasticity model of Engle (1982) and its extensions. Analysing the previous literature in this section will partially focus on the importance of de-noising the return data for the purpose of forecasting. Then, chapter two reviews some applications of DWT and MODWT for both asset pricing and financial markets co-movement. The final section of the chapter will be devoted to discussing the current state of the literature, and setting the research questions for the empirical chapters.

Chapter three addresses the first couple of research questions of the thesis. These are, does wavelet de-noising improve volatility forecasting? Does de-noising impact on risk management decisions? The study employs daily closing price index returns for eight international stock markets covering the period 01/ 01/1998 to 31/12/2013. In the first stage, the return series for each market has been de-noised using one of the most popular approaches for determining level-dependent threshold limit, namely, soft thresholding. Having the de-noised and raw return data ready to use, the next step involved forecasting the volatility one step-ahead into the future, using a group of symmetric, asymmetric and long-memory models from GARCH family.

The results show that while statistical forecast error measures are used, wavelet-based forecasts are generally an improvement over raw returns-based forecasts across the range of models employed. The same conclusion is reached using tests of equal predictive accuracy.

Furthermore, the study has highlighted how de-noising the data affects the ranking of the models. Studies in the literature suggested, for example, that the impact of the error distribution assumption (Wilhelmsson, 2006) or the choice of the true volatility proxy (McMillan and Speight, 2004) affect the final performance of the GARCH (1, 1) model. This model, which accounts for volatility clustering has been mostly considered the benchmark in the volatility forecasting exercise. Our results after de-noising the return series reveals that the asymmetric-GARCH are typically preferred over the GARCH and the other models considered. Hence, this study clearly contributes to the growing research that considered different factors for recommending the best model in volatility forecasting. More importantly, we aimed to answer the second research question regarding the economic benefit of de-noising the data, using both 1% and 5% initial probability coverage rates in a Value-at-Risk (VaR) exercise with three main tests. The associated results suggest that at the 5% level using de-noised data does not provide an obvious improvement over the original returns series. However, at the 99% VaR, models were more likely to pass the three tests of coverage after de-noising with soft thresholding. The findings from the wavelet de-noising VaR exercise within the context of the few related studies which exist. The analysis in this study and more specifically the suitability of the asymmetric GARCH models, is further enhanced after performing the rolling in-sample estimation and getting the GARCH and EGARCH models parameters during and outside several turmoil periods.

The second empirical study (**Chapter four**) investigates whether the effects of sixteen macroeconomic surprises persist on the stock-bond dynamic correlation in the U.S., throughout and around the crisis periods. The crises considered for the analysis are the 2008 crisis the 2001 Dot-com crisis and the 2011 U.S. government debt ceiling dispute periods. The analysis first used the MODWT wavelet transform to decompose the return series, before estimating the dynamic correlation on different time-scales. In order to estimate the correlation, the diagonal version of the asymmetric DCC-GARCH model of Cappiello et al. (2006) has been used. This model was already developed to examine asymmetric correlation between the global stock and bond returns. In terms of data, the study used the daily DJIA closing price index as a representative for the stock indexes in the U.S., along with the 2 year and 30 year Datastream benchmark government bond indexes. The sample period is from 3 January 2000 to 25 December 2013. On the other hand, the macroeconomic surprises series are constructed by taking the difference between the actual releases and their corresponding expectations. The standardised components of the surprises are then used in the analysis.

The next stage involved regressing the dynamic correlations series for each macro surprise series separately. This, however, has been done with both linear and non-linear regressions that account for the impact of news during the crisis period. The regressions used the raw dynamic correlation series and those based on the first three time-scales series, namely, [2-4], [4-8] and [8-16] day-periods.

This research has been motivated by the findings in the related academic literature. The studies concerned the quick reaction of the individual equity series to the macroeconomic news, with most of the impact documented as being during the crises periods. Yet, nothing has been said about the speed of reaction of correlation between equities and the news. Based on this strand of literature, both the sentiment and the uncertainty are found to slow down the reaction to the macroeconomic news during the crisis. This research came then to address this issue, which we believe has not yet been examined in the finance literature.

The following conclusions are reached in chapter four. First, over the full sample period, very little evidence was found that macroeconomic news surprises affect the stock-bond return dynamic correlation. This finding changed after controlling for the 2008 global crisis period, with several announcements being found to be significant both on the announcement day and even afterwards. Finally, in an interesting finding, news released early in the day and early in the month, is observed to exhibit a slower effect on the dynamic correlation relative to those released later in the month. In other words, a link is observed between the speed of the reaction in correlations to news surprises and the timing of announcements.

In terms of the general news effects, several announcements exhibit significance in their impact during a crisis period. Whereas, only the housing starts and the consumer price index news show significant and consistent effects on the correlation outside the crisis period. Moreover, after replacing the 2008 crisis with the 2001 and 2011 crises, the effects of most surprises are found to disappear, though, the non-crisis announcements effects remained significant.

In **Chapter five**, the return-trading volume relation has been analysed in a new framework using wavelet. That is, the related literature used the overconfidence hypothesis to explain the most recent trading. Yet, studies conducted tend to ignore the roles of other factors other than lagged return in predicting the subsequent trading. The main research questions were; do the recent return and the time scaled return significantly explain the subsequent trading volume in stock markets? Then, up to how many days after is the subsequent trading volume affected by these factors?

Our sample in chapter five comprises the daily stock market return and trading volume series for ten countries and for the sample period spanning 1 January 2002 to 31 December 2013. The analysis is first started by decomposing the trading volume with the MODWT. Next, the decomposed trading volume series are regressed on the recent return in one equation and on the decomposed return along with recent trading volume in another equation. The main estimation procedures used the linear and non-linear regressions, as well as the wavelet-variance estimator.

The results obtained from the analysis can be summarised as follows. First, little statistical evidence on the predictability of the subsequent trading is found for the recent return, though it is for the long-run, [8-16] and [16-32] day period horizons. Second, subsequent trading is found to be the most statistically explained by subsequent returns over the same long-term investment horizons. Third, in terms of the sign of subsequent trading–return relation, a negative sign is generally observed, but positive for the developing countries. Last, from the nonlinear estimation, economically stronger relations are observed during bull periods compared to those during the bear periods. Both, the bull and bear regimes are defined using the simple regime switching model. Moreover, we reached the same finding regarding the positive relation between the subsequent return trading volume by doing the wavelet variance and correlation based analysis on eight more emerging stock markets. Further discussion and interpretation of the results are provided at the end of the chapter.

Overall, the analysis in chapter five differentiates between short-term and long-term horizon investors, assuming that risk and liquidity factors contribute differently to the asset pricing process across the investment horizons.

Finally, **Chapter six** summarises and concludes the research questions and the main findings. It also discusses the limitations of this thesis and offers recommendations for future research.

CHAPTER TWO

Wavelet Methods: Theoretical and Empirical Literature in Finance

"*Imagine a sequence of traders that make decisions over different horizons; for example, one can visualize traders operating minute by minute, or hour by hour, or day by day, or month by month, or year by year. Or consider the difference in time horizon and its effects on bond holdings between short term money managers and those determining the investment portfolio for an insurance company. Alternatively, imagine an individual deciding on the purchase of a house, a car, groceries, a chocolate bar. In these examples, it is clear, that those variables that would receive the most attention, or weight in the decision process, and likely the structure of the relationship itself will vary over the different time scales that are implicitly defined by the different decision making horizons".* Ramsey (2002, p.13)

2.1 Introduction

To what extent is the investment horizon an important factor in explaining the behaviour of an investor in financial markets? Recent studies over the last twenty years or so seem to agree that the behaviour of an investor varies over different time horizons, when it comes to portfolio formulation, the investment horizon cannot be ignored. For example, Liu and Loewenstein (2002) find that the short-term investor in the market, who has a finite time horizon and faces transaction cost, tends to avoid buying risky assets and follows a simple buy-and-hold strategy. According to Dierkes et al. (2010), the attractiveness of the investment strategy itself depends on the investment horizon. Their study clearly documents that the combination between the stock and the Treasury bond equities in the investor's portfolio depends on the time horizon. That is, the mix between these two equities, using a buy-and-hold strategy, is only preferable for the investor working to a long-term investment horizon. Concerning the behaviour of the 13F institutional investor in the U.S. stock market, Cella et al. (2013) find that those with short-term horizons sell their stocks during episodes of market crisis[2], the selling pressures of short-term investors are greater, relative to long-term investors. The evidence of Cella et al. (2013) is over the period 1986 to 2009 and therefore examined the behaviour of the investors during the 2008 crisis.

In an even more recent study, Han et al. (2016) construct a trend factor from the past moving averages of the prices spanning 3 to 1000 days. The new trend comprises the short, intermediate and the long-term components. It is found to be a better predictor for the next period stock market return relative to short and/or long-term reversal and momentum factors, which ignore the information accumulated over the different horizons. The performance of Han et al (2016)'s trend

[2] According to the study, 13F investors are the pension funds, endowments, insurance companies, bank trusts, mutual funds, hedge funds and independent advisors.

factor has been tested during both recession and expansion periods in the U.S. The constructed factor has superiority over others in terms of the Sharpe ratio during the global crisis period.

To add to the investor's time-horizon approaches, wavelet transforms have become applicable methods in finance over the last twenty years. A natural question emerges here; what makes wavelet transform preferable as a pre-processing technique compared to others? Wavelet helps to examine how relations within the area of asset pricing change their strengths and signs within time and frequency domains. Unlike other pre-processing tools, wavelet can tackle how a given statistical relation varies at a pre-specified time interval. Other methods such as the Fourier filter, Kalman filter and moving average filter are more basic in that they focus on the frequency basis.

Clearly, it has been identified as necessary to produce a decomposition of the time series over time and this is the key reason for using the wavelet transform in different contexts in finance. For instance, Gençay et al. (2005) find that the systematic risk as measured by the beta coefficient in the CAPM model tends to increase at the higher wavelet-based long-run time-horizons. Using wavelet, Fernandez (2006) supports Gençay et al. (2005) and finds that not only the beta coefficient increased at higher time scales, but also the market risk premium[3]. Shrestha and Tan (2005) document a strong relationship between the real interest rate in the U.S. and that in the other G7 countries at the higher timescales compared to the lower ones. For both in-sample and out-of sample analyses on 23 future markets, Lien and Shrestha (2007) find that the hedge ratio increases at the higher time-horizons as defined by the wavelet decomposition.

Moreover, several attempts have been made by researchers since 1991 to empirically predict volatility in the international stock markets. Some of these studies employ conventional statistical methods such as autoregressive moving average (ARMA), exponential smoothing and their extensions which are based on simple assumptions of normality and stationary for the time series under consideration. Others, however, favour employing more complicated techniques as they aim to deal with the complexity of the whole system under which the stock market fluctuates over time. The question of which group of methods to use, conventional or complex, is still a part of ongoing debate and each have their merits. It also became clear to the researchers in stock market volatility that many factors must be considered before trying to select the best forecasting method those, for example, include the length of the forecasting horizon, micro- and macro-economic factors that might affect the market structure. Furthermore, one of the main concerns in finance today is to investigate the characteristics of the stock market data or the time series at hand before

[3] Very early study by Levhari and Levy (1977) also find that the systematic risk changes with the investment horizon. However, their methodology is more complicated compared to the wavelet decomposition approach used by Fernandez (2006) and Gençay et al (2005).

selecting the model. For example, there has been ample evidence that stock market returns do not follow a linear pattern, but rather a random walk process. Taking this into consideration, theories of over-reaction (under-reaction) and rational (irrational) bubbles have suggested, to some extent, the existence of the nonlinearity of the financial market, as advocated by several studies (see, for example, Abhyankar et al., 1995; Abhyankar et al., 1997; McMillan, 2001).

What is more, over the last three decades, there have been great advances in the forecasting of time series in general and stock market volatility in particular. The real turning point in forecasting volatility literature began after the introduction of the Autoregressive Conditional Heteroscedasticity (ARCH) model by Engle (1982) examining non-linearity in time series data and documenting that the variance that generates the unexplained variation in the simple regression model is not constant. Developments of the ARCH model include Generalized-ARCH (GARCH) of Bollerslev (1986), Exponential GARCH (EGARCH) by Nelson (1991) and Glosten et al. (1993) (GJR-GARCH). All these extensions and other ARCH models aim to enhance forecasting performance by considering asymmetry and other properties such as long memory, usually found in time series data. For example, the empirical suitability of GARCH symmetric and asymmetric models has been investigated by many studies (see, for example, Franses and Van Dijk, 1996; McMillan and Speight, 2004; Awartani and Corradi, 2005; Karanasos and Kim, 2006).

However, having employed these parameterised models in forecasting, special analysis of the nature of the time series data under examination is required. (Engle and Patton, 2001; Nelson and Foster, 1995). To empirically consider this, wavelet transforms have been applied. A study by Hong and Kao (2004), for instance, develops a new wavelet statistical estimator to deal with the serial correlation of the unknown form of the residuals in the panel regression methods. Relying also on the wavelet decomposition, Chen et al. (2008) succeed in detecting the jumps and break points in the weekly yields data of three-months treasury bills and the volatility data of IBM in the U.S. In another study, Elder and Jin (2007) find that the wavelet decomposition approach is effective in detecting similarities of the long-memory in 14 commodities future markets.

Therefore, we may begin to see much more clearly that forecasting is just one stage in the analysis of financial markets and financial data at hand can be contaminated with noise and outliers. Special pre-processing techniques are required to clean the data to allow the discovery of otherwise hidden short-term patterns, more attention needs to be paid to how the forecasting performance of the models may be enhanced using time-scale analysis with the application of wavelet in finance research. Wavelet transformations can efficiently offer this multidimensional type of analysis, by distinguishing between the performances of the investors with different time horizons.

All in all, wavelet transform appears to be a promising technique to decompose the financial time series and extract the hidden information that are localised in specific time intervals. It is appropriate for examining both the statistical relations in the financial markets and forecasting volatility.

Following this brief introduction, the next section revises some relevant basic volatility notions. Section 2.3 provides an overview on the pre-processing techniques for the time series data, while highlighting more the distinct features of wavelets. Section 2.4 provides empirical evidence on the volatility forecasting with GARCH models, and on how forecasting stock market volatility should be improved after pre-processing the financial data. Thereafter, the most recent literature on the applications of wavelets in finance and economics is summarised in Section 2.5. Lastly, Section 2.6 concludes the chapter and discusses the potential contributions of this thesis.

2.2 Basic Concepts for Time Series Analysis:

Before proceeding further in this chapter, it is important to understand some basic concepts that are directly related to the models under investigation in this thesis, principal among these concepts are outliers and over-fitting and under-fitting, described now in Sections 2.2.1 and 2.2.2 respectively.

2.2.1 Outliers

It is normal in the time series data to have an aberrant point or sequence of points that are external to the original data and those are described as outliers.

The source of these outliers in the financial data sets might be a financial crisis or any other irregular event that a given financial data set might be affected by. Hotta and Tsay (2012)[4] were the first to discuss and investigate the effect of two types of outliers within a volatility modelling framework. They discussed are additive outliers and studied them as two main groups; additive level outliers (ALO) which affect the level of time series and additive volatility outliers (AVO) which reflect on the conditional volatility process.

[4] They empirically explained the basic concepts of outliers within the Autoregressive Conditional Heteroskedasticity (ARCH) modelling framework.

The innovation outlier (IO) is another type that is introduced but rarely studied in the finance literature, because their effects are usually spread along the time series and therefore can be neglected. A comprehensive survey on the outliers and their effects on volatility forecasting are conducted by Peña (2001).

2.2.2 Over-fitting and Under-fitting

One critical issue in time series prediction is how to select and build the forecasting model. Before the assessment and selection of the model, the nature of the data set must be carefully examined and understood to ensure an appropriate fit between model and data set. In random systems with little clear idea about the data garnering process, one should consider more complex models that can help better understand possible hidden relationships between the data sets. What is more, in most cases of volatility modelling, the selection of a complex model is preferred when the data has some noisy points that can mask the true statistical relationship between data points. On the other hand, less noisy data requires a simple model. Two key issues relevant to complexity are over-fitting and under-fitting.

While the over-fitting problem is usually due to selecting a too complicated model for simple and less noisy data, the under-fitting case is different in terms of selecting a simple model for noisy and too complicated data. The decision here of which model to use, however, requires consideration of Occam's razor principle, where the simple model might bias the result, even whilst being effective in forecasting volatility. The best way to judge the suitability of the model is to look at the generalising ability by estimating the size of the forecasting error, with the supposition that selecting the right model will result in low forecasting error. Another possible explanation for the problem of over-fitting is the choice of the sample size for training the model. A lot of data will allow the model with a certain level of complexity to differentiate the noisy from the relevant data (Hellström and Holmström, 1998). The concepts described here are important for volatility forecasting. A given sample size should be divided into two parts; the in-sample for training the data and the out-of sample for forecasting into the future. A good approximation for these two sub-periods is required to avoid the problems associated with fitting the data for a given model.

2.3 Pre-processing of Time Series[5]

[5] The size of theoretical literature concerning the development of the filtering methods for the financial time series is large and it is briefly summarised in Sections 2.4.1. and 2.4.2. Descriptions in these sections are mainly based on the work of Gançay et al. (2001) for the applications of wavelet and other filtering methods in finance and economics. For more details on how wavelet works for the time series, Percival and Walden (2000) book was used. The modelling details from their work are included in section 2.5. For

It is very important to extract the features from the time series that are unseen during the analysis of components of the time series. Several approaches are introduced in the finance and economic literature which aim to filter the time series data and the most important are discussed here.

2.3.1 Traditional Pre-processing Techniques

In order to pre-process the time series, we must decide on which ideal filter can extract important features from the time series. An ideal filter removes the frequency components of time series that lie within a particular range of frequencies such as a business cycle. One of the main filters introduced within finance is the exponential weighted moving average (EWMA). This filter plays a major role in risk management. The *Risk Metrics* program developed by J.P, Morgan in 1994 already relied on the EWMA to find an almost accurate estimate of volatility and correlation of financial instrument for market risk calculations in the value-at-risk (VaR) framework. The main advantage of the EWMA model in the filtering of time series is that the output of its filtering process contains more high-frequency dynamics and a better local estimate of volatility than that of a simple moving average (Gançay et al. 2001). Another widely employed filter in finance is the Hodrick and Prescott (HP) filter which aims to remove the cyclical components of the time series from the data (Hodrick and Prescott, 1997).

However, the performance of the HP has been criticised because it distorts the dynamics of the original time series (Cogley and Nason, 1995). Further problems of HP have been identified including the unusual behaviour of the cyclical components near the end of the sample (Baxter and King, 1999) and the production of flexible trends that follow the time path of the original time series (McCallum, 2000). A further filter was introduced by Baxter and King (1999) aiming to avoid the shortcoming of previous filters, which captures the fluctuations within a specific period of length of 6 to 32 quarters in each quarterly time series.

Nonetheless, the main criticism of the Baxter and King filter is that it might induce both spurious dynamic properties and the cyclical component which fail to capture a significant fraction of variability in business-cycle frequencies (Guay and St.-Amant, 2005; Murray, 2003). However, using the HP on return does not provide any idea of how high-frequency information is embedded into return series on time-scales. Therefore, a more advanced filter is still required to partition aggregate return data and obtain more information on the details rather than focusing on low-frequency components.

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a comprehensive review on the application of wavelet on time series data, the reader may refer further to Percival and Walden (2000).

2.3.2 Fourier and Short-term Fourier Transforms

The complex statistical nature of most time series requires advanced filters that can represent the frequency and time scale in a proper way. One of the filters introduced to deal with this issue is the discrete Fourier transform (FT) which can decompose the discrete time series in a linear combination of sine and cosines. The Fourier basis function is very efficient when representing return series with a pattern that does not change over time and therefore it assumes that the process is stationary. However, the Fourier transform lacks the power to represent the time series over time.

(Gabor, 1946) recognises the shortcomings of the FT by developing an extension to a sliding a window across the time series and taking the FTof the subsets of the series. This type of filter became known as the Short Time Fourier Transform (STFT) and it can represent the time series in both the time and frequency domain but the window size is kept fixed with respect to the frequency (see Figure 2.1.) Having the fixed time window size makes the STFT inefficient particularly when the events in the time series appear within the width of the window size (Gançay et al., 2001).

2.4 Wavelet Transform

The next section briefly introduces the basics of wavelet. Section 2.4.2 describes the most commonly used wavelet methods in finance and economics. Section 2.4.3 describes some wavelet families and their main properties, while Section 2.4.4 introduces the notions of wavelet variance, covariance and correlation. All the notations and equations in the subsequent sections are from Percival and Walden (2000).

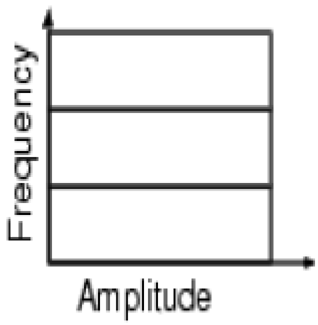
2.4.1 What Does Wavelet Mean?

Wavelets are successfully employed in many fields of research other than finance, such as statistics. It is a pre-processing function that aims to discover the property of the time series (Signal) by allowing the wavelet filter to move over the time series data, before decomposing the main series into sub series with a local time and frequency domain. Therefore, wavelet methods differ from the Fourier and STFT as they not only cover the frequency but also the exact time where a given event occurred in the time series.

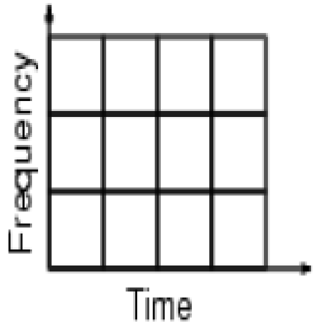
More specifically, the concept of wavelet denotes a ‘small part (wave)’ of the signal that appears in a specific time and disappears afterward. In contrast to a ‘big wave’, which performs differently

Figure 2.1 Fourier Transform (a) and (b) Short-Time Fourier Transform

(a)



(b)



Source: Crowley (2007)

over frequent patterns, without a limited time duration for each. An example of the big wave is the sine function.

To clarify further, Figure 2.2 plots both the wavelet and the sine functions of the real value of x. A simple type of wavelet, namely the Morlet function is considered here for this example. The graph shows that the sine function keeps oscillating up and down on the plot of $x \in (-20, 20)$. By contrast, relying on the small wave function introduces what is called the 'mother' wavelet filter. Here the real-valued function is $\psi(\cdot)$ defined over the *x*-axis and it must satisfy the following two conditions:

$$\int_{-\infty}^{\infty} \psi(x)dx = 0 \tag{2.6}$$

$$\int_{-\infty}^{\infty} \psi^2(x)dx = 1 \tag{2.7}$$

These two conditions for the wavelet indicate that the integral of $\psi(\cdot)$ is zero, while the square of $\psi(\cdot)$ must integrate to unity. On the other hand, for the sine function, the integral should be infinite, which in turn means that the $\sin^2(\cdot)$ cannot integrate to unity[6].

Figure 2.2 keeps the defined interval of (-T, T) = $(-20, 20)$. If the condition of unity in equation 2.7 holds for any ε satisfying that 0< ε <1, then the sub interval (-T, T) must be defined as:

[6] For further clarification see Percival and Walden (2000).

$$\int_{-T}^{T} \psi^2(x)dx < 1-\varepsilon \tag{2.8}$$

Here, taking ε as a value close to zero, should enforce $\psi(\cdot)$ to deviate insignificantly from zero outside of the given interval (-T, T). This interval is small relative to the infinite space that the sine function works over.

The non-zero moment of $\psi(\cdot)$ is also limited over a specific time interval. The wavelet works in a way that any excursions above zero should cancel out those below zero and an outcome of that must be the detection of a small wave that dies out because of this cancellation. A good representation of that small wave is given by the Morlet wavelet in Figure 2.2[7]. The Morlet wavelet is suitable for a continuous time series. There is no scaling function associated with the Morlet wavelet and it is usually considered the simplest function for two reasons. First, it must taper to zero at both ends and have a mean value of zero. Second, there is no scaling function associated with the Morlet wavelet and that should provide redundant information while decomposing return series data. Morlet wavelet can be used, however, for analysing the coherence in return and price data. Yet, some researchers consider Haar the simplest wavelet for analysing the price, though not the return. This is because applying the Haar wavelet on returns can generate spurious spikes and remove more relevant information from the data, Percival and Walden (2000).

The essence of wavelet can be described further depending on the weighted averages of certain functions that vary from one sub-period to the another, inside the main interval (-T, T). To begin, let N= number of observations and $x(\cdot)$ be again the real value function of the time *t* which represents the signal or the time series at hand. Accordingly, the sample mean of a set of N observations within the sub-interval is:

$$\frac{1}{b-a}\int_{a}^{b} x(u)du \equiv a(a,b) \tag{2.9}$$

Where: $a(a,b)$ is the average value of *x* within the sub-interval, with a and b being the lower and upper band of the sub-interval and $a < b$[8].

[7] Section 2.4.3 briefly describes other types of mother wavelets. For further details, refer to Percival and Walden (2000).

[8] That, however, is a more general definition for the scale and does not apply to the Daubechies wavelet. Generally, scale represents frequency band and every scale covers part of the frequency spectra. We can

At a specific time, *t*, we obtain:

$$x(\cdot) = x_j \text{ for } A(b-a) \equiv (t-\frac{\lambda}{2}, t+\frac{\lambda}{2}) = \frac{1}{\lambda}\int_{t-\frac{\lambda}{2}}^{t+\frac{\lambda}{2}} x(u)du \text{ and } j = 0,\ldots, N-1 \quad (2.10)$$

The Mother wavelet here divides the whole-time series into time-scales and each one represents $\lambda \equiv (b-a)$ and the centre of this time interval must be $t \equiv (a+b)/2$. After defining the scales based on the mother wavelet, the average value of the time series over the scale $\lambda(t)$ can be defined by:

$$A(b-a) \equiv (t-\frac{\lambda}{2}, t+\frac{\lambda}{2}) = \frac{1}{\lambda}\int_{t-\frac{\lambda}{2}}^{t+\frac{\lambda}{2}} x(u)du \quad (2.11)$$

The above introduction to wavelet describes the notion of time-scaling and explains how it works with the mother wavelet. Yet, it is important to understand what complement the mother wavelet filter in the decomposition process and how exactly that decomposition works. The answer here is that the main aim of wavelet is to decompose the given time series (S) into both approximation (low-frequency) (A) domain and details (high-frequency) (D) component. According to wavelet transform, the decomposition of series into timescale at *n*-level is as follows:

$$S_n = A_n + \sum_{t=1}^{n} D_t \quad (2.12)$$

Where: **S** is the main signal (time series), A and D are the approximation and details components respectively, n is the number of resolution levels, and λ is the decomposition level, which is denoted in the text before by λ .

While the detail coefficient is important to capture the high-frequency events, the approximation coefficient provides a general visualization of the time series with its low-frequency components. Both components here (details and approximation) result from a pair of high-pass and low-pass filters respectively.

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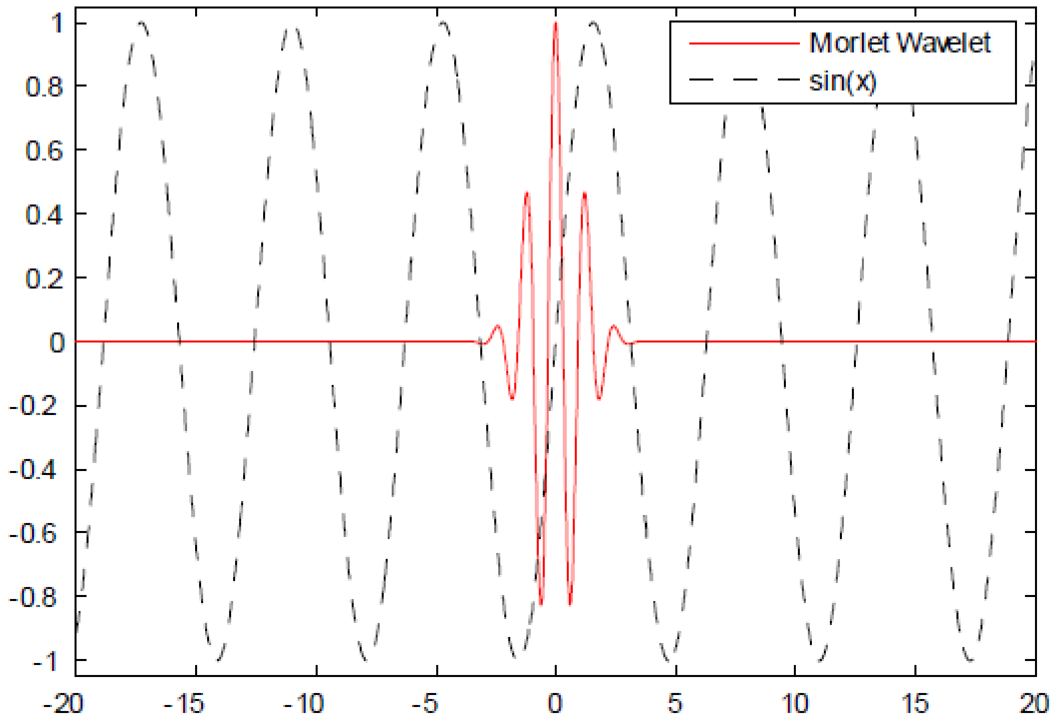
have different wavelets, but the principle is the same. So, for the daily data, the first scale covers the highest frequency (1/2 - 1/4), i.e., [2-4] days. For the second scale, you have 1/4 - 1/8, i.e., 4-8 days.

Figure 2.2 Morlet Wavelet and Sin(x) function



Source: Masset (2008).

The decomposition process starts by dividing the signal into two series, A and D. In other words, the filter that produces the approximation series can be very similar to the moving average filter. That is, they both focus on the cyclical, seasonality and other long-term components. With this decomposition approach, the components in each series at the subsequent resolution levels have to be given by CA and CD for the approximation and details series respectively. In wavelet language, each of these coefficients is called an 'atom' and the coefficients for each scale are termed a 'crystal'.

During the pass filtering process, two main types of filter wavelets Father ϕ and Mother ψ are always incorporated. However, the following conditions must be met:

$$\int \phi(\mathrm{t}) d_t = 1 \tag{2.13}$$

$$\int \psi(\mathrm{t}) d_t = 0 \tag{2.14}$$

This means, mother (wavelet) integrates to zero and the father (scaling) integrates to one. While the mother wavelet mainly represents the details coefficient, the father filter creates the smooth coefficient through the multi-resolution process as follows

$$S_n = \phi A_n + \sum_{\lambda=1}^{n} \Psi D_\lambda \tag{2.15}$$

Where: λ= the time-scale.

The multiresolution process employs the 'pyramid algorithm', which was introduced by Mallat (1989) to work in the context of wavelet. The algorithm further works by considering the approximation series at the second time-scale as the original series. Hence, the decomposition continues using the approximation series until the final resolution level *n* is reached.

The importance of the wavelet is that it can extract more hidden details, such as the irregular elements or the noise that usually contaminate a given original data. Several studies in the literature discuss the importance of wavelet in finance and economics (see, for example, Ramsey, 2000; Masset, 2008). However, there are mainly two specifications of wavelet transform that are used in the finance literature; the discrete wavelet (DWT) and the maximum overlap discrete wavelet transform (MODWT), both are discussed in Section 2.5.2 below.

2.4.2 Properties of Wavelet Transform:

This section provides a brief theoretical description of the most popular wavelet properties and their related wavelet families.

2.4.2.1 The Discrete Wavelet Transform (DWT)

The DWT relies on keeping the half number of wavelet coefficients every time the wavelet decomposition is applied. The process is known as subsampling (down-sampling), where the number of coefficients in the time-scale $\lambda = 2$ should be half of that at scale $\lambda = 1$. Yet, before initiating the decomposition process, the maximum number of scales should be decided only based on the dyadic signal. Specifically, when it comes to DWT, it is essential that $N \geq 2^{\lambda}$ where again the N is the number of observations in the signal.

The Pyramid algorithm for the decomposition process can either use a linear filtering operation or matrix manipulations[9]. The first stage in the DWT involves using the mother (wavelet) and the father (scaling) filters to decompose the original signal. The mother real-valued wavelet filter, if denoted by h_i, must satisfy three main conditions:

[9] Both approaches have been described in detail in Percival and Walden (2000). The matrix manipulation describes better how the wavelet filter with a specific width convolves over the time series.

$$\sum_{i=0}^{L-1} h_i = 0; \qquad (2.16)$$

$$\sum_{i=0}^{L-1} h_i^2 = 1; \qquad (2.17)$$

and

$$\sum_{i=1}^{L-1} h_i h_{i+2n} = \sum_{i=-\infty}^{\infty} h_i h_{i+2n} = 0; \qquad (2.18)$$

Where: L is the width of the wavelet filter and should be an integer. n values in the above conditions must also be non-zero integers.

In other words, the first condition implies that the mother wavelet works with a difference operator. The second condition ensures the decomposing of the data in a way that keeps the original variance of the series. That means, the variance of the signal should be equal to the sum variances over the time-scales. The last condition ensures that the analysis is being conducted on the finite variance series. Yet, according to these conditions and for h_i to have the width of L, we must keep $h_{L-1} \neq 0$ and $h_0 \neq 0$. The h_i mother wavelet is a filter which has a finite sequence with the maximum L non-zero values.

Nevertheless, the second part of the analysis which is responsible for obtaining the approximations is the father filter g_i. This filter is a quadratic mirror function and should be defined by:

$$g_i \equiv (-1)^{i+1} h_{L-1-i} \qquad (2.19)$$

Where the inverse relationship between the mother and father wavelet can be given by:

$$h_i = (-1)^i g_{L-1-i} \qquad (2.20)$$

Before representing multiresolution analysis with the matrices, let the time series data be denoted by S and its length, as emphasised above, be $N = 2^j$. Here the number of subsequent steps in the pyramid algorithm must be $j-1$. For the first stage in the multiresolution analysis the mother and father filters convolve over the S series to generate the approximation $CA_1^t = \sum_{i=0}^{L-1} g_t S(t)$ and the detailed coefficients, $CD_1^t = \sum_{i=0}^{L-1} h_t S(t)$. This stage of analysis can instead be expressed in a matrix by:

$$P_1 S = \begin{bmatrix} CA_1 \\ CD_1 \end{bmatrix} X = \begin{bmatrix} A_1 \\ D_1 \end{bmatrix} \tag{2.21}$$

Where: P_1 denotes the output of the pyramid algorithm at stage one. All the indexes values must be used here to form the first approximation series.

The DWT approach performs the down-sampling. The idea is applying each filter on the data and the wavelet filter with specific length should convolve at specific dates. For other dates, different lengths of filters must be applied as well. The whole decomposition process at the first scale can be described as interleaving the outputs from two cross-correlations as follows:

$$S_t = \sum_{i=0}^{\frac{L}{2}-1} g_{2i+1} A_{1,\frac{t}{2}+i \bmod \frac{N}{2}} + \sum_{i=0}^{\frac{L}{2}-1} h_{2i+1} D_{1,\frac{t}{2}+i \bmod \frac{N}{2}} \tag{2.22}$$

For t= 0, 2,…, N-2

and

$$S_t = \sum_{i=0}^{\frac{L}{2}-1} g_{2i} A_{1,\frac{t-1}{2}+i \bmod \frac{N}{2}} + \sum_{i=0}^{\frac{L}{2}-1} h_{2i} D_{1,\frac{t-1}{2}+i \bmod \frac{N}{2}} \tag{2.23}$$

With t= 1, 3,…, N-1.

On the other hand, reversing the process with the up-sampling will re-construct the signal by inserting zeros between the elements of D_1:

$$D_{1,t} \equiv \sum_{i=0}^{L-1} h_l D^{\uparrow}{}_{1,t+i \bmod N} \tag{2.24}$$

Where: $D^{\uparrow}{}_{1,t} \equiv \begin{cases} 0, t = 0, 2, ..., N-2 \\ D_{1,\frac{t-1}{2}}, t = 1, 3, ..., N-1 \end{cases}$.

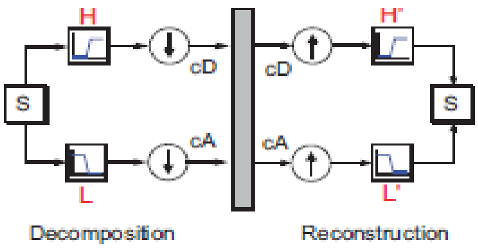
The same up-sampling procedure applies to the approximation series A_1. After that, the final reconstructed time series can be given by:

$$S_t = \sum_{i=0}^{L-1} g_i A^{\uparrow}{}_{1,t+i \bmod N} + \sum_{i=0}^{L-1} h_i D^{\uparrow}{}_{1,t+i \bmod N} \tag{2.25}$$

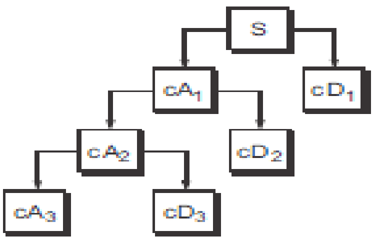
The whole decomposition (down-sampling) and reconstruction (up-sampling) stages using the DWT are depicted below in Figure 2.3[10]. The reconstruction step reversed the start of the decomposition process by up-sampling before applying the wavelet filters.

Figure 2.3 (a) High-Low Pass Filters, (b) Multi-Levels Decomposition Scheme of Discrete Wavelet Transform Using the Pyramid Algorithm

(a)



(b



Source: Misiti et al. (1996).

[10]The decomposition to generate the first detailed component in the DWT is just the output of passing (convolving) the specific length filter of odd values with the dates of the time series to end with the matrix 81c on page 81 in Percival and Walden (2000), clarified in figure 80 on page 80. However, in the MODWT we pass all the filters lengths on the time series twice. More specifically, we select the output of filtering with the odd values in the first time, and with the even values in the second time before interleaving between both to produce the matrix 165a in page 165 and as clarified in figure 175 on page 175 in Percival and Walden (2000).

2.4.2.2 The Maximum Overlap Discrete Wavelet Transform (MODWT)[11]

The MODWT was proposed to overcome the drawbacks of the DWT. Based on Percival and Walden (2000), the MODWT does not require a dyadic length of data (i.e. $N = 2^{\lambda}$), hence it can handle any sample size[12]. Second, in contrast to the DWT, the MODWT is a shift invariance process. In other words, any circular shift in the starting point of the series must shift in the detail and the smooth components by the same amount[13].

The existence of the zero filters in both high- and low-pass process can ensure that 'no circular shift' effect holds. This as well produces more efficient way of the MODWT's wavelet variance decomposition (see Section 2.4.4 below). Lastly, the MODWT maintains the same number of wavelet and scaling coefficients for all time-scales. That means, the number of observations in the original series, before decomposition starts, must be equal to that at each time-scale.

To begin the MODWT decomposition process, the 'rescaled' wavelet filter must meet the following conditions:

$$\sum_{i=0}^{L-1} \tilde{h}_i = 0; \tag{2.26}$$

$$\sum_{i=0}^{L-1} \tilde{h}_i^2 = \frac{1}{2}; \tag{2.27}$$

and

$$\sum_{i=-\infty}^{\infty} \tilde{h}_i \tilde{h}_{i+2n} = 0; \tag{2.28}$$

Similarly, the scaling filter must meet the above conditions where the 'rescaled' wavelet $\tilde{h}_i$ must be replaced by the $\tilde{g}_i$.

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[11] For more details on the properties of the MODWT, see Percival and Walden (2000, pp. 159-205).

[12] Some solutions documented in Percival and Walden (2000) deal with the restriction dyadic length. For example, the "polynomial approximation" which replaces non-existing data at each end of the series using a polynomial model. Another approach is called "reflection" and involves completing the end of a given time series by mirroring the last observations. Yet, as Masset (2008) argued, when it comes to analysing the stock return data, the "reflection" approach must be the most appropriate as it accounts for the volatility clustering in the return series.

[13] For more clarification see pages 160-162 on Percival and Walden (2000).

The quadratic mirror relationships between the two filters defined in equations 2.19 and 2.20 also holds for the new rescaled MODWT filters. The detailed coefficients at any time-scale λ can be constructed in terms of the filtering operation and with the signal S and starting with a zero-phase filter, such as:

$$\tilde{D}_{\lambda,t} = \sum_{i=0}^{L-1} \tilde{h}_{\lambda,i} S_{t+i \bmod N} = \sum_{i=0}^{L-1} \tilde{h}^{0}_{\lambda,i} S_{t+i \bmod N} \tag{2.29}$$

Similarly, the approximation series at i has to be:

$$\tilde{A}_{\lambda,t} = \sum_{i=0}^{L-1} \tilde{g}_{\lambda,i} S_{t-i \bmod N} = \sum_{i=0}^{L-1} \tilde{g}^{0}_{\lambda,i} S_{t-i \bmod N} \tag{2.30}$$

As it is clearly shown in the Equations 2.29 and 2.30, no down-sampling is performed during the decomposition with the MODWT.

Where: $\tilde{g}^{0}_{\lambda,i}$ and $\tilde{h}^{0}_{\lambda,i}$ are respectively the periodised versions of $\tilde{g}_{\lambda,i}$ and $\tilde{h}_{\lambda,i}$ to length *N*. Yet, the inverse MODWT can be obtained at scale $\lambda - 1$ as follows:

$$\tilde{A}_{\lambda-1,t} = \sum_{i=0}^{L-1} \tilde{g}_i \tilde{A}_{\lambda,t+2^{\lambda-1} i \bmod N} + \sum_{i=0}^{L-1} \tilde{h}_i \tilde{D}_{\lambda,t+2^{\lambda-1} i \bmod N} \tag{2.31}$$

Yet, regardless of the decomposition method (i.e. the DWT or the MODWT) the matching scheme with the frequency of data must be standard. That is, with the daily data, the first time-scale corresponds to [2-4] day-period, the second scale= [4-8] day-period, the third scale= [8-16], the fourth scale= [16-32], the fifth scale with [32-64] and the sixth scale represents [64-128] day-period. These time-scales overlap where, for example the scale [2-4] covers 2 and up to 4 days. The next time-scale [4-8] then continues from the day 4 and up to 8 days, and so forth for the subsequent time-scales. The optimal number of scales to be included for such a case study in finance can be advised based on the variance decomposition of the time series at hand (see Section 2.4.4 for further details).

Moreover, according to Percival and Walden (2000), the discussion made above can appeal to an appropriate extension of the Central Limit Theorem where the distribution of the time series data should converge to gaussian as the time-scale (i.e. λ) increases. In other words, Percival and

Walden (2000) points out that, at small and moderate scales, the tails of the distribution are far from gaussian, but tend to become gaussian at the higher time-scales[14].

2.4.3 Wavelet Families

Wavelet filter has different forms that range from symmetric to asymmetric and the choice between them depends on the time series to be studied. The most common symmetric wavelet is Haar which has a square form and suits more the smooth time series data. Examples of a near symmetric wavelet are symmlets and coifletes and for asymmetric ones the Daubechies are the most widely used. In practice, selecting the filter length that attached to the wavelet name is more important than selection itself (Masset, 2008). Two main important properties for wavelet are the scale and translation (shifting). Whilst the translation aims to scan for the high-frequency part of the signal, low-frequency events can be found by the scaling property. Figure 4.2 represents respectively the scaled and translated properties of Symmlet 's8' Wavelets. The first number between the brackets and below each graph denotes for scale. The mother wavelet scans for different types of information at higher scales. More details to be discovered at the lower time-scales through translation property. The real values of the filters are calculated in Daubechies (1992, 1993) and described further in Percival and Walden (2000, p.109).

Yet, as Masset (2008) argued, careful selection of the wavelet filter is required depending on several conditions. The first condition is the symmetry where the wavelet filter coefficient must match the output of the decomposing process. Yet, the MODWT has already been introduced to avoid this problem and allows for using any asymmetric wavelet filter instead of a symmetric one. Second, the orthogonality of both filters should also apply while decomposing the data. Specifically, this property addresses the importance of simultaneously using both the wavelet and scaling filters with no overlapping between them. This notion applies where different information can be extracted using different filters. Crowley (2007) argues that this is an important assumption for the coefficients decomposition to be able to preserve the variance of the original series. Third, the filter's degree of smoothness is an important consideration. According to this, the asymmetric filter must be more appropriate when the time series at hand is more volatile. Practically, Percival and Walden (2000) find that using, for example, the symmetric Haar filter for analysing a volatile time should provide more smooth details and the approximation components. Hence, this means losing more information from the original series. The last condition concerned the number of vanishing moments. That is, if a signal has a polynomial structure with an order of q, then the

[14] It can be argued that the assumption of normality of the Central Limit Theorem contradicts that of the non-normality of wavelet methods being described in this chapter. Yet, applying the nearly asymmetric filter on the changes of the log of the series should solve this issue.

wavelet transform can exactly capture this polynomial structure only if it has q vanishing moments. The number of vanishing moments equals half the length of the filter.

2.4.4 Wavelet Variance, Covariance and Correlation

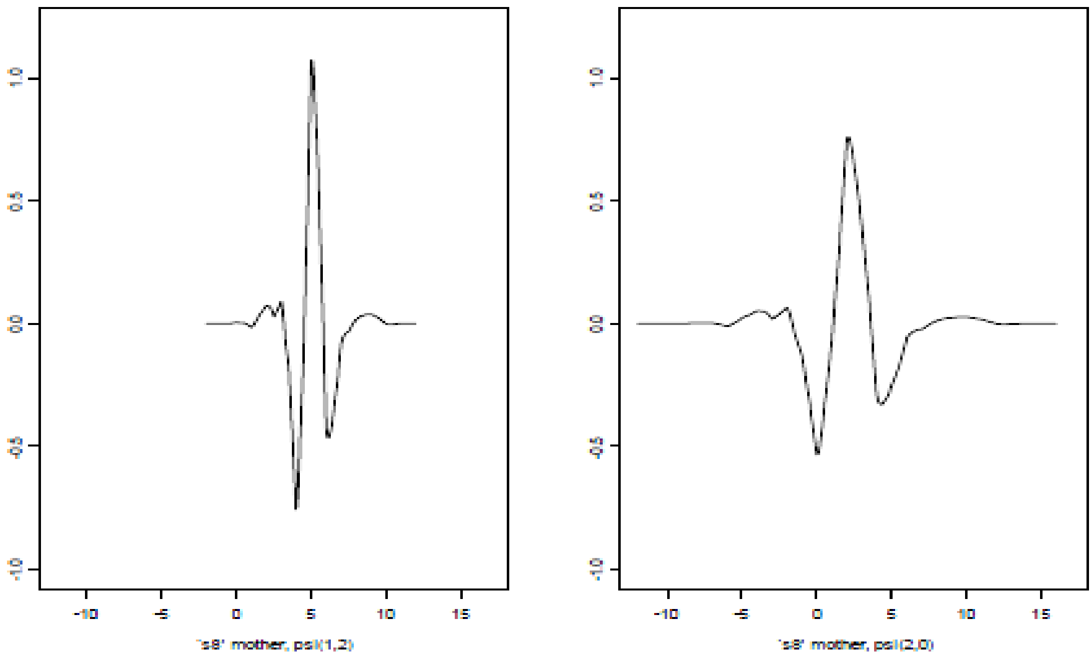
One of the main properties of the wavelet transforms is to decompose variance of the time series at hand across the time-scales. Based on that, the optimal number of scales can be decided. Hence, an interesting exercise based on that is to examine which time-scale contributes more to this variation. Steps to follow can also use produced variance-based decomposition to give a better insight into the covariance between any pair of time series and the correlation change over time. The two signals are denoted here by *X* and *Y*.

According to Percival and Walden (2000), estimating the variance over scales involves a few steps. But before proceeding, the approach they follow requires the times series to be a nearly stationary process with the backward differences. The appropriate filter and its width should be selected to avoid the leakage problem which usually arises from using the small filter width and leads to the misleading decomposition. This can be true with a simple wavelet filter such as Haar which produces a wavelet variance that is systematically higher than that produced by other filters at the distant times-scales (Percival and Walden, 2000). The resulting detail coefficients at a given scale *j* and at time *t* are then given by $D_{j,t}$. For the ease of interpretation, we denote the scale of the wavelet filter by τ_j and its length $L_j = (2^j - 1)(L-1)+1$, where L is the width of the unit scale filter. With the total number of observations in our time series being n, the analysis employing only the detailed coefficients which are not affected by the boundary conditions, namely $\tilde{N}_j = n - L_j + 1$. As emphasised by Percival and Walden (2000), the wavelet variance-estimator must be unbiased to reserve the same amount of variance (energy) in the signal while decomposing over time-scales. In this case, the variance-decomposition builds on the basic notion that the variance of either time series *X*, $[\nu_s^2(\tau_j) - \Phi^{-1}(1-p)\sqrt{\mathrm{var}(\nu_s^2(\tau_j))}, \nu_s^2(\tau_j) + \Phi^{-1}(1-p)\sqrt{\mathrm{var}(\nu_s^2(\tau_j))}]$ or *Y*, $\nu_Y^2(\tau_j) \equiv \mathrm{var}\{\tilde{D}^{Y}_{j,t}\}$ is simply made-up. That is, the variance at a given scale takes the difference between the weighted average of the process at interval τ_j and those outside. The wavelet-variance estimator is also unbiased because when it is applied to the stationary time series, it produces a zero mean for $\tilde{D}_{j,t}$ at any time-scale with the differencing being embedded within the filter (Percival and Walden, 2000). Altogether, taking the assumptions of unbiased estimator and no effect coming from the boundary condition[15], variance at scale τ_j can be given by:

$$v_S^2(\tau_j) = \frac{1}{\tilde{n}_j}\sum_{t=L_j}^{n}\left[\tilde{D}^{S}_{j,t}\right]^2 \tag{2.32}$$

Where: S is either the X or Y signal. Next, for the covariance of between the two series, the estimation is defined as:

Figure 2.4 Scaled and Translated Symmlet 's8' Wavelets. Source: Crowley (2007).



$$Cov_{X,Y}(\tau_j) = \frac{1}{\tilde{n}_j}\sum_{t=L_j}^{n}\tilde{D}^{X}_{j,t}\,\tilde{D}^{Y}_{j,t} \tag{2.33}$$

Based on these unbiased properties, the final correlation between the two series can be defined using the usual fashion by dividing the covariance by the variance:

[15] It is the case where the signal must be extended in order to apply the filter on it and ensure that all the elements of the filter are convolved over the data. Extending the signal can be done in different ways. In all the empirical chapters in this thesis, the reflection boundary condition is applied as it is suitable for the volatile time-series data. In the first empirical chapter, for example, I extended the signal from both sides by no more than 350 observations. I could ignore these extra observations after applying the wavelet filter on the data.

$$\rho_{X,Y}(\tau_j) = \frac{Cov_{X,Y}(\tau_j)}{\nu_X^2(\tau_j)\nu_Y^2(\tau_j)} \tag{2.34}$$

As a further step, Percival and Walden (2000) defined a random confidence interval that must vary each time the variance, covariance or the correlation is estimated on scales. At p=5% significance level, the (1-p) ×100% the confidence interval with the lower and upper intervals can then be obtained from:

$$[\nu_s^2(\tau_j) - \Phi^{-1}(1-p)\sqrt{\mathrm{var}(\nu_s^2(\tau_j))}, \nu_s^2(\tau_j) + \Phi^{-1}(1-p)\sqrt{\mathrm{var}(\nu_s^2(\tau_j))}] \tag{2.35}$$

Where: the assumption made here with $\Phi^{-1}(1-p)$ being the $(1-p)$ percentage point for the Gaussian distribution and this holds throughout the analysis. This, however, has been confirmed further in robustness checks in all chapters where different distributions are assumed. I end with similar quantitative results regarding the correlation coefficient on time-scales.

2.5 Empirical literature

This section outlines the empirical literature. Section 2.5.1 discusses the importance of examining the return series data at hand before forecasting the volatility using parametric approaches. Section 2.5.2 summarises the recent studies concerned with the applications of wavelet in finance and economics.

2.5.1 The status of financial data and volatility forecasting with ARHC/GARCH models[16]:

2.5.1.1 Improving the forecasting performances of GARCH models

Stock market volatility is an important topic with more studies being conducted to forecast the excess volatility using a wide range of models. The fact is that more research came after the seminal work of Mandelbrot (1963) to build on his findings regarding the existence of volatility clustering in the financial time series. From this point several models are used which range from simple econometric models to those much more complicated in nature. For example, models such

[16] In a part of this section, both the terms outliers and noise are used separately as there is a difference in meaning between them. Outliers can be just points in the noisy process and they are difficult to detect and handle. However, pre-processing techniques such as wavelet can deal with both (i.e. noise and outliers) but with caution. For more details on the related topic of outliers, see Aggarwal (2013).

as random walk, moving average, autoregressive moving, exponential smoothing and some of their extensions have been used in the literature due to their simplicity but one major drawback of these is the assumption of a constant conditional variance over time. Recognising this, Engle (1982) created the corner stone in time series forecasting and introduced the new model namely autoregressive conditional heteroscedasticity (ARCH) that allowed for the conditional variance to vary over time. Following Engle's work, researchers built more extensions (e.g. GARCH, TGARCH and IGARCH, CGARCH[17]) in order to enhance the performance of the ARCH modelling in dealing with phenomena such as asymmetry and long memory in the time series data.

To investigate the usefulness of GARCH models in practice, Frances and Van Dijk (1996) compare the performance of two asymmetry models, namely the Quadratic GARCH of Engle and Ng (1993) and the threshold GARCH model and find that the QGARCH model is superior in providing more accurate forecast during the crisis period. Analysing the monthly stock index from emerging markets, Gokcan (2000) finds that simple GARCH model (1, 1) performs better in an out-of sample analysis than the asymmetry EGARCH. By contrast, Alberg et al. (2008) find that asymmetry models represented by EGARCH, TGARHC, and APARCH can forecast the Tel Aviv stock index returns better than the simple GARCH model.

The performances of GARCH models in forecasting have also been examined by studies such as Akgiray (1989), Brailsford and Faff (1996), McMillan et al. (2000) and McMillan and Speight (2004). Due to the popularity of GARCH models in forecasting, the interest has shifted from using the models as they are in forecasting towards enhancing their performance. That has been done in different ways. For instance, Wilhelmsson (2006) reassesses the performance of GARCH (1,1) using different distributions and finds that using the leptokurtic distribution in his study which comprises daily, weekly and monthly data provides better forecast than using the normal distribution. Furthermore, regarding the true volatility proxy that the forecasts must be compared with, researchers also concentrated on selecting perfect actual forecast measures and this is considered an important shift even in finding a reasonable ranking for the forecasting models. From this point, studies such as Andersen and Bollerslev (1998) and Andersen et al. (1999) favour the realised volatility measure (i.e. intraday daily and high-frequency data) as a less noisy proxy among the simple and usually employed squared daily returns measure. The importance of using the appropriate true volatility proxy has also been documented by Patton (2011) and he finds that it is crucial to use less noisy volatility proxies as this is found to generate fewer distortions in

[17] These denote Generalised ARCH, Threshold ARCH, Integrated ARCH and Component ARCH, respectively.

forecasting. Further studies have concentrated on the way of enhancing the performance of ARCH/GARCH models by use of realised volatility directly in forecasting instead of just using the daily data.

However, the redundancy of high-frequency data might require special treatment in the presence of noise[18]. A good early argument for this is made by Magdon-Ismail et al. (1998, p.2):

"*We could choose to use the tick-by tick data because we will then have many data points, but the price we have to pay is that these data points are much noisier. The tradeoff will depend on how much noisier the tick-by-tick data is and the details of the learning scheme. Market analysts would like to quantify this tradeoff by how it affects performance*".

Developments in the area of microstructure noise and financial markets forecasting are concerned with the volatility as true estimator. Research in this area is still growing. In their study, Corsi et al. (2001) perform the time-scaling analysis with the aim of achieving improved realised volatility estimator. They prove that the bias in the estimator increased as the frequency of the data increases. The negative bias they documented originates from microstructure noise which in turn causes price negative autocorrelation in the return series itself. Furthermore, Corsi et al. (2001) show that the level of bias differs both in sign and magnitude between the exchange rate and the stock market return series. Focusing on the high time frequency components of the intraday day data, Bandi and Russel (2006) separate the noise from the efficient price. Their work analysed carefully the variance of the noise itself and documented a positive relation between the optimal sampling frequency of the realised volatility estimator and the signal-to-noise ratio. Yet, with these attempts and others to decide on the best true volatility estimator, there is still much work to be done before it can be said that the true estimator is completely free of noise.

In an influential research on the suitability of ARCH/GARCH models, Hansen and Lunde (2005) find that the daily data simple model GARCH (1, 1) can provide a powerful forecast in comparison with other models. This finding has been further empirically examined by McMillan and Speight (2012) but with an intraday and daily data and they find that the standard GARCH model was bettered when using the daily, but not intraday data which generated a contradiction to the finding of Hansen and Lunde (2005).

In sum, the suitability of the model in asset pricing and the characteristics of financial data at hand both affect the forecasting in practice and there continues to be no agreement on the best model for forecasting.

[18] Hansen & Lunde (2006) studied the effect of microstructure noise in sample of stocks in DJIA index and provide some implications, so the reader can refer to their work.

2.5.1.2 Does accounting for noise and outliers in return series improve the forecasting performance?

Poon and Granger (2005) provide a comprehensive survey on stock market forecasting and they considered practical issues in forecasting in 93 studies that employed the time series models and implied volatility models. In their conclusion, Poon and Granger highlighted the importance of using exogenous variables in forecasting but the future recommendation they made was the need to understand how the relation between the volatility models and the incremental factors can improve the prediction of volatility. One issue ignored by Poon and Granger (2005) is the characteristics of the financial data at hand.

One of the stylised facts of the stock market time series data is the volatility clustering, where the highly-fluctuated period in the stock index usually followed by high and the low–period repeats itself as well. This is again what it is economically described by ARCH effect. However, several studies in the literature tried to understand why this effect exists, and which factors make specific volatile periods in the index connected to each other. Generally, the fact of extreme events (i.e. outliers) that exist in the markets is a possible reason to have that clustering pattern. Ignoring the outliers might harm the estimation of GARCH models or even on the forecasting accuracy. Franses et al. (2004) examine the evidence of ARCH process under the presence of additive outliers in their isolated and short patch form. The study found that isolated outliers mostly reduced the appearance of ARCH effect. In another study, Franses and Ghijsels (1999) investigate further the effect of additive outliers on the forecasting accuracy of GARCH-normal and GARCH-t models. They take both the sign of stock index return and the sub-periods in consideration while correcting and accounting for the additive outliers. In an interesting finding, Franses and Ghijsels (1999) reject the normality assumption for the corrected returns. They also conclude that the out-of sample forecasts for all the models they employ are more accurate for the corrected time series in most of the sub-samples.

Unlike previous studies that aimed to investigate the effect of outliers, Carnero et al. (2008) employ different robust tests along with the GARCH-normal. Their study considers the impact of the volatility outlier (VO) in addition to the level outlier. In a sample of daily stock market indexes, those robust tests employed provide general evidence that both the prediction power, as documented by the magnitude of mean square error (MSE), and the parameter estimates were both affected by the outliers in the data.

In another way, Gregory and Reeves (2010) examine the effect of the outliers on the GARCH (1, 1) replacing the outliers by their expected (conditional) values in order to have the most superior out-of sample results. With a quasi-maximum likelihood function, the conditional-based predictor significantly improved the forecasts when these are compared with the contaminated-based model.

Moreover, Charles (2008) studies the effect of additive and innovative outliers on the pure forecasts obtained by GARCH-normal (1, 1), GARCH-Student (1, 1) against the benchmark GARCH (1, 1) unadjusted-based model. Generally, under different forecasting time horizons, the corrected data sets provided better out-of sample predictions. The most interesting finding in his study was in obtaining the better out of sample forecasts after using the hard thresholding wavelet transform.

It is apparent that ignoring the outliers while estimating GARCH models could wrongly effect the volatility modelling process. Following this, a few studies conducted recently tried to use such a robust test that can pre-process efficiently the time series data before using the model directly to forecast. One formal approach that has been employed is the wavelet transform which decomposes the time series into both time and frequency domain, by which it allows for more subsets from the same time series to be taken into consideration while estimating and forecasting the volatility. Wavelet transforms are used in most of the studies to decompose the main time series into detail and approximation sub sets and then to carry out the forecasting on each sub series.

Put differently, Mendel and Shleifer (2012), find that the price in the financial markets must be affected by the noise. According to their work, the fraction of both the informed and uninformed investors should determine the level of noise. That is, the uninformed but rational investors tend to chase the price of equity as if it were information and trade based on this, while in fact they amplify the sentiment shocks. Mendel and Shleifer's (2012) finding is argued to hold when there are only few noise traders in the market. It is further supported by the reaction to the price spring of 2007 and lowering market risk during that period. Banerjee and Green (2015) argue that the uncertainty of the uninformed investors as to whether other parties in the market are informed or noise traders should make the price nonlinear. It also leads to volatility clustering and magnifies the leverage effect in the return.

In order to examine the effect of wavelet de-noising in forecasting, Capobianco (1999) employs both DWT and SWT to de-noise long daily closing price index time series for the Nikkei. His method for de-noising included three steps: first, decomposing the main time series on multi-level using both the DWT and SWT. Second, de-noising the details coefficients only as they represent the high-frequencies patterns in the main time series. Then, the last step is reconstructing the series by combining the de-noised details coefficients and the approximation one. He found that de-noising the time series can provide better estimates for GARCH in-sample and out-of sample with one step ahead forecasting. Capobianco (2002, 2004) employ high-frequency data for the same Nikkei index and he again demonstrated that de-noising the time series will improve the forecasting accuracy for one step ahead. However, in all his studies Capobianco used the same data set (i.e. Nikkei) and the same model (i.e. GARCH with asymmetry component) and he assessed the forecasting performance always with the same risk metric (RMSE). He only changed the wavelet procedure without using new forecasting models or a new data set. Similarly, the work of Chen et al. (2015) shows that improving an algorithm with wavelet is found to gain an additional statistical benefit using the simple ARMA, ARMA-GARCH specifications and with intra-day data. Yet, neither Capobianco nor Chen et al. used an advanced GARCH model in their studies, and they both focused on a single stock market index. Using wavelet transform as well, Fan and Wang (2007) extract the jumps from the continuous part of the price. The new wavelet based-estimator is found to be superior to others considered in providing the least mean square forecasting error.

Recently, Schlüter and Deuschle (2010) conduct a study on four different data sets from different samples rather stock markets and evaluate the forecasting performance for a group of autoregressive moving average ARMA models over one day and one week ahead. However, commenting on the suitability of wavelet for stock market forecasting, Schlüter and Deuschle (2010, pp. 2-3) argue that:

"*It pays off to use wavelets to reduce forecasting errors, however, there is no method performing best across all scenarios. The optimal choice depends both on the time series characteristics like volatility or existence of long-term trends and forecasting horizon*".

The finding of Schlüter and Deuschle (2010) and their final argument suggest, however, that wavelet transform is a powerful pre-processing technique, but their study did not employ any model from the ARCH genre and the study concentrated only on ARMA models. Conversely, only few attempts have been made to examine the economic implications of de-noising the return series. For example, using the Kalman filter, Cartea and Karyampas (2011) obtain low systematic risk from the CAPM model for most of the individual stocks in the DJIA index. Hence, their approach stresses on the importance of removing the microstructure noise from the return series data.

In order to obtain more accurate risk management estimations, Frésard et al. (2011) find that using the contaminated intraday return series should result in underestimating the capital risk requirement as measured by the Value-at-Risk (Hereafter, VaR) approaches. This, in other words, leads to the bias in the backtesting stage. With wavelet decomposition approach, Berger (2015) obtains less daily 99% VaR forecasts relative to that at 95% confidence interval for all the stocks listed in the DJIA index with more scales being included in the analysis. His analysis for both intervals used joint wavelet-decomposed return from time-scales. More specifically, using more time scales is found to be necessary to obtain the 99% forecast, while just the lower scales are needed to generate the 95% forecast. Yet, Berger's (2015) estimation assumes that the first decomposed return series are mainly noise. While in fact they are not and the noise has to be extracted from them before proceeding in estimating the VaR.

2.5.2 Wavelet decomposition approaches and some of their applications in finance and economics

2.5.2.1 Wavelet application for asset pricing

The dynamic relations between variables in the financial markets have been addressed in different studies using wavelet analysis. Employing monthly wholesale and retail managed funds return data, In et al. (2008) find that the Sharpe ratio for each fund becomes higher as the time-scale increases and it even reached the maximum at the horizon of [32-64] months. In a portfolio allocation setting, Kim and In (2010) find that more weighting has been allocated to stocks rather than to long-term government and treasury bills in the long-term horizons. Their result has been justified by the mean reverting process in the stocks return and confirmed using the wavelet variance decomposition. With the aim of getting better insight on the role of scaling in portfolio formulation, In et al. (2010) apply wavelet with the Fama and French (1992) three factors and the CAPM models. They generally find stronger relations between the risk factors and the market return at the long time-horizons, with this relation being more evident for the big stocks. With the CAPM model as well and for the analysis on seven gulf stock markets, Masih et al. (2010) find that the beta value, as a proxy for the systematic risk, tends to increase at high investment horizons. Overall, this study documents the most contributions to VaR from the first three time-scales.

Concerning the role of time-scaling in examining regimes of volatility, Gençay et al. (2010) find that when the high time scales exhibit a low realised volatility regime, then it is likely to be followed by low volatility at shorter time scales. However, the reverse relation starting with the high volatility regime is not supported. Based on their results, Gençay et al. (2010) identify what they call the "asymmetric in information flow between volatilities across scales". The volatility scaling approach is developed in a different way by Sun et al. (2011). Their study examines the effects of four representative macroeconomic releases on the volatility of high tick exchange rate data. Decomposing the volatility series using wavelet revealed that the intraday volatility clustering is more likely to be observed after the releases rather than before.

Sun et al. (2011) construct the volatility proxy from the exchange rate closing prices, before using its detailed decomposed components for the analysis. The appropriateness of wavelet decomposition has been examined further by Conlon and Cotter (2012) for hedging purposes. The study used the long-spot exposures in the West Texas Crude oil, the S&P 500 index along with the British Pound/U.S. Dollar exchange rate. Decomposing the cash and future returns, Conlon and Cotter find that the portfolio's hedging effectiveness reaches the maximum level at the long-time horizon. Interestingly, the hedge ratio was exactly one at the 12 day horizon.

2.5.2.2 Applying wavelet to examine the linkages and co-movements

Recent studies start applying wavelets to investigate the linkages between financial (economic) variables (e.g., Gallegati et al., 2011; Rua, 2012; Reboredo and Rivera-Castro, 2013) and the interrelations between financial markets (e.g., Kiviaho et al., 2014; Alzahrani et al., 2014; el. Alaoui et al., 2015; Bekiros et al., 2016; Ftiti et al., 2015; Dewandaru et al., 2016). In their study for the period 1948 to 2009, Gallegati et al. (2011) find that the negative relationship between the quarterly wage inflation and unemployment rate in the U.S. is more evident at the short time horizons. Yet, estimating the Phillips curve regression detects more stable relations between these two variables for the sub-period 1948 to 1993, but not after that. The reason for that instability, as the study argued, is the change which occurred to the wage setting process in the U.S to adapt to the low level of inflation in late 1990's. Rua (2012) conducts a study on the relation between the aggregate M3 money growth and the inflation for the Euro area using continuous wavelet analysis. Their analysis documented less relation at the low time frequencies. Rua's (2012) finding is then in line with that of Gallegati et al. (2011) on the importance of examining the relations between the economic variables on time-scales. Benhmad (2012) proposes an alternative method using the DWT to examine the causality between monthly oil price and the U.S. dollar price. Evidence of both linear and nonlinear bidirectional relations appears at the time horizon of [32-64] month period and higher. Yet, the oil price is found to granger cause the dollar price, only at the short-investment horizons of [2-4] and [8-16] month periods. Robredo and Rivera-Castro (2013) show that the interdependence between the daily exchanges rates against the U.S. dollar and West Texas crude oil is more stable over time horizons before the 2008 crisis but not afterwards. Robredo and Rivera-Castro (2013) reach their finding based on the graphical wavelet-based cross correlation analyses.

Similarly, relying on the wavelet correlation analysis, Martín-Barragán et al. (2015) find that the linkages between oil price and the four developed stock markets vary the most at long timescales during both oil and major financial shocks. Their sample covers, for example, the Dot-com bubble of 2001, the Lehman Brothers bankruptcy in 2008 and the 2011 episodes. Yet, while Reboredo and Rivera-Castro (2013) employ the DWT to obtain the wavelet details prior to conducting the cross-correlation analysis, Martín-Barragán et al. (2015) start with the MODWT approach. For the analysis on the G7 countries and contradicting Martín-Barragán et al. (2015), Ftiti et al. (2015), find that co-movement between the oil and stock prices in the G7 countries is greatest at the short and intermediate timescales. Focusing on S&P 500 and eleven U.S commodity markets, Bekiros et al. (2016) reveal evidence of co-movements between these markets that vary over the timescales and increase after the global crisis.

In a further example of its application within the field of finance, wavelet decomposition serves as an important technique to analyse the causality between three foreign exchange returns in Bekiros and Marcellino (2013). They reported evidence of different causality characteristics between the return series over the timescales, with no global causal aspect being dominant over all time horizons. A slightly different approach is selected by Benhmad (2013) to examine the correlation between the S&P 500 and other international stock market returns. The study used the wavelet correlation in a rolling regression framework (of 250 day a head window size) and found that correlation dynamic is greatest during the crisis and varies significantly from one scale to another. The same conclusion is reached by Kiviaho et al. (2014) using a different wavelet approach, confirming that the correlations between the stock markets are a function of the timescales and tend to increase during the crisis period.

The findings of Kiviaho et al. (2014) is based on the weekly data and considered the continuous wavelet on different time scales as a proxy of correlation. The study also reported evidence that the effects of some macroeconomic factors affect the co-movements differently over the time horizons. That is, the effect of the same macroeconomic factors differs from one frequency to another. Concerning the wavelet-based causality relations, Alzahrani et al. (2014) examine the lead-lag relation between the oil spot and future markets in the U.S. Using the daily data, the study found bidirectional causality between the two markets at all the time horizons. Evidence of this causality is also confirmed during the 2008 crisis. Focusing on the behaviour of Islamic investors, Rahim and Masih (2016), use both the continuous wavelet and the MODWT methods and documented evidence of different levels of independence across the timescales. The study focused principally on the Malaysian Shari'ah investors and how they adjust their portfolios within other Shari'ah markets.

2.6 Summary of literature

The literature discussed above has clearly demonstrated the importance of examining dynamic relations and movements in the financial markets on timescales. It has principally applied the wavelet in two areas of finance, de-noising and time-scaling, to examine the dynamic relations. First, before de-noising the return series seems important for improving both the statistical model performance and the VaR estimation. Of course, more comprehensive analysis is still required to investigate to what extent removing noise will affect the ranking of a given model in different markets. Such further research needs to include an extensive out of sample analysis. In addition to this, an index return smoothing approach that starts with the timescale decomposition is also required to enhance the economic implication from forecasting. A wavelet de-noising employs the signal-to-noise ratio to arrive at a reliable threshold limit before thresholding the return data based on it. It is helpful to consider some of the opportunities to contribute to this growing area of research. For example, a question whether the co-movement between equity markets is affected by the arrival of macro news over time-horizons is an issue that has not been examined yet in the literature. More specifically, if the co-movement patterns changes during the crises and across the time-horizons, then the effect of other macro factors should change as well. During the crises, the media, investor sentiment and stock market uncertainty all play roles in formulating the reaction to the macroeconomic news. The informativeness of this macroeconomic news should be related to their release times and to the state of the market itself. Altogether, investors in equity markets are assumed to switch their investments from one market to another depending on their investment horizon, the arrival of the macroeconomic news and the state of the markets they are investing in.

Some final observations on the literature regarding how the statistical relations change between the variables over the timescales seems to establish more debate. First, most of the findings on the wavelet-dynamic relations do not have a strong theoretical basis. Second, this strand of literature seems to perform the analysis on the full sample period, whilst at the same time ignoring the market regimes and how these can affect the relations between variables. Third, the studies made no comparison on the same dynamic relation between the markets located within different geographic locations. In other words, such a relation over the timescales can be more evidenced in developing markets compared to developed markets. This, however, would depend on the variables to be used and the theory that the research relates to. Finally, studies in this area reach their findings either with the statistical approaches or with the wavelet-variance, covariance and correlation estimators. Hence, a research here must combine these two methods to gain a better understanding of how the statistical relations change over time. This thesis aims to fill the three gaps in the following ways. The first study investigates the role of wavelet in de-noising and volatility forecasting. The next study covers the area of equity markets correlation and the reaction to the news during the crises periods and over time-horizons. The last chapter extends the research on wavelet time–scaling and examines how the trading volume-return interplay in international stock markets over different market states. Both the theoretical justifications for doing the research and the related literature will be summarised in each study as well. Furthermore, the MODWT approach, due to their advantages over the DWT, will be used in all three studies.

2.7 Illustrating the steps of data pre-processing in the subsequent empirical chapters

The chart below describes the steps to be followed while pre-processing the financial time series data in Chapters 3, 4 and 5. In all these chapters, Daubechies filter with a length of 8 will be applied for the reasons discussed above. Moreover, the financial data itself has to be decomposed at six time-scales. Other types of filters and different selections for the optimal number of timescales for decomposition will also be used in the robustness checks in either reported or omitted analysis.

Figure 2.5 Steps for applying the wavelet filter on the financial data in Chapters 3, 4 and 5.

Panel A: In Chapter 3

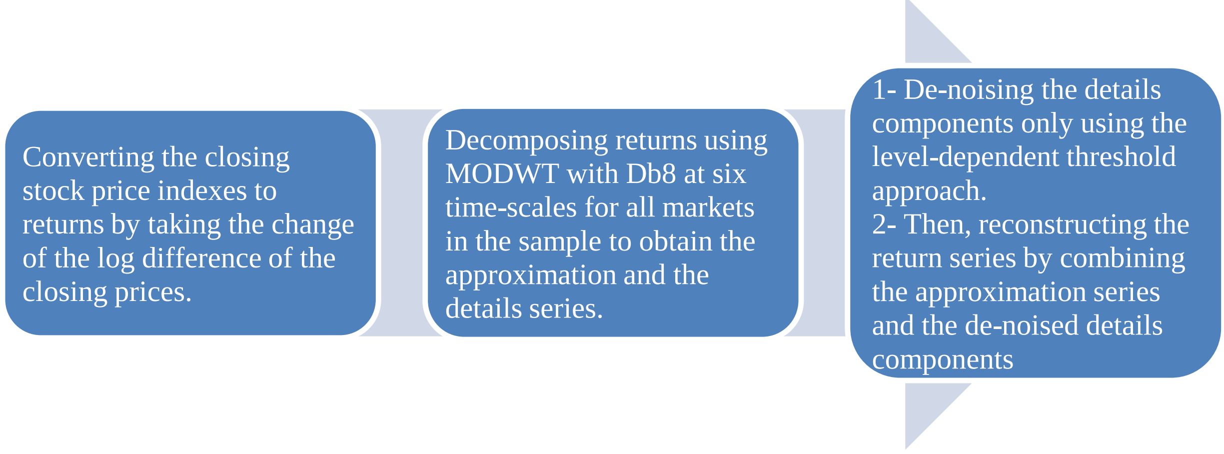
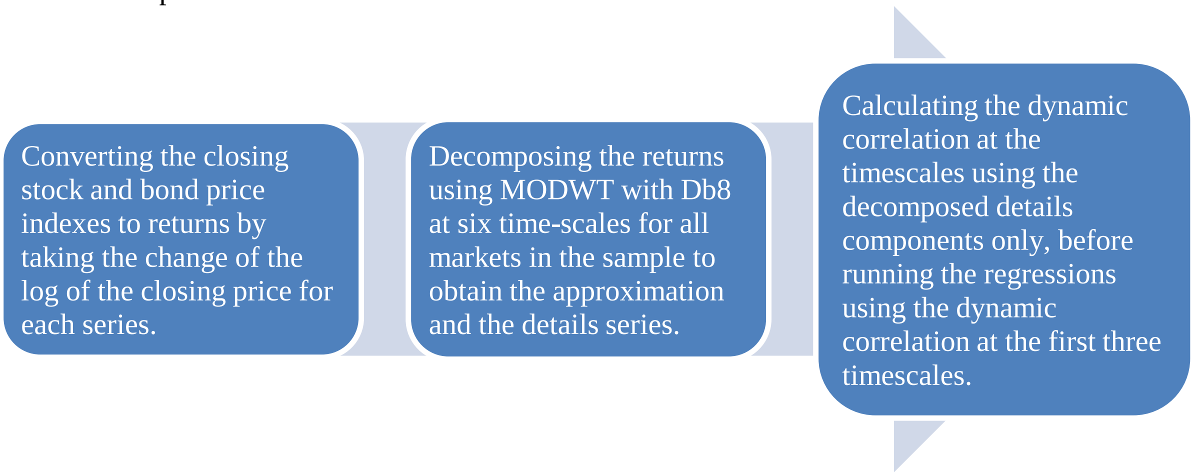
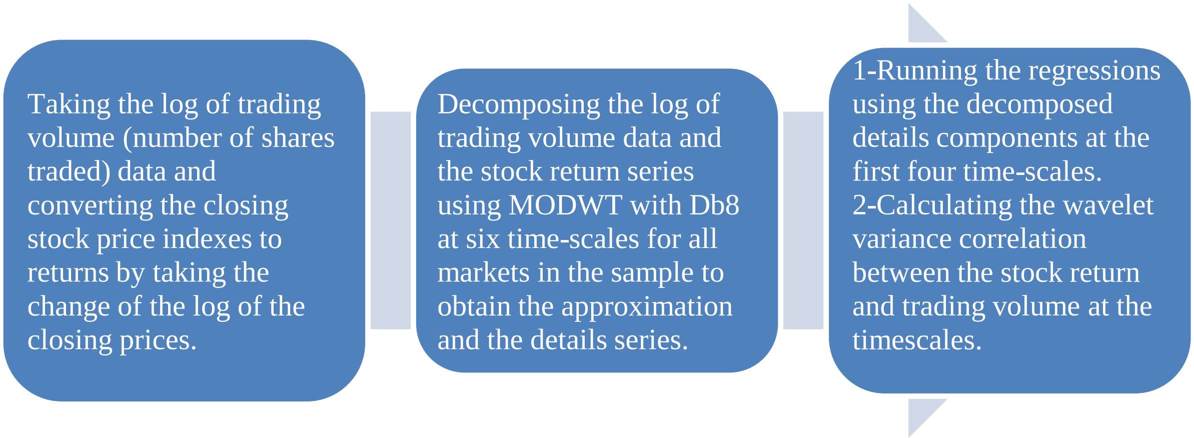


Figure 2.5 (*Continued*).

Panel B: In Chapter 4



Panel C: In Chapter 5



CHAPTER THREE

Volatility and Value-at-Risk Forecasting: Does Wavelet De-Noising Help?

Abstract

This paper examines the ability of GARCH models to forecast stock return volatility under a range of forecast metrics, including both statistical and economic evaluation. Our particular interest is whether wavelet de-noising of the data prior to estimation affects the ability of the models to provide accurate forecasts. To de-noise the data, we use soft thresholding and Stein's Unbiased Risk Estimator in order to obtain the decomposition level-based threshold limit. Our key results demonstrate that de-noising returns improves the accuracy of volatility forecasts regardless of whether we use statistical metrics or tests of equal predictive accuracy. Moreover, in terms of a particular volatility model, the asymmetric GARCH approach tends to be preferred although this result is not universal. Indeed, the central result from our analysis is that the process of de-noising is more important than the specific model. When considering VaR forecasting, wavelet de-noising is found to be more accurate at the key 99% level but less so at the 95% level.

Keywords: Wavelet; De-noising; Volatility; Forecasting; Value-at-Risk.

3.1 Introduction

Forecasting volatility remains a key empirical issue within finance, given its importance across a range of investment decisions (e.g., volatility estimates appear in CAPM betas, hedge ratios, option pricing, market timing decisions and so forth). Despite a large literature, there exists no consensus as to the preferred modelling approach, although recent research indicates a preference for asymmetric GARCH models (e.g., Kambouroudis et al, 2016). This paper enhances this discussion by moving in a new direction. We consider the forecasting ability of GARCH models after accounting for the presence of noise through a wavelet procedure.

A range of studies have sought to link volatility with specific factors, including, macroeconomic fundamentals (e.g., Officer, 1973; Engle et al., 2013), trading volume (e.g., Bohl and Henke, 2003; Ané and Ureche-Rangau, 2008) and business cycles (Hamilton 1996). However, the success of such studies is limited. This, it is argued, is because stock returns contain noise not related to fundamental information but arising from market imperfections and swings in investor beliefs. This makes both trading and forecasting in stock markets difficult even before selecting a preferred forecast model. Black (1986) notes that noise trading occurs when investor trade on noise as if it were information when they may be better off not trading. Black argues that such traders may believe noise is information or they may just like trading. The effect of this, is that informed traders may be hesitant in taking large positions due to the risk of noise traders moving the market away from fundamental value.

Trueman (1988) argues that even in the presence of noise, rational investors will engage in trading. Notably, fund managers will trade as this generates signals to investors about their ability to obtain information on investment performance. Trueman links manager's behavior to the level of incentives and that excess trading, regardless of the level of accurate information, will provide greater incentives. Schutte and Unlu (2009) argue that the presence of noise can impact on decision-making. They note excessive amounts of noise can affect managerial choice adversely as noise reduces price stability. Such stability is crucial for corporate decision-making as managers rely on forecasts to make long term decisions regarding capital structure (issuance of equity versus debt), payout policy (dividends and share repurchases) and corporate acquisions/divestitures.

Given the presence of noise within markets, this raises issues that have hitherto been considered only sparingly within the empirical forecasting literature. Notably, we wish to consider how the influence of noise, and its removal, impacts the performance of GARCH models and the ranking between them. The GARCH genre of models is widely implemented and considered largely successful due to their ability to account for key features in the data. The evolution of the GARCH approach can be seen in three steps, from the standard GARCH model (Engle, 1982; Bollerslev, 1986), which accounts for volatility clustering, to models designed to capture asymmetry, e.g., the EGARCH (Nelson, 1991) and TGARCH (Golsten et al., 1993) models and to long memory models, including the CGARCH (Engle and Lee, 1999), FIGARCH (Baillie et al., 1996) and HYGARCH (Davidson, 2004) models.

In order to extract noise, while filtering techniques (such as Hodrick-Prescott, Fourier and Kalman) are employed, more recently, wavelet methods are considered, given their abilities to examine multiple frequencies within the time series. Research examining de-noising stock returns, although in its infancy, is growing. Capobianco (1999) employs a discrete wavelet transform and stationary wavelet transform to de-noise the daily NIKKEI 225 returns. The study finds that removing noise reduces the one-step ahead out-of sample forecast errors. Capobianco (2002, 2004) reports the same result using high-frequency data. Schlüter and Deuschle (2010) argue that the performance of autoregressive moving average models is improved through wavelet analysis, although they find that no single model dominates across all data and forecast horizons. Of note, Capobianco (1999, 2002, and 2004) and Haven et al. (2012) use the same de-noising procedure regardless of the data frequency and whether price or return data are used in de-noising. Specifically, they rely on the variance of data at different investment horizons before determining the threshold limit, an approach we also take.

This research investigates the forecasting performance of a range of GARCH models using daily data for a selection of international stock markets when removing noise using a wavelet procedure. In particular, we are interested in whether wavelet de-noising leads to improved forecast performance, while also considering if de-noising affects the ranking of alternate models. We further consider how the parameters of selected models change over the time, both before and after de-noising and with particularly around main crisis periods of 1997-1998 (Asian crisis) and 2008-2009 (financial crisis). In considering these questions we examine volatility forecasts using a range of statistical metrics of forecast size and sign accuracy, an evaluation of equal and superior forecast accuracy and importantly, whether de-noising leads to better interval based Value-at-Risk (VaR) estimates.

Only a few studies consider the economic implications of cleaning the return series. Using the Kalman filter, Cartea and Karyampas (2011) report low systematic risk from the CAPM model for stocks in the DJIA index. Hence, they stress the importance of removing microstructure noise. In order to obtain more accurate risk management estimation, Frésard et al. (2011) find that using the contaminated intraday return series will result in underestimating the capital risk requirement as measured by VaR. Using wavelet decomposition, Berger (2015) examines both 99% and 95% VaR forecasts for all stocks listed in DJIA index and notes that more scales are required at the former confidence level. This study, therefore, adds to this limited evidence set.

The finding from this chapter can be summarised as follows. First, de-noising the data leads to statistical improvement in forecasting volatility. This finding is reached based on the risk metric analysis and a series of equal predictive ability tests and regardless of the model being used for forecasting the volatility. Second, in ranking the models, our results show that the asymmetric-GARCH approach and in particular the EGARCH model is typically preferred. our results here are robust to other specifications including the error distribution, the wavelet filter, thresholding approach, and somewhat robust to the alternative true volatility proxy. Third, an interesting finding has been revealed after performing the rolling-regression exercise. That is, both the asymmetry and volatility clustering patterns are found to vary more around and during the market turmoil periods after de-noising the return. Finally, and most importantly I found that de-noising that data brings more economic benefit by allowing for more forecasting models to pass the VaR backtesting tests. Yet, this is found to be more accurate at the key 99% level but less so at the 95% level.

This chapter is organised as follows: Next section reviews the key literature on the "Noise trader" hypothesis. Section 3.3 describes the methods used for both forecasting and de-noising the data. Section 3.4 describes the data and introduces the empirical results. Section 3.5 introduces the results from the robustness checks. The rolling in-sample exercise for selected models is shown in Section 3.6, before offering the summary and conclusion in Section 3.7.

3.2 Theoretical background: The Noise Trader hypothesis

As a contrast to the efficient markets hypothesis, rational investors in the market do not always justify the excess volatility in price or return by the flow of fundamental news. Several studies do concern about this issue and, therefore, try to find an explanation from a behavioral perspective. Such a hypothesis has been widely studied in this area called the 'Noise trader' and it is built on the assumption that 'the noise traders' in the market are uninformed, or partially informed investors, who usually rely on their beliefs rather the fundamental-related information to trade in the market. Although, there is no agreement under which group of investors the noise trader should be classified, and how they can forecast the future. For example, Bhushan et al. (1997, p. 27) argue that:

"*Noise traders are a subset of the investors; they forecast with error the information that the future, investors will obtain and they misperceive the relation between future prices and noise. The reminders are sophisticated arbitrageurs. These traders correctly anticipate future stochastic realizations of noise and they recognize the equilibrium variation in the finite supply assets price due to noise*".

The same study further examines the De Long et al. (1990)'s assumption that both the noise trader, when they are rational, and arbitrageurs have equal assessments of future price volatility. Bhushan et al. (1997) suggest that, considering the irrational assessments of noise trader and the exogenous marginal requirements, that noise traders will find themselves unable to create their own spaces in the market, and hence the riskless assets, correlated with noise, are more likely to be priced by the arbitragers. This study, however, contradicts the findings of Campbell and Kyle (1993) who assume that both noise traders and the smart-money investors interact with each other to affect annual stock price index of standard and poor's composite index, but the noise trading effect was higher at the discount interest rate equal to 5% or above.

Kelly (1997) classifies the investors in the market into three groups according to the income level. The smart money investors were in the first group and they considered there as a very high-income household, while those with low-income are considered the noise traders and the lastly the passive traders are those who are in the middle class-income household. Kelly's (1997) classification is built on the assumption that the rich investors are more interested in obtaining the reliable information about the market, while the other two groups are not. By considering the general population, the study found that market participation is a negative predictor of the stock return, and that is justified predominating of the noise traders in the market. The result obtained here supports the early argument of Shleifer and Summers (1990), where they suggest that many trading strategies in the market are highly correlated as they based on noise which resulting in more shift in the aggregate demand. That was justified by the psychological experiment where the investors are assumed to make the same mistakes, assuming the source of information is the same, but that is unlikely to be true in the long run. From the same study, over the time the noise trader is said to be more aggressive, where they acquire more skills from trading to be used in affecting the demand again.

Moreover, concerning the private stock endowment-related information for the strategic trader, Vayanos (2001) finds that in an attempt to reduce the risk exposure, the strategic trader (i.e. large trader) sell and buy some of the stocks sold, and the length between the two positions can affect the size of information revealed to the other investors in the market. This information is said to be transmitted quickly, within time approaches zero, when the level of noise is high in the market and when the strategic traders themselves are very risk averse.

In another study, Mailath and Sandroni (2003) link the ability of gathering the exogenous information to the level of noise in the market. They generally argue that the investors are able to survive in the market if the level of noise is only low. However, the wealthy are the investor, the more information out of trading will be revealed and then became available to the public. The study also assumes the under the high level of noise, all the wealth will be held by the noise trader. Regardless of the consumption level and the risk that the noise traders have to bear from trading, Bradford et al. (1991) connect the ability of noise traders (as a group) to survive in the market with a high total share of wealth relative to market participants. According to their study, the noise traders can dominate in the market in the long-run period.

Based on the laboratory markets, Bloomfield et al. (2009) consider the noise trader as a special case of liquidity traders who have no logical reasons to trade. Those traders are found to employ ineffective trading strategies that can leave a mixed effect on financial markets. The negative effect of noise trading was that both market volume and liquidity were increased. Opposite effects are to reduce the bid-ask spread and to minimize the losses of the liquidity traders who trade for the reasons of various consumption and risk sharing needs.

3.3 Empirical Methodology

3.3.1 Forecasting Models

While different models are considered within the finance literature to forecast stock market volatility, the generalized autoregressive conditional heteroscedasticity (GARCH, Engle, 1982; Bollerslev, 1986) approach is found to be the most successful. This is due to the models ability to capture volatility clustering within series, while extensions account for further data characteristics, notably asymmetry and long-memory. To that end, in addition to the GARCH model, we consider the EGARCH (Nelson, 1991), TGARCH (Golsten et al, 1993), APARCH (Ding et al., 1993), CGARCH (Engle and Lee, 1999), FIGARCH (Baillie et al., 1996) and HYGARCH (Davidson, 2004) models. Our primary interest here concerns the forecasting performance of these models and how the ranking between them is affected by de-noising using a wavelet procedure. As the GARCH genre of model is well-known, we intend to keep discussion brief, see Poon and Granger (2003) for a greater discussion.

In order to generate volatility forecasts, the return process is defined as a function of conditional mean μ and the disturbance term, ε_t :

$$r_t = \mu_t + \varepsilon_t \tag{3.1}$$

The conditional volatility (h_t^2) in the return series is given by the variance of the random error term (ε_t) conditional on the past information set Ω_{t-1} :

$$h_t^2 = Var(\varepsilon_t \,|\Omega_{t-1}) \tag{3.2}$$

The GARCH model is then given by:

$$h_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2 \tag{3.3}$$

Where the non-negativity constraint must hold for all parameters in the model (α , β , ω) and the measure of persistence of shocks to volatility is given by $\alpha+\beta<1$. An identified drawback of the GARCH model is that it does not account for possible asymmetry between positive and negative shocks (Black, 1976; Christie, 1982). Hence, we consider the exponential GARCH (EGARCH) model of Nelson (1991):

$$\log(h_t^2) = \omega + \alpha \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta \log(h_{t-1}^2) \tag{3.4}$$

Where asymmetry is captured by γ, such that negative shocks have a greater impact than positive shocks when $\gamma<0$. An alternative approach to model asymmetry is provided by the model of Golsten et al. (1993) and referred to as the GJR-GARCH (or TGARCH) model. Here a dummy variable, I_t captures asymmetry and it is defined by:

$$h_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} + \beta h_{t-1}^2 \tag{3.5}$$

Where I_t =1 for negative shocks (ε_{t-1}<0) and I_t = 0 for positive shocks (ε_{t-1}>0). Thus, the impact of positive (negative) news is given by α $(\alpha+\gamma)$. Asymmetry is further considered by Ding et al. (1993) in the Asymmetric Power-ARCH (APARCH) model. This model imposes the Box-Cox power transformation, δ, for both the conditional standard deviation and the absolute lagged residuals. The general formula for APARCH is:

$$h_t^\delta = \omega + \alpha(\left|\varepsilon_{t-1}\right| - \gamma\varepsilon_{t-1})^\delta + \beta_1 h_{t-1}^\delta \tag{3.6}$$

Where $\omega > 0$ and α , β and $\delta \geq 0$,$-1<\gamma<1$.

A further line of research has identified long memory within volatility. This triggered the development of further models, including the Fractional Integrated GARCH (FIGARCH; Baillie et al., 1996) model, which incorporates a differencing parameter, d :

$$\phi(L)(1-L)^d \varepsilon_1^2 = \omega + [1-\beta(L)]v_t \tag{3.7}$$

Where $0<d<1$, $\phi(L)$ and $[1-\beta(L)]$ both lie outside the unit circle. The conditional variance of ε_t is given by:

$$h_t^2 = \omega + [1-\beta(1)]^{-1} + \{1-\beta(L)-\phi(L)(1-L)^d\,]\varepsilon_t^2 \equiv \omega + [1-\beta(1)]^{-1} + \lambda(L)\varepsilon_t^2 \qquad (3.8)$$

The FIGARCH model reduces to a GARCH model with *d*=0 and to the IGARCH model when *d*=1.

In order to test the restrictions in the FIGARCH model and to make it later distinguishable from GARCH and IGARCH models, Davidson (2004) introduced the Hyperbolic GARCH (HYGARCH) model, given by:

$$h_t^2 = \omega + [1-\beta(L)]^{-1} + \{1-[1-\beta(L)^{-1} - \phi(L)[1+\alpha((1-L)^d - 1]\varepsilon_{t-1}^2 \qquad (3.9)$$

The HYGARCH model nests the FIGARCH when α =0 and nests standard GARCH for α *=1* under the condition *0 <d <1*. Engle and Lee (1999) separate short- and long-run volatility dynamics in the component GARCH (CGARCH) model, whereby the unconditional variance is not necessarily constant. While mean reversion in GARCH model is to the constant parameter, ω, the CGARCH model allows reversion to varying component ζ.

$$h_t^2 - \zeta_t^2 = \alpha(\varepsilon_{t-1}^2 - \zeta_{t-1}^2) + \beta(h_{t-1}^2 - \zeta_{t-1}^2);\, \zeta_t^2 = \omega + \rho\zeta_{t-1}^2 + \beta(\varepsilon_{t-1}^2 - h_{t-1}^2) \qquad (3.10)$$

The main elements of the CGARCH are the transitory component $h_t^2 - \zeta_t^2$ which converges to zero with powers of $(\alpha+\beta)$ and the long-run component ζ which converges to ω with by ρ. Stationary condition are met by $(\alpha+\beta)(1-\rho)+\rho<1$ given that $\rho<1$ and $(\alpha+\beta)<1$.

3.3.2 Data Pre-processing

Our key interest here is in extracting the signal element from the return series by removing noise. The presence of noise can adversely affect the forecasting performance of forecast models resulting in potentially inaccurate comparisons between them. Thus, we need to select the appropriate wavelet estimator. Here we use the maximum overlap discrete wavelet transform given its ability to cope with any sample size and any shift in the variance without any effect on the pattern of the coefficients. The de-noising (or pre-processing) procedure starts by decomposing the main signal into both approximation, *A*, and detailed, *D*, coefficients generated from high-pass and low-pass filters respectively, at a given decomposition level *n* as follows:

$$S_n = \phi A_n + \sum_{t=1}^{n} \Psi D_t \tag{3.11}$$

During the band pass filtering process, two main types of wavelets, father ϕ and mother Ψ, are incorporated. In the de-noising process, we are more interested in the details coefficients than in approximation ones. This is because the detail coefficient, at a given resolution level, is required to capture high-frequency events and is more sensitive to small shocks in the data. The approximation coefficient, on the other hand, is only useful in showing the effect of low-frequency components through keeping the main elements of the original time series.

A further important factor that affects the decomposition process is the type of mother wavelet. Here, we decide to use Daubechies (hereafter, Db) wavelet, as it has an asymmetric property that better suits our return data. The wavelet filter can have different forms that range from symmetric to asymmetric and the choice depends on the time series to be studied. The most common symmetric wavelet is Haar, which has a square form and suits smoother time series data. Examples of symmetric wavelet are symmlets and coiflets. For data that likely to display near asymmetric behaviour, the Daubechies wavelet is the most widely used. Daubechies filter with the length of 8[19].

A further important element in the decomposition process is to decide on the number of resolution levels. Here, we decompose the return series at six levels (J=6). The selection of the MODWT is also based on the variance decomposition. According to MODWT, higher time-scales than six usually contribute less to the overall variance of the original time series data. The decomposition process with the MODWT preserves the variance of the original return series.[20] Scales between five and seven are usually considered appropriate for the task of decomposition irrespective of the frequency of data at hand. For instance, up to seven scales with monthly data are used by Kim and In (2005), while Galagedera and Maharaj (2008) decompose their daily return data at six scales. The first resolution level corresponds to time horizon between 2 and 4 days, scale two represents the [4-8] time period, scale 3= [8-16], time-scale 5= [16-32] day-period and scale 6 represents the [32-64] day-period.

[19] For further details about the property of the mother wavelet, refer to Section 2.4.3.
[20] Applying the wavelet-based variance decomposition as described by Percival and Walden (2000) shows that the first three time scales contribute the most to the overall variance of the signal. The results from the variance decomposition are presented in appendix 2. The variance of noise at each time scale shows a positive relation with the median of the wavelet coefficients at that scale. For further treatment, see Percival and Walden (2000, pp. 441-444).

We also need to consider the boundary condition for the wavelet filter. This arises when the wavelet gets close to the edge of the data and requires non-existing values beyond the boundary. Thus, boundary effects are caused by incomplete information. Percival and Walden (2000) consider several solutions to deal with this issue. These, for example, include the polynomial approximation, which replaces non-existing data at each end of the series using a polynomial model. Another approach, called reflection, involves completing the end of a given time series by mirroring the last observations. Masset (2008) argues, when it comes to stock return data, the reflection approach is preferred as it accounts for the volatility clustering in return series. We, thus, follow this advice.

In the next step, only the detailed coefficients w_{jk} will be de-noised using wavelet soft thresholding, *S*:

$$\delta_{\lambda}^{S}(w_{jk}) = \begin{cases} 0, \ \ if\ |w_{jk}| \le \lambda \\ w_{jk} - \lambda, \ \ if\ |w_{jk}| > \lambda \\ w_{jk} + \lambda, \ \ if\ |w_{jk}| < -\lambda \end{cases} \tag{3.12}$$

Where λ is threshold limit. Soft thresholding pushes all the coefficients above the threshold toward zero and sets all the coefficients with magnitudes below (or equal to) the threshold to zero.

For the purpose of determining the threshold limit, we employed the Donoho and Johnstone (1995) measure which works based on the minimum Stein's unbiased risk estimator (SURE). Given the level wavelet coefficient {*Xi: i =1…, d*}, which is six levels in our procedure and for the total number of observations equal *d*, the threshold parameter will be evaluated as follows:

$$\hat{X} = \eta(X) \tag{3.13}$$

Where η denotes the threshold parameter, $\hat{X}$ is soft threshold estimator. Stein's unbiased risk estimator can be given by:

$$SURE(\mathrm{d};\eta) = d - 2\#\{i : |X_i| \le \eta\} + \sum_{i=1}^{d} \min(|X_i|, \eta)^2 \tag{3.14}$$

and the final estimate an adaptive threshold based on the datasets with minimizing the SURE will be:

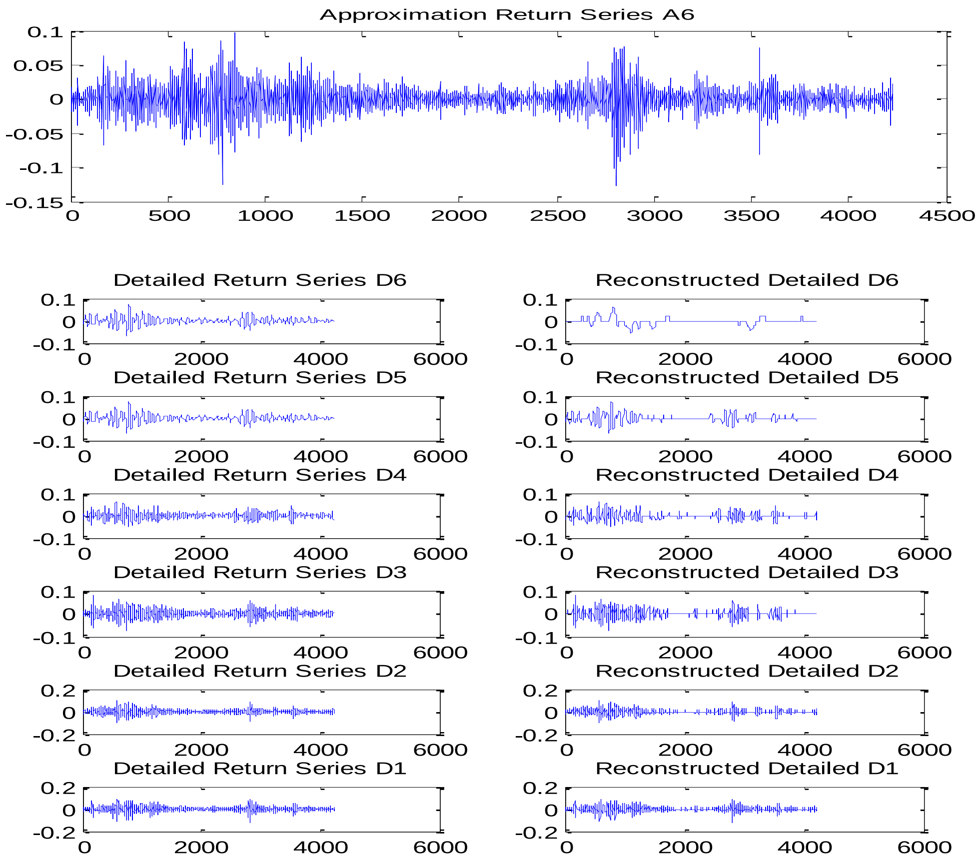
$$\eta^S = \arg\min SURE(d;\eta) \tag{3.15}$$

In final step of the pre-processing stage, we apply the inverse stationary wavelet transform (ISWT) to both the contaminated approximation return series at level six (A6) and the reconstructed detailed series generated from each level of the decomposition process. The process ends by producing the de-noised return series.

To illustrate the wavelet procedure, Figure 3.1 presents graphically the de-noised data for the NASDAQ return series. The original return series de-noised over six levels using the wavelet transform. We then produce the reconstructed, de-noised, returns, from which we can see that these series show a lower degree of variability.

Figure 3.1 Graphical Representation of De-noising process of NASDAQ return series using Soft thresholding D8 Wavelet at six Decomposition levels.

The following Figure shows the overall process of de-noising using soft thresholding. The procedure consists three steps; first the contaminated (original) return series is decomposed using stationary wavelet transform at six levels. In the next step only detailed return coefficients are de-noised using the noise level dependence and Rigours Minimum Stein's unbiased risk estimator and the approximation level is remained untouched. The process ends by combining between both the approximation and reconstructed (de-noised) detailed series to produce de-noised return series in the last stage.



3.3.3 Evaluating Forecasting Performance

Statistical Loss Functions Evaluation

A major consideration in forecasting is selecting the appropriate metric in order to evaluate the forecasts generated from a given model. As argued by Bollerslev et al. (1994), every forecast evaluating criterion has it is own merits and demerits and deciding which one to use is not an easy task. Therefore, we consider a range of measures here.

We begin with three well-known statistical loss functions, the root mean squared error (RMSE) and mean absolute error (MAE).[21] Each metric is given by:

$$\text{RMSE} = \sqrt{\tau^{-1}\sum_{t=T_1}^{\tau}(h_t^2 - \sigma_t^2)} \qquad (3.16)$$

$$\text{MAE} = \tau^{-1}\sum_{t=T_1}^{\tau}\left|h_t^2 - \sigma_t^2\right| \qquad (3.17)$$

Where τ is the number of observations in the out-of sample period, σ_t^2 is a proxy for actual volatility and h_t^2 the forecasted volatility series from the model.[22] These evaluation measures capture a different aspect of the forecasting performance. The RMSE gives greater weight to large forecast errors over small forecast errors, while the MAE are more robust to the possible existence of noisy points in the data.

To further evaluate the forecasting performance of our competing models, we use the R^2 from the Mincer-Zarnowitz (MZ) regression of true volatility σ_t^2 on the forecasted series $\hat{\sigma}_t$ generated from each model:

[21] We also consider the MSE measure, which Patton (2011) also argues is robust to noise. Our finding remains almost the same with the EGARCH model is the best performer in six out of eight markets.

[22] For actual volatility, we utilise both squared returns and realised volatility based on intra-day data. The qualitative nature of the results is unaffected by this choice i.e., model ranking and the comparison between raw and filtered data. The results presented are based upon squared returns.

$$\sigma_t^2 = \alpha + \beta\hat{\sigma}_t + e_t \tag{3.18}$$

Rather than just considering the size of the forecast error, it may be useful to consider the direction (sign) of the forecasts. Hence, we employ the success ratio, which reports the proportion of volatility forecasts whose direction of change is the same as for true volatility:

$$\text{SR} = T^{-1}\sum_{t=1}^{T} I_{\{\hat{\sigma}_t\tilde{\sigma}_{t|t-1}\}} > 0 \tag{3.19}$$

Where $\hat{\sigma}_t$ is the true volatility proxy minus the non-zero mean, $\tilde{\sigma}_{t|t-1}$, $\tilde{\sigma}_{t|t-1}$ is demeaned volatility forecast, and $I_{\{\hat{\sigma}_t\tilde{\sigma}_{t|t-1}\}}$ is the full indicator function and will equal 1 if $\hat{\sigma}_t\tilde{\sigma}_{t|t-1}$ is positive and to be zero otherwise.

Comparing Predictive Accuracy

To examine the significance of any gains in forecasting from the de-noising process as well as between models, we consider tests of equal predictive accuracy. Such tests can be classified into two main groups, one to evaluate the forecast over a pairwise comparison and the other a joint test of models. One of the more popular tests for pairwise comparison is the Diebold and Mariano (1995) test (DM hereafter). This test is based on the loss differential between two forecast error series. Where two series of forecasting errors are given by e_{it} and e_{jt} with model *i* as benchmark and model *j* as the competing forecast, the loss differential, *d*, is given by:

$$d_{ijt} = L(e_{it}) - L(e_{jt}) \tag{3.20}$$

Here *L* denotes the function of forecasting error. According to the test, the sample mean loss differential is given as follows

$$\bar{d}_{ij} = \tau^{-1}\sum_{t=1}^{\tau} d_{ijt} \tag{3.21}$$

The key assumption of the DM test is that both models have equal predictive accuracy under the standard normal asymptotically distribution, with the DM test given by:

$$DM_{ij} = \frac{\bar{d}ij}{\hat{\sigma}_{\bar{d}_{ij}}} \sim N(0,1), \tag{3.22}$$

Where $\hat{\sigma}_{\bar{d}ij} = \sqrt{\tau^{-1}\hat{g}(0)}$ and here $\hat{g}(0)$ is a consistent estimator of the loss differential. However, the DM test has been criticized that it might result in an inaccurate comparison when it employs a small sample and for a long forecast horizon. To avoid these drawbacks, Harvey et al. (1997) modified DM (MDM hereafter) test includes the forecasting horizon *h* into the calculation as such:

$$MDM = DM_{ij} \times \sqrt{\tau^{-1}[\tau + 1 - 2h + \tau^{-1}h(h-1)]}, \tag{3.23}$$

Two further equal predictive accuracy tests are also employed to evaluate the forecasting performance of the benchmark model against all the competing models. The first test is constructed by White (2000) and referred to as the Reality Check (RC) has the null hypothesis that none of the competing models *j* are better than the benchmark *0* in terms of forecast errors. The RC analysis has been done with the bootstrap approach. Based on the asymptotic and normal distribution the null hypothesis of White's (2000) test is:

$$H_0^j : \mu_j \leq 0, j = 1, ..., m, \tag{3.24}$$

Where μ_j is the expected performance of the competing model against the benchmark and *m* is the number of competing models. Under this hypothesis, the competing model is said to outperform the benchmark if only its expected performance is positive. Here the test statistic for μ_j can be calculated as follows:

$$T_{j,n}^{RC} = \max n^{1/2} \bar{d}_{j,n}, j = 1, ..., m \tag{3.25}$$

Where $\bar{d}_{j,n} = n^{-1}\sum_{t=1}^{n} d_{j,t}$ is the sample average obtained by evaluating the performance of the competing model relative to the benchmark and given by $d_{j,t} = d_{t,0} - d_{t,j}$ for $t = 1, ..., n$. One drawback of White's test is that it conducts a comparison over non-standardized forecasts and including a competing forecast might bias the estimate of test statistic. Starting from this point, Hansen (2005) developed a Superior Predictive Accuracy (SPA) test that studentize the individual statistics from the competing models and then converting them to *p*-values. The new refinement in the test is made by employing the conservative measure of expected performance denoted by $\hat{\mu}_j^c$. By using this measure, Hansen (2005) aims to keep all the alternatives in the test, including the poor competing model with $\mu_j < 0$. The new adopted method also employs a threshold parameter, $-\sqrt{2\log\log n}$, that can work correctly for the finite sample size *n* and is able to discriminate between poor competing models and good ones. The null hypothesis of Hansen's (2005) studentized test is:

$$H_0^j : \hat{\mu}_j^c / \sqrt{\text{var}(n^{1/2}\bar{d}_{j,n})} \leq 0,\ j = 1,\ldots,m, \tag{3.26}$$

and the conservative measure $\hat{\mu}_j^c$ is obtained by:

$$\hat{\mu}_j^c = \bar{d}_{j,n} 1_{\{n^{1/2}\bar{d}_{j,n}/\hat{\sigma}_j \leq -\sqrt{2\log\log n}\}},\ j = 1,\ldots,m, \tag{3.27}$$

Where $\hat{\sigma}_j$ is the variance of $n^{1/2}\bar{d}_{j,n}$ that is calculated from the stationary bootstrap method of Politis and Romano (1994) and $1_{\{.\}}$ is the indicator function. In the last stage, the studentized test statistic is obtained by:

$$T_{j,n}^{SPA} = \max[\max \sqrt{n}\bar{d}_{j,n} / \hat{\sigma}_j, 0],\ j = 1,\ldots,m, \tag{3.28}$$

Hansen (2005) further argues that different threshold values can yield different *p*-values in the finite sample size, and therefore he considered two bounds, upper SPA_c^0 given by $\min(\bar{d}_{j,n}, 0)$ and lower SPA_l^0 = 0 for all $j = 1,\ldots,m$. The former bound coincides with the RC model by assuming that all the competing models are good as a benchmark, the latter bound considers a limit when comparing the worst model with the benchmark.

Given that stock return volatility forecasting has a direct implication for risk management, we proceed in our forecast evaluation process by conducting tests based on Value-at-Risk (VaR). The VaR measure acts as an indicator of the potential loss arising from holding a portfolio for a given period of time. In this study, the VaR for a given model *i* in the out-of sample period *t* and at the significant level α is calculated as follows:

$$VaR_t^i\{\alpha\} = \mu_t(r) + (\phi(\alpha)\sqrt{\sigma_t^{2i}}) \tag{3.29}$$

Where $\mu_t(r)$ is the conditional mean of the return series, ϕ denotes cumulative distribution function and σ_t^{2i} is the conditional variance series generated from the model *i*.

Having obtained VaR estimates, the adequacy of the models can be tested following the procedure set out by Christoffersen (1998). Christoffersen's approach is based on interval forecasts, where the interval forecast must be wide enough in volatile periods such that observations that lie outside the interval will not be clustered. Given the VaR forecasts *y* at time *t* estimated from time $t-1$, $\{y_{t,t-1}\}_{t=1}^{T}$, at the sample path *T* and the return series *r*, the indicator sequence developed to be as follows:

$$I_t = \begin{Bmatrix} 1, r_t < y_t \\ 0, r_t \geq y_t \end{Bmatrix} \tag{3.30}$$

Here the outputs obtained from the indicator function will be either *0* or *1* depending on the comparison between the actual return series and the ex-post forecast. The construction of this interval forecast is said to be efficient at time t relevant to the information set at time $t-1$ (i.e. Ψ_{t-1}) if it provides the correct conditional coverage *p*, that is, $E(I_t | \Psi_{t-1}) = p$ where $\Psi_{t-1} = \{I_{t-1}, I_{t-2}, ..., I_1\}$. Starting from this general hypothesis, Christoffersen (1998) formulated his backtesting methodology using the likelihood ratio framework. He developed three tests in order to assess the adequacy of difference aspects of the VaR forecast. The first test investigates whether the forecast can provide a correct unconditional coverage, as such:

$$LR_{uc} = -2\log[(1-p)^{n_0} p^{n_1} / \hat{\pi}; I_1, I_2, ..., I_T] \sim \chi^2(1) \quad (3.31)$$

Where n_0 and n_1 are the total number of zeros and ones in the indicator function respectively, and $\hat{\pi} = n_1 / (n_0 + n_1)$ is maximum likelihood estimate of the correct coverage *p*. This test is criticized as it does not consider the case when both values 0 and 1 come in a time-dependent fashion and here the main variable is the pre-specified coverage rate. In the second test for independence the path-dependent problem is solved by testing null hypothesis of independence between the values of zeroes and ones, against the alternative that the full generated sequence from the indicator function follows first-order Markov chain process:

$$LR_{ind} = -2\log[(\hat{\Pi}_2; I_1, I_2, ..., I_T) / L(\hat{\Pi}_1; I_1, I_2, ..., I_T)] \sim \chi^2(1) \quad (3.32)$$

Where $\hat{\Pi}_1 = \begin{matrix} \frac{n_{00}}{n_{00}+n_{01}} & \frac{n_{01}}{n_{00}+n_{01}} \\ \frac{n_{10}}{n_{10}+n_{11}} & \frac{n_{11}}{n_{10}+n_{11}} \end{matrix}$ and $\hat{\Pi}_2 = (n_{01} + n_{11}) / (n_{00} + n_{10} + n_{01} + n_{11})$.

The last test developed by Christoffersen investigates the adequacy of the forecast in providing the correct conditional coverage. This test combines the methods of independence and the unconditional coverage, and it works by examining the null hypothesis of unconditional coverage against the alternative of independence test. The test here considers both the value of observation (i.e. 0 or 1) in the sequence and the prior coverage rate. The new joint is asymptotically distributed χ^2 with two degrees of freedom and is given by:

$$LR_{cc} = -2\log[(1-p)^{n_0} p^{n_1} / L(\hat{\Pi}_1; I_1, I_2, ..., I_T)] \sim \chi^2(2) \quad (3.33)$$

3.4 Data and Empirical Results

The dataset employed in this study comprises daily closing price index for several major global stock markets, namely AEX for Netherlands, DAX for Germany, CAC40 for France, FTSE100 for the UK, IBEX35 for Spain, DJIA and NASDAQ composite for the US and NIKKEI225 for Japan. The time period for the data spans from 01/01/1998 to 12/31/2013. These particular markets are selected for two main reasons. First, most of these markets represent countries from the G20 nations. Second, all these markets are developed and the complexity with the wavelet approach should suit the rational investors in these markets more than the irrational investors in the developing markets. In other words, the trading in the developing markets is in general irrational and the investors in these markets might not be interested in removing the noise before forecasting volatility. During the sample period stock markets have witnessed several crises, those, for example, of the Dot-com crash from 2000, the uncertainty in the stock markets after the 2003 invasion of Iraq, energy crisis of Argentina 2004 and the global crisis of 2008 having its effect spread over world stock markets.

The index level data is converted to returns using the standard log-difference of the closing prices. The return series is divided between the in-sample period from 01/01/1998 to 03/13/2009 (about 70% of the full sample) and the out-of sample period from 03/16/2009 to 12/31/2013 (30% of the data). Descriptive statistics of the full sample period are calculated before and after de-noising return series and are presented in Table 3.1, Panel (a) presents the original series for all stock market indexes and shows the usual characteristic of a near zero mean and a larger standard deviation. Further, all series clearly exhibit excess kurtosis and negative skewness, with the assumption of normality, under the Jarque-Bera test, clearly rejected. Descriptive statistics of wavelet de-noised return series are presented in panel (b). In comparison with the original return series, there are some noticeable differences. For example, in panel (b), we can see that the skewness values have changed, although not in any consistent direction, while the kurtosis values have increased for all series. Thus, normality it still rejected for the de-noised returns. Finally, the mean value of all the series remain very close to zero, while the standard deviation is reduced marginally following de-noising. Yet, the mean values turn from positive to negative in 6 out of 8 cases and that is resulted after performing the soft thresholding approach. Our result here means that the distribution of return can be biased somewhat before deciding on the threshold limit at each time scale. In other words, part of the variations in the return at a given time scale can be related to the noise and not to the information. This turns to be consistent with (Capobianco, 2002) study.

3.4.1 Statistical Evaluation Criteria

Tables 3.2 to 3.4 present the outcomes of the volatility forecasts under different statistical evaluation methods (i.e., root mean squared error, mean absolute error and Mincer-Zarnowitz Regression R-squared respectively). The top panel of each table presents the results obtained on the original return series while the second panel presents the results after de-noising.

Table 3.1 Summary Statistics

The following table presents the descriptive statistics for all return series for the full sample from January 1, 1998 to December 31, 2013. Normality test is the Jarque-bera test with χ^2 and 2 degrees of freedom under the null hypothesis of no normality distributed errors. Panel (a) presents the statistics for original return series and panel (b) for wavelet soft-based return series after de-noising. * denotes statistical significance at 1% level.

	AEX	DAX	CAC40	DJIA	FTSE100	IBEX35	NASDAQ Composite	NIKKEI225
				Panel (a)				
Mean	-7.53E-06	0.000142	0.000252	0.000177	6.71E-05	0.000131	0.000234	6.67E-05
Max	0.100283	0.121434	0.123697	0.105083	0.122189	0.149682	0.132546	0.125711
Min	-0.095903	- 0.117370	- 0.096010	-0.082005	- 0.105381	-0.106569	-0.101684	-0.111856
STD	0.015084	0.016608	0.017054	0.011947	0.014103	0.017163	0.017103	0.015922
Skewness	- 0.103513	- 0.011364	-0.059135	-0.092231	- 0.113288	0.028330	-0.018769	-0.032934
Kurtosis	8.738391	8.443435	7.164046	10.66761	10.91635	8.408217	7.813081	7.472451
Normality Test	5733.004*	5152.178*	3017.299*	10228.40*	10905.43*	5086.196*	4028.190*	3478.745*
				Panel (b)				
Mean	-0.000112	2.56E-04	-0.000166	2.76E-05	-9.37E-05	-0.000132	-1.24E-04	-7.50E-05
Max	0.100052	0.058564	0.122283	0.105054	0.12074	0.149805	0.133795	0.116543
Min	-0.092537	-0.060567	-0.113704	-0.08128	-0.104685	-0.108077	-0.10083	-0.112770
STD	0.014054	0.009548	0.015436	0.01112	0.013009	0.016063	0.016158	0.013914
Skewness	-0.082141	-0.540025	0.047053	-0.08587	-0.062985	0.126196	0.063615	0.048274
Kurtosis	10.58574	9.431745	10.24336	12.92391	13.90771	10.12283	9.159815	9.590512
Normality Test	10010.05*	7395.573*	9124.116*	17129.03*	20690.08*	8832.561*	6600.21*	7553.855*

Table 3.2 Out-of sample Forecast Statistics- RMSE.

The following table presents the root mean squared forecast error statistic for all indexes on (a) original return series and (b) wavelet soft-based return series. Models in each panel are sorted according to the risk measures. Model with the smallest forecasting error value was given the best rank, while the worst model in each panel has the highest rank (*Continued on the next page*).

	AEX		DAX		CAC40		DJIA		FTSE100		IBEX35		NASDAQ Composite		NIKKEI225	
Model		*Rank*		*Rank*		*Rank*		*Rank*		*Rank*		*Rank*		*Rank*		*Rank*
								Panel (a)								
GARCH	0.5612	4	0.6619	7	0.6902	7	0.3981	7	0.5600	6	0.7452	7	0.6950	7	0.6062	6
EGARCH	0.5478	1	0.6481	3	0.6781	3	0.3870	2	0.5500	5	0.7320	3	0.6806	1	0.6022	3
TGARCH	0.5482	3	0.6463	2	0.6748	2	0.3884	3	0.5430	1	0.7301	2	0.6808	3	0.6005	1

APARCH	0.5480	2	0.6452	1	0.6743	1	0.3862	1	0.5440	2	0.7294	1	0.6807	2	0.6010	2
CGGARC	0.5576	7	0.6584	4	0.6886	4	0.3970	6	0.5612	7	0.7440	5	0.6930	4	0.6014	4
FIGARCH	0.5574	6	0.6600	6	0.6892	6	0.3967	5	0.5594	4	0.7422	6	0.6940	6	0.6030	5
HYGARCH	0.5568	5	0.6583	5	0.6887	5	0.3961	4	0.5593	3	0.7420	4	0.6939	5	0.6030	5
Panel (b)																
GARCH	0.5420	7	0.4460	4	0.6625	4	0.3786	4	0.5439	4	0.7251	6	0.6752	7	0.5228	5
EGARCH	0.5252	1	0.4261	1	0.6428	1	0.3641	1	0.5241	1	0.7014	1	0.6589	1	0.5167	1
TGARCH	0.5300	3	0.4321	3	0.6474	3	0.3678	3	0.5272	3	0.7086	2	0.6605	2	0.5178	2
APARCH	0.5299	2	0.4312	2	0.6454	2	0.3657	2	0.5253	2	0.7086	2	0.6610	3	0.5180	3
CGGARC	0.5375	5	0.4543	5	0.6625	4	0.3792	5	0.5469	5	0.7246	5	0.6735	4	0.5244	7
FIGARCH	0.5356	4	0.4543	5	0.6649	5	0.3793	6	0.5469	5	0.7213	3	0.6738	5	0.5220	4
HYGARCH	0.5385	6	0.4559	6	0.6694	6	0.3796	7	0.5490	6	0.7242	4	0.6744	6	0.5229	6

Table 3.3 Out-of sample Forecast Statistics- MAE.

The following table presents the mean absolute forecast error statistic for all models on (a) original return series and (b) wavelet soft-based return series. Models in each panel are sorted according to the value of the forecasting error.

Model	AEX	*Rank*	DAX	*Rank*	CAC40	*Rank*	DJIA	*Rank*	FTSE100	*Rank*	IBEX35	*Rank*	NASDAQ Composite	*Rank*	NIKKEI225	*Rank*
Panel (a)																
GARCH	0.2364	7	0.3041	6	0.2888	6	0.1525	5	0.2087	4	0.3092	6	0.3022	6	0.2671	6
EGARCH	0.2244	1	0.2901	1	0.2743	1	0.1444	1	0.1961	1	0.2935	1	0.2925	1	0.2636	1
TGARCH	0.2284	3	0.2963	3	0.2799	3	0.1492	3	0.2003	3	0.3000	3	0.2958	2	0.2657	3
APARCH	0.2273	2	0.2932	2	0.2776	2	0.1464	2	0.1980	2	0.2980	2	0.2958	2	0.2642	2
CGGARC	0.2343	5	0.3017	5	0.2880	4	0.1549	7	0.2090	5	0.3087	5	0.3006	5	0.2661	5
FIGARCH	0.2352	6	0.3069	7	0.2916	7	0.1538	6	0.2094	6	0.3100	7	0.3000	4	0.2653	4
HYGARCH	0.2325	4	0.3014	4	0.2885	5	0.1516	4	0.2090	5	0.3080	4	0.2994	3	0.2653	4
Panel (b)																
GARCH	0.2108	7	0.1633	1	0.2565	5	0.1327	7	0.1817	6	0.2796	6	0.2706	6	0.2048	6
EGARCH	0.1987	1	0.1728	6	0.2438	1	0.1237	1	0.1702	1	0.2631	1	0.2600	1	0.1998	1
TGARCH	0.2045	4	0.1691	3	0.2513	3	0.1302	3	0.1757	2	0.2730	3	0.2644	2	0.2028	3
APARCH	0.2044	3	0.1685	2	0.2487	2	0.1283	2	0.1729	3	0.2730	3	0.2650	3	0.2033	4
CGGARC	0.2046	5	0.1714	4	0.2565	5	0.1318	4	0.1801	5	0.2752	4	0.2655	4	0.2049	7
FIGARCH	0.2031	2	0.1716	5	0.2553	4	0.1319	5	0.1800	4	0.2729	2	0.2650	3	0.2015	2
HYGARCH	0.2082	6	0.1730	7	0.2588	6	0.1324	5	0.1826	7	0.2787	5	0.2669	5	0.2037	5

Examining the results in Table 3.2, we can see that the use of wavelet de-noising leads to a decrease in all forecasting error values for all series without exception. Examining the model ranking, a number of important features emerge. For the unadjusted returns, the APARCH model emerges as the clear winner, producing the lowest forecast errors for four of the eight series (DAX, CAC40, DJIA and IBEX35). The EGARCH model is preferred in two of eight (AEX and NASDAQ composite) and TGARCH model proves to be the best performing model for FTSE 100 and NIKKEI 225. The worst performer is the GARCH model, which has the highest forecast error for six of the eight series, while the CGARCH model appears as the second weakest performance. In some contrast, panel (b) shows that after de-noising, the EGARCH model clearly becomes preferred for seven out of eight series. Again, the GARCH model is among the worst performers, for two of eight return series, while the long-memory CGARCH and HYGARCH models perform worst for the remaining series (of interest, the FIGARCH model also performs poorly except for the DAX, where it is preferred). Yet, explaining the differences among the countries and the best performing model requires performing the in-sample rolling regression estimates. This has been done in Section 3.5 where more variations in the level of asymmetry and the volatility persistence have been found after de-noising[23].

Table 3.3 presents the results using the MAE forecast metric. As in our previous analysis and starting from Panel (a) of the Table, we can see that the EGARCH model performs best in producing the lowest forecast error, while the APARCH model is the second preferred model and this is true for all return series. Regarding the lowest ranking, the GARCH and FIGARCH models perform the worst, for five series and three series respectively. The results for the wavelet de-noised return series, presented in the Panel (b), also reveal that the best model is EGARCH and that is true for seven out of eight return series, while FIGARCH found to be the best for one series. Again, the GARCH model performs poorly.

Yet, two reasons can explain why the EGARCH model is generally the best performer in Tables 3.2 and 3.3 after de-noising. First, de-noising the return series should decrease the autocorrelation in the first lag of return series hence add more favour to the asymmetry over the volatility clustering and the long memory. Our unreported analysis proved that for all the markets in the sample. Second, the conditional volatility pattern should change over time during and around the crises after removing the noise. This, in turn, is going to be examined later on in this chapter with a rolling regression. According to this, more variation in the conditional volatility can diminish the importance of the long memory and clustering patterns giving the fact that these two patterns

[23] More differences between the markets need to be examined by incorporating the sentiment and the uncertainty proxies in forecasting volatility.

usually arise from the the persistence in the voaltility rather than fluctuation.

Table 3.4 reports the R^2 value generated from the MZ regression. Comparing the results before and after de-noising, we note that removing noise from the return series increases the R^2 value, hence the forecasting performance. In terms of model ranking, for forecasts based on the original return series, the EGARCH model is the best performing model for four series, while other asymmetric models also perform well with APARCH being the best for two series and TGARCH for two. The second-place ranking gives similar results for asymmetric models and EGARCH again is the best among others with high R^2 obtained for three return series. We further notice that FIGARCH and GARCH models are the worst performers, each for three return series followed by HYGARCH model for two series. In panel (b) the results do not substantially change, with evidence that the EGARCH model is preferred for several of the series. However, it is now noticeable that the long-memory FIGARCH, HYGARCH and CGARCH models are preferred for a few of the de-noised return series.

To provide some understanding of whether the forecasts tend to over- or under-state volatility, we consider the success ratio measure, which measures whether the forecast correctly predicts an increase or decrease in volatility. The results of this test are presented in Table 3.5, where it can be observed that for all series after performing wavelet de-noising, the standard GARCH and asymmetric GARCH models tend to be preferred. That said there is no clear ranking of either a preferred or least preferred model. Furthermore, the values tend to be close in magnitude.

Overall, this set of statistical forecast metrics suggests a few pertinent points. First, the asymmetric models, and notably the EGARCH model, generally perform well, however, this result is far from ubiquitous. Second, models based on wavelet de-noising are preferred over those based on unadjusted returns series. Third, that the difference in statistics between models is often small, suggesting any forecast gain is marginal and thus a ranking may not be overly informative. This motivates the use of statistics that seek to discriminate between models.

3.4.2 Tests of Equal Predictive Accuracy

In this section, we consider those tests designed to discriminate between alternative forecasts. We use the Modified Diebold Mariano (MDM) test of Harvey, Leybourne and Newbold (1997), the reality check test of White (2000) and the superior predictive ability test of Hansen (2005). Using these methods requires deciding on the appropriate benchmark to use.

Table 3.4 MZ *R^2 Statistic*.

The following table presents R^2 computed using Mincer-Zarnowitz Regression Test forecast error statistics for all models on (a) original return series and (b) wavelet soft-based de-noised return series. Models in each panel are sorted according to the value of R^2. Model with the largest R^2 value was given the best rank, while the worst model in each panel has the highest rank.

	AEX		DAX		CAC40		DJIA		FTSE100		IBEX35		NASDAQ Composite		NIKKEI225	
Model		*Rank*		*Rank*		*Rank*		*Rank*		*Rank*		*Rank*		*Rank*		*Rank*
Panel (a)																
GARCH	0.090	6	0.116	7	0.078	5	0.129	5	0.096	3	0.057	6	0.138	5	0.048	4
EGARCH	0.125	1	0.134	2	0.106	1	0.163	1	0.131	1	0.088	1	0.154	2	0.056	3
TGARCH	0.122	3	0.131	3	0.099	3	0.160	2	0.127	2	0.082	3	0.165	1	0.062	1
APARCH	0.123	2	0.135	1	0.103	2	0.159	3	0.131	1	0.085	2	0.165	1	0.059	2
CGGARC	0.091	5	0.126	4	0.080	4	0.130	4	0.095	4	0.058	5	0.142	4	0.021	5
FIGARCH	0.092	4	0.123	6	0.078	5	0.128	6	0.091	5	0.062	4	0.148	3	0.020	6
HYGARCH	0.091	5	0.124	5	0.078	5	0.129	5	0.091	5	0.062	4	0.148	3	0.020	6
Panel (b)																
GARCH	0.120	4	0.152	3	0.093	4	0.174	4	0.111	4	0.067	3	0.182	6	0.089	4
EGARCH	0.147	1	0.178	1	0.118	1	0.200	2	0.148	1	0.099	1	0.191	3	0.110	7
TGARCH	0.144	2	0.171	2	0.112	3	0.202	1	0.140	3	0.089	2	0.209	2	0.112	6
APARCH	0.144	2	0.171	2	0.115	2	0.199	3	0.147	2	0.089	2	0.212	1	0.113	5
CGGARC	0.121	3	0.139	4	0.089	5	0.173	5	0.109	5	0.065	4	0.183	5	0.092	3
FIGARCH	0.120	4	0.135	5	0.087	6	0.170	6	0.108	6	0.069	3	0.188	4	0.095	2
HYGARCH	0.119	5	0.135	5	0.087	6	0.170	6	0.108	6	0.069	3	0.188	4	0.097	1

Table 3.5 Success Ratio.

The following table presents success ratio from the forecast for each model. This test measures to what extent volatility forecast correctly predicts the true volatility process. Models in each panel are sorted according to the value of success ratio. Model with the largest success ratio was given the best rank, while the worst model in each panel has the highest rank.

	AEX		DAX		CAC40		DJIA		FTSE100		IBEX35		NASDAQ Composite		NIKKEI225	
Model		*Rank*		*Rank*		*Rank*		*Rank*		*Rank*		*Rank*		*Rank*		*Rank*
Panel (a)																
GARCH	0.6808	4	0.6648	2	0.6616	3	0.7400	3	0.6520	4	0.6560	2	0.7072	3	0.6184	5
EGARCH	0.7000	1	0.6576	4	0.6616	3	0.7328	6	0.6704	2	0.6496	4	0.7032	6	0.6208	3
TGARCH	0.6976	2	0.6552	6	0.6632	2	0.7424	2	0.6656	3	0.6544	3	0.7120	1	0.6312	1
APARCH	0.6760	5	0.6608	3	0.6680	1	0.7384	4	0.6720	1	0.6544	3	0.7104	2	0.6280	2
CGGARC	0.6840	3	0.6728	1	0.6576	4	0.7432	1	0.6512	5	0.6584	1	0.7064	4	0.6216	4
FIGARCH	0.6760	5	0.6560	5	0.6496	5	0.7400	3	0.6472	6	0.6432	6	0.7032	6	0.6176	6
HYGARCH	0.6744	6	0.6544	7	0.6496	5	0.7368	5	0.6464	7	0.6448	5	0.7040	5	0.6176	6
Panel (b)																
GARCH	0.7290	2	0.8000	5	0.6723	2	0.7626	4	0.6843	5	0.6723	2	0.7530	1	0.6811	4
EGARCH	0.7306	4	0.8024	4	0.6731	3	0.7586	2	0.6906	3	0.6619	6	0.7338	4	0.6707	5
TGARCH	0.7378	1	0.7984	6	0.6795	1	0.7674	3	0.6970	1	0.6731	1	0.7482	3	0.6827	3
APARCH	0.7378	1	0.8024	4	0.6795	1	0.7690	1	0.6962	2	0.6731	1	0.7498	2	0.6867	1
CGGARC	0.7306	4	0.8040	3	0.6771	4	0.7626	4	0.6867	4	0.6691	3	0.7530	1	0.6859	2
FIGARCH	0.7314	3	0.8056	1	0.6707	5	0.7618	5	0.6835	6	0.6667	4	0.7498	2	0.6859	2
HYGARCH	0.7306	4	0.8048	2	0.6675	6	0.7626	4	0.6835	6	0.6635	5	0.7498	2	0.6827	3

The decision taken here is based on the statistical evaluation as to the preferred model in the previous sub-section. Tables 3.6 and 3.7 report the result of MDM where, according to results of RMSE, the wavelet-EGARCH (WS-EGARCH) is selected as the benchmark**.**

From Table 3.6 we can see that the WS-EGARCH model cannot be significantly beaten by any competing models (with the noted exceptions below). Specifically, a negative sign on the MDM statistic indicates that the benchmark model achieves a lower forecast error than the competing model.

To further examine the performance of the benchmark model but this time against all other models employed we consider the reality check (RC) test of White (2000) and the superior predictive ability (SPA) test of Hansen (2005). These tests will provide a clear picture on the performance of the benchmark model. Here, we consider these tests based on both the MSE and MAE metrics with the results reported in Tables 3.7 and 3.8, respectively.

In conducting these tests, we consider all models as applied on the original return series as the benchmark model and compare it to all other competing models. Each model in the row in the table is considered as a benchmark against all others and under the null hypothesis that the average performance of the benchmark is as small as the minimum average performance across the models. The alternative is that the minimum average loss across the models is smaller than the average performance of the benchmark.

Examining the performance of the models across the two tables, we can see that the models that have no prior de-noising are all rejected against other models. In contrast, several benchmark models after de-noising are not rejected. In particular, for the MAE based criteria, this includes the WS-EGARCH and WS-FIGARCH, with the only exceptions being the DAX (and more marginally the NIKKEI) for former model and the DAX at all significance levels and AEX, CAC and IBEX at the 5% for the latter model. For the MSE metric, no single model dominates. Overall, the results in this section are supportive of using the de-noising approach and, in general, asymmetric GARCH models.

3.4.3 Value-at-Risk Forecast Evaluation

In evaluating the volatility forecasts, we apply them to a risk management context in Tables 3.9 to 3.12. The volatility forecasts are used to the produce 95% and 99% confidence intervals for the Value-at-Risk (VaR) estimates.

Table 3.6 Modified Diebold Mariano MDM Test. (Benchmark: WS-EGARCH)-MSE.

Table presents MDM statistics. * denotes rejection of null hypothesis of equal predictive accuracy at 1% significant level. *P*-values are given in brackets. Signs of statistics is negative indicating that the benchmark implies lower loss. The forecasting risk metric selected is mean square error (MSE).

AEX		DAX		CAC40		DJIA		FTSE100		IBEX35		NASDAQ		NIKKEI225	
GA	-5.704	GA	-5.938	GA	-5.298	GA	-4.256	GA	-4.106	GA	-5.322	GA	-7.044	GA	-4.047
	(0.000) *		(0.000) *		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*
EG	-5.420	EG	-6.038	EG	-5.136	EG	-4.302	EG	-3.933	EG	-5.355	EG	-6.960	EG	-4.030
	(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*
TG	-5.677	TG	-6.335	TG	-5.490	TG	-4.625	TG	-4.328	TG	-5.542	TG	-7.364	TG	-4.128
	(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*
AP	-5.812	AP	-6.271	AP	-5.413	AP	-4.550	AP	-4.217	AP	-5.521	AP	-7.360	AP	-4.079
	(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*
CG	-5.732	CG	-5.970	CG	-5.337	CG	-4.542	CG	-4.020	CG	-5.355	CG	-7.101	CG	-4.118
	(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)		(0.000)*
FI	-5.686	FI	-6.028	FI	-5.339	FI	-4.396	FI	-4.045	FI	-5.346	FI	-6.748	FI	-4.066
	(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*
HY	-5.622	HY	-5.958	HY	-5.306	HY	-4.349	HY	-4.042	HY	-5.320	HY	-6.734	HY	-4.066
	(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*		(0.000)*

Table 3.7 Reality Check and Superiority Predictive Ability Tests (All Models)-MAE.

This table presents the z-score of white's (2000) reality check (RC) and *P*-values of lower bound (SPA*l*^{o}) and consistent (SPA*c*^{o}) of Hansen (2005) superior predictive ability studentized test. Each model in the row considered as a benchmark against all others and under the null hypothesis that the average performance of the benchmark is as small as the minimum average performance across the models. The RC analysis has been done with the bootstrap approach. The alternative is that the minimum average loss across the models is smaller than the average performance of the benchmark. Number of bootstrap replications to calculate the *P*-values is selected to be 1000 and the block length is 0.10. The forecasting risk metric selected is mean square error (MAE). *, ** and *** denote no rejection of null hypothesis at 10%, 5% and 1% significance level respectively.

Benchmark		AEX	DAX	CAC40	DJIA	FTSE100	IBEX35	NASDAQ Composite	NIKKEI225
GARCH	SPA_l^0	0	0	0	0	0	0	0	0
	SPA_c^0	0	0	0	0	0	0	0	0
	RC	0	0	0	0	0	0	0	0
WS-GARCH	SPA_l^0	0.003	0	0.005	0.001	0.003	0.002	0	0
	SPA_c^0	0.003	0	0.005	0.001	0.003	0.002	0	0
	RC	0.003	0	0.005	0.001	0.006	0.002	0	0
EGARCH	SPA_l^0	0	0	0	0	0	0	0	0
	SPA_c^0	0	0	0	0	0	0	0	0
	RC	0	0	0	0	0	0	0	0
WS-EGARCH	SPA_l^0	1***	0	1***	1***	1***	1***	0.429***	0.017*
	SPA_c^0	1***	0	1***	1***	1***	1***	0.482***	0.030*
	RC	1***	0	1***	1***	1***	1***	0.777***	0.089**
TGARCH	SPA_l^0	0	0	0	0	0	0	0	0
	SPA_c^0	0	0	0	0	0	0	0	0
	RC	0	0	0	0	0	0	0	0
WS-TGARCH	SPA_l^0	0.004	0	0.010*	0.005	0.032*	0.001	0.016*	0.001
	SPA_c^0	0.004	0	0.010*	0.005	0.041*	0.001	0.016*	0.001
	RC	0.005	0	0.011*	0.007	0.067**	0.002	0.019*	0.001
APARCH	SPA_l^0	0	0	0	0	0	0	0	0
	SPA_c^0	0	0	0	0	0	0	0	0
	RC	0	0	0	0	0	0	0	0
WS-APARCH	SPA_l^0	0	0	0.001	0.001	0.014*	0.002	0.002	0
	SPA_c^0	0	0	0.001	0.001	0.016*	0.002	0.002	0
	RC	0	0	0.001	0.001	0.024*	0.002	0.002	0
WS-APARCH	SPA_l^0	0	0	0.001	0.001	0.014*	0.002	0.002	0
	SPA_c^0	0	0	0.001	0.001	0.016*	0.002	0.002	0
	RC	0	0	0.001	0.001	0.024*	0.002	0.002	0
CGARCH	SPA_l^0	0	0	0	0	0	0	0	0
	SPA_c^0	0	0	0	0	0	0	0	0

Table 3.7 *Continued.*

Benchmark		AEX	DAX	CAC40	DJIA	FTSE100	IBEX35	NASDAQ Composite	NIKKEI225
	RC	0	0	0	0	0	0	0	0
WS-CGARCH	SPA_l^0	0.065**	0	0.024*	0.086**	0.100***	0.022*	0.102***	0
	SPA_c^0	0.086**	0	0.024*	0.086**	0.116***	0.022*	0.117***	0.005
	RC	0.132***	0	0.030*	0.267***	0.220***	0.041*	0.225***	0.005
WS-FIGARCH	SPA_l^0	0.042*	0	0.013*	0.217***	0.055**	0.020*	1***	1***
	SPA_c^0	0.080**	0	0.014*	0.402***	0.109***	0.021*	1***	1***
	RC	0.145***	0	0.025*	0.711***	0.189***	0.035*	1***	1***
HYGARCH	SPA_l^0	0	0	0	0	0	0	0	0
	SPA_c^0	0	0	0	0	0	0	0	0
	RC	0	0	0	0	0	0	0	0
WS-HYGARCH	SPA_l^0	0	0	0	0	0	0	0	0
	SPA_c^0	0	0	0	0	0	0	0	0
	RC	0	0	0	0	0	0	0	0

Table 3.8 Reality Check and Superiority Predictive Ability Test (All Models)-MSE.

This table presents the z-score of white's (2000) reality check (RC) and *P*-values of lower bound (SPAl^o) and consistent (SPAc^o) of Hansen (2005) superior predictive ability studentized test. Each model in the row considered as a benchmark against all others and under the null hypothesis that the average performance of the benchmark is as small as the minimum average performance across the models. The RC analysis has been done with the bootstrap approach. The alternative is that the minimum average loss across the models is smaller than the average performance of the benchmark. Number of bootstrap replications to calculate the *P*-values is selected to be 1000 and the block length is 0.10. The forecasting risk metric selected is mean square error (MSE). *, ** and *** denote no rejection of null hypothesis at 10%, 5% and 1% significance level respectively.

Benchmark		AEX	DAX	CAC40	DJIA	FTSE100	IBEX35	NASDAQ Composite	NIKKEI225
GARCH	SPA_l^0	0	0	0	0.001	0.004	0	0	0.002
	SPA_c^0	0	0	0	0.001	0.004	0	0	0.002
	RC	0	0	0	0.001	0.004	0	0	0.002
WS-GARCH	SPA_l^0	0.019*	0.071**	0.060**	0.001	0.520***	0.038*	0.004	0
	SPA_c^0	0.024*	0.081**	0.070**	0.001	0.596***	0.041*	0.004	0
	RC	0.025*	0.082**	0.073**	0.001	0.640***	0.041*	0.004	0
EGARCH	SPA_l^0	0	0	0	0	0.008	0	0	0.003
	SPA_c^0	0	0	0	0	0.008	0	0	0.003
	RC	0	0	0	0	0.008	0	0	0.003
WS-EGARCH	SPA_l^0	1***	0.036*	0.023*	0	0.538***	0.138***	0.001	0.002
	SPA_c^0	1***	0.037*	0.023*	0	0.730***	0.338***	0.001	0.002
	RC	1***	0.037*	0.023*	0	0.804***	0.393***	0.001	0.002

Table 3.8 *Continued.*

Benchmark		AEX	DAX	CAC40	DJIA	FTSE100	IBEX35	NASDAQ Composite	NIKKEI225
TGARCH	SPA_l^0	0	0	0	0	0.001	0	0	0.001
	SPA_c^0	0	0	0	0	0.001	0	0	0.001
	RC	0	0	0	0	0.001	0	0	0.001
WS-TGARCH	SPA_l^0	0.095**	0.033	0.040*	0	0.428***	0.063**	0.004	0.008
	SPA_c^0	0.090**	0.047*	0.049*	0	0.569***	0.076**	0.004	0.008
	RC	0.166***	0.051**	0.050**	0	0.590***	0.081**	0.004	0.008
APARCH	SPA_l^0	0	0	0	0.001	0.002	0	0	0.002
	SPA_c^0	0	0	0	0.001	0.002	0	0	0.002
	RC	0	0	0	0.001	0.002	0	0	0.002
WS-APARCH	SPA_l^0	0.045*	0.043*	0.058**	0	0.798***	0.074**	0.005	0.006
	SPA_c^0	0.055**	0.048*	0.058**	0	0.959***	0.124***	0.005	0.006
	RC	0.085**	0.049*	0.060**	0	0.967***	0.143***	0.005	0.006
CGARCH	SPA_l^0	0	0	0	0.002	0.014*	0	0	0
	SPA_c^0	0	0	0	0.002	0.014*	0	0	0
	RC	0	0	0	0.002	0.014*	0	0	0
WS-CGARCH	SPA_l^0	0.075**	0.076**	0.126***	0.002	0.236***	0.018**	0.002	0.001
	SPA_c^0	0.084**	0.094**	0.145***	0.002	0.258***	0.020*	0.002	0.001
	RC	0.075**	0.099**	0.156***	0.002	0.300***	0.018*	0.002	0.010*
FIGARCH	SPA_l^0	0	0	0	0.001	0.004	0	0	0.004
	SPA_c^0	0	0	0	0.001	0.005	0	0	0.004
	RC	0	0	0	0.001	0.005	0	0	0.004
WS-FIGARCH	SPA_l^0	0.036*	0.072**	0.069**	0.001	0.631***	0.020*	0.002	0.003
	SPA_c^0	0.044*	0.089**	0.092**	0.001	0.774***	0.022*	0.002	0.005
	RC	0.049*	0.103**	0.108***	0.001	0.842***	0.022*	0.002	0.005
HYGARCH	SPA_l^0	0	0	0.094**	0	0.004	0	0	0.001
	SPA_c^0	0	0	0.112***	0	0.004	0	0	0.001
	RC	0	0	0.123***	0	0.004	0	0	0.001
WS-HYGARCH	SPA_l^0	0.014*	0.051**	0.066**	0.067**	0.080**	0.054**	0.006	0.042*
	SPA_c^0	0.017*	0.051**	0.070**	0.067**	0.120***	0.060**	0.007	0.044*
	RC	0.017*	0.051**	0.071**	0.078**	0.127***	0.063**	0.008	0.044*

As noted above, we employ several tests to examine the suitability of the volatility forecasts, namely the likelihood ratio test of unconditional coverage (LRuc), likelihood ratio test of independence (LRind) and joint likelihood ratio test of conditional coverage (LRcc).

It can be seen from Table 3.9, when the evaluation is based on the original return series, that all the models passed the tests for AEX, FTSE 100, and DJIA and NIKKEI 225 return series. None of the asymmetric model passes the tests of unconditional coverage and conditional coverage for CAC 40 and DAX return series, however, the GARCH, FIGARCH and HYGARCH models do. The result of the IBEX series is similar, with additionally the APARCH and CGARCH models also passing the adequacy tests. For the NASDAQ composite return series only the CGARCH model performs adequately.

Table 3.9 Risk Management Evaluation on Original Return Series: 95 % VaR.

The following Table presents results of Christoffersen, 1998)'s backtesting procedure. This composed of three tests, likelihood ratio of unconditional coverage denoted by *LRuc,* likelihood ratio of independence *LRind* and likelihood ratio of conditional coverage *LRcc.* Figures in Table represents the *P*-values for the null hypothesis of correct coverage (H0: f = 5%). * denotes that the model is adequate and it passed the test.

	LRuc	*LRind*	*LRcc*	*LRuc*	*LRind*	*LRcc*	*LRuc*	*LRind*	*LRcc*
Model		CAC40			DAX			AEX	
GARCH	0.069*	0.363*	0.126*	0.090*	0.148*	0.083*	0.339*	0.608*	0.555*
EGARCH	0.002	0.734*	0.007	0.011	0.470*	0.031	0.481*	0.691*	0.721*
TGARCH	0.002	0.931*	0.008	0.011	0.258*	0.031	0.406*	0.649*	0.639*
APARCH	0.001	0.829*	0.003	0.011	0.435*	0.031	0.406*	0.649*	0.639*
CGARCH	0.025	0.334*	0.096*	0.069*	0.554*	0.161*	0.406*	0.919*	0.705*
FIGARCH	0.280*	0.985*	0.558*	0.481*	0.691*	0.721*	0.652*	0.777*	0.868*
HYGARCH	0.146*	0.843*	0.342*	0.090*	0.854*	0.233*	0.564*	0.824*	0.826*
		FTSE100			DJIA			NIKKEI225	
GARCH	0.280*	0.238*	0.278*	0.647*	0.200*	0.397*	0.124*	0.532*	0.251*
EGARCH	0.069*	0.708*	0.178*	0.747*	0.383*	0.649*	0.206*	0.860*	0.443*
TGARCH	0.228*	0.937*	0.482*	0.948*	0.963*	0.997*	0.093*	0.999*	0.245**
APARCH	0.069*	0.708*	0.178*	0.652*	0.777*	0.868*	0.093*	0.999*	0.245*
CGARCH	0.747*	0.113*	0.270*	0.845*	0.528*	0.804*	0.093*	0.491*	0.193*
FIGARCH	0.469*	0.239*	0.385*	0.555*	0.219*	0.395*	0.093*	0.491*	0.193*
HYGARCH	0.555*	0.219*	0.395*	0.647*	0.604*	0.787*	0.093*	0.491*	0.193*
		NASDAQ Composite			IBEX35				
GARCH	0.846*	0.008	0.031	0.069*	0.554*	0.161*			
EGARCH	0.564*	0.006	0.019	0.006	0.180*	0.009			
TGARCH	0.845*	0.012	0.043	0.021	0.435*	0.052*			
APARCH	0.845*	0.012	0.043	0.061*	0.780*	0.051*			
CGARCH	0.652*	0.102*	0.237*	0.069*	0.554*	0.161*			
FIGARCH	0.555*	0.017	0.049	0.339*	0.579*	0.543*			
HYGARCH	0.555*	0.017	0.049	0.280*	0.622*	0.494*			

Table 3.10 presents the results from wavelet de-noising. Performance here is noticeable worse, with no model passing all tests for the majority of the series. Indeed, only for the CAC and AEX do any models perform adequately. In particular, for the CAC, only the FIGARCH and HYGARCH models are acceptable, while only the GARCH model is for the AEX series.

Table 3.10 Risk Management Evaluation on Wavelet Soft-Based De-noised Return Series: 95 % VaR.

The following table presents results of Christoffersen, 1998)'s backtesting procedure. This composed of three tests, likelihood ratio of unconditional coverage denoted by *LRuc,* likelihood ratio of independence *LRind* and likelihood ratio of conditional coverage *LRcc.* Figures in Table represents the *P*-values for the null hypothesis of correct coverage (H0: *f* = 5%). * denotes that the model is adequate and it passed the test.

	LRuc	*LRind*	*LRcc*	*LRuc*	*LRind*	*LRcc*	*LRuc*	*LRind*	*LRcc*
Model	CAC40			DAX			AEX		
GARCH	0.021	0.087*	0.016	0.228*	0.003	0.006	0.391*	0.260*	0.367*
EGARCH	0.000	0.029	0.000	0.039	0.001	0.000	0.321*	0.283*	0.343*
TGARCH	0.002	0.006	0.000	0.052*	0.001	0.000	0.555*	0.017	0.049
APARCH	0.002	0.006	0.000	0.039	0.001	0.000	0.555*	0.017	0.049
CGARCH	0.039	0.108*	0.032	0.228*	0.003	0.006	0.391*	0.022	0.049
FIGARCH	0.184*	0.198*	0.181*	0.481*	0.005	0.015	0.259*	0.027	0.046
HYGARCH	0.280*	0.238*	0.278*	0.481*	0.005	0.015	0.161*	0.033	0.039
	FTSE100			DJIA			NIKKEI225		
GARCH	0.280*	0.003	0.008	0.555*	0.017	0.050*	0.007	0.080*	0.006
EGARCH	0.146*	0.002	0.003	0.747*	0.007	0.027	0.005	0.087*	0.004
TGARCH	0.011	0.000	0.000	0.948*	0.010	0.039	0.050*	0.050*	0.022
APARCH	0.011	0.000	0.000	0.948*	0.010	0.035	0.025	0.061*	0.014
CGARCH	0.652*	0.007	0.023	0.948*	0.010	0.035	0.000	0.144*	0.000
FIGARCH	0.564*	0.006	0.019	0.391*	0.022	0.050*	0.000	0.155*	0.000
HYGARCH	0.652*	0.007	0.023	0.069*	0.045	0.026	0.000	0.155*	0.000
	NASDAQ Composite			IBEX35					
GARCH	0.093*	0.041	0.030	0.029	0.000	0.000			
EGARCH	0.161*	0.033	0.039	0.000	0.003	0.000			
TGARCH	0.391*	0.022	0.049	0.003	0.000	0.000			
APARCH	0.321*	0.024	0.048	0.002	0.000	0.000			
CGARCH	0.321*	0.024	0.048	0.146*	0.002	0.003			
FIGARCH	0.124*	0.037	0.035	0.481*	0.005	0.015			
HYGARCH	0.036	0.055*	0.017	0.065*	0.007	0.023			

Turning to the 99% VaR, a different picture emerges. In particular, examining the VaR estimates based on the original data (Table 3.11), we can see that only a limited number of models pass all the tests across the range of markets considered and for the DJIA and NASDAQ no model passes all tests. More specifically, the FIGARCH model appears adequate for the CAC, DAX, FTSE, NIKKEI and IBES series. For other models, the HYGARCH passes the tests for the DAX and FTSE, while one or more of the TGARCH, EGARCH and APARCH models pass the tests for the AEX, NIKKEI and IBEX. However, the performance of the models after wavelet de-noising (Table 3.12) are further significantly improved. Indeed, for the majority of the series (AEX, FTSE, DJIA, NIKKEI, NASDAQ and IBEX), all models can be regarded as adequate by passing all tests. For the CAC the GARCH, EGARCH, TGARCH and APARCH models fail only the unconditional test, while for the DAX only the GARCH model fails the unconditional test. Consequently, it can be seen that wavelet de-noising can improve risk management-based evaluation forecasts at the 99% confidence level.

Table 3.11 Risk Management Evaluation on Original Return Series: 99 % VaR.

The following table presents results of Christoffersen, 1998)'s backtesting procedure. This composed of three tests, likelihood ratio of unconditional coverage denoted by *LRuc*, likelihood ratio of independence *LRind* and likelihood ratio of conditional coverage *LRcc*. Figures in Table represents the *P*-values for the null hypothesis of correct coverage (H0: $f = 1\%$). * denotes that the model is adequate and it passed the test.

	LRuc	*LRind*	*LRcc*	*LRuc*	*LRind*	*LRcc*	*LRuc*	*LRind*	*LRcc*
Model		CAC40			DAX			AEX	
GARCH	0.000	0.612*	0.001	0.007	0.353*	0.018*	0.004	0.332*	0.009
EGARCH	0.000	0.275*	0.000	0.002	0.312*	0.004	0.015*	0.374*	0.034*
TGARCH	0.000	0.275*	0.000	0.002	0.312*	0.004	0.007	0.353*	0.018*
APARCH	0.000	0.240*	0.000	0.002	0.312*	0.004	0.015*	0.374*	0.034*
CGARCH	0.002	0.524*	0.006	0.028*	0.397*	0.612*	0.007	0.440*	0.020*
FIGARCH	0.015*	0.401*	0.036*	0.086*	0.444*	0.171*	0.000	—	—
HYGARCH	0.004	0.481*	0.012*	0.015*	0.374*	0.034*	0.000	—	—
		FTSE100			DJIA			NIKKEI225	
GARCH	0.002	0.312*	0.004	0.004	0.332*	0.009	0.676*	0.145*	0.317*
EGARCH	0.000	0.240*	0.000	0.000	0.195*	0.000	0.676*	0.145*	0.317*
TGARCH	0.000	0.224*	0.000	0.000	0.240*	0.000	0.888*	0.122*	0.300*
APARCH	0.000	0.224*	0.000	0.000	0.224*	0.000	0.678*	0.145*	0.317*
CGARCH	0.000	0.293*	0.002	0.000	0.567*	0.003	0.491*	0.170*	0.308*
FIGARCH	0.049*	0.420*	0.106*	0.000	0.612*	0.001	0.888*	0.122*	0.300*
HYGARCH	0.015*	0.374*	0.034*	0.000	0.612*	0.001	0.000	0.491*	0.000
		NASDAQ Composite			IBEX35				
GARCH	0.000	0.275*	0.000	0.008	0.353*	0.018*			
EGARCH	0.000	0.224*	0.000	0.004	0.332*	0.009			
TGARCH	0.000	0.257*	0.000	0.049*	0.420*	0.106*			
APARCH	0.000	0.257*	0.000	0.015*	0.374*	0.034*			
CGARCH	0.000	0.275*	0.000	0.004	0.332*	0.009			
FIGARCH	0.007	0.353*	0.018*	0.028*	0.397*	0.062*			
HYGARCH	0.007	0.353*	0.018*	0.007	0.353*	0.018*			

3.4.3.1 Comment on the results from the Value-at-Risk exercise

The results from the above VaR analysis can be linked to previous work that considers the effect of outliers or microstructure noise on risk modelling. More specifically, improving the performance of GARCH models while de-noising indicates that using contaminated financial data can have negative economic implications. Our findings here appear in line with Cartea and Karyampas (2011) who report that removing microstructure noise leads to less systematic risk as measured by the CAPM model. Frésard et al. (2011) reach a similar conclusion when examining noisy intraday day data, which results in underestimating the capital risk requirement. Hence, although these studies utilize intraday data and used different empirical approaches, their final conclusion is similar to ours regarding the negative effects of using contaminated data for risk estimation. On the other hand, our finding appears to contradict Berger (2015). Using all stocks listed in DJIA index, Berger examines VaR forecasts at the 95% and 99% level and reports that at the 95% level the forecasts are driven by volatility at the first scale, whereas for the 99% VaR higher scales are required.

Table 3.12 Risk Management Evaluation on Wavelet Soft-Based De-noised Return Series: 99 % VaR.

The following table presents results of Christoffersen, 1998)'s backtesting procedure. This composed of three tests, likelihood ratio of unconditional coverage denoted by *LRuc*, likelihood ratio of independence *LRind* and likelihood ratio of conditional coverage *LRcc*. Figures in Table represents the *P*-values for the null hypothesis of correct coverage (H0: *f* = 1%). * denotes that the model is adequate and it passed the test.

	LRuc	*LRind*	*LRcc*	*LRuc*	*LRind*	*LRcc*	*LRuc*	*LRind*	*LRcc*
Model	CAC40			DAX			AEX		
GARCH	0.007	0.353*	0.018*	0.142*	0.468*	0.262*	0.663*	0.658*	0.825*
EGARCH	0.000	0.275*	0.000	0.007	0.353*	0.018*	0.886*	0.629*	0.881*
TGARCH	0.004	0.332*	0.009	0.015*	0.374*	0.034*	0.886*	0.629*	0.881*
APARCH	0.004	0.332*	0.171*	0.015*	0.374*	0.034*	0.886*	0.629*	0.881*
CGARCH	0.086*	0.444*	0.171*	0.225*	0.493*	0.379*	0.886*	0.629*	0.881*
FIGARCH	0.142*	0.468*	0.262*	0.225*	0.493*	0.379*	0.663*	0.658*	0.825*
HYGARCH	0.142*	0.468*	0.262*	0.225*	0.493*	0.379*	0.663*	0.658*	0.825*
	FTSE100			DJIA			NIKKEI225		
GARCH	0.028*	0.397*	0.062*	0.142*	0.468*	0.262*	0.663*	0.658*	0.825*
EGARCH	0.002	0.312*	0.004	0.015*	0.374*	0.034*	0.663*	0.658*	0.825*
TGARCH	0.015*	0.374*	0.034*	0.015*	0.374*	0.034*	0.886*	0.629*	0.881*
APARCH	0.007	0.353*	0.018*	0.049*	0.420*	0.106*	0.886*	0.629*	0.881*
CGARCH	0.086*	0.444*	0.171*	0.676*	0.573*	0.782*	0.088*	0.779*	0.225*
FIGARCH	0.676*	0.573*	0.782*	0.461*	0.688*	0.703*	0.171*	0.748*	0.372*
HYGARCH	0.676*	0.573*	0.782*	0.461*	0.688*	0.703*	0.171*	0.748*	0.372*
	NASDAQ Composite			IBEX35					
GARCH	0.340*	0.519*	0.516*	0.028*	0.397*	0.062*			
EGARCH	0.049*	0.420*	0.106*	0.000	0.257*	0.000			
TGARCH	0.049*	0.420*	0.106*	0.028*	0.397*	0.062*			
APARCH	0.049*	0.420*	0.106*	0.028*	0.397*	0.062*			
CGARCH	0.225*	0.493*	0.379*	0.049*	0.420*	0.106*			
FIGARCH	0.491*	0.546*	0.657*	0.142*	0.468*	0.262*			
HYGARCH	0.676*	0.573*	0.782*	0.225*	0.493*	0.379*			

3.5 Robustness checks

3.5.1 Alternative distributional assumption

The GARCH models are estimated under the assumption of normality, while the descriptive statistics for both the original and de-noised series exhibits evidence of non-normality. Although non-normality will not affect the volatility estimates themselves, it will affect the values obtained in the VaR exercise. To check that our out-of sample results are not driven by the wrong error distributional assumption, we also consider the *t*-distribution, which allows for the fatter tails typically found in the distribution of financial returns. However, the estimated results are very similar to those reported in the text. Notably, the EGARCH model still performs the best across all models and markets after de-noising. The results are available upon request.

3.5.2 Alternative wavelet filter

The wavelet de-noising in this paper uses the Daubechies least asymmetric filter with a length of 8. This use of this filter is consistent with the literature on the optimal wavelet choice. Kim and In (2010) find that this filter is sufficient in representing volatile time series. Nonetheless, we consider alternative wavelet filters to see if our results change. To this end, we use the simple Haar and Daubechies with the width of 4. These filters are likely to make the return series smoother and thus could alter the out-of sample forecasting conclusion. Our (untabulated) findings with both the RMSE and MAE metrics and soft thresholding are quantitatively and qualitatively similar to our main results in this paper. Generally, our result reveals that the de-noising approach still improves the forecasting accuracy for all models. Also, the EGARCH continues to be the preferred model.

3.5.3 Alternative true volatility proxy

We check further whether using alternative true volatility proxy will change our results. The realized five minutes data for all the eight markets in the sample are collected and used in the analysis.[24] The data is available since 03/01/2000. That excludes the first two years from the sample covering 09/01/1998 Asian crisis period. The results can be summarized as follows; first, the forecasting performances of all models is still better for all series after de-noising and regardless of the GARCH modelling approach used. Second, the asymmetric GARCH models continue to provide a better forecast after de-noising with the RMSE. For example, the TGARCH model is preferred for five out of eight series. The EGARCH model is still the best performing model for the DAX30 volatility after de-noising with both the RMSE and MAE metrics. Using the later risk metric, however, the TGARCH model appears to be the second performer for CAC40 and DJIA indexes.

3.5.4 Alternative thresholding approach

We use the hard instead of the soft thresholding approach for de-noising. The main difference between the threshold procedures is that hard thresholding has only one choice to ‘keep or kill’

[24] The data can be found at Oxford-Man Institute of Quantitative Finance Realized Library http://realized.oxford-man.ox.ac.uk/ .

the decomposed coefficients as it considers those located below or at the threshold limit as noise. This, in turn, will smooth the time series more. As an aside, we seem to reject the presence of ARCH effect more under hard thresholding, while this is not the case with soft thresholding. However, the overall conclusion still holds, namely, forecasts improve after de-noising and the asymmetric GARCH models, specifically the EGARCH model, continues to provide the performing models. The models are still also adequate and they are able to pass the 99% VaR-based tests used after de-noising compared to that used the original series data.

3.5.5 Different out-of sample period: Starting from 09/08/2007

We further examine whether selecting different out-of sample period could affect the estimates from forecasting with the wavelet de-noising. Henceforth, we make the starting date of the forecasting performance 09/08/2007 as a date coincides with the beginning of 2007-2008 crisis. Our forecasting performance with all models ends to be immune to the new out-of sample date. In terms of forecasting comparison, the asymmetric models, and more specifically the EGARCH model, are still the best among all models for all series.

3.6 Rolling Window In-Sample Exercise

This section presents the effect of de-noising the data on the in-sample estimation by examining parameter stability over time, before and after de-noising. The models selected for this exercise are based on their RMSE and MAE performance is the GARCH and EGARCH models. We perform the rolling regression estimation using a window size of 1251 observations, which corresponds to (approximately) five years. The choice is motivated by a desire of sufficient size to incorporate the effects of regime change and its effects on noise trading (see, Rapach and Strauss, 2008).

Figure 3.2 shows the volatility persistence component from the GARCH model (Panel a) and the asymmetric parameter from the EGARCH model (Panel b). Within this figure we also highlight several crisis periods, notably, the 1998 Asian crisis on 09/01/1998, the Dot-com crash (14/03/2000), the Iraq invasion (20/03/2000), the terrorist attack (11/09/2001) and the global crisis (15/09/2008). Taking an overall view of the graphs, we can see that changes in behavior within the dynamics of the volatility process do occur at these crisis points.

Examining Panel (a) we can see that using the original series (red line) or the filtered series (blue line), the persistence of conditional volatility declines on the crisis date. This is most noticeable at the time of the Iraq invasion with a large decline in persistence except for Japan (NIKKEI225), which in turn is strongly affected by the 1998 Asian crisis. The NASDAQ index is also particularly affected by the Asian crisis, while the effect is more muted for other markets. The graphs also reveal that persistence across all the markets is high in the calmer period following the Dot-com crash and before the financial crisis. Persistence also noticeably increased after the Asian crisis and in the run up of the Dot-com bubble. In comparing the time-varying persistence between the original and de-noised series we can see that the general pattern of behavior is highly similar. In general, the filtered series exhibits higher persistence than the original series but with some notable exception around the Iraq invasion period. This suggests that failure to account for noise produces a more stable level of persistence throughout the sample period but this masks understatement in tranquil periods and overstatement in crisis periods.

Examining Panel (a) we can also see that the ((α+β) <1) condition is violated on occasion. In observing a similar finding Capobianco (2002, p.99) argues:

"*In particular, one of the consequences of de-noising is the change of the relative contribution of the parameters to the persistence of volatility*".[25]

However, Capobianco (2002) provides no further explanation for this finding. Other studies also address this issue including, for example, Hillebrand (2005) and Rapach and Strauss (2008).[26] In the former study, one part of the violation, namely (α+β =1), is described by a "spurious almost integration" assumption. This case arises due to breaks in the series, particularly with long dataset. According to the study, this assumption holds because long-run persistence ignores the averages of different persistence levels with the data caused by break points. Hillebrand (2005) provides simulation evidence to further support this argument. The impact of structural breaks is also considered by Rapach and Strauss (2008). They find that a GARCH (1, 1) model that accounts for breaks as well as a GARCH model estimated from the break date provides better volatility forecasts. In a closely related study, Bollerslev et al. (2016) apply the notion of parameter changes by incorporating time-varying variance of the measurement error into the heterogeneous autoregressive (HAR) model.

[25] After de-noising, the one minute return data using the MODWT approach, the β (GARCH) parameter decreased from 0.66 to 0.34, while the α parameter increased from 0.12 to 0.69. His sum of the autoregressive parameters after de-noising is, then, 0.34+0.69=1.03 which is more than 1.
[26] Both studies used daily financial markets data.

Figure 3.2 Rolling GARCH Exercise.

Panel A: Persistence of shocks to volatility ($\alpha+\beta$) from the GARCH (1, 1) model.

The areas where the lines located represent the Asian contagion crisis (September 1998), the Dot-com crisis (March 2000), the terrorist attack (September 2001), the invasion of Iraq (March 2003) and Bankruptcy of Lehman brothers (September 2008). Blue lines in all Figures represent the persistence estimation using the filtered return series, while the red lines show the estimation that from the contaminated series.

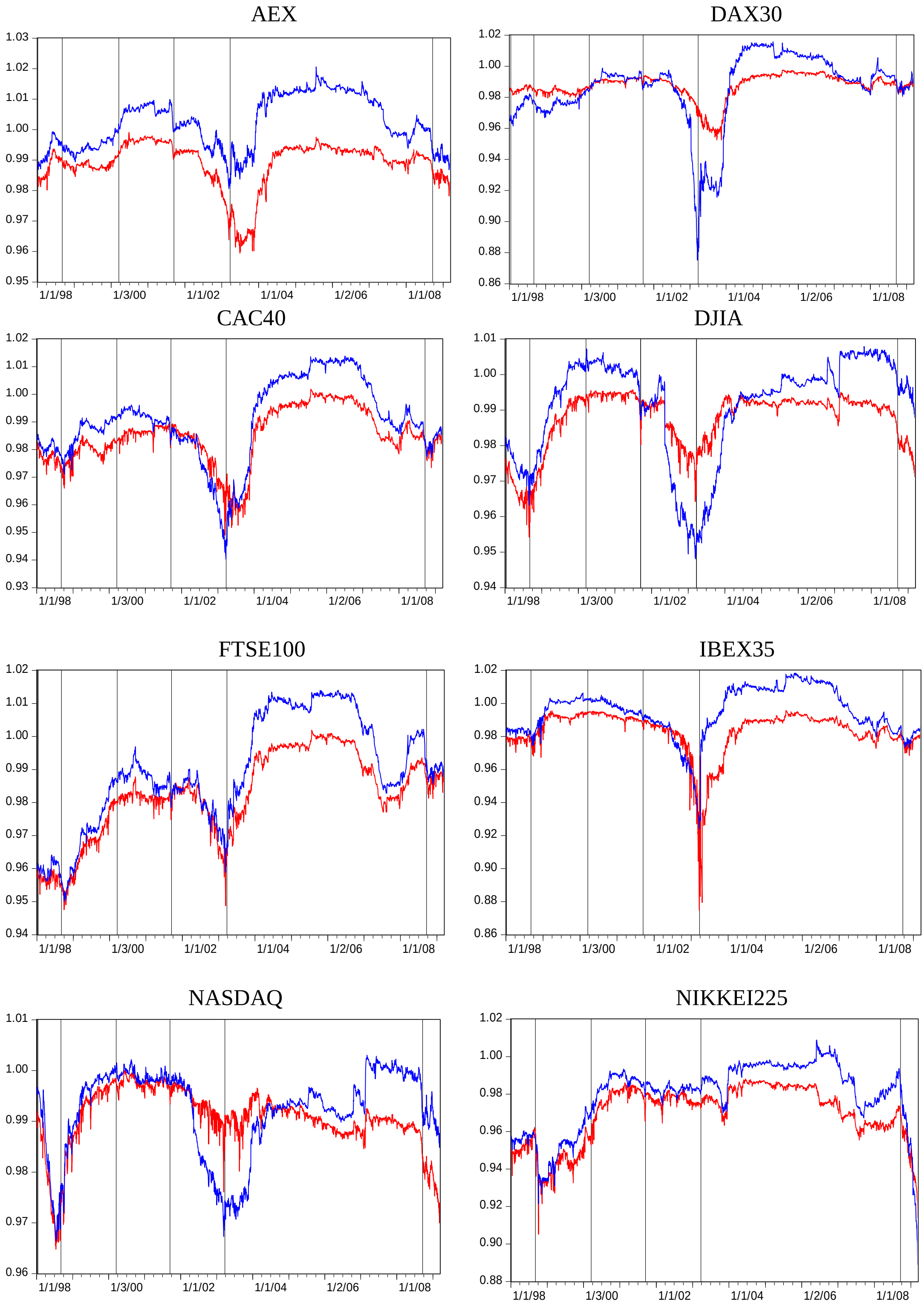
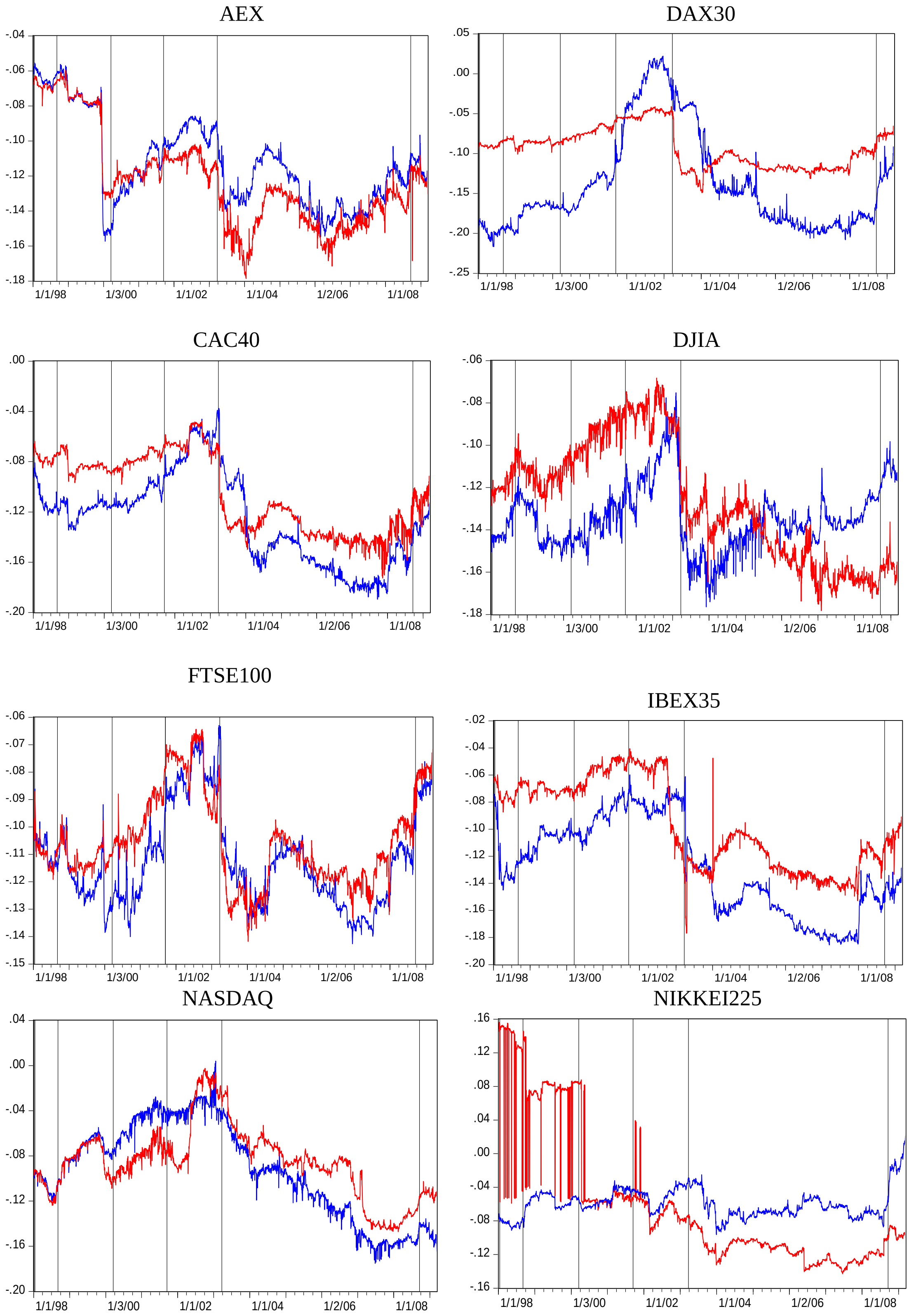


Figure 3.2 *Continued.*

Panel B: Estimation of the asymmetric effect (γ) from the EGARCH (1, 1) model.



They find that allowing for the model's parameters to change over time should improve the forecasting performance.

Moreover, they emphasize the importance of considering the variance of returns when it comes to volatility forecasting. Notably, a period characterized by more variation in returns resulting from noise trading will alter the performance of the considered GARCH models in forecasting. Hence, removing noise is of high importance to the ranking of the model performance.

Examining Panel (b), the Iraq invasion episode continues to cause the largest structural break in parameter values, this time the asymmetric effect (γ) from the EGARCH model. Again, this effect is obvious for all markets except for NIKKEI225. It is noticeable, however, that removing noise from the Japanese market pushes the asymmetry from positive to negative, and for all remaining market the asymmetry is negative. As before, the original and de-noised series move together over time, with the exception of the DAX series. There is also some evidence that the original series exhibits a lower degree of asymmetry, although this result is not ubiquitous. Yet, one possible explanation for the result in the NIKKEI225 around the 1998 and the 2001 crises index is nature of the crises themselves. That is, the 1998 is Asian crisis which might explain why the NIKKEI225 index as the only Asian market in the sample can be the most affected market by the crisis itself. The same idea holds for the 2000 crisis, with the performances of the components of the index itself have to be influence by the high levels of uncertainty and sentiment before the Dot-crash. The 2000 crisis mainly resulted from the technology sector and that should explain the finding in the NIKKEI225 index which in turn has, for example, the electric machinery component. There is also some evidence that the original series exhibits a lower degree of asymmetry, although this result is not ubiquitous.

The results here suggest that failure to account for noise that leads to incorrect inferences with regard to both volatility persistence and asymmetry. Notably, the variability of volatility persistence is greater in the de-noised data while the strength of asymmetry is stronger, although with few exceptions.

3.7 Summary and Conclusion

Using daily closing price index returns for eight major international stock markets over the period from January 01, 1998 to December 31, 2013, this study provides empirical evidence that extracting the latent volatility part from the noisy return series is important in the context of forecasting. Wavelet transform is employed as a pre-processing technique that can decompose the series into multi-levels and filter out the noise components. In the next stage, the de-noised rerun series are fed into a group of symmetric, asymmetric and long-memory models belonging to GARCH family in order to generate one step-ahead forecast. During the de-noising process, soft thresholding procedure is used. Our key implications and contributions lie in whether and how such a pre-processing procedure affects forecast performance and how that should also affect the decision to be taken by risk managers when considering the VaR estimation. Our first important result supports the view that, using statistical forecast error measures, wavelet-based forecasts are generally preferred to raw returns based forecasts across the range of models employed. These results are then additionally supported using tests for equal predictive accuracy. In ranking the models, our results show that the asymmetric-GARCH approach and in particular the EGARCH model is typically preferred. Our results here are robust to other specifications including the error distribution, the wavelet filter, thresholding approach, and somewhat robust to the alternative true volatility proxy. Turning to any economic benefit of wavelet de-noising through considering the performance of VaR measures using both 1% and 5% probability coverage rates. Results suggest that at the 5% level the use of de-noised data does not provide an obvious improvement over the original returns series, however, at the 99% VaR, models were more likely to pass the three tests of coverage after de-noising with soft thresholding.

Emanating from this paper are two key results that we hope are of interest to both the academic and practitioner community. First, with respect to volatility forecasts, the process of de-noising is more important than the choice of specific GARCH model, although asymmetric models are generally preferred. Second, that while de-noising is less important when forecasting the 95% VaR, for the 99% VaR preferred by the Basel Committee, then soft-based de-noising is clearly preferred. This final evidence highlights the importance of de-noising the daily return series data before applying the volatility forecasting for risk management.

CHAPTER FOUR

Stock-Bond Return Dynamic Correlation and Macroeconomic Announcements: Time-Scale Analysis and the Effects of Financial Crises

Abstract

This study examines the impact of fourteen macroeconomic news announcements on the stock and bond return dynamic correlation. In addition to announcement day effects, using wavelet analysis we can examine the effect up to sixteen days afterwards. We also distinguish the effect between crisis and non-crisis periods. Results conducted over the full sample suggest very little evidence that macroeconomic news surprises affect the stock-bond return dynamic correlation. However, after controlling for the financial crisis of 2007-2008 several announcements become significant both on the announcement day and afterwards. Further, we observe a link between the speed of the reaction in correlations to news surprises and the timing of announcements. Notably, news released early in time and in the month, exhibit a slower effect on the dynamic correlation than those released later in the month. While several announcements exhibit significance in the crisis period, only two show a significant and consistent effect on the correlation outside the crisis period. We also note that the effects of most of surprises disappear if we replace the 2008 crisis with the 2001 Dot-com crisis or 2011 U.S. government debt ceiling dispute periods. Although the out-of-crisis announcements remain significant. Robustness tests involving small stocks, the inclusion of a variable for policy uncertainty, isolating the effect of macro news on volatility, different multivariate model to estimate the dynamic correlation, alternative 2008 crisis period, different decomposition approach and multivariate regressions continue to broadly support our results. It is hoped these results will enhance our understanding of the links between financial markets and the macroeconomy and will benefit investors, regulators and academics alike.

Keywords: Stock-bond Dynamic Correlation; Macroeconomic Surprises; Financial Crises; Wavelet.

4.1 Introduction

The need for improved portfolio allocation during times of financial crises has encouraged researchers to shift their interests from being focused on the performance of stocks (e.g., Cutler et al., 1989) or government bonds (e.g., Fleming and Remolona, 1997) to the study of their correlation (e.g., Campbell and Ammer, 1993; Ilmanen, 2003; Gulko, 2002). Constructing a portfolio of fixed weights over time does not account for prevailing market conditions, while a simple view that risk averse investors will naively add treasury bonds to their portfolio in times of financial turmoil ignores how the two assets interact. What is required, and what this paper seeks to contribute, is a better understanding of the determinants of the correlation dynamics between these asset types.

Previous research incorporates several factors in their models to better understand the dynamic correlation between equities. Notably, macroeconomic news, especially those published by U.S. reporting agencies due to their global influence on the equity markets around the world, are the most commonly employed. Research in this context not only considers raw macroeconomic data, but also the expectations for future performance and measures of investor sentiment. Importantly, the macro-news surprise component, which represents the difference between the raw macro data and its corresponding expectation, is considered. One strand of this research examines the effect of U.S. macro surprises on European markets (e.g., Becker et al., 1995; Hanousek et al., 2009), Asian markets (e.g., Wongswan, 2009) and on global emerging and developed markets, including the G7 (e.g., Nikkinen et al, 2006). The general finding from these studies is that news from the U.S. economy can signal to international markets about the health of global economy.

However, it remains to fully understand to what extent U.S. financial markets are sensitive to the arrival of new macroeconomic news. Therefore, building upon the above lineage of research, the main focus of this paper is to investigate how long it takes for price data to react to news surprises and whether this reaction is impacted by different regimes over the economic cycle, including recent periods of markets stress associated with the Dot-com bubble, the global liquidity crisis and the European sovereign debt crisis. However, our interest lies in the effect of such news upon the equity-bond correlation instead of the reaction of any individual asset.

Existing research points to the state of the economy as one of the main factors that determines how the market reacts to news (e.g., the unemployment rate; Boyd et al., 2005). Using the federal fund rate, Kurov (2010), seeks to investigate the reaction of the stock market during the bull- and bear-periods and finds that investor sentiment plays a major role during bear periods in strengthening the reaction. Kontonikas et al. (2013) investigate the impact of Fed policy on the market during the recent financial crisis. They find that the crisis caused a structural shift in the macro news-stock market relation from being significant outside the crisis but not throughout.

Recent work also considers the role of market uncertainty in formulating the reaction to news. Given that investors were more uncertain about their investment decisions during the 2008 crisis (Easley and O'Hara, 2010), this can result in a delayed reaction by investors to macroeconomic news. Zhang (2006) argues that the reaction of daily market excess returns to earnings announcements tends to drift when there is a high level of uncertainty. Bird and Yeung (2012) find that the reaction to bad news (negative surprises) is stronger than to good news (positive surprises) when investors face a high level of uncertainty. These, and other, studies related their findings to theories of under- and over-reaction, which, in turn, may explain investor behaviour through the 2008 crisis. In addition to the role of uncertainty, the financial media effect may become more intensive during a crisis, with investors paying increased attention to some news announcements over others. Peress (2008) finds that investors seem to react strongly to positive earnings news when there is greater coverage in the media.

While there is a perception that the media and uncertainty alter investor's response to macroeconomic news, other studies (see, for example, Tetlock, 2007; Garcia, 2013) use the media as a sentiment proxy and investigate the effect on index returns and trading volume. Both noted studies construct a pessimistic investor proxy from scanned negative words in the media. Tetlock (2007) conducts his study on the "Abreast of the Market" column of the Wall Street Journal and finds that the pessimistic index negatively predicts the next day DJIA return, while the effect tends to reverse and the market returns to its fundamental valuation about four days later. Garcia (2013) obtains similar results and further finds that this effect on the DJIA return is more noticeable during recessionary rather than expansionary periods. The index Garcia constructs uses both negative and positive words from the "Financial Markets" and "Topics in Wall Street" columns from the New York Times.

Recent studies consider the attitude of the investors during the 2007-2008 crisis period. For example, Marsh and Pfleiderer (2013) argue that both the level of risk and risk tolerance changed during this crisis period, which led to an imbalance between the demand of and supply for risky assets. While the risk averse investor became more willing to sell risky assets, it was difficult to find another, risk-taking, investor willing to buy. Füss et al. (2015) find that both the default premia and the liquidity premia became significantly enhanced throughout the 2008 crisis. Using a proxy for macroeconomic uncertainty recently developed by Jurado et al. (2015), the U.S. stock market was found to be more affected by uncertainty during the 2008 crisis than during the 2001

Dot-com period. These findings appear to be consistent with the earlier argument of Easley and O'Hara (2010) that a high level of uncertainty forces financial markets to enter a freezing stage. In order to examine how the arrival of news impacts the stock-bond correlation over time, we wish to decompose our time series overall several intervals where each one represents a specific time horizon. To do this, we can employ the wavelet transform which can decompose series in time and frequency domains. Kim and In (2007) use this approach to examine the relation between stock prices and bond yields in the G7 countries and finds that the sign and strength of the relation depends on the scale. Using wavelet transform, recent studies (see, for example, Graham & Nikkinen, 2011; Lehkonen and Heimonen, 2014) find that the level of co-movement between the international stock markets differ across the time-scales. Hence, our study aims to contribute to this growing research by using wavelets to decompose the U.S. equity and bond series across different scales before estimating the dynamic correlation between them. From this, we can then examine how the correlation changes across scales following macroeconomic news announcements.

Our study is perhaps most closely related to, and builds on, the work of Christiansen and Ranaldo (2007), Brenner et al. (2009) and Baker and Wurgler (2012). Christiansen and Ranaldo focus on the effect of macroeconomic surprises on the stock-bond realized correlation during expansionary and contractionary periods in the U.S. However, their study pre-dates the recent financial crisis and does not examine how news impacts over different time frames. Brenner et al. (2009) consider the effect of four news surprise series (consumer price index, unemployment rate, target Federal fund rate and nonfarm payroll) on the excess daily holding return, volatility and covariance of stocks, corporate bonds and government bonds of different maturities. They note that news affects the co-movement of different classes of assets one day before, the same day and one day after the announcement. Baker and Wurgler (2012) document that macroeconomic and financial factors as well as investor sentiment affect the co-movement between stocks and government bonds. Using a cross-sectional analysis, they note that investor sentiment acts as a strong predictor for this co-movement.

Our study expands on these in several ways. First, we keep our main focus on the effect of news surprises components rather the raw macroeconomic data. Second, we analyse the dynamic correlation between the stocks and bonds, which makes our results more relevant in the portfolio construction process. Third, our research examines the speed of reaction to the macroeconomic news and not the magnitude of their effects on the stock-bond dynamic correlation. Fourth, we consider the effect of news announcements across several crisis periods and examine whether different macroeconomic factors are more influential than others through crisis periods.

Our results are informative and can be summarised as follows. First, and consistent with the majority of the literature, we find little evidence that macroeconomic news surprises affect the equity price and stock-bond return dynamic correlation over our full sample period from 2000 to 2013. However, our evidence reveals that when controlling for the Lehman brothers 2008 crisis, some announcements significantly affect the correlation series on the first day, with this impact notably observed during the crisis period. Second, examining the analysis using the wavelet scales, we find a link between the speed of reaction of dynamic correlations to news surprises and the time of announcements. For example, news such as factory goods order, industrial production, consumer credit and the new-single family house sales, which are released early in the day and month, show a slower effect on the dynamic correlation than those released later. The impact of early macroeconomic news seems to be fully incorporated into the correlation process [4-8] days after the announcement. Third, of all the series, the effects of CPI and housing starts news surprises tends to persist up to [2-4] days after of the announcement day. However, they are the only two releases to show significant and consistent effect on all the correlation series outside the crisis period. Fourth, we observe a notable difference in the effect of news surprises between the three different crisis periods in our sample (2001 Dot-com, 2008 financial crisis, 2011 U.S. government debt ceiling dispute periods). In particular, this may be related to inflation, sentiment and uncertainty across the crisis periods. Fifth, results are robust to correlations obtained from market index returns as well as small value and growth index returns. Although, the result generally supports the belief that the pricing of small companies is more affected by investor sentiment (see, for example, Lemmon & Portniaguina, 2006; Baker & Wurgler, 2007). Our results in this study continue to be broadly the same even after the inclusion of a variable for policy uncertainty, after isolating the effect of macro news on volatility, after using different multivariate model to estimate the dynamic correlation, with alternative 2008 crisis period, after decomposing the return series with different decomposition approach and after examining the joint effect of all macro series when they have been included in one multivariate regression.

The remainder of the chapter is organised as follows: We summarise the related literature in Section 4.2 we describe the methodology and data in Section 4.3. The empirical results are provided in Section 4.4, while Section 4.5 shows concerns the robustness checks. Finally, we summarise and conclude the main findings from this chapter in Section 4.6.

4.2 Previous studies

4.2.1 The Effect of Macro News on Equity Price and Volatility

Our key interest is examining the effect of news on the stock-bond correlation, however, we briefly touch on the effect of news on individual markets that formed much of the earlier research. Pearce and Roley (1985) use macro surprises of inflation, money growth and real output activity to investigate the effect on the daily S&P 500 price index. They find that only money growth announcements significantly affect the stock price. Jain (1998) building upon that work, examines the speed of hourly stock price adjustment to the release of macroeconomic news announcements. This study finds that the price adjusts quickly to the release of CPI news, the effect of which persist for only four hours. Ederington and Lee (1993) using 5-minute data, find that macro news has a significant effect on price over the interval 8:30-8:35AM. This study also finds that the price adjustment occurs within one minute of the announcement, while volatility is affected by for at least fifteen minutes after the release.

McQueen and Roley (1993) consider the state of the economy as a determining factor in the stock markets response to news and find when the economy is performing well stock markets react negatively to news about future activity. Also, the expectations for cash flow differ across economic states. A similar conclusion is reached by Boyd et al. (2005) who find that news of an unemployment rate higher than expected is good for the economy during an expansion and bad during a contraction.

There also exists a voluminous literature on investigating the effect of macro news on the equity volatility. Ederington and Lee (1995) find a conspicuous jump in volatility on the day of news announcements. They also report that volatility remains at a higher level for only three minutes following the announcement, while the price tends to keep fluctuating as investors are uncertain about the significance of the news content. Flannery and Protopapadakis (2002) note an impact on stock market volatility of CPI, PPI, housing starts and unemployment news.

Fleming and Remolona (1997) consider to what extent macro news factors are responsible for bond market movements. They find that the surprise components associated with CPI, PPI, industrial production, retail sales and capacity utilisation have the greatest effect on the 5-year Treasury bond. Jones et al. (1998) use daily excess returns for 5, 10 and 30-year bond maturity. Within a regime-switching GARCH framework, they find that following announcement days (PPI and unemployment), neither the risk premium nor volatility effects persist. Although, they find that the volatility level was higher on announcements days. Christiansen (2000) reports similar results using bond data with a maturity of lower than 5 years. Moreover, while Christiansen finds no significant difference between effects of negative and positive shocks, Andersen et al. (2003) argue that positive and negative shocks exert an asymmetric effect, with bad news having a greater effect on volatility. A result also reported by Kim et al. (2004), who examines the effect of raw news and expectations.[27]

Balduzzi et al. (2001) use a 30-minute price interval of 2, 3, 10, 30-year bond data. This study finds a strong reaction to announcements for CPI, PPI, housing starts and new house sales. This reaction, however, only lasts 25 minutes following the news arrival. Furthermore, the authors argue that the strengthen of the effect of news on bond returns depends positively on bond maturity, with long maturity bonds considered more volatile than those with lower maturity. Further studies, including the work of Green (2004) and Rangel (2011) argue that news released in the first half of the month is associated with a high level of uncertainty compared to those released later in the month, with macro forecasts having a greater effect on both trading volume and volatility.[28]

Using 5-minute data, Lahaye et al. (2011) show that CPI announcements are responsible for causing jumps in both price and volatility in the bond futures market, while PPI announcements explain jumps in stock index futures market and exchange rate markets. The presence of jumps is also corroborated by Rangel (2011) and Savor and Wilson (2013).

4.2.2. Macro News and Stock-Bond Dynamics

Considering the nature of the stock-bond dynamics, Shiller and Beltratti (1993) demonstrate the time-varying nature of the excess stock-bond correlation and reveal its link to the one-year inflation rate. Using expectations of inflation, future dividends and the short-term real interest rate, Campbell and Ammer (1993) are able to partly explain the stock-bond dynamic relation. Notably, a change in the direction of the relation is evident around crisis periods. Gulko (2002) investigates the decoupling of stocks and bonds that occurred after the crash of Black Monday in 1987. Gulko finds that the correlation, but not volatility, reverts to its pre-crash level after moving sharply during the crisis. Ilmanen (2003) examines the stock-bond relation across different states of the economic cycle and finds that the correlation is low near business cycle peaks.[29]

[27] More studies examine the accuracy of the median expectations including, for example, Pearce and Roley (1985) and Aggarwal et al. (1995). The studies prove the unbiasedness of the median expectations as provided by Money Market Services (MMS), after regressing the actual reported values on the expectations for some economic news, and empirically found the slope coefficient is significantly different than zero. Other study by Gilbert et al, (2010) instead look at the factors that determine the significance of the news themselves, and prove that more revised news by their reporting agencies, early announced and those include more information content as related to the state of the economy, exert more impact on the market.

[28] This, however, contradicts one of the main results of Flannery and Protopapadakis (2002) of that some late releases have more effect than the earlier ones. Their explanation is in consistent with the the importance of the macro news identity in determining their strength.

[29] The analysis is carried out using the national bureau of economic research’s contraction and recession indicators. The study found that both the economic growth and the volatility mainly push the correlation to

Li (2002) fits the dynamic correlation using a bivariate-GARCH (BV-GARCH) model, which is conditioned using a set of macro factors. The study notes that a sharp decline in the correlation was partially caused by lower inflation risk. Yang et al. (2009) document an increase in the time varying correlation using a BV-GARCH model following higher short-term interest rates and, to some extent, higher inflation. Kim et al. (2006) find that economic integration within the Euro region leads to an increase in market integration.

Baele et al (2010) consider a range of macroeconomic factors, together with proxies for liquidity. Using a dynamic factor model, they find that liquidity plays a key role in the dynamic movement of the stock-bond correlation. Using the S&P 500 and 10-year Treasury note intraday futures contract, Christiansen and Ranaldo (2007) find that the realized volatility of both series as well as the realized correlation is higher on the news announcement days. Further, the study concludes that the reaction of the stock-bond correlation is stronger during a recession period than in expansion. However, they only report limited evidence of the realized correlation using news surprise components.[30]

Brenner et al. (2009)[31] report that the effect of macroeconomic news on the co-movement between daily excess stock returns, corporate bond and government bond returns tends to persist over the day following the announcement. This finding is contrary to the generally held view of previous studies that it takes only few minutes for the effect of macroeconomic news to be incorporated into prices (see, for example, Balduzzi et al., 2001). Schopen and Missong (2011) use the DCC-GARCH model and include a set of macro news surprises, a financial crisis dummy and the change in the implied stock market volatility index in the conditional variance equation. Using five-minute data, they find that both macro news and the financial crisis dummy contribute less than stock market uncertainty to the dynamic correlation.

Given the foregoing, this study contributes by examining which news announcements impact the

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the negative direction, while the inflation, as argued helps in dominating the positive relationship due to its effect on the common discount rate for both stock and bonds. However, the study found that economic growth, volatility and inflation rate as changed across the states of the economy can interact and affect each other.

[30] Following Balduzzi et al. (2001) and Andersen et al. (2003), the study first run a separate regression for each announcement by regressing the realized correlation (i.e. on the individual surprises, next the study included in the announcement dummies in the regression and classified them into two groups, one before 10 a.m. and another for those announced after. One of the main findings also came in consistent with Lee (2012) on the higher impact of the macro news on the bond volatility compared with that on stock. The same explanation is hold again regarding the role of firm-level news which in turn make the difference with a little significant effect of the news on volatility.

[31] The representatives for macro news employed were CPI, unemployment rate, nonfarm payroll and the target fund rate. The study uses an extension to the DCC-GARCH model of Engle (2002), and directly incorporate the news components into GARCH (1, 1) conditional variance equation.

stock-bond correlation over time and different market phases. Notably, we examine how news affects the correlation across the bursting of the Dot-com bubble, the financial crisis and the European sovereign debt crisis. And we do so by utilising the wavelet approach that allows us to comment on the period over which the news announcement will affect the correlation.

4.3 Data and Methodology

4.3.1 Data Description

Our asset price data consists of the daily closing price for the DJIA Composite index as the equity series and the daily U.S government benchmark bond index for 2 year and 30-year maturity over the period January 3, 2000 to December 25, 2013. Both the stock and the bond data are collected from DataStream.[32] Our choice for the sample period is, in part, restricted by the availability of the macroeconomic news data which is only available from January 2000. Returns are calculated in the usual way by taking the difference of the logarithm of prices on two consecutive days.
We obtain time series data on macro-economic news and their expectations from Informa global markets, which for the majority of the macroeconomic indicators, reports the data on a monthly frequency from January 2000 and until December 2014.[33] Following Balduzzi et al. (2001) we construct our main independent variable, the macro news surprise, using the following equation:

$$u_{k,t} = \frac{A_{k,t} - E_{k,t}}{\sigma_t} \qquad (4.1)$$

Where $A_{k,t}$ and $E_{k,t}$ are the actual value and its corresponding expected value respectively for the news k at time t.[34] In order to compare the size effect of each macro news announcement, the surprise component $(A_{k,t} - E_{k,t})$, is divided by it is corresponding standard deviation σ_t across

[32] We believe that DJIA is a fairly representative of the U.S. stock indexes. The index experienced the largest one day drop on December 2008 following the Lehman brothers collapse before it started to recover. However, our sample initially includes the closing price index data for NASDAQ Biotechnology, DJIA transportation and the S&P composite index. Using those indices, our results are almost qualitatively similar. Other studies also used the Datastream benchmark indexes include, for example, Cappiello et al. (2006) and Connolly et al. (2007).
[33] We focus on fourteen news announcements (see Table 4.3) for the following reasons. First, they provide a representative measure for the overall performance of the economy. Second, for consistency, we decided not to use news for which there is missing data for more than one year.
[34] MMS conducts a telephone survey of about forty money market managers on the Friday of the week before the release of the actual value of each macroeconomic factor. MMS then publish the median expectation from the survey. For more details on the MMS survey data, see Balduzzi et al. (2001) and Andersen et al. (2003).

the entire sample period.

4.3.2 Summary statistics

Table 4.1 reports the basic descriptive statistics for all return series over the full sample period, on days when macro announcements are made and on days without announcements. Of notable interest in this Table is that the standard deviation of the stock return series is slightly higher on announcement days than on non-announcement days. Bond market returns, however, are marginally less volatile on announcement days.

Table 4.2 reports the unconditional correlation matrix between the equity return series and each of the bond return series. It can be seen in this Table that the correlation is negative between stock and bond return series for the 2 year and 30-year bond series. When comparing the strength of the correlations, we note that there is a decrease on announcements days for all the stock and bond correlations.

Table 4.1
Summary Statistics of Stock and Bond Return Series

This table shows the summary statistics for stock and bond index return series. The full sample period from 03/01/2000 to 25/12/2013 with 3649 daily observations, after the deletion of the no announcement days, the sample left with 1540 observations.

	Full Sample		Announcement Days (1540 Obs.)		Non- announcement Days (2109 Obs.)	
	Mean	SD	Mean	SD	Mean	SD
DJIA	0.000	0.135	0.000	0.012	0.000	0.011
Bond 2-year	0.000	0.433	0.000	0.001	0.000	0.001
Bond 30-year	0.000	0.009	0.000	0.008	0.000	0.009

Table 4.2
Correlation Matrix

	Full Sample	Announcement days	Non- announcement days
	DJIA	DJIA	DJIA
Bond 2-year	-0.316	-0.290	-0.316
Bond 30-year	-0.330	-0.280	-0.321

Table 4.3 presents the source and summary for the fourteen macroeconomic announcements used

in our analysis. In terms of the sign of the surprise, the housing starts has no zero surprise,[35] while both new single house sales and the consumer credit show only one zero surprise. For other news announcements, namely the average hourly earnings, CPI, personal income and unemployment rate, the expectations seem to be more accurate with a high number of zero surprises obtained. Furthermore, the largest number of positive surprises is for the PMI, while the difference between the positive and negative surprises is the highest for the unemployment news which has only 44 positive surprises against 82 negative ones.

The distribution of all the announcements throughout the trading week from Monday to Friday is reported in Table 4.4. It is noticeable that the least number of announcements across all the days is on Monday. Most of the announcements, however, have been released on Friday with a total of 854 releases. The number has almost doubled from Monday to Tuesday (from 218 to 409) and the same can be seen between Thursday and Friday.

Table 4.3 Summary for the predictors

This table shows the description of the predictors used in the regression models in this study. The macroeconomic surprise series u_k is calculated for each economic variable k using the approach of Balduzzi et al. (2001) with $u_{k,t} = \frac{A_{k,t} - E_{k,t}}{\sigma_t}$, where $A_{k,t}$ is the monthly actual value obtained from the reporting agency mentioned in the Table, $E_{k,t}$ the corresponding median expectation as collected from Informa global markets database, σ_t is the standard deviation of the unexpected component of *kth* economic variable. [a] (BLS) denotes the Bureau of Labor Statistics, (BC) Bureau of the Census, (FRB) Federal Reserve Board, (BEA) Bureau of Economic Analysis (BC), Bureau of the Census and (ISM) institute of supply management. [b] denotes all in Eastern time.
The macroeconomic Figures of average hourly Earnings and unemployment rate are announced in the same day.

	Source of Report[a]	Number of Positive	Number of Negative	Release Time[b]
Average Hourly Earnings	BLS	50	66	8:30
Business Inventory	BC	76	70	10:00
Consumer Credit	FRB	88	79	15:00
CPI (Consumer Price Index)	BLS	55	69	8:30
Factory Goods Orders	BC	88	73	10:00
Housing Starts	BC	87	81	8:30
Import Price	BC	73	81	8:30
Industrial Production	FRB	68	81	9:15
New Single Home Sales	BC	85	82	10:00
Personal Income	BEA	66	63	8:30
PMI (Purchasing manager index)	ISM	94	70	9:45
PPI (Producer Price Index)	BLS	76	73	8:30
Retail Sales	BC	75	81	8:30
Unemployment Rate	BLS	44	82	8:30

Furthermore, among all macro indicators, more news have been reported for the CPI on Monday. In the same day, only 9 releases for housing starts, 2 for import and 1 for the PPI are shown.

[35] That is, of the 168 months in the sample, all the surprises are either positive or negative.

Table 4.4
Distributions of the Announcements during the Trading Week

This table shows the exact announcement days for each macroeconomic factor as obtained from the reporting agencies described in Table 3. Each macroeconomic Figure is released 186 times over the full sample period from 03/01/2000 to 25/12/2013.

	Day of the week				
Macro news	Monday	Tuesday	Wednesday	Thursday	Friday
Average Hourly Earnings	13	2	2	3	148
Business Inventory	13	34	36	45	40
Consumer Credit	28	41	32	35	32
CPI (Consumer Price Index)	0	29	59	30	50
Factory Goods Orders	13	34	36	45	40
Housing Starts	9	60	45	31	23
Import Price	2	18	43	66	39
Industrial Production	17	37	39	19	56
New Single Home Sales	19	24	56	35	34
Personal Income	50	16	10	18	74
PMI (Purchasing manager index)	25	22	25	24	72
PPI (Producer Price Index)	1	49	20	43	55
Retail Sales	15	41	32	37	43
Unemployment Rate	13	2	2	3	148
Total/day	218	409	437	434	854

During the rest of the trading week, the housing starts announcements seem to decrease over time from being 60 on Tuesday before reaching 23 releases on Friday. All other news for the remaining macro factors, except the average hourly earnings and the unemployment are almost well-distributed during the trading week. Announcements associated with these two simultaneous indicators are mostly reported on Friday with 148 releases for each one of them.

4.3.3 Wavelet transform

The decomposition for the stock and government bond series have been performed with MODWT as described in Section 2.5.2.2.

For the selection of the appropriate filter, this study follows the recommendations of other seminal works on wavelet and their applications on time series data. The analysis has been done with Db8 filter and at the six time-scales. After that the first three details components from both the stock and bond return series are employed to calculate the dynamic correlation at time-scales.

4.3.3.1 the results from wavelet variance, co-variance and correlation analysis

One of the main properties of the MODWT transform is to decompose variance of the time series at hand across the time-scales. Hence, an interesting exercise based on that is to examine which time-scale contributes more to this variation. Steps to follow can also use the produced variance-based decomposition to give a better insight on how the covariance between any pair of time series and the correlation changes over time. Our aim here is to make the decision for the selection of the reasonable number of time-scales using the wavelet analysis for the unbiased variance, correlation and covariance over the different investment horizons up to 64 days. More specifically, the time scales that contribute the most to the variations in the time series must be considered for the empirical analysis.

According to Percival and Walden (2000), the estimation of the variance over scales involves few steps. But before proceeding, the approach they follow requires the times series to be almost approximately stationary with backward differences. For the purpose of our analysis, both the changes in the stock and bond return can be denoted by X_t and Y_t, respectively. The process by decomposing the time series before applying the wavelet correlation method as described in Section 2.4.4. Using the wavelet-based variance approach, Hasbrouck (2016) analyse the subsequent short-term variances in the bid and offer levels in the U.S. equity market. Hasbrouck, also, considers, the incremental variance as the difference between the variances over the two subsequent time-scales. His study seeks to explain the subsecond horizons volatility in bid and ask offers by other than the long-term fundamentals.

4.3.4 Dynamic Conditional Correlation Model

The dynamic conditional correlation (DCC) GARCH model of Engle (2002), which builds upon the constant conditional correlation (CCC) model of Bollerslev (1990) is considered to be a successful method of investigating time varying correlations.[36] However, Cappiello et al. (2006)[37] consider the fact that the DCC model does not allow for the asymmetric impact of shocks on the dynamic correlation. Hence, they developed the asymmetric conditional correlation (henceforth, ADCC-GARCH).

Estimating the ADCC-GARCH models involves of several steps. Consider the return series $r_i \mid \Omega_{t-1}, \sim N(0, H_t)$, with *i*= 1, 2,..., *n*, where Ω_{t-1} is the information set at time *t-1*. First, we estimate the conditional variance using a univariate GARCH model. We chose to use the

[36] For more detailed presentations of the multivariate GACRH extensions, see Bauwens et al. (2006) and Silvennoinen and Teräsvirta (2009). Engle and Colacito (2012) evaluated some extensions of the DCC-GARCH, including the ADCC-GARCH model, for the purpose of the portfolio construction.
[37] Although it is not of our main interests, the model allows for the inclusion of any variable in the dynamic correlation to can account for the possible structural breaks in the correlation, Li and Zou, for example, (2008) use the same idea in their study.

threshold GARCH model of Glosten, Jagannathan and Runkle (1993) as it can capture asymmetry and is preferred based on the Schwartz–Bayesian information criterion when compared to a selection of alternative models. The model, denoted by GJR-GARCH, can be given as follows:

$$h_t^2 = \omega + \sum_{i=1}^{p} \alpha \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \gamma \varepsilon_{t-i}^2 I_{t-i} + \beta h_{t-1}^2 \tag{4.2}$$

Where $I_t[\cdot]$ is and indicator function which takes the value of one when the lagged shock is negative (ε_{t-1}<0) and zero for positive shocks (ε_{t-1}>0).

The main assumption of the model is that the effect of negative shock on the volatility as measured by ($\alpha + \gamma$) is higher than the positive one, which is captured by α only. Therefore, the asymmetry is capture by γ, with negative (positive) news having a greater impact on volatility when γ>0 (γ<0). In estimating the models, the lag lengths, *p* and q, are set to one for both the stock and the bond return equations. the standardized residuals $\varepsilon_{i,t}$ are normally and *iid* distributed.[38]

Using the estimated volatility, $h_t^{1/2}$, and the error term, $\varepsilon_{i,t}$, from the first stage, second, the model proceeds by setting the conditional covariance matrix as follows:

$$D_t P_t D_t \tag{4.3}$$

Where, D_t is the (n × n) diagonal matrix of time-varying conditional volatility from GJR-GARCH model on *i*th diagonal, such as D_t= *diag* $\left\{h_t^{1/2}\right\}$ for each return series. The term P_t denotes the conditional correlation matrix as constructed from the standardized residuals and specified as follows:

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{4.4}$$

Where Q_t^*= $\left\{diag[Q_t]\right\}^{-1}$, the diagonal matrix with the main elements of Q_t, the conditional

[38] While we also assume the standardised residuals are normally distributed, following Cappiello et al. (2006), we note that the choice of distribution is found not to affect the estimation of conditional variance significantly.

covariance matrix of the vector ε_t in the *i*th diagonal. Between two asset return series, the conditional covariance matrix can be denoted by q_{ijt} and the conditional correlation, $\rho_{ij,t}$ which represents diagonal entries of P_t can be computed as $\rho_{ij,t}= q_{ij,t} / q_{ii,t}^{1/2} q_{jj,t}^{1/2}$.

In order to account for the possible impact of the past news shocks on both the future volatility and the evolution of covariance, Cappiello et al. (2006) accommodate for the asymmetries in their model and it is given as follows:

$$Q_t = (\bar{P} - A'\bar{\mathrm{P}}A - B'\bar{\mathrm{P}}B - G'\bar{N}G) + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + G'\xi_{t-1}\xi_{t-1}'G + B'Q_{t-1}B \tag{4.5}$$

Where A, B and G are the parameter matrices and the latter term captures the asymmetric impact given that, $\xi_{t-1} = I[\varepsilon_t < 0] \; o\varepsilon_t$, (with $I[\cdot]$ being initially $k \times 1$ indicator function that takes on value of 1 if the argument is true and zero otherwise), while o is the element-by-element Hadamard product function. The other terms in the equation $\bar{P}$ and $\bar{N}$ are expectations and replaced with their sample analogous such as $\bar{N} = \frac{1}{T}\sum_{t=1}^{T} n_t n_t'$ and $\bar{N} = \frac{1}{T}\sum_{t=1}^{T} n_t n_t'$. Cappiello et al. (2006) refer to the model described in equation (8) as the asymmetric generalized AG-DCC and made it as a special case of the DCC model of Engle (2002). For our study, we use the diagonal version of ADCC model, where the matrices *A*, *B*, and *G* are replaced by their diagonal elements *a*, *b* and *g* and the model to be given by:

$$Q_t = (i\bar{\mathrm{P}}i' - a\bar{\mathrm{P}}a' - b\bar{\mathrm{P}}b' - g\bar{N}g') + a\varepsilon_{t-1}\varepsilon_{t-1}'a' + g\xi_{t-1}\xi_{t-1}'g' + bQ_{t-1}b' \tag{4.6}$$

Here *i* is the vector of ones and in order to get a positive definite value of Q_t for all observations *t*, the intercept term $(i\bar{\mathrm{P}}i' - a\bar{\mathrm{P}}a' - b\bar{\mathrm{P}}b' - g\bar{N}g')$ must be positive semi definite. Throughout our analysis in this paper, we use the diagonal version of the ADCC as the model which assumes that dynamic correlation are not necessarily the same at each time when bonds of different maturity are used in the portfolio. Thus, the equity-bond correlation can differ across different maturity bonds.

4.3.5 Returns, Correlations and Macroeconomic News

Our baseline models examine the effect of macro surprises on the return and correlation series over the full sample. Subsequently, we then consider the impact of crisis periods. By doing this, we are able to compare our results with those from the literature that examine the effect of macroeconomic news on return series. Therefore, we regress the return series on the surprises associated with each macroeconomic variable as such:

$$r(\rho SBm)_t = \alpha + \sum_{k=1}^{n} \beta u_{k,t} + e_t \tag{4.7}$$

Where the dependent variable is stock return series, bond return (r_t) or the dynamic correlation (ADCC model) series between both of them, (ρSBm_t) at time *t* and u_k is the standardized surprise for the macroeconomic announcement *k* at time *t*[39].

In estimating the above regression, we only include observations on days when a macroeconomic announcement is made. These announcement days are matched with the dependent variable on the same days. Given this, we have 168 announcement days in our sample.

We then expand this analysis to consider the different effects concerning the crisis and a non-crisis periods given the potential for investors to apply different weights to some macroeconomic news announcements during the crisis where the degree of uncertainty in the market changes. Thus, we estimate:

$$\rho SBm_t = \alpha + [(1 - D_t^{CRISIS}) \sum_{k=1}^{n} \beta_1 u_k + D_t^{CRISIS} \sum_{k=1}^{n} \beta_2 u_k] + e_t \tag{4.8}$$

Where D_t^{CRISIS} is a dummy variable that equals 1 during the crisis and zero otherwise. The key financial crisis period is defined from September 30, 2008 to March 27, 2009, β_1 is the sensitivity of return series to macro surprises outside the crisis period (i.e. $1 - D_t^{CRISIS}$) and β_2 is the sensitivity of return series to macro surprises during the crisis.

To examine how long the response to an announcement continues beyond the announcement day, we use dynamic correlation generated using the original return series and the decomposed correlation series of [2-4], [4-8] and [8-16] days following the announcements.

[39] Our method for regressing the correlation on the macro surprise is very similar to the work of Christiansen and Ranaldo (2007) who uses realized correlation instead of the dynamic correlation as a dependent variable. Other studies consider the dynamic correlation as a depended variable in their analysis include, for example, Li (2002) and Kim et al. (2006).

4.4 Empirical Results

4.4.1. Estimation of the ADCC-GACRH model

Panel A of Table 4.5 reports the estimated parameters of the ADCC-GARCH model on the original return series, with all parameters statistically significant at 1% level (*t*-test not reported). The Panels B to D report the results using the wavelet decomposed series, again all the parameters are significant at the 1% level. In comparing the models, we note that the value of α (impact of news) increases and β (persistence) decreases as we move from a lower scale to a higher scale. In terms of the overall persistence of correlation to a shock (i.e., α + β), it can be seen (from the original series) that persistent on the announcement day is high with the average of 0.989 across all estimated correlations.[40] This average value decreases for the next scale (0.833) before starting to increase again, (0.917) and (0.926) for the 4-8 and 8-6 days, respectively. We also note that the log likelihood values are higher for the scales than for the same days of the announcement.

Table 4.5
Estimation of ADCC-GARCH Model

This table presents the parameter estimates from the diagonal version of the asymmetric dynamic conditional correlation ADCC-GARCH model of Cappiello et al. (2006). The model is estimated in three stages, with the GJR-GARCH (1, 1) model of Golsten, Jagannathan and Runkle (1993) is used first to estimate the conditional volatility. The sample period spans from January 3, 2000 to December 25, 2013. α denotes the ARCH effect, β is the GARCH effect, asymmetric effect is g and LL is the log likelihood value. All estimated parameters in the Table are significant at 1% significance level.

	α	β	g	LL
Panel A: Original return series				
DJIA, $B2$	0.011	0.978	0.008	32547.55
DJIA, $B30$	0.022	0.969	0.000	24291.57
Panel B: [2-4] days scaled return series				
DJIA, $B2$	0.277	0.555	0.013	33100.42
DJIA, $B30$	0.277	0.563	0.024	24645.52
Panel C: [4-8] days scaled return series				
DJIA, $B2$	0.555	0.349	0.011	34564.21
DJIA, $B30$	0.569	0.357	0.018	26343.71
Panel D: [8-16] days scaled return series				
DJIA, $B2$	0.737	0.184	0.000	36835.75
DJIA, $B30$	0.789	0.133	0.029	28738.02

[40] The same decomposition approach (i.e. MODWT) is also used by Lehkonen & Heimonen (2014) as a robustness check to get the corroborating estimates for dynamic correlation from the DCC-GARCH model on the daily-based time-horizons. Their study, however, obtained their main findings from down-sampling (by two) through decomposition approach with discrete wavelet transform. In Cipollini et al. (2015), the MODWT is used as a first step to examine the volatility co-movement at different time-scales.

Figure 4.1, in panels A and B, examines the effect of the 14 news releases on the mean and the standard deviation of the dynamic correlations, respectively. Both statistics are plotted in the same graph once for the announcement days (AD) and days with no announcement at all (NAD). In comparison between the AD and NAD and from panel A, several observations can be noticed. First, those days with macro announcements tend to have higher mean for either correlation on Tuesday between the DJIA and 2-year bond (top left) and 30-year bond (top right). Second, the gap between the means with AD and NAD is the most on Tuesday with that on the former seems to far exceed the later. This is true whether we used the 2 year or 30-year bond to estimate the correlation. Yet, this gap is at minimum level on Monday and Wednesday, while it is slightly moderate on Monday and Thursday. On both Wednesday and Friday and for both series, the mean on AD is larger than that on NAD. Panel B also brings several observations. First, the standard deviation of the stock-2-year bond dynamic correlation tends to increase on Tuesday by 0.002 while considering the AD (see bottom left of the panel). This, however, is less evident, for other dynamic correlation series (top right). Second, the only difference between the analysis used the two series is now on Thursday and Friday. That is, on both days and when the 30-year bond is employed, the Std. on AD is now far less than on NAD. The reverse observation is true for the analysis on DJIA and 2-year bond returns.

In sum, the graphical analysis in Figure 4.1 indicates to the day-of-the-week (DOW, hereafter) effect of the macroeconomic news on either the mean and the standard deviation of the dynamic correlation series. In other words, the dynamic correlation between the stock and bond returns seems to vary throughout the trading days as more macroeconomic news being released in the market[41].

In order to decide on the optimal number of time-scales to be used in the regression analysis, we used the wavelet-variance unbiased estimator as described in Percival and Walden (2000). The estimated wavelet variances on up to six time-scales are plotted in Figure 4.2. The estimates for the stock, 2 year and 30 year returns are plotted in panels A, B and C, respectively. It can be generally observed from the graph (all the three panels) that the first three investment horizons contribute the most to the variance of the decomposed series. The confidence intervals associated

[41] The DOW effect has been already examined in the macro news-asset pricing literature by incorporating the trading days as dummies in the analysis. One way to do so is to insert the dummies directly into the GARCH conditional variance and mean equations (see, for example Flannery and Protopapadakis, 2002, among others). In our analysis, controlling for the DOW effect using the trading days dummies approach seems not to affect our final results, however, can be normal finding since the day of the week effect is not expected to persist on the dynamic correlations for the subsequent trading sessions. To our knowledge, evidence on that persistence at the correlation between the equity markets in the U.S is not also reported on the finance literature. Due to this reason, we concern about the all regression estimates without accounting for the DOW effect.

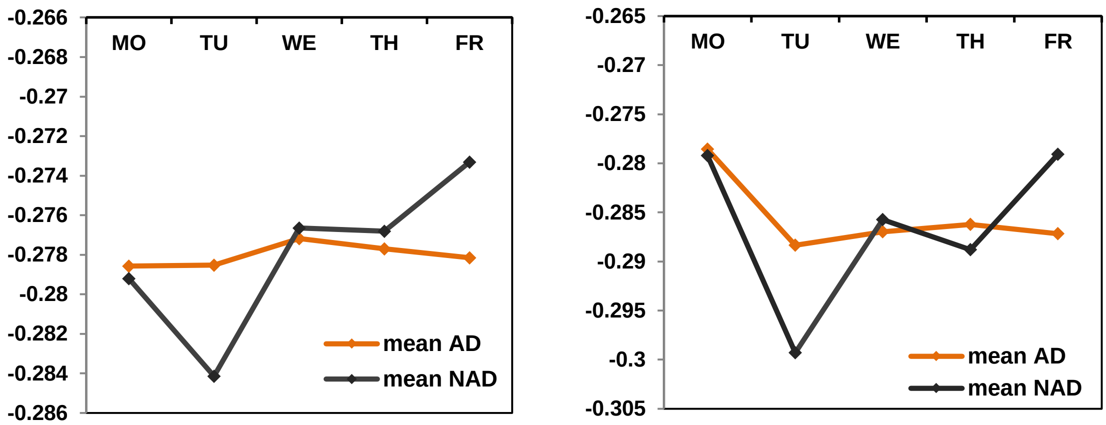
with these estimates are also wide compared to those at the higher investment horizons. This finding becomes in line with Kim and In (2007) who used the same approach and wavelet filter for examining the statistical relation between the monthly stock return and government bond yields in the G7 countries. It also supports the finding of Kim and In (2005) for the relation between the monthly stock return and inflation. From the same graph, also, we notice that the largest drop in the variance from investment horizon 1 to 2 is for the DJIA stock return (approx. 5.00E-05), while the least drop on the same time scale is for 30-year bond (approx. 3.00E-06).

Figure 4.1

Mean and the Std. Deviation for the Dynamic Correlations throughout the Trading Week

This graph shows the mean (Panel A) and the standard deviations (Panel B) of the dynamic correlation series on days with macro news announcement (AD) and days with no announcements (NAD). The summary statistics are plotted from Monday (MO) to Friday (FR). The left-side plots are for the correlation between the stock and 2-year bond returns, while these in the right-side are for the correlation between the stock and 30-year bond returns. Announcement day is a day when any of the fourteen-macro news has been released. Both statistics are calculated over the full sample period.

Panel A: Mean of the dynamic correlation series



Panel B: Standard deviation of the dynamic correlation series

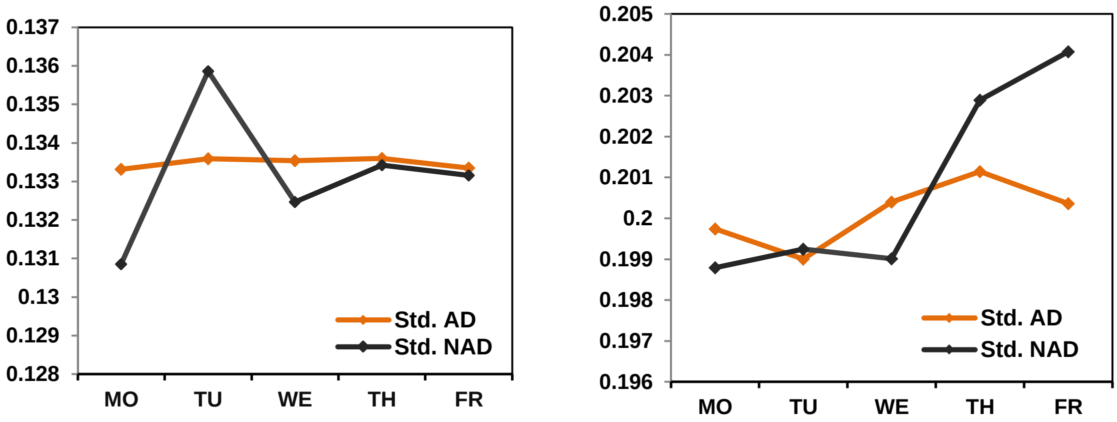
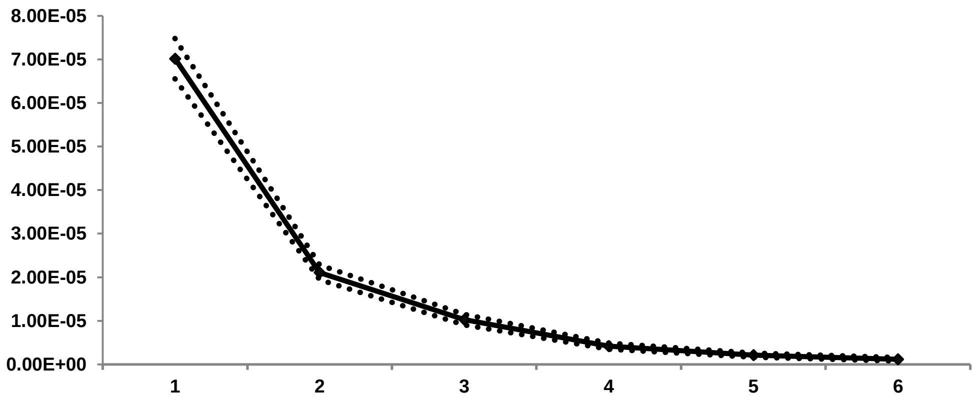


Figure 4.2

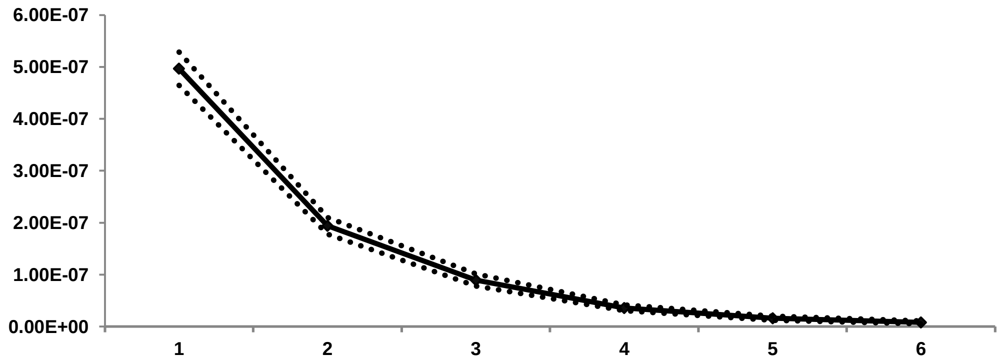
Wavelet-Based Variance Estimation on the Investment Horizons

The below graphs show the results of the wavelet variance analysis as carried out based on MODWT wavelet transformation with Db8 wavelet filter and up to the sixth time-scale. The solid line shows the unbiased wavelet variance, while the upper and lower lines represent the 95% upper and lower confidence intervals. Panel A shows the variance decomposition for the DJIA return, while panels B and C are for the Bonds 2 and 30 years, respectively. The estimates used the equations and written MATLAB codes from Percival and Walden (2000).

Panel A



Panel B



Panel C

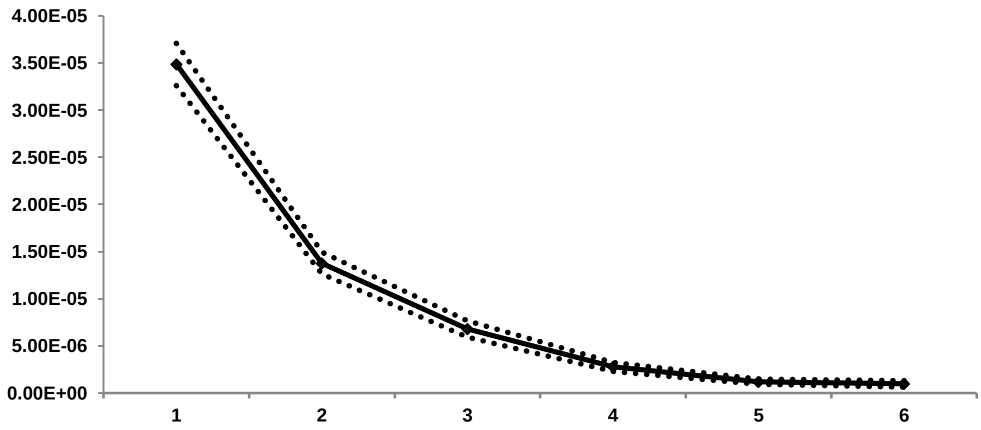


Figure 4.3, Panel A plots the dynamic correlation series on the day of announcements and [2-4] days afterward. The correlation across the two bond series is broadly similar. We also note that the level of correlation tends to decrease and becomes negative (or more negative) around the 2001 Dot-com crisis, the 2008 global financial crisis and the 2011 Euro and U.S. debt crisis periods. This provides strong evidence of a flight-to-quality where investors move from equity to government bonds during periods of crisis. The right-side panel of the Figure shows that dynamic correlation tends to be higher [2-4] days following the announcement.

Panel B of Figure 4.3 plots the wavelet-based correlation from time scale 1 to 6 with the 0.05 unbiased confidence interval. The estimates between the stock and 2-year bond returns are plotted in the left side panel, while those considering 30-year bond are depicted in the right-side panel. Examining both relations with either bond series indicates that wavelet correlation almost remains at the same level on the first three time-scales. The value tends to decrease after that at the [16-32] time scale between the stock and 2-year bond, while it slightly increases at the same scale for the other correlation series. Moreover, the wavelet-correlation coefficient is approaching the maximum at the sixth investment horizon of [32-64] day period. This general observation from the Panel A casts some doubts on whether effects of external factors are generating more uncertainty on the statistical interaction between the stock and bond returns at the shortest (one to three) investment horizons. Example on these factors could be the macro news.

Table 4.6 reports the results of the news surprises on returns (Panel A) and the asymmetric dynamic correlation (Panel B). Clearly evident in this table is that almost none of the announcements impact either stock or bond returns and none have an impact on the dynamic correlation series. Indeed, only PMI has a significant effect and this is only for the 2-year series. It is our contention however, that the results in this table are likely to be misleading, with the effects of some macroeconomic announcements cancelling out over the full sample period. That is, the effect of news under different economic conditions will vary such that when it is viewed over the whole sample the result may become insignificant. To examine this further, we next consider the results where the 2008 crisis dummy is incorporated into our regression.

4.4.2 Macroeconomic Surprises and the Dynamic Correlation: The 2008 Crisis

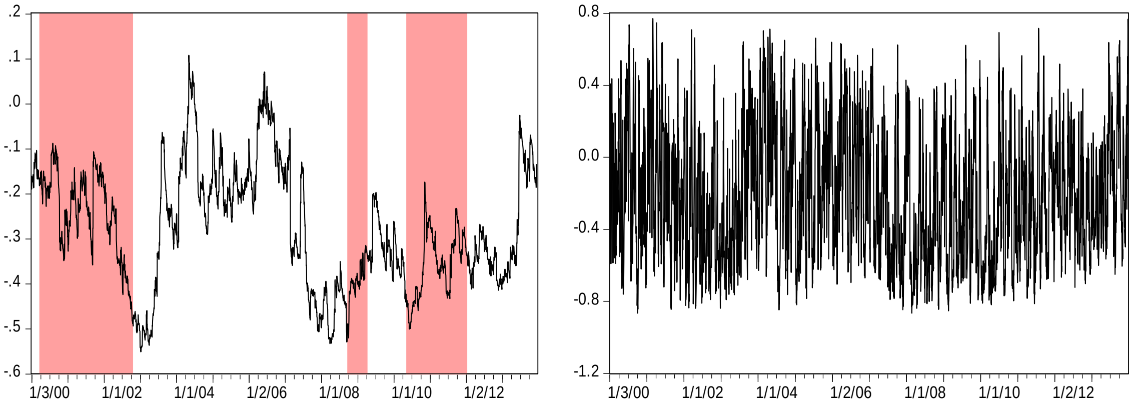
To ensure that our findings are comparable with those in the literature, we first estimate the model using a 2008 dummy before replacing that with recession and expansion dummies from NBER. This table uses the raw data.

Figure 4.3

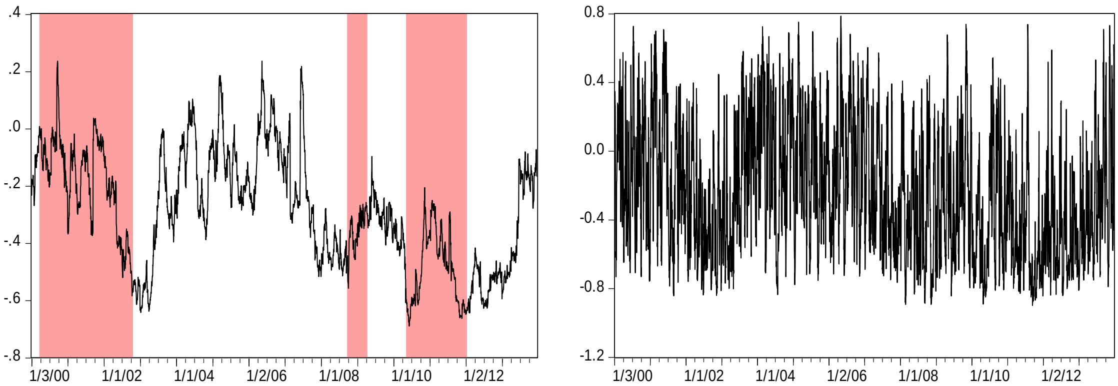
Plots of the dynamic and Wavelet-based correlation (03/01/2000-25/12/2013)

This graph plots the dynamic correlation from the ADCC-GARCH. Left-side panels A and B show the dynamic conditional correlation estimated based on the first day of the return series, while the right-side panels show the correlation accumulated over [2-4] days horizon. Panel C shows the wavelet -based correlation between the stock and 2-year bond return (the left panel) and the stock and 30 bond year return (the right panel). The upper and lower lines in panel C represent the unbiased 95% upper and lower confidence intervals, respectively. Shadings in the left panels represent the crisis bubbles bursting stage from Dot-com crisis as defined from 14/03/2000 to 10/10/2002, from the global financial crisis: 15/09/2008 to 31/03/2009 and from the US government debt crisis: 30/04//2010 to 30/12/2011.

Panel A: Stock Market and 2-Year Bond



Panel B: Stock Market and 30-Year-Bond



Panel C: Wavelet-Based Correlation on Time-Scales

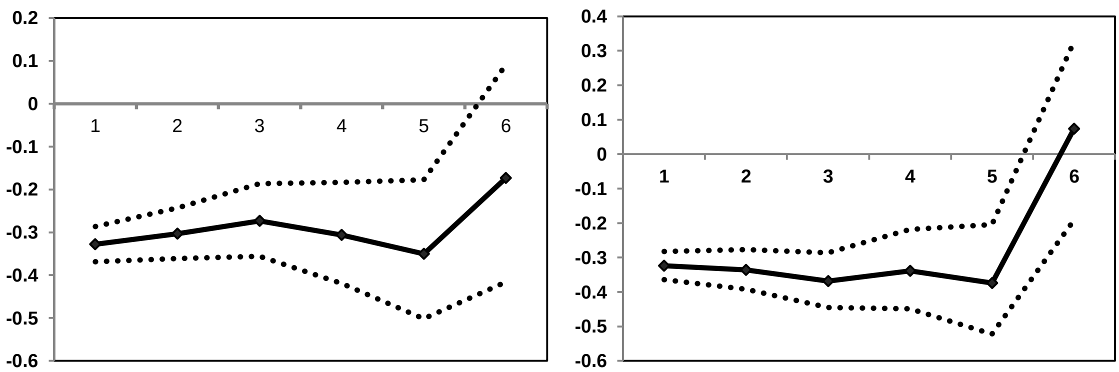


Table 4.6

Baseline Model: Return (Dynamic Correlation) News OLS Regression.

This table reports the beta coefficient estimates from the linear regression model:

$$r(\rho SBm)_t = \alpha + \sum_{k=1}^{n} \beta u_{k,t} + e_t$$

Where: r_t denotes either the DJIA or the bond index return defined as the first difference of the natural log of the closing price. ρSBm is the dynamic correlation for each pair of stock and bond as estimated from ADCC model. u_k denotes the standardized unexpected component of economic variable k and calculated using the approach of Balduzzi et al. (2001) with $u_{k,t} = \frac{A_{k,t} - E_{k,t}}{\sigma_t}$, where $A_{k,t}$ is the monthly actual value obtained from the reporting agency, $E_{k,t}$ is the corresponding median expectation as collected from Informa global markets database, σ_t is the standard deviation of the unexpected component of *kth* economic variable for the full sample period from January 2000 to December 2013. The original sample for return series covers the period from January 3, 2000-Decmber 25, 2013 (3648 observations) and the estimates reported in the Table are based on the announcement dates only with 168 observations. In panel A, an under the column (I), the dependent variable used is the DJIA return series, while in (II) and (III) the dependent variable is the 2 and 30-year bond index return series, respectively. Panel B shows the estimates of the regression with the dynamic conditional correlation is used as a depended variable with (I) and (II) show the results when the correlation between the stock and 2 and 30-year bond is used in the regression. *, ** and *** denote statistical significant at 10%, 5% and 1%, respectively. The crisis period is defined from September 2008 to March 2009.

Panel A: $r_t = \alpha + \sum_{k=1}^{n} \beta u_{k,t} + e_t$

	(I)		(II)		(III)	
Variable	β	Adj. R^2	β	Adj. R^2	β	Adj. R^2
Average Hourly Earnings	0.00	0.06	0.00	0.00	0.00	0.01
Business Inventory	0.00	0.00	0.00	0.00	0.01	0.00
Consumer Credit	0.00	0.00	0.00	0.00	0.00	0.00
CPI	0.00	0.00	0.00	0.02	0.00	0.01
Factory Goods Orders	0.00	0.02	0.00	0.00	0.00	0.01
Housing Starts	0.00	0.00	0.00	0.00	0.00	0.02
Import Price	0.00	0.01	0.00	0.01	0.00	0.00
Industrial Production	0.00	0.00	0.00	0.00	0.00	0.00
New Single-Family Home Sales	0.00	0.00	0.00	0.00	0.00	0.00
Personal Income	0.00	0.01	0.00	0.00	0.00	0.00
PMI	0.00	0.01	0.01***	0.08	0.00	0.02
PPI	0.00	0.00	0.00	0.00	0.00	0.02
Retail Sales	0.00	0.00	0.00	0.00	0.00	0.01
Unemployment Rate	0.00	0.00	0.00	0.00	0.00	0.00

Panel B: $\rho SBm_t = \alpha + \sum_{k=1}^{n} \beta u_{k,t} + e_t$

	(I)		(III)	
Variable	β	Adj. R^2	β	Adj. R^2
Average Hourly Earnings	0.00	0.00	0.01	0.01
Business Inventory	0.01	0.00	-0.01	0.00
Consumer Credit	0.00	0.00	0.00	0.00
CPI	0.00	0.00	0.00	0.00
Factory Goods Orders	0.00	0.00	0.01	0.00
Housing Starts	0.00	0.00	-0.01	0.00
Import Price	0.00	0.00	0.00	0.00
Industrial Production	0.01	0.01	0.02	0.01
New Single-Family Home Sales	0.02	0.02	0.03	0.02
Personal Income	0.00	0.00	0.01	0.00
PMI	0.00	0.00	-0.01	0.00
PPI	-0.01	0.01	-0.02	0.01
Retail Sales	0.01	0.00	0.01	0.01
Unemployment Rate	-0.01	0.01	0.00	0.00

Table 4.7 presents the slope estimates, t-statistics and the adjusted R^2 out from equation (8)[42]. To

[42] Our main concern throughout the analysis is the significance of the coefficient and not the value of the Adj. R^2. Negative Adj. R^2s are also obtained by Kothari et al. (2006) when they regressed the subsequent

ensure that our findings are comparable with those in the literature, we first estimate the model using a 2008 dummy before replacing that with recession and expansion dummies from NBER. This table uses the raw data.

Regardless of the maturity of the bond, in estimating the dynamic correlation model some announcements now exhibit a significant impact on the correlation with the inclusion of the 2008 crisis dummy. These announcements are average hourly earnings, business inventory, personal income and the unemployment rate. Among these, the unemployment rate and the average hourly earnings news, which are simultaneously announced, have, on average, the highest slope coefficient (approx. 9.6% and 10.3%, respectively) across the dynamic correlation series. However, when the NBER indicators are used, the effect of unemployment news on the stock and 2-year bond dynamic correlation becomes small and statistically insignificant. Other announcements including retail sales, import, PPI index and factory goods orders have a significant impact on all series during the recession period, but not when the 2008 crisis dummy is used.

Interestingly, new single-family house sales (and housing starts, but not significantly) is the only factor that exhibits the same coefficient sign regardless of which dummy variable we use (2008 or NBER). They have both positive effects on the two correlation series. Thus, we can summarise that investors appear to agree regarding the effect of housing-related macro news on their stock-bond constructed portfolios, at least on the days when the Figures are announced. Further, two of the macroeconomic news, CPI and consumer credit only show an impact during the recent crisis on stock and 2-year bond series. When considering the direction of effect, it is noticeable that the dynamic correlation between the stock and 2-year and 30-year bond reacts in the same way to macroeconomic news.

Several general findings can be drawn from these results. First, the effect of most announcements outside the crisis period or during an expansionary period are negligible with very small coefficient values that are typically insignificant. Second, the adjusted R^2 values are equally small, on average, 1.0%. Thus, supporting the view that these announcements do not exert much influence when it comes to movement in dynamic correlations. In contrast, greater significance is found during contractionary periods. Hence, third, the results reported for bear periods are significantly different from those noted during bull-periods, a difference statistically supported by a Wald test. Last, all significant news announcements during the crisis period are early, 10am,

quarterly returns on both the earning changes and surprises, separately. Their analysis for that used Fama–MacBeth regressions.

releases.

Table 4.7

Stock-bond Dynamic Portfolio Allocation Today and Macroeconomic News, 2008 Crisis against NBER Recession Dummies

This table reports the non-linear regression estimates with White (1987) standard errors of the model:

$\rho SBm_t = \alpha + [(1 - D_t) \sum_{k=1}^{n} \beta 1 u_{k,t} + D_t \sum_{k=1}^{n} \beta 2 u_{k,t}] + e_t$

Where: ρSBm_t is the dynamic conditional correlation between the given stock index return under consideration, *S*, and the benchmark bond market index return *B* at either *m* equals to 2 and 30 years of maturity respectively, where here *B* denotes the number of years to maturity. r_t denotes stock index return defined as the first difference of the natural log of the closing price D_t is either a crisis dummy (equals to one for the period from 15/09/2008 to 31/03/2009 and zero otherwise) or a dummy variable equals to 1 during the recession period and zero during the expansion. NBER peak and trough indicators are used to define the recession and expansion sates. The regression is estimated first with the 2008 crisis dummy then with the NBER indicators. u_k denotes the standardized unexpected component of economic variable *k* and calculated using the approach of Balduzzi et al. (2001) with $u_{k,t} = \frac{A_{k,t} - E_{k,t}}{\sigma_t}$, where $A_{k,t}$ is the monthly actual value obtained from the reporting agency, $E_{k,t}$ the corresponding median expectation as collected from Informa global markets database, σ_t is the standard deviation of the unexpected component of *kth* economic variable for the full sample period from January 2000 to December 2013. The original sample for return series covers the period from January 3, 2000-Decmber 25, 2013 (3648 observations) and the estimates reported in the Table are based on the announcement days for each macroeconomic news only with 168 days have been used in the regression, the exact dates on the announcements have been matched with the corresponding dynamic correlation with different dynamic correlation dates have been selected for each macroeconomic factor. The columns in the Table (I) and (II) show the cases when the dependent variable is the dynamic correlation between the DJIA and benchmark index bond return at two years and thirty years, respectively. Figures in bold belong to the variable for which the null hypothesis of the equality ($\beta_1 = \beta_2$) from the Wald test has been rejected at 1% or higher significant level. *, ** and *** denote statistical significant at 10%, 5% and 1%, respectively.

		(I)					(II)				
Variable	Dummy	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2
Average Hourly Earning	2008	0.00	0.36	**-0.12*** **	-3.84	0.00	0.02	0.98	**-0.07***	-1.77	0.00
	NBER	0.00	-0.07	0.07	0.93	0.00	0.01	0.85	0.03	0.33	-0.01
Business Inventory	2008	0.00	-0.13	**0.08*** **	3.02	0.01	-0.02	-0.79	**0.13*** **	2.88	0.00
	NBER	0.01	1.20	**-0.05***	-1.83	0.01	0.00	0.26	**-0.09*** **	-3.72	0.02
Consumer Credit	2008	0.00	-0.13	**0.09***	1.85	0.00	0.00	-0.21	0.06	1.46	-0.01
	NBER	0.01	0.64	-0.04	-0.96	0.00	0.00	0.20	-0.05	-1.00	-0.01
CPI	2008	-0.01	-0.95	**0.03***	1.89	0.00	-0.01	-0.32	0.03	1.56	-0.01
	NBER	-0.01	-0.66	0.02	0.54	-0.01	0.00	-0.03	-0.02	-0.38	-0.01
Factory Goods Orders	2008	0.00	-0.11	0.03	1.02	-0.01	0.01	0.72	0.03	1.11	-0.01
	NBER	0.01	0.68	-0.07	**-2.21****	0.01	0.02	1.27	**-0.09****	-2.05	0.01
Housing Starts	2008	0.00	-0.08	0.03	0.67	-0.01	-0.01	-0.61	0.02	0.66	-0.01
	NBER	0.00	0.10	0.03	0.33	-0.01	-0.01	-0.66	0.10	1.06	0.00
Import	2008	0.00	-0.24	0.02	-0.59	0.00	0.00	-0.12	0.01	0.49	-0.01
	NBER	0.01	0.66	**-0.06*** **	-3.51	0.01	0.01	0.74	**-0.10*** **	-9.38	0.02
Industrial Production	2008	0.01	0.72	0.03	1.32	0.00	0.02	0.81	0.03	1.59	0.00
	NBER	0.01	1.33	0.01	0.17	0.00	0.02	1.46	-0.03	-0.53	0.00
New Single-Family Home Sales	2008	0.02	1.45	0.03	1.14	0.01	0.03*	1.72	**0.03****	1.95	0.01
	NBER	0.02	1.39	0.10	1.44	0.02	0.02	1.64	**0.12***	2.02	0.01
Personal Income	2008	0.00	0.09	**-0.05***	-1.90	-0.01	0.01	0.72	**-0.06*** **	2.78	-0.01
	NBER	0.00	-0.07	-0.01	-0.09	-0.01	-0.01	-0.56	-0.03	-0.32	-0.01
Chicago PMI	2008	0.00	-0.11	**0.03**	1.35	-0.01	-0.01	-0.53	-0.01	0.19	-0.01
	NBER	0.00	-0.16	0.03	0.99	-0.01	-0.01	-0.72	0.04	0.81	-0.01
PPI	2008	-0.02	-1.34	**0.04**	1.51	0.01	-0.03	-1.64	**0.02**	1.02	0.01
	NBER	-0.01	-0.49	**-0.07*** **	-2.96	0.01	-0.01	-0.93	**-0.11*** **	-7.54	0.02
Retail Sales	2008	0.01	0.58	0.03	1.35	0.00	0.01	0.74	0.03	1.33	0.00
	NBER	0.01	0.52	0.01*	1.79	-0.01	0.00	0.06	0.03***	5.71	0.00
Unemployment Rate	2008	-0.01	-0.92	**-0.10****	-2.72	0.01	-0.01	0.53	**-0.09****	-2.03	0.00
	NBER	-0.02	-1.54	0.00	0.12	0.00	0.00	0.13	0.02	0.51	-0.01

In Table 4.8 we replace the obtained dynamic correlation series for the announcement day with the decomposed wavelet series that covers the days following announcements. Scales are denoted as (1-3) where scale 1 refers to [2-4] days, while scale 2 and 3 represent the days [4-8] and [8-16] respectively. This approach shifts the focus away from just the announcement day. Such dynamics may arise due to, for example, under-reaction in the market, which may be associated with the existence of noise traders (Vega, 2006). Further, the quality of private information that investors acquire during the crisis may change and this can affect the dynamic interaction between stocks and bonds. Daniel et al. (1998) argue that investors tend to underreact to public information and overreact to private information. Furthermore, the timing and day of the announcement in the month may matter. For example, different investors may not rebalance their portfolio after each news item but may wait until all news are released during a month.

From our analysis in this table, we can observe that the reaction to most of the macroeconomic news announcements increases (in absolute value) in the first scale [2-4] days when compared to the first day (see Table 4.7). For example, the impact of average hourly earnings' noticeably increases and, indeed, almost doubles. The response to business inventory news is now significance for the first scale regardless of the bond series used. Interestingly, outside the crisis period, and on the first scale, investors now seem to significantly react to both CPI and the housing starts macroeconomic news.

The strongest effect (based on the highest Adjusted R^2) is for housing starts and CPI. Interestingly, the reaction to these two announcements outside the crisis suggest a consistency in terms of statistical significance such that investors agree on the importance of this news. Prior to the crisis, CPI has a positive impact on the short and long bond rate correlation and negative one with the medium-term bond. The reverse is true for housing starts. On higher scales, however, the effects of CPI and housing starts generally to decrease outside the crisis.

Other news, such as new single house sales seem to have no impact on the correlation series immediately after the announcement, however, it is significant on the third scale. Similarly, announcements released at 8:30, such as average hourly earnings, housing starts, import and unemployment, seem to affect the dynamic correlation between stock and 2-year bond returns after the first scale. Equally, industrial production shows a significant impact on the second scale for all the correlation series.

When it comes to the timing and the day of the release, an interesting conclusion can be reached. Three out of fourteen announcements used as predictors, namely consumer credit, factory goods order and new single house sales strongly affect the correlation series on scale 3, days [8-16].

This strong effect can be explained whereby these three announcements are the only ones released either in the first week of the month (consumer credit, factory good order) or in the last business week of the month (new single house sales). Also, the time of these announcements is at or after 10am, indeed, consumer credit, which has the strongest effect among these three, is released at 3pm. This supports the notion that investor's reaction is slower to late announcements in time and announcements released in a day early in the month[43].

4.4.3. Do Same Macroeconomic News have an Effect During the 2001 and 2011 Crises?[44]

In this section, we repeated our analysis from Equation (4.8) but replace the 2008 crisis with the 2001 Dot-com crash (from 14/03/2000 to 10/10/2002) and the 2011 US government debt crisis (30/04//2010 to 30/12/2011).

Panel A of Table 4.9 presents the results for the 2001 crisis. Compared to the results from Table 4.6, we find that the effect of average hourly earnings (in absolute value) decreases on the first day and becomes insignificant. For example, for the stock and 2-year bond correlation, the announcement day beta coefficient is very small (with a t-statistic of -0.22). The same is found for the effect for the second scale where the significance for the crisis period is lost. From Table 4.8 we note that CPI and housing now start appearing important. Here, we can see that CPI remains important during the crisis period and especially so for the stock and 2-year bond dynamic correlation. Regarding housing starts, this news announcement continues to be important outside of the crisis period, although with some significance for the stocks and short bond correlation on the second scale but no longer at the third scale.

In Panel B, average hourly earnings news seems to be of less economic (and statistical) importance on the day of it is release and on [2-4] days afterward. CPI exhibits significance outside of the crisis period but also during the crisis for both the short and long bond correlation with stocks.

[43] Further analysis can be done to examine whether the sign of the news itself is partially driving this relation. This is beyond the scope of this paper. Our unreported graphs, however, also confirmed the statistical relations in Table 4.8 at the higher time-scales during the 2008/2009 crisis period.

[44] The results for only five macroeconomics news of which we found are significantly important in any of the scales are shown here. The complete findings for all news used in our analysis are available upon request. From the untabulated results and on the same day of announcements, for example, import and PPI news only show a significant impact during the 2011 crisis on all the series. The personal income tends consistently to affect on all series during the 2001 crisis. The effect of early released news both on time and the day of the week, such as consumer credit and the factory goods show small and insignificant impact on the third scale. This again, suggests doing the analysis on the single crisis-based regression, rather with the NBER's recession (expansion) dummies. Using the later dummies will suppose that the effect of one macro news is the same during all the crisis periods, while in fact it is different as shown here in our analysis.

Table 4.8

Macroeconomic News and the Near-Term Future Stock-Bond Portfolio Correlation, 2008 Crisis Dummies

This table reports the non-linear regression estimates with White (1987) standard errors of the model:

$$\rho SBm_t = \alpha + [(1 - D_t^{CRISIS}) \sum_{k=1}^{n} \beta_1 u_k + D_t^{CRISIS} \sum_{k=1}^{n} \beta_2 u_k] + e_t$$

Where ρSBm_t is the dynamic conditional correlation between the given stock index return under consideration, S, and the benchmark bond market index return B at either m equals to 2 and 30 years of maturity respectively, where here B denotes the number of years to maturity. r_t denotes stock index return defined as the first difference of the natural log of the closing price and D_t^{CRISIS} is the global crisis dummy variable which is equal to 1 during the crisis and zero otherwise. The crisis period is defined from September 2008 to March 2009. t-statistics are reported in parenthesis. *, ** and *** denote statistical significant at 10%, 5% and 1%, respectively. Scales 1, 2 and 3 denote [2-4] days, [4-8] and [8-16] days following the announcements, respectively. For the rest of notations, see Table 4.6.

		(I)					(II)				
Variable	Scale	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2
Average Hourly Earning	1	-0.02	-0.85	**-0.21*** **	-2.55	0.00	0.01	0.32	**-0.16***	-1.71	-0.01
	2	-0.06	-1.28	-0.19	-0.55	0.00	0.04	0.76	-0.20	-0.75	-0.01
	3	0.07	1.18	**-0.53*** **	-3.80	0.01	-0.03	-0.47	0.25	0.53	-0.01
Business Inventory	1	0.03	0.95	0.07	0.71	0.00	0.00	-0.07	0.07	0.68	-0.01
	2	-0.04	-0.83	**-0.20****	-1.98	-0.01	-0.03	-0.61	-0.01	-0.06	-0.01
	3	0.06	-1.06	-0.04	-0.19	-0.01	0.04	0.72	-0.13	-0.55	-0.01
Consumer Credit	1	0.00	-0.08	0.10	0.69	-0.01	-0.02	-0.71	-0.01	-0.05	-0.01
	2	0.00	-0.12	0.02	0.08	-0.01	-0.07	-1.50	0.05	0.25	0.00
	3	0.04	0.63	0.31	1.50	0.00	-0.06	-1.00	**-0.54***	-1.70	0.01
CPI	1	**0.07*** **	2.48	-0.03	-0.41	0.02	**0.08*** **	2.72	-0.03	0.31	0.03
	2	-0.01	-0.11	0.09	0.82	-0.01	0.03	0.65	0.10	0.86	-0.01
	3	-0.06	-0.95	-0.19	-1.35	0.00	0.02	0.29	-0.14	-0.69	-0.01
Factory Goods Orders	1	-0.02	-0.63	-0.03	-0.48	-0.01	**-0.05***	-1.78	-0.01	-0.07	0.00
	2	-0.03	-0.61	0.10	0.83	-0.01	0.00	0.02	0.14	1.03	0.01
	3	0.05	1.10	-0.01	-0.05	-0.01	0.08	1.55	**-0.29****	-2.05	0.01
Housing Starts	1	**-0.10*** **	-3.83	-0.12	-1.66	0.07	**-0.08*** **	-3.08	-0.08	-0.96	0.04
	2	0.03	0.72	-0.14	-1.31	0.00	0.04	0.74	**-0.21****	-2.10	0.00
	3	-0.02	-0.31	**-0.31*** **	-3.59	0.01	-0.06	-0.96	-0.16	-1.19	0.00
Import	1	**0.05***	1.75	0.06	1.37	0.01	0.03	0.92	**0.12****	2.19	0.00
	2	-0.02	-0.59	**0.18*** **	4.06	0.00	0.06	1.14	0.06	0.39	0.00
	3	-0.08	-1.32	**-0.45*** **	-5.29	0.03	-0.05	-0.83	-0.10	-0.42	-0.01
Industrial Production	1	-0.05	-1.41	0.00	0.03	0.00	-0.04	-1.25	-0.01	-0.28	0.00
	2	0.05	0.96	**-0.11****	-2.24	0.00	-0.01	-0.22	-0.10**	-2.23	0.00
	3	0.09	1.35	0.03	0.26	0.00	0.02	0.27	0.11	1.51	0.00
New Single-Family Home Sales	1	0.01	0.42	-0.08	-1.20	-0.01	-0.01	-0.34	0.03	0.65	-0.01
	2	-0.04	-0.99	-0.06	-0.56	-0.01	-0.04	-0.96	0.00	0.04	-0.01
	3	0.03	0.43	**0.30***	1.82	0.01	0.00	0.00	**0.35*** **	2.59	0.00
Personal Income	1	0.03	1.08	**0.25*** **	3.86	0.00	0.07**	-2.12	0.01	0.10	0.02
	2	-0.05	-1.22	**0.48*** **	8.24	0.02	-0.05	-1.05	**0.32*** **	3.40	0.00
	3	-0.01	-0.16	0.02	0.09	-0.01	0.12***	2.73	0.11	0.61	0.02
Chicago PMI	1	0.01	0.34	0.19*	1.78	0.00	0.01	0.27	0.17	1.43	0.00
	2	0.05	1.27	-0.07	-0.32	0.00	0.03	0.64	0.10	0.57	-0.01
	3	0.07	1.23	-0.04	-0.29	0.00	0.08	1.46	0.18	1.08	0.00
PPI	1	0.00	0.07	-0.04	-0.31	-0.01	-0.01	0.23	-0.06	-0.65	-0.01
	2	-0.01	-0.29	-0.02	-0.18	-0.01	0.04	1.09	0.03	0.21	-0.01
	3	-0.09	-1.49	-0.23	-1.31	0.01	-0.06	-0.96	-0.14	-0.79	0.00
Retail Sales	1	0.02	0.56	-0.03	-0.40	-0.01	-0.01	-0.21	**-0.10****	-1.99	0.00
	2	**-0.08****	-1.99	0.01	0.06	0.01	0.01	0.17	-0.07	0.61	-0.01
	3	-0.04	-0.80	-0.06	-0.34	-0.01	**-0.11***	-1.70	-0.01	-0.04	0.03
Unemployment Rate	1	-0.02	-0.65	-0.14	-1.18	0.00	-0.01	-0.46	-0.07	-0.52	-0.01
	2	-0.01	-0.15	**0.40****	1.97	0.00	0.01	0.17	0.05	0.19	-0.01
	3	**0.15*** **	2.97	**-0.45*** **	-3.71	0.04	0.03	0.61	-0.09	0.24	-0.01

For housing starts, again, of most significance is when announcements are made outside of the crisis period but on scale 1 rather than the announcement day itself.

For the other series, PMI generally shows a lower effect during the 2001 crisis for all correlation series from the first day of announcements to [8-16] days following it is release. During the 2011 crisis the impact on the same day of announcements increases and becomes significant for the portfolios constructed with 10 and 30-year bond returns. Similar finding can be observed from the third scale only for the longest maturity of bonds. For retail sales, the announcement shows noticeable significance during both the 2001 and 2011 crises. It shows a significant effect on the portfolios of stock and 2-year bond of maturity during the 2001 crisis period but with a higher effect during 2011. On the second scale, the impact of retail sales in 2011 crisis decreased comparing to that during the 2008 crisis.

In brief, the results in Table 4.9 show that none of the macro news announcements has a similar impact on the different scales across all the recent crisis periods (2001, 2008 and 2011). Housing starts, however, has an impact outside the crises periods on the first scale, regardless of which crisis we control for in our regression.

To provide some additional insight, Figure 4.4 plots the dynamic correlation between stocks and the 30-year government bond returns on days matched with the housing starts news surprises. On the same day of announcement (Panel A), the correlation appears to be less related to surprises which supports our finding in Table 4.8 that housing starts does not significantly affect the correlation on the first day.

The scaled dynamic correlation series on [2-4] and [4-8] days in Panels B and C, respectively are highly correlated with the housing the surprises. The dynamic correlation seems to be more connected to the surprises between the 2001 and 2008 crises, the period when U.S. investors were perhaps more affected by house prices and inflation in general. In the third scale, notably early before the 2001 crisis and at the end of 2011 crisis, investors appear to quickly adjust their portfolios following housing starts news. On the contrary, on [8-16] days following the announcements, as shown in Panel C, the portfolio rebalancing tends to be less affected by housing starts news. Suggesting that the adjustment occurs over the previous days, with the effect of housing start surprises being fully incorporated into the portfolio pricing process.

Table 4.9

Macroeconomic News and the Near-Term Future Stock-Bond Portfolio Correlation, 2001 and 2011 Crises

This table reports β_1 and β_2 coefficient estimates from the non-linear regression with White (1987)'s standard errors of the model:

$$\rho SBm_t = \alpha + [(1 - D_t^{CRISIS}) \sum_{k=1}^{n} \beta_1 u_k + D_t^{CRISIS} \sum_{k=1}^{n} \beta_2 u_k] + e_t$$

Where ρSBm_t is the dynamic conditional correlation between the given stock index return under consideration, S, and the benchmark bond market index return B at either m equals to 2 and 30 years of maturity respectively, where here B denotes the number of years to maturity. D_t^{CRISIS} is either the 2001 or the 2011 debt crisis period, the dummy variable which is equal to 1 during the crisis and zero otherwise. Dot-com crisis is defined from 14/03/2000 to 10/10/2002, the US government debt crisis: 30/04//2010 to 30/12/2011. Scales 0, 1 2 and 3 denote the day of announcement, [2-4] days, [4-8] and [8-16] days following the announcements respectively. *, ** and *** denote statistical significant at 10%, 5% and 1%, respectively. For rest of notations, see Table 4.6.

Panel A: the 2001 crisis

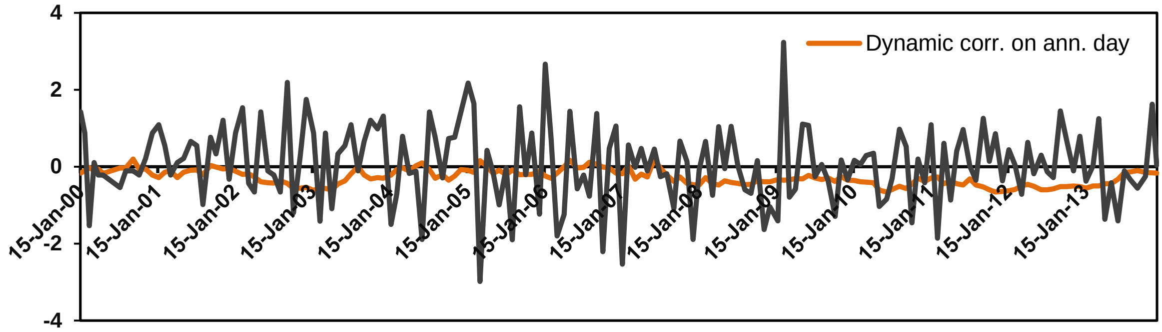
		(I)					(II)				
Variable	Scale	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2
Average Hourly Earning	0	0.00	0.20	0.00	-0.22	-0.01	0.02	0.88	0.01	0.22	-0.01
	1	-0.03	-1.03	-0.02	-0.25	-0.01	0.01	0.31	-0.01	-0.19	-0.01
	2	-0.09*	-1.91	0.10	-0.97	0.01	0.03	0.50	0.06	0.48	-0.01
	3	0.07	1.11	0.00	-0.03	0.00	-0.01	-0.20	-0.06	-0.45	-0.01
CPI	0	0.00	-0.42	-0.01	-0.35	-0.01	0.00	0.12	-0.02	-0.61	-0.01
	1	0.05	1.63	**0.12****	2.45	0.02	0.05	1.51	**0.24*****	6.72	0.06
	2	0.00	-0.04	0.04	0.40	-0.01	0.03	0.58	0.10	0.78	-0.01
	3	-0.04	-0.65	-0.24*	-2.25	0.01	0.04	0.63	-0.22	-1.42	0.00
Housing Starts	0	0.00	0.19	0.00	-0.12	-0.01	-0.01	-0.64	0.02	0.53	-0.01
	1	-0.10***	-3.59	-0.17***	-2.55	0.07	-0.08***	-3.02	-0.08	-1.18	0.04
	2	0.00	-0.12	0.02	0.08	-0.01	-0.07	-1.50	0.05	0.25	0.00
	3	0.04	0.63	0.31	1.50	0.00	-0.06	-1.00	**-0.54***	-1.70	0.01
PMI	0	0.00	0.10	0.00	-0.11	-0.01	-0.01	-0.44	-0.01	-0.25	-0.01
	1	0.02	0.73	0.00	0.02	-0.01	0.02	0.50	0.02	0.28	-0.01
	2	0.04	1.02	0.06	0.53	0.00	0.04	0.79	0.00	0.04	-0.01
	3	0.10*	-1.78	-0.13	-0.86	0.01	0.12**	2.14	-0.08	-0.53	0.01
Retail Sales	0	0.01	0.33	**0.01*****	2.64	-0.01	0.00	0.11	**0.03****	2.41	0.00
	1	0.03	0.70	-0.01	-0.22	-0.01	0.01	0.28	**-0.05*****	-2.71	0.00
	2	-0.06	-1.18	-0.08	-1.52	0.00	0.00	0.02	0.14	1.03	-0.01
	3	-0.09	-1.12	0.01	0.16	0.00	-0.11	-1.46	-0.09	-1.07	0.01

Panel B: the 2011 crisis

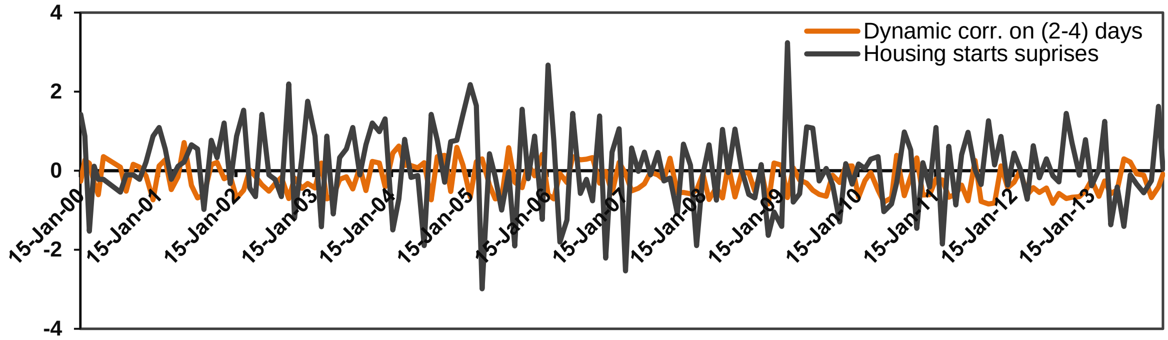
Variable	Scale	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2
Average Hourly Earning	0	0.00	-0.13	0.02	0.88	-0.01	0.01	0.54	0.05	1.02	0.00
	1	-0.04	-1.18	0.02	-0.29	0.00	-0.01	-0.21	-0.08	1.30	-0.01
	2	-0.03	-0.58	-0.24***	-2.68	0.01	0.01	0.26	0.14	1.17	-0.01
	3	0.03	0.56	0.17	1.31	0.00	-0.04	-0.67	0.09	0.70	-0.01
CPI	0	-0.01	-0.48	0.00	-0.15	-0.01	-0.01	-0.51	0.05	0.81	-0.01
	1	**0.05***	1.72	**0.18*****	2.68	0.03	**0.07****	2.33	0.14	1.52	0.03
	2	0.00	0.04	0.03	0.21	-0.01	0.02	0.43	**0.22****	2.14	0.00
	3	-0.06	-1.04	-0.15	-0.91	0.01	-0.01	-0.11	0.08	0.43	0.00
Housing Starts	0	0.00	0.01	0.02	0.72	-0.01	-0.01	-0.46	-0.01	-0.14	-0.01
	1	-0.11***	4.19	-0.03	-0.40	0.07	-0.09***	-3.18	-0.07	-0.70	0.04
	2	0.01	0.19	0.06	0.47	-0.01	0.00	-0.08	0.14	1.02	-0.01
	3	-0.05	-0.91	-0.02	-0.11	0.00	-0.05	0.77	-0.30*	-1.80	0.01
PMI	0	0.00	0.30	-0.03	-1.10	-0.01	0.00	0.23	**-0.11*****	-2.52	0.02
	1	0.03	1.03	-0.08	-1.46	0.00	0.02	0.81	-0.06	-0.64	-0.01
	2	0.04	0.94	0.12	0.82	0.00	0.03	0.65	0.05	0.39	-0.01
	3	0.08	1.27	-0.02	-0.14	0.00	0.10*	1.76	-0.03	-0.20	0.00
Retail Sales	0	0.01	0.79	0.05	1.58	0.00	0.01	0.61	**0.12***	1.87	0.00
	1	0.00	0.14	0.18	1.48	-0.01	-0.03	-1.09	0.14	1.30	0.00
	2	-0.07*	-1.91	-0.04	-0.26	0.00	-0.02	-0.40	**0.27***	1.73	0.00
	3	-0.04	-0.89	0.00	-0.01	-0.01	-0.10	-1.58	-0.23	-1.51	0.01

Figure 4.4 Plot of the Stock and Bond 30-Year Dynamic Correlation and the Housing Starts Surprises

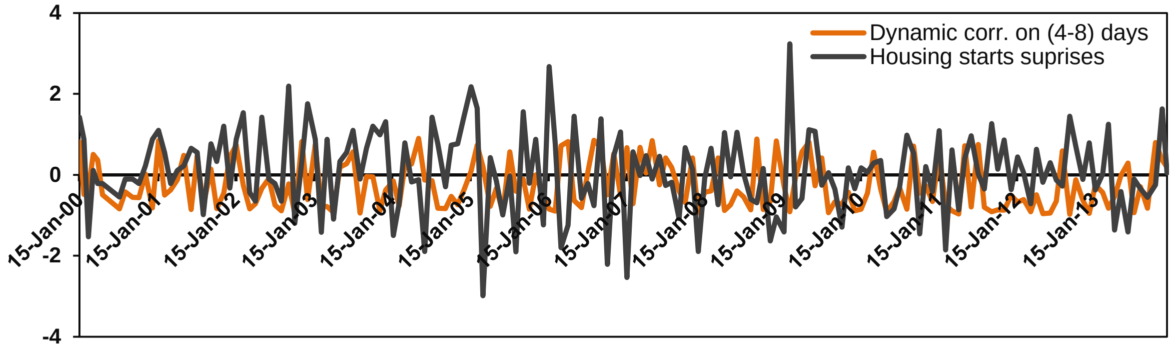
Panel (A) the Dynamic Correlation on the Day of Announcement and the Surprises Series.



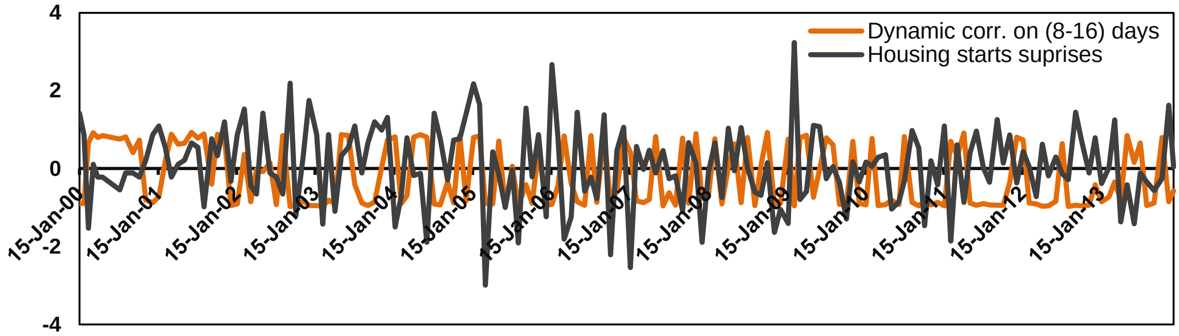
Panel (B) the Dynamic Correlation on the First Scale [2-4] days and the Surprises Series.



Panel (C) the Dynamic Correlation and the Surprises Series on the Second Scale [4-8] days.



Panel (D) the Dynamic Correlation and the Surprises Series on the Third Scale [8-16] days.



4.5 Robustness Checks

4.5.1 Extending the model: controlling for the economic policy uncertainty

The modelling approach we use above includes macroeconomic news as a single predictor. However, we may reasonably expect that the response to news is affected by uncertainty in the market. Several proxies for uncertainty have been employed in the literature, such as, the implied volatility VIX index (e.g. Kontonikas et al., 2013), the macroeconomic uncertainty measure of Jurado et al. (2015), the Cleveland financial stress index (e.g. Cardarelli et al., 2011; Fricke and Menkhoff, 2015) and the daily news-based economic policy uncertainty index (hereafter, EPU) of Baker et al. (2013).[45]

Using a policy uncertainty index for the period from 1985 to 2010, Pástor and Veronesi (2013) find that the U.S. government is to more likely change policy when economic conditions are weak and that the change is followed by high market implied and realized volatility and higher risk premiums. This, therefore, highlights the importance of considering the effects of uncertainty. As such, we now control for the level of daily EPU, both during and outside the 2008 crisis period:

$$\rho SBm_t = \alpha + (1 - D_t^{CRISIS}) \ \left[\textstyle\sum_{k=1}^{n} \beta_1 \, u_k + \ \beta_2 \, EPU_t\right] + D_t^{CRISIS}\left[\textstyle\sum_{k=1}^{n} \beta_3 \, u_k + \beta_4 \, EPU_t\right] + \ e_t$$

(4.9)

Where the level of $\mathrm{EPU_t}$ is scaled down by 100, then matched with the macroeconomic announcement days for each month. We focus on the effect of both macroeconomic news and economic policy uncertainty during the 2008 crisis as measured by β_3 and β_4 . We expect that the impact of some news on the dynamic correlation to vary after controlling for policy uncertainty. In particular, we are interested in possible under-reaction or over-reaction to announcements, where there is the potential for investors to react differently to news received during the crisis and with uncertainty. Both the availability of the EPU index on a daily basis and its construction based on the tone of economic newspapers can help in examining the robustness of our main

[45] The EPU index has been developed based on the newspaper archives from the Access word NewsBank Service. The index is updated every day at around 6: A.M. Pacific Standard Time and constructed by counting the number of articles contain at least one of three main terms. First term is the economic or economy, second, uncertain or uncertainty and last legislation or deficit, regulation, congress, Federal Reserve or white house. The index started to be available on the daily basis in August, 2013 after being only published on a monthly frequency. For more details on the index and it is construction, see Baker et al. (2015) and www.policyuncertainity.com/us_daily.html.

findings.[46]

Figure 4.5 plots that the economic policy uncertainty variable, which exhibits substantial variability and reaches peak levels during the 2001 and 2008 crises. Periods shortly before and after the crises are also characterized by slightly higher levels of uncertainty. Surprisingly, the 2011 U.S. government debt crisis, which simultaneously occurred with Euro area debt crisis, brings much lower uncertainty than other crises, although still higher than non-crisis periods. We also note the period between January 2004 and January 2008, which lies between crisis periods, saw lower uncertainty.

Figure 4.5

Daily News-based Economic Policy Uncertainty Index of Baker et al. (2013) on Days with Macroeconomic News

This figure shows the level of EPU index divided by 100 on the days coincide with the macroeconomic news announcements. The full sample period from 03/01/2000 to 25/12/2013 with 3649 daily observations. Any day with no macroeconomic news at all is excluded from the sample. We left with 1540 observations where one of our fourteen macroeconomic news has been released.

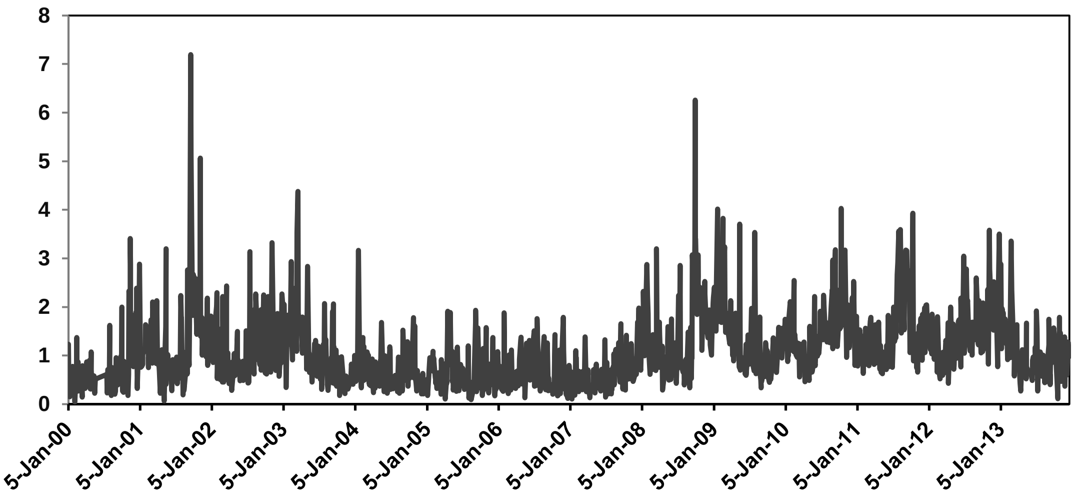


Table 4.10 reports the correlation matrix between the economic policy uncertainty and the series of original and scaled dynamic correlations. It is noticeable that the policy uncertainty variable is statistically and economically correlated with the dynamic correlation series on the same day of

[46] The EPU index as a proxy for U.S. political economic tension is almost a comparable measure with the daily sentiment media index of Tetlock (2007) and Garcia (2013). All of these proxies are based on the U.S. newspapers and constructed from pessimistic words. We expect that including the level of any one of them in our regression to confound our findings. Both studies (Tetlock (2007) and Garcia (2013)) found that the effect of negative sentiment media on DJIA return tends to reverse in about a week and we expect to find similar reversed effect on the stock-bond dynamic correlation using the EPU index. Moreover, the data for their media sentiment index is only available until January 2006 which prevents us from using this proxy with the EPU index.

announcement, regardless of which macro news is announced. In terms of the correlation sign, it is negative when both the bond of 2- and 30-years maturity are used to construct the portfolio. This suggests that policy uncertainty and the stock-bond correlation do not respond in a consistent manner to the announcement of macroeconomic news. The absolute magnitude of the correlation on average is stronger with the stock-bond correlation series at the higher maturity bonds, albeit the changes are small. The average value is -0.381 on the announcement days for the 30-year bond and -0.354 for the two-year bond and stock correlation.

Turning our attention to the days following the announcements, the correlation level decreases and is particularly low for the stock and bond 2-year return correlation. Comparing the results across different announcements, the correlation tends to stay statistically significant in the second and third scales for each correlation series only when EPU is matched with the consumer credit releases. While for imports and retail sales, the correlation typically remains significant. Also for three of the announcements, housing starts, CPI and industrial production, the correlation is significant in the first day.

Table 4.10
Correlation Matrix: Economic Policy Uncertainty and the Dynamic Correlation on Announcement Days

This table repots the contemporaneous correlation between the level of the economic policy uncertainty of Baker et al. (2015) and the stock-bond dynamic correlation. For each macroeconomic factor only the 168 days of announcements are selected. The columns in the Table (I), (II) show the cases when the dependent variable is the dynamic correlation between the DJIA and standard bench mark index return at 2 years and 30 years, respectively. Scales 0, 1 2 and 3 denote the day of announcement, [2-4] days, [4-8] and [8-16] days following the announcements respectively. The last row shows the average correlation across all the macroeconomic factors. The sample period from January 2000 to December 2013. *, ** and *** denote statistical significant at 10%, 5% and 1%, respectively.

	(I)				(II)			
	0	1	2	3	0	1	2	3
Average Hourly Earning	-0.391***	-0.086	0.073	0.049	-0.434***	-0.240***	-0.208***	0.027
Business Inventory	-0.381***	-0.057	-0.060	-0.019	-0.394***	-0.138***	-0.212***	-0.029
Consumer Credit	-0.382***	-0.141*	-0.153**	-0.022	-0.386***	-0.284***	-0.181*	-0.065
CPI	-0.294***	-0.004	0.018	-0.032	-0.317***	-0.077	0.043	-0.019
Factory Goods Orders	-0.381***	-0.057	-0.060	-0.019	-0.394***	-0.138*	-0.212***	-0.029
Housing Starts	-0.269***	0.033	-0.073	0.068	-0.274***	-0.045	-0.034	0.016
Import	-0.368***	-0.084	-0.195***	0.010	-0.458***	-0.211***	-0.253***	-0.169*
Industrial Production	-0.363***	-0.072	-0.021	-0.028	-0.366***	-0.123	-0.014	-0.093
New Single-Family Home Sales	-0.335***	-0.107	-0.038	-0.024	-0.344***	-0.169*	-0.106	-0.010
Personal Income	-0.348***	-0.087	-0.052	0.003	-0.382***	-0.202***	-0.167*	0.002
Chicago PMI	-0.335***	0.028	-0.104	-0.003	-0.330***	-0.038	-0.247***	-0.025
PPI	-0.371***	-0.149*	-0.134*	-0.106	-0.356***	-0.233***	-0.035	-0.164**
Retail Sales	-0.352***	-0.161*	-0.085	0.003	-0.463***	-0.242***	-0.210***	-0.180*
Unemployment Rate	-0.391***	-0.086	0.073	0.049	-0.434***	-0.240***	-0.208***	0.027
Average	-0.354	-0.074	-0.058	-0.005	-0.381	-0.170	-0.146	-0.051

Table 4.11 reveals that across all the macro news in the regression, the effect of EPU appears highly significant on the news announcement day during the 2008 crisis period. Of note, on the announcement day, average hourly earnings, import, retail sales and unemployment show the

strongest overall effect as measured by the adjusted R^2. In this exercise, we are particularly interested to examine how the reaction to macroeconomic news is affected once we control for the EPU level. Three news announcements, average hourly earnings, personal income and unemployment lose their statistical significance on the day of the announcement. Business inventory, on the other hand, maintains it is significance level but at a lower level compared to when the effect of policy uncertainty was ignored. Notably, four of the macro news announcements, business inventory, consumer credit, industrial production and new single-family house sales, show an immediate highly significant impact across all series. While business inventory appears to have a significant effect across most scales. Notably, this macro news is released earlier in the day and week.

For the analysis that considers [2-4] days (scale 1) following the announcement, the significance of EPU disappears except for consumer credit. Business inventory news shows a gradual and strong impact on the stock and 2-year bond dynamic correlation from one scale to another. The impact that housing starts, unemployment and retail sales are now significant at the second scale for both estimated dynamic correlation series. This can support our initial assumption of under-reaction to some news announcements during the crisis period due to a high level of uncertainty. On the third scale, consumer credit still has a strong impact on the dynamic behavior of stock and 2-year bond returns.

Overall, the findings in Table 4.11 suggest that when U.S. investors are confronted with a high level of uncertainty during the recent crisis period, they tend to under-react to some news (consumer credit and new single-family house sales) that are released early both on time and in the month. On the contrary, they over-react to other news announcements released later in time.[47]

[47] We replaced the EPU with an index of weekly sentiment as constructed by subtracting the bear from the bear series of the Investor Intelligence Sentiment Index Survey. We assumed that the weekly values of bull-bear are constant during the week. The sentiment, as described by Datastream, is released every Wednesday morning and reflects the outlooks of over 100 independent financial markets newsletters writers. The series data are provided to us by Datastream. The outlook is one of three. First, ''Bull'', optimistic with a recommendation to buy stocks. Second, ''Bear'', which is a negative outlook with a suggestion to raise cash and sell stocks. Last, ''Correction'' position preferably to be in one of the two directions, one to buy with newsletter writers being cautiously optimistic when the market is rising, the other when they recommend to sell when the market is declining. In our untabulated results, we also find that effect of bull-bear investor sentiment is always significant in the first day, but notably on the dynamic correlation between the stock and bond 2-year of maturity bond returns. This effect, however, tends to reverse on the next days following the announcements, with the impact of consumer credit, for example, became significant on all the series on the same day of announcement. Our finding here of the reversal effect of either the bull-bear sentiment or the EPU supports that of Tetlock (2007) and Garcia (2013).

Table 4.11

Controlling for the Economic Policy Uncertainty with the 2008 Crisis Dummy

This table reports the macroeconomic announcement effect as measured by β_3 and the economic policy uncertainty effect, $\beta_{4,}$ from the model:

$$\rho SBm_t = \alpha + [(1 - D_t^{CRISIS}) \sum_{k=1}^{n} \beta_1 \, u_k + \beta_2 \, EPU_t + D_t^{CRISIS} \sum_{k=1}^{n} \beta_3 \, u_k + \beta_4 \, EPU_t] + e_t$$

Where ρSBm_t is the dynamic conditional correlation between the given stock index return under consideration, *S*, and the benchmark bond market index return *B* at either *m* equals to 2 and 30 years of maturity respectively, where here *B* denotes the number of years to maturity. D_t^{CRISIS} is the global crisis dummy variable which is equal to 1 during the crisis and zero otherwise. *EPU* is the level of the daily news-based economic policy uncertainty index of Baker et al (2015)'s, where only the days of macroeconomic news announcement are matched with those from the EPU series. Scales 0, 1 2 and 3 denote the day of announcement, [2-4] days, [4-8] and [8-16] days following the announcements respectively. The crisis period is defined from September 2008 to March 2009. *, ** and *** denote statistical significant at 10%, 5% and 1%, respectively. The estimation used White (1987) test.

		(I)					(II)				
Variable	scale	β_3	*t*-stat	β_4	*t*-stat	Adj. R^2	β_3	*t*-stat	β_4	*t*-stat	Adj. R^2
Average Hourly Earning	0	-0.03	-0.93	**-0.09*** **	-8.09	0.13	-0.03	-0.47	**-0.11*** **	-5.67	0.18
	1	-0.22	-1.54	**-0.02**	-0.29	-0.01	-0.25	-1.42	-0.05	-0.57	0.05
	2	-0.30	-0.83	0.10	1.05	-0.01	0.00	0.02	-0.23***	-3.31	0.02
	3	**-0.08**	-0.96	-0.17***	-3.71	0.03	-0.09	-0.17	0.18	1.41	-0.01
Business Inventory	0	**0.03** **	2.29	-0.10***	-6.03	0.13	**0.07*** **	4.08	**-0.09*** **	-4.04	0.14
	1	**0.15*** **	3.42	0.07	0.93	-0.01	**0.11* **	1.86	-0.02	-0.19	0.00
	2	**-0.33*** **	-2.87	-0.16	-1.27	0.00	**-0.29*** **	-3.00	**-0.40*** **	-3.99	0.03
	3	**-0.47*** **	-4.05	**-0.42*** **	-5.09	0.01	-0.08	-0.26	0.02	0.10	-0.02
Consumer Credit	0	**0.05*** **	4.47	**-0.10*** **	-9.25	0.14	**0.05*** **	2.83	-0.11***	-5.99	0.14
	1	0.02	0.20	-0.15***	-3.87	0.01	-0.06	-0.35	-0.17***	-3.20	0.04
	2	-0.09	-0.40	-0.09	-0.91	-0.02	-0.11	-0.97	**-0.16*** **	-2.88	0.00
	3	0.09	1.20	**-0.28*** **	-4.23	0.00	**-0.49* **	-1.70	0.07	0.59	0.00
CPI	0	-0.02**	-2.30	**-0.09*** **	-6.44	0.08	-0.02	-1.44	-0.09***	-3.96	0.08
	1	-0.03	-0.27	-0.01	-0.07	0.01	0.05	0.35	-0.01	-0.08	0.03
	2	0.16	1.03	0.09	0.57	-0.02	0.15	0.76	0.07	0.39	-0.02
	3	-0.27*	-1.85	-0.11	-0.76	-0.01	-0.21	0.97	-0.10	-0.65	-0.02
Factory Goods Orders	0	0.01	0.70	**-0.14*** **	-7.00	0.17	0.03	1.16	**-0.15*** **	-6.06	0.14
	1	-0.04	-0.73	-0.03	-0.48	-0.02	-0.05	-0.63	-0.07	-0.88	0.01
	2	0.13	1.58	**-0.04**	-0.35	-0.01	0.17***	2.74	**-0.33*** **	-4.18	0.04
	3	-0.01	-0.10	-0.22**	-2.42	0.00	-0.07	-0.44	0.14	0.92	0.00
Housing Starts	0	0.00	0.19	**-0.07*** **	-5.07	0.06	0.00	0.07	-0.06***	-3.52	0.05
	1	-0.13**	-2.27	-0.02	-0.37	0.06	-0.09	-1.32	-0.03	-0.52	0.03
	2	-0.14*	-1.93	-0.03	-0.31	-0.01	-0.21***	-2.65	-0.01	-0.14	-0.01
	3	-0.31***	-3.86	**0.01**	0.12	0.00	-0.12	-0.73	0.09	0.91	-0.01
Import	0	0.01*	1.71	**-0.11*** **	-8.61	0.12	0.01	0.54	**-0.13*** **	-7.37	0.19
	1	0.05	1.02	-0.08	-0.88	0.00	0.12*	1.92	-0.08	-1.03	0.04
	2	**0.16** **	2.00	-0.21***	-2.17	0.03	0.06	0.30	-0.20	-1.21	0.05
	3	**-0.43*** **	-4.41	0.07	0.57	0.02	-0.11	-0.51	-0.20	-1.17	0.01
Industrial Production	0	**0.03*** **	4.09	**-0.09*** **	-8.20	0.13	0.04***	4.36	-0.10***	-5.77	0.12
	1	0.01	0.22	0.01	0.15	0.00	0.00	-0.08	-0.01	-0.11	0.01
	2	**-0.12* **	-1.95	**-0.16** **	-1.93	0.01	-0.11***	-2.38	-0.13	-1.52	-0.01
	3	0.03	0.29	0.00	-0.02	-0.01	0.13**	2.02	0.01	0.07	0.00
New Single-Family Home Sales	0	0.05***	3.07	**-0.09*** **	-5.50	0.11	0.05***	3.34	-0.08***	-4.21	0.11
	1	-0.06	-0.92	**-0.04**	-0.61	-0.01	0.05	1.20	-0.03	-0.55	0.01
	2	-0.05	-0.52	-0.04	-0.33	-0.02	0.03	0.34	-0.12	-1.06	-0.01
	3	**0.30**	1.58	**0.31*** **	3.24	0.03	**0.36*** **	3.17	0.12	1.04	-0.01
Personal Income	0	0.00	-0.21	-0.09***	-9.28	0.11	-0.03	-1.33	-0.09***	-5.66	0.13
	1	**0.22** **	2.21	0.00	0.03	0.02	0.00	-0.03	-0.04	-0.46	0.06
	2	**0.49*** **	7.66	**-0.05**	-0.89	0.01	0.32	2.47	-0.10	-0.99	0.03
	3	-0.13	-0.65	**0.17**	1.69	-0.01	-0.04	-0.17	0.17	1.46	0.02

Table 4.11 (Continued)
Controlling for the Economic Policy Uncertainty with the 2008 Crisis Dummy

		(I)					(II)				
Variable	Scale	β_3	*t*-stat	β_4	*t*-stat	Adj. R^2	β_3	*t*-stat	β_4	*t*-stat	Adj. R^2
Chicago PMI	0	**0.04*** **	3.47	-0.05***	-9.58	0.10	0.03*	1.77	-0.06***	-6.82	0.11
	1	0.18	1.64	0.00	0.02	-0.01	0.19	1.57	0.01	0.14	-0.01
	2	-0.04	-0.17	-0.02	-0.51	0.00	0.13	1.09	-0.16***	-3.88	0.04
	3	0.07	0.61	0.13***	2.47	0.01	0.25	1.55	0.06	0.94	0.00
PPI	0	0.00	-0.14	-0.07***	-3.64	0.13	-0.01	-0.45	-0.07	-3.00	0.13
	1	-0.03	-0.20	-0.03	-0.25	0.01	-0.06	-0.61	-0.06	-0.78	0.05
	2	**-0.19*** **	-2.84	**-0.24*** **	-4.64	0.01	-0.08	-0.62	-0.12	-1.37	-0.01
	3	-0.20	-0.82	-0.03	-0.15	0.02	-0.35**	-2.40	-0.31***	-4.55	0.02
Retail Sales	0	0.00	-0.41	**-0.11*** **	-8.79	0.11	0.00	0.00	-0.12***	-7.66	0.20
	1	-0.01	0.10	-0.01	0.11	0.01	**-0.11*** **	-2.56	-0.10	-1.45	0.05
	2	-0.11***	-3.00	**-0.27*** **	-4.33	0.01	-0.14*	-1.86	-0.24***	-2.92	0.03
	3	0.10	0.83	**0.33*** **	3.04	0.00	-0.05	-0.32	**-0.20**	-1.12	0.03
Unemployment Rate	0	-0.02	-0.59	-0.09***	-8.97	0.13	-0.05	-1.09	**-0.10*** **	-7.02	0.19
	1	-0.14	-0.98	-0.01	-0.20	-0.01	-0.09	-0.67	-0.06	-0.82	0.05
	2	**0.67*** **	3.36	**-0.14**	-1.65	0.01	**0.45** **	2.03	-0.37***	-3.86	0.03
	3	**-0.06**	-1.28	**-0.19*** **	-3.72	0.05	-0.31	-0.88	0.25	1.56	-0.01

4.5.2 Dow Jones small-cap value and small-cap growth indexes

Another issue that might confound our results is that the use of the DJIA composite index comprises of large companies in the U.S. market. An argument for this choice is that large companies will be more affected by macroeconomic news compared to small companies, whose price, return and volatility are more likely to be driven by investor sentiment. Several studies address the role of sentiment in mispricing. For example, Lemmon and Portniaguina (2006) find that high consumer confidence predicts lower future returns of small cap value stocks but not of the growth stocks. Baker and Wurgler (2007) argue that the index construction process influences the effect of sentiment on the return; the value weighted index with low institutional ownership will be less affected by the investor sentiment. Based on this argument, we replaced our DJIA composite index with DJIA small value and the small growth indexes. Here, we expect a lower reaction to news in the behaviour of the dynamic correlation series.

Table 4.12 replicates the analysis in Equation (4.8) using the small value and growth return series.[48] Panel A presents the results using the small value index and Panel B for the small growth index. We can see that on the announcement day, average hourly earnings news still exhibits a significant effect on all series. For other news announcements, single-family house sales also shows an impact on all the correlation series in both panels in the first day outside the crisis, with this effect more pronounced on small value stocks.

[48] The regression estimates for other macroeconomic news are available upon request.

Table 4.12
Small Cap Value and Growth Indexes, 2008 Crisis Dummies

This table reports β_1 and β_2 coefficient estimates from the non-linear regression with White (1987) standard errors of the model:

$$\rho SBm_t = \alpha + [(1 - D_t^{CRISIS}) \sum_{k=1}^{n} \beta_1 u_k + D_t^{CRISIS} \sum_{k=1}^{n} \beta_2 u_k] + e_t$$

Where ρSBm_t is the dynamic conditional correlation between either the Dow Jones small cap value index return (panel a) or Dow Jones small cap growth index return (panel b) and the benchmark bond market index return B at either m equal to 2 and 30 years of maturity respectively, where here B denotes the number of years to maturity. $D_t^{CRISIS}$is the global crisis dummy variable which is equal to 1 during the crisis and zero otherwise. Scales 0, 1 2 and 3 denote the day of announcement, [2-4] days, [4-8] and [8-16] days following the announcements respectively. *, ** and *** denote statistical significant at 10%, 5% and 1%, respectively. For rest of notations, see Table 4.6.

Panel A: Using the Dow Jones small cap value index return

		(I)					(III)				
Variable	scale	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2
Average Hourly Earning	0	0.00	0.16	**-0.16*** **	-5.72	0.01	-0.01	0.86	**-0.01*** **	-2.49	0.00
	1	0.04	-1.29	**-0.22***	-2.01	0.00	0.00	0.06	**-0.18**	-1.68	-0.01
	2	-0.01	-0.22	-0.25	-0.83	-0.01	0.03	0.50	0.06	0.48	-0.01
	3	0.05	0.86	**-0.54*** **	-3.42	0.00	-0.07	-1.19	0.16	0.34	0.00
Consumer Credit	0	0.00	0.25	0.07	1.62	0.00	0.02	0.98	0.07	1.54	0.00
	1	-0.01	-0.23	-0.20	-1.27	0.00	0.03	0.79	-0.03	-0.24	-0.01
	2	0.01	0.27	**0.59*** **	4.39	0.02	-0.01	-0.11	**0.58*** **	4.92	0.02
	3	-0.03	-0.48	-0.18	-0.58	-0.01	0.02	0.38	-0.12	-0.50	-0.01
CPI	0	-0.02	-1.54	0.05	-1.55	0.01	-0.01	-0.83	0.04	1.18	0.00
	1	0.04	1.22	-0.07	-0.96	0.00	0.06*	1.93	0.03	0.26	0.01
	2	0.05	1.00	0.07	0.65	0.00	-0.01	-0.22	0.10	0.83	-0.01
	3	0.04	0.66	**-0.21***	-2.00	0.00	0.08	1.29	0.13	1.15	0.00
Factory Goods Orders	0	0.00	0.02	0.02	0.66	-0.01	0.00	0.23	0.06	1.04	-0.01
	1	-0.01	-0.17	0.12	0.95	-0.01	-0.04	-1.18	0.04	0.35	0.00
	2	-0.01	0.04	0.12	0.12	-0.01	0.02	0.48	0.26**	1.98	0.00
	3	0.07	1.11	-0.11	-0.50	0.00	0.07	0.99	-0.23	-1.49	0.00
Housing Starts	0	0.00	-0.21	0.04	0.82	-0.01	-0.01	-0.65	0.04	0.94	-0.01
	1	-0.11***	-3.65	**-0.12***	-1.79	0.07	-0.08***	-2.67	**-0.13**	-1.36	0.04
	2	0.02	0.51	-0.14	-1.45	0.00	0.02	0.45	-0.21**	-2.18	0.00
	3	-0.02	-0.35	-0.19*	-1.73	0.00	0.02	0.27	-0.01	-0.05	-0.01
Industrial Production	0	0.00	-0.20	0.03	0.89	0.00	0.01	0.36	0.04	1.37	0.00
	1	-0.01	0.72	0.00	0.96	-0.01	-0.01	-0.24	-0.04	-0.62	-0.01
	2	0.01	0.22	**-0.08***	-1.69	-0.01	-0.02	-0.32	**-0.07***	-1.81	-0.01
	3	0.02	0.24	0.10	1.58	-0.01	0.13**	1.93	0.03	0.33	0.01
New Single-Family Home Sales	0	0.02*	1.71	0.05*	1.72	0.01	0.03*	1.71	**0.06*** **	3.21	0.01
	1	0.01	0.46	**-0.20*** **	-2.64	0.00	0.00	-0.15	-0.01	-0.10	-0.01
	2	-0.04	-0.83	-0.04	-0.22	-0.01	-0.07	-1.46	0.01	0.08	0.00
	3	0.03	0.55	**0.28***	1.69	0.00	0.05	0.91	**0.35***	2.64	0.00

Panel B: Using the Dow Jones small cap growth index return

Variable	scale	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2
Average Hourly Earning	0	0.00	0.20	**-0.17*** **	-5.86	0.01	0.01	0.87	**-0.14*** **	-2.93	0.00
	1	-0.03	-1.42	-0.03	0.49	0.00	-0.01	-0.31	**-0.08***	2.04	-0.01
	2	0.00	0.07	**-0.35***	-2.11	0.01	0.05	1.27	-0.12	-0.38	0.00
	3	0.07	1.30	0.33	1.15	0.00	-0.02	-0.31	0.11	-0.25	-0.01
Consumer Credit	0	0.00	-0.07	0.00	-0.16	-0.01	0.00	0.04	0.03	0.66	-0.01
	1	-0.03	-1.03	0.23*	-1.76	0.01	0.02	0.70	-0.27*	-1.76	0.01
	2	0.00	-0.03	**0.43*** **	3.61	0.00	-0.01	-0.25	**0.57*** **	4.96	0.02
	3	-0.11	-1.92	-0.11	-0.39	0.01	-0.01	-0.17	0.13	-0.54	-0.01
CPI	0	-0.02	-1.32	0.05*	1.70	0.01	-0.01	-0.60	0.04	1.35	-0.01
	1	0.00	0.01	-0.06	-1.33	-0.01	0.01	0.26	0.03	0.24	-0.01
	2	0.01	0.27	-0.04	-0.24	-0.01	0.01	0.12	0.06	0.46	-0.01
	3	0.01	0.22	**-0.41*** **	-8.30	0.02	0.12**	2.04	0.02	0.11	0.01

Table 4.12 (Continued)
Small Cap Value and Growth Indexes, 2008 Crisis Dummies

	(I)						(III)				
Variable	Scale	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2	Scale	β_1	*t*-stat	β_2	*t*-stat
Factory Goods Orders	0	0.00	0.07	0.07	1.55	0.00	0.01	0.61	0.07	1.52	0.00
	1	-0.01	-0.46	0.02	0.30	-0.01	0.01	0.33	**-0.08*** **	-3.28	-0.01
	2	-0.02	-0.45	0.11	0.76	-0.01	0.02	0.45	0.16	1.29	-0.01
	3	0.07	1.32	-0.20	-0.86	0.00	0.08	1.22	-0.21	-1.30	0.00
Housing Starts	0	0.00	-0.10	0.04	0.78	-0.01	-0.01	-0.29	0.03	0.70	-0.01
	1	-0.06**	-2.38	**0.00**	0.02	0.02	-0.01	-0.33	-0.09	-0.94	-0.01
	2	0.03	0.56	-0.05	-0.50	-0.01	0.04	0.83	-0.19**	-1.96	0.00
	3	-0.02	0.39	-0.28***	-2.74	0.00	0.00	0.03	-0.15	-0.11	-0.01
Industrial Production	0	0.00	-0.07	0.03	0.84	0.00	0.01	0.39	0.03	1.26	0.00
	1	0.06*	1.85	**0.09*** **	6.48	0.04	0.06*	1.85	**0.06**	1.66	0.02
	2	0.03	0.50	-0.04	-0.85	-0.01	-0.02	-0.34	**-0.11*** **	-2.33	0.00
	3	-0.04	-0.61	0.14**	2.01	0.00	0.08	1.15	0.01	0.07	0.00
New Single-Family Home Sales	0	0.02	1.64	0.05	1.62	0.01	0.03*	1.75	0.04**	2.20	0.01
	1	0.01	0.23	0.01	0.17	-0.01	-0.02	-0.63	0.02	0.10	-0.01
	2	0.00	0.10	-0.01	-0.05	-0.01	-0.04	-0.93	**0.03**	0.19	-0.01
	3	0.05	0.74	**0.32*** *	2.20	0.00	0.03	0.59	**0.30***	1.92	0.00

Beyond the announcement days and from both panels, the impact of the consumer credit becomes significant in the [2-4] days scale, but is not significant on the third scale. The strong reaction to both average hourly earnings and the consumer credit news seems to be consistent. That is because the individual investors who own the small stocks are usually concern about the macro news which affects their investment positions as well as personal spending. Furthermore, comparing Panels A and B regarding the reaction across different scales, some pertinent points can be raised. First, housing starts news seems to significantly affect the two series, outside the crisis on the first scale when we include the small value stock return in the portfolio, yet this is less evident for the small growth stocks. Second, the impact of the CPI at all the series in the first scale is small outside the crisis and even less when the small growth indexes are used in our analysis. Third, industrial production brings an economically small, though significant, effect for both second scaled-correlation series during the crisis period. Similarly, it significantly affects the correlation series comprising of the 30-year bond return in the first scale as shown in Panel B.

From Table 4.12, we find that the reaction of the stock-bond correlation to news for the small value and growth returns is generally lower than for larger firms. Yet, the results for some news, including the average hourly earnings, CPI, housing starts and industrial production, somewhat resembles those in Tables 4.7 and 4.8.

4.5.3 The simultaneous effect of all macroeconomic news announcements

Announcing more than one piece of macro news in the same day has the potential to raise conflicting information with investors, which may in turn affect how they intend to rebalance their portfolios, potentially at the end of month. To check whether our findings are affected by this issue, we estimate a regression with all the macroeconomic news acting as predictors at the same time. We exclude any observation from the correlation series that is not matched with the occurrence of one or more macroeconomic news. Hence, we are left with 1540 observations. Our (untabulated) findings are analogous to those presented in Tables 4.7 and 4.8. For example, the surprises of average hourly earnings, industrial production, personal income, still show a significant effect on the series on the announcement day. Macro surprises such as housing starts, CPI maintain their significant effect outside the crisis on the first scale. Yet, [4-8] days following the release, the reaction to the housing starts became significant and even economically stronger, and this again consistent across all the series. The explanation of 'late releases-slow dynamic correlation's reaction' still holds for industrial production on the second scale, for consumer credit, new single-family house sales, factory goods order on [8-16] days.

4.6 Other (untabluated) robustness checks[49]

4.6.1 Different model to estimate the dynamic correlation

We argue that our main results using the 2008-2009 crisis setting might also be sensitive to the selection of the multivariate model GARCH. To examine this issue further, we used the diagonal versions of BEKK-GARCH model of Engle and Kroner (1995) and the DCC-GARCH model of Engle (2002). These two other competing models have been compared in the literature based on the similarities and differences (see, for example, Caporin and McAleer, 2012). Yet, our results using the DCC model are qualitatively and quantitatively similar to our main findings. For example, the CPI and housing starts surprises still show a significant effect on both the correlation series outside the crisis on the first scale. Furthermore, 'late releases-slow dynamic correlation's reaction' is again presence in our analysis.

Applying the BEKK model still shows significant effects for the average hourly earnings, business inventory and personal income at the first scale. The findings for other news and the BEKK model are qualitatively similar. In sum, our findings are not driven by the selection of the model to estimate the dynamic correlation. This is more evident with the DCC version than with the BEKK model.

[49] These are available upon request.

4.6.2 Controlling for the effect of news on volatility

Following Brenner et al. (2009), we control for the effect of news on the volatility as interacted with the 2008 crisis dummy and the coefficient for the non-crisis period, before we estimate the dynamic correlation. More specifically, the new analysis mainly involved inserting the macro news surprises on the variance equation for the EGACRH model, before fitting the model on the time scales. In the next step, the standardised residuals are extracted at each time-scale and the new correlation series has been prepared for the regression analysis. Our results are very similar to our main findings. Additionally, both the CPI and consumer credit tend now to show a significant effect on both correlation series during the crisis at the first time-scale. The results from this robustness check then confirm that the effects of our macro surprises on the volatility do not persist to the higher investment horizons. This later finding becomes in line with the related literature summarised in Section 4.2.1.

4.6.3 Alternative definitions for the 2008 crisis

Two definitions for the 2008/2009 are used again in the analysis. Often the point in time when credit spreads started to increase substantially (around mid-2007) is used as a starting date for the crisis period. This is also graphically documented as a break date in both correlation series in Figure 3. The new starting date of 13/06/2007 is then considered. The other date we assumed is 09/08/2007. However, the effects of most of the announcements still significantly exist with almost the same sign. For example, the CPI and housing starts exhibit significant impact at the first-time scale outside the crisis period, regardless of it is definition. Our finding for the effect of late releases still holds for factory goods on the stock-2-year bond correlation at the second-time scale during the crisis, though it is positive and economically high on all other series with both definitions. The same is true for the industrial production at the second time-horizon and the consumer credit with high economic impact at the third time-scale. Considering either of the crisis new starting dates, personal income shows a negative and significant effect on the 2-year bond at the third scale, while significantly positive non-crisis effect on the stock-30-year bond correlation series. New single house sales surprises continue to have significant impact on the series on the same day of announcement under both crisis settings. Their clear high economic effect on the higher time scales is still presence in our analysis. Generally, the definitions of the 2008 crises do not to matter too much, the idea that the real crisis started in 2008 seems to be more reasonable. This is what we noted when it comes to analysing the impact of macro news. The same conclusion is statistically reached by Kontonikas et al. (2013) for examining the impact of fed funds rate surprises on the U.S. stock return.

4.6.4 Alternative Wavelet Decomposition Approach: the Haar à trous wavelet (HTW) transform

We also use the Haar à trous wavelet (HTW) transform of Murtagh et al. (2004) as alternative to MODWT multiresolution approach. HTW combines between the non-decimated trous and the Haar wavelet. The advantage of HTW wavelet is that it does not suffer from the boundary problems. Yet, same as MODWT, HTW keeps the same number of observations at each resolution level and it is also a translation invariant approach. Mathematically, HTW also relies on the mother (father) wavelet to extract the details (approximation) components from the original time series. The results we obtain after applying the HTW at 6 time-scales are qualitatively similar to what we obtained before for the regressions with the 2008 crisis. For example, the impact of average hourly earnings at the first time-scale on the both correlation series is still obvious (from the graphs) and even significant on the stock and bond 2-year correlation series. It is effect is now significant and negative at time scale=3 on stock and bond 2-year correlation. Negative and significant effect of consumer credit is found on the third-time scale on the stock and bond 30-year correlation during the crisis period.

The impact is significantly different across the crisis and non-crisis periods. The same finding we observe from the graphs. The results for the impact of the CPI outside the crisis on the first scale is qualitatively similar and that is obvious from the graphs and especially for the period before the crisis, but not after- the reverse is true (more outside the crisis) for the impact on stock-bond 30-year bond. On the other hand, the impact of factory goods on the stock-bond 30-year correlation at the third-time scale became positive and highly significant. Regarding the impact of housing starts, it is negative and significant outside the crisis on the stock and bond 30- year correlation, and this relation is qualitatively (graphically) similar on the stock and bond 2- year correlation series. Industrial production surprises show positive and significant effect at the third-time scale on both series. The impact of personal income, is now positive and economically higher at the third time-scale, while it shows a significant impact on the stock and bond 2-year correlation series. The same is also graphically observed on the stock and bond 30-year correlation. Significant, but negative impact of the new single house sales is, on the other hand, found at the third-time scale during the crisis and more specifically when the 2-year bond is used. The same relation is qualitatively observed from graph for on the stock-bond 30-year correlation series.

To sum up, the results with the HTW are then qualitatively similar for: 1-the outside impact of housing and CPI on the first time-scale and 2- for the late macro news announcement-delay in response of the correlation to those macro announcements.

4.6.5 The asymmetric effect of the macroeconomic news

We used the absolute values of the macro news in all the regressions again to check further whether the results are nor driven by the sign of the macro news. The results end up being qualitatively and quantitatively the same regarding the effect of CPI and Housing starts outside the crises periods and the 'late releases-slow dynamic correlation's reaction' evidence.

4.7 Summary and Conclusion

This study analyses the effect of macroeconomic news on the stock and bond return dynamic correlation in the United States. Our interest centres on the impact of fourteen macro news announcements on the correlation both on the announcement day and up to sixteen days afterward. Moreover, we separate out the impact during and around the recent 2008-2009 crisis and provide comparison to other crisis periods. Using the wavelet transform, we are able decompose the original return series across scales that cover [2-4], [4-8] and [8-16] days after the announcements before estimating the dynamic correlation with each scaled return series using the diagonal version of the asymmetric DCC-GARCH model of Cappiello et al. (2006).

After regressing the scaled dynamic correlation on each macro news series, our results can be summarised as follows. First, and consistent with the majority of the literature, we find very little evidence that the macroeconomic news surprises affect the equity price and stock-bond return dynamic correlation over our full sample period from 2000 to 2013. However, our evidence reveals that when controlling for the financial crisis of 2007-2008, some announcements tend to significantly affect all the correlation series on the first day with this impact being notable throughout the crisis period. Second, and for analysis performed on the wavelet scales, we find a link between the speed of reaction of the dynamic correlation to news surprises and the timing of announcements both in terms of time of the day and day of the week. For example, news such as factory goods order, the industrial production, the consumer credit and the new-single family house sales which are released early in terms of both the time of day and time of the month, show a slower effect on the dynamic correlation than those released later in the month. The impact of early macroeconomic news seems to be fully incorporated into correlation process 4-8 days after they have been announced. Third, from all the surprises series, the CPI and housing starts effects tends to persist up to [2-4] days after the announcement day. Moreover, these are the only two releases to show a significant and consistent effect on all the correlation series outside the crisis period. Finally, as an additional analysis, we find that the effect of most surprises, either on the day of announcements or up to 16 days later, disappears after replacing the 2008 crisis with the

2001 Dot-com crisis or 2011 U.S. government debt ceiling dispute periods. Yet, the effect of both CPI and housing starts as the most prominent outside the crisis periods remain. This supports our approach in which investigating the effect of news surprises by separating the effects between crisis and non-crisis periods. Moreover, this appears to be preferred over an analysis that differentiates between recession and expansion periods. We believe this is because the latter approach ignores differences in the level of the inflation, sentiment and uncertainty across the crisis periods.

In robustness checks, we find that our results are, largely, qualitatively robust to using the DJIA small value and growth index returns to construct the new correlation series. Although, as expected, it is noticeable that these small equities return based correlation series tend to be less affected by macroeconomic news, with some announcements exhibiting lower significance or losing their significance. This result supports the general belief that the pricing of small companies is more affected by the investor sentiment (e.g. Lemmon & Portniaguina, 2006; Baker & Wurgler, 2007). In further tests, we find that due to the high level of daily U.S. news-based economic policy uncertainty as proxied by the measure of Baker et al. (2013), the reaction of some news, including consumer credit, that tends to appear small on the announcement day, becomes higher and significant after controlling for uncertainty. We find that the effect of policy uncertainty is strong only when matched with the days of announcements and tends to revert to fundamentals afterward with the correlation being affected again by the same macroeconomic news. In a further test, in which rather than running a separate regression for each macroeconomic factor we jointly estimate all announcements effects, we find that the macroeconomic news identified as significant in individual regressions, maintain their significance in the joint regression. Doing more tests such isolating the effect of new news volatility, using different multivariate model to estimate the dynamic correlation, alternative starting date 2008 crisis and different decomposition approach continues to support more findings. Overall, it is hoped these results will enhance our understanding of the links between financial markets and the macroeconomy and will benefit investors, regulators and academics alike. Notably, a yet finding that requires further investigation is the result that early news announcements (both in the day and in the month) differ from later announcements. In particular, the effect of the announcement impacts the correlation over a longer time frame

CHAPTER FIVE

Explaining the Subsequent Trading Activity: Time-Scale Analysis for 10 Countries

Abstract

This study seeks to examine the behaviour of subsequent trading activity in the stock market. We investigate whether stock return dynamics can explain subsequent trading using wavelet time-scaled returns and volume. We begin with a wavelet decomposition of trading volume over time-scales of up to 32 days. This trading volume is then regressed on recent and decomposed returns. Furthermore, we consider both the linear and non-linear regressions and the wavelet-variance estimator. We find little evidence that recent returns predict subsequent trading, but stronger evidence is observed at longer horizons. Notably, there is greater evidence of a statistical relation over the investment horizons of [8-16] and [16-32] days. Yet, this relation has mostly a negative sign, but it is positive for two emerging markets. It also tends to be economically stronger during bull-market periods and is robust to the crisis period. We also find that stock market volatility tends to be significantly correlated with recent trading and at the longest timescale [16-32] day. The results in this paper should enable participants in the stock market as well as regulators to better understand the interrelation between returns and trading activity and the changes over different time horizons.

Keywords: Investor Overconfidence; Subsequent Trading; Recent Return; Subsequent Return; Wavelet.

5.1 Introduction

Research argues that current stock returns are related to subsequent trading volume. In answering the question as to why stock returns have such predictive power, several studies examine the role of overconfidence (e.g. Odean, 1999; Gervais and Odean, 2001; Statman et al., 2006). Accordingly, high preceding market returns leads investors to become overconfident with the result that they subsequently trade more. Research examines the behaviour of portfolio (Barber and Odeon, 2002) and market (Statman et al., 2006) returns as well as both return types (Glaser and Weber, 2009) and across international markets (Griffin et al., 2007). An open issue, however, for which the literature currently makes no prediction, regards the time scale on the interaction between returns and subsequent trading volume. Current research is typically couched in terms of whether a single lag of stock returns has predictive power for volume. This research expands that to ask over what time scale a change in returns will have a predictive effect over subsequent volume. By using a wavelet approach, we can decompose both trading volume and stock returns across different time scales and examine their interactions.

Thus, the main objective is to examine whether the recent returns significantly explain subsequent trading volume within a range of international stock markets with the specific aim of examining the time scale of predictability. The supportive evidence of predictability reported in the literature leaves open the question as to how many subsequent days trading volume is affected. Standard econometric models, such as a vector autoregressive model (see, for example, Griffin et al., 2007, among others), makes analysing trading performance beyond the first day following the past return difficult. Hence, a decomposition method is required to achieve this goal. Here, we analyse the daily trading return-trading volume relation in ten international stock markets over a twelve-year period. To examine this relation, we employ a wavelet transform to decompose trading volume over different time-scales.

The results of this study will allow us to gain a greater understanding of how investors use returns generated in the market to inform trading in the subsequent period. In doing so, we consider how past returns affect trading and over what period. Moreover, the results will be of use in understanding the functioning of markets. Taking the standard view that trading is driven by disagreement in interpreting newly arrived information to the market (see, for example, Harris and Raviv, 1993). The results here will shed light on whether movement in recent returns has predictive power for near-term trading activity, which would suggest an overstatement of the role of information arrival in trading behaviour.

Employing wavelet analysis in our study, contributes to the growing amount of research that applies wavelet transform to analyse dependencies within the area of asset pricing and the dynamic relation between the economic variables. That includes, for example, Kim and In (2005) who re-examine the relation, over a monthly frequency, between inflation and nominal returns in the U.S in accordance with the Fisher hypothesis. The study finds that both the sign and strength of relation differs across scales. Using daily Australian data, Galagedera and Maharaj (2008) demonstrate that the relation between the systematic risk and portfolio returns varies across scales. For the analysis of portfolios, Kim and In (2010) find that investors put more weight on stocks and less on Treasury bonds as the time scale increases. Gallegati and Ramsey (2013) show that both corporate stock and bond prices are proven to have different relations with the aggregate investment in the U.S. at different time-scales.

In analysing the return and trading volume relation, it has been suggested that an asymmetric rather than linear relation may prevail. Kim et al. (2003) find that individual investors in Japan tend to be more overconfident in bull-markets, while they bear high systematic risk during the bear-markets. A similar finding by Chuang and Lee (2006) suggest that U.S. investors trade more in a bull-market state. By incorporating trading volume into a simple regime switching model, Chen (2012) finds a positive and significant contemporaneous relation, and more evidence of overconfidence during bull-market periods. Thus, we will consider whether the predictive ability of returns for subsequent trading differs across different periods of market behaviour. To do so, we define the bull and bear-market regimes and investigate the relation across such market states.

A further aspect of this study is to consider behaviour around the 2008-2009 crisis period. The rationale for doing so arises from the general observation within the literature that evidence in favour of overconfidence weakens over time. From an analysis across 46 countries, Griffin et al. (2007) find that overconfidence is more pronounced for developed markets during the period from 1983 to 1992 compared to the period afterwards. Likewise, Chen (2012) demonstrates that a one month lagged market return significantly predicts the trading volume in U.S. markets for the period from 1973 to 1999 but not afterwards.[50] Thus, we are able to add to this body of evidence by considering how the relation between stock returns and volume varies over the crisis period.

The main findings can be summarised as follows. Firstly, we find only a small amount of evidence that recent returns predict the subsequent trading. However, greater evidence of predictability is

[50] However, Chen (2012)'s sample period ends on September 2008, and hence excludes the period from the Lehman brothers collapse and afterward which is usually described by the real crisis period.

observed over the longer horizons. Secondly, we find that the subsequent trading and return relation is more statistically related over the investment horizons of [8-16] and [16-32] day periods. However, this relation has mostly a negative sign, albeit positive for two developing countries. Moreover, it tends to be economically stronger during bull-market periods. This last result is robust to using the crisis related sub-periods and to an alternative selection of stock market indexes. We also find that stock market volatility tends to be significantly correlated with recent trading.

Overall, our results allow the participants in the stock market a better understanding of how the trading in financial markets takes place over time. Our study clearly differentiates between short-term and the long-term horizon investors, where the risk and liquidity factors are assumed to contribute differently to the asset pricing process across different time-scales.

The rest of the study is organised as follows. The next section summarises the related literature. Section 5.3 describes the data and the methodology used. Section 5.4 shows the empirical results. We discuss the results from the robustness checks in Section 5.5 and from the additional analysis in Section 5.6, before offering a direct discussion and interpretation for the results in Section 5.7. We summarise and conclude in Section 5.8.

5.2 Related work

In recent years several studies have considered the reasons that cause investors to trade within financial markets. In a seminal paper, Odean (1998a) presents empirical evidence that individual investors follow their previous performance before deciding to trade. Odean finds that investors are more likely to realise their winning investments and hence sell them early, while they tend to hold losers for a long period. This behaviour is consistent with the disposition effect.

Another explanation for subsequent trading behaviour is based on the work of Odean (1998b), in which overconfidence is believed responsible for excess trading. However, the study claims that whether this assumption holds or not depends on the fraction of informed investors in the market. That is, subsequent trading changes are also a function of the current proportion of the informed investors in the market as well as overconfident traders.

Barber and Odean (1999) add further evidence to the overconfidence theory and provide evidence to support the view that investors trade more when they are overconfident. The study also argues that with more successful traders in the market, the level of trading is likely to increase, but that the losses from trading may increase too. Beside confirming the findings of Odean (1998a, 1998b), Odean (1999) shows that there exists a group of investors who while initially displaying overconfidence, will continue to trade in the market in an attempt to cover any reduced returns from trading.

More recently, a further stream of research tries to understand what differentiates overconfidence from the disposition effect.[51] Statman et al. (2006) assume that overconfidence generates excess trading at the aggregate market level, while the disposition effect is related to individual stock trading. From their study on individual investors in China and in line with Odean (1998a), Chen et al. (2007) find that the disposition effect causes investors to sell early after gaining profit but to hold a losing position for a long time. Overconfident investors, instead, are assumed to trade more often.

According to Kumar (2009), a high level of market uncertainty will lead to both stronger disposition and overconfidence effects. Using data from Taiwan, Chou and Wang (2011) provide further evidence on the difference between the disposition and overconfidence effects based on investor type. Their study introduces a measure for investor aggressiveness toward the subsequent trading. They report that international institutional investors in Taiwan suffer only from overconfidence, while the behaviour of individual traders seems to be affected by both overconfidence and disposition bias effects.[52]

Daniel at al. (1998) argue that the degree of overconfidence changes both dynamically and asymmetrically in the market. They note investor confidence rises more than it falls when they received confirmatory or contradictory evidence to their private information.[53] According to Souminen (2001), information alone is not enough to generate trading and investors in the marketplace benefit from previous trading as well. They look at the availability of private information as embedded in the previous session's trading volume and consequently adjust their trading strategies using that extracted information.

[51] Other psychological biases rarely examined along with overconfidence in the same regression include, for example, investor competence (Graham et al. 2009) and sensation seeking (Grinblatt and Keloharju 2009). It is found that investors who are prone to theses biases also trade more frequently. According to Graham et al. (2009), investor competence is defined as a fitted response to the question "how comfortable do you feel about your ability to understand investment products alternative and opportunities?". In the other study, sensation seeking is the number of final convections for speeding trading.

[52] Using trading volume and price data for all common stocks listed in the Taiwan stock exchange, Chuang and Susmel (2011) further find that individual investors are more overconfident relative to the institutional investors.

[53] Also, as they argue, more overconfidence will generate long-log price reversal preceded by short-run price continuation. Also, they argue that an overconfidence in the market leads to excess volatility. This later conclusion is also confirmed by Odean (1998b). Hirshleifer (2001) and Daniel and Hirshleifer (2015) further confirm the dynamics of overconfidence as suggested by Daniel at al. (1998).

This process, along with that of how investors learn in financial markets, is widely studied within different contexts (see, for example, Geravis and Odean 2001; Seru et al., 2010; Nicolosi et al., 2009).[54] Based on a multi-period market model with one risky asset, Geravis and Odean (2001) suggest that a trader tends to be more overconfident following their own success. They assume that this level of overconfidence tends to decrease in the latter stage of their career. They also argue that older traders will be driven out of the market when new investors begin trading. Seru et al. (2010) analyse two cases in which a trader might learn in the market. The first one is referred to as "learning by doing", where investors are assumed to become more experienced after more trading. The second notion is "learning by ability", here traders will stop trading at some point in the future when they realise their abilities are in decline.

From a multiple regression analysis, Seru et al. (2010) find more evidence towards the second view, which is consistent with the "late career-diminishing trading ability" conclusion of Geravis and Odean (2001). This general finding suggests that overconfident investors are always in danger given the fact that their ability to make successful trades diminishes over time. Nicolosi et al. (2009) also consider the role of experience and information arrival. They confirm that individual investors tend to trade more in the future based on their previous trade experience. Notably, investors attribute their last success to the precision of their private information and subsequently gain more confidence. Thus, an individual investor's last successful experience is assumed to be a proxy for the precession of their private information.

The existing literature thus considers whether overconfident traders can survive in the market (e.g. Wang, 2001; Hirshleifer and Luo, 2001; Oberlechner and Osler, 2012) or are driven out (e.g. Geravis and Odean, 2001). A further strand of literature examines the consequences of the diffusion of overconfidence in the market. Scheinkman and Xiong (2003) argue that disagreement about the future dividends of a single-risky asset will generate trading and can induce a bubble component. They suggest that overconfident traders believe that the price of equity exceeds their own valuation of its future dividends. Hence, they will be willing to pay more for the equity in the hope of gaining higher capital in the future from selling the same equity to another overconfident investor.

Ko and Huang (2007) argue that private information will diffuse into the market as investors overinvest in their acquired private information. Hence over time, this type of information, which was kept private, will be revealed to the market through trading and thus efficiency will improve

[54] For a general reference, see Pastor and Veronesi (2009).

accordingly.[55] Although Ko and Huang note that for this to hold true, the amount of private information should be more relative to publicly available information.

Other studies document a diminishing overconfidence effect as the order of lagged return increases. Griffin et al. (2007) argue that current returns will not matter to highly overconfident investors who have performed well over a significant period. To support this argument, they study both weekly and daily data collected for 46 countries and employ a vector autoregressive model. They find less support for the overconfidence theory at the first lag but more support at lags five and ten. Although, a decreasing effect as the number of lags increases is documented by others at the monthly frequency (e.g. Statman et al., 2006; Chen, 2012).

The literature seems to agree that overconfidence and other alternative behaviour-based theories can explain subsequent trading in the market. Although, mixed evidence seems to appear and casts some doubt on whether investors in the market might switch to rely more on the most recent return and the time-scaled return beyond the first day in order to lead the subsequent trading activity. Hence, we examine that in our study by decomposing the trading volume on timescales before investigating its statistical relation to both the most recent return and the timescale return in ten stock markets. The above literature suggests doing more research on which other factors might explain the subsequent trading. This current research addresses this without relying on the behavioural explanation since that needs further examination with technical evidence based on a real trading platform.

5.3 Data and methodology

This section describes the data and the methodology used in this paper. Section 5.3.1 provides a description of the data. In Section 5.3.2 we briefly describe our decomposition method using wavelet transform. Section 5.3.3 shows summary statistics for the variables used and under Section 5.3.4 we give details about the models employed in the analysis.

5.3.1 Data description

The data employed in this study comprises daily trading volume and stock market return series from ten international stock markets. Due to the missing values in most of the trading volume data, the sample only ends with seven developed markets: Austria (AU), Australia (AR), Canada

[55] This is similar to the finding of an early study by He and Wang (1995). Further, they contend that private information being revealed by trading are responsible for generating current and future trading, while public information generates only current trading.

(CA), France (FR), Spain (SP), the United States (US) and the United Kingdom (UK) and three emerging markets: South Africa (SA), Thailand (TH) and Turkey (TU)[56].

The time period spans from 1/1/2002 to 31/12/2013 for all markets, except for Canada and South Africa due to these two countries trading volume data availability. For Canada, the starting date is 01/05/2003 and 24/06/2003 for South Africa. Our sample clearly excludes most of the Dot-com crash period, or at least all of it is bubbles surviving stage. Hence, we focus on the sample period which mainly includes the 2008 crisis period. The decision regarding the inclusion of the 2008 crisis period is extrapolated based on the main findings of previous studies. For example, Hoffmann et al. (2013) find that individual investors in the Netherlands do not seem to price their risk correctly and even traded more actively during the 2008-2009 crisis period. They find that investor’s risk perception increased, while the risk tolerance decreased. Similarly, in the U.S market, Marsh and Pfleiderer (2013) argue that both the risk and the risk tolerance have changed during the recent 2008 crisis which caused an imbalance between the demand and the supply for the risky assets. This documented major shift in investor’s risk perception during the recent crisis justifies our focus on it, but not on other crises.

Regarding the selection of indices, some previous research employs those constructed for countries by the Datastream database to examine the return-trading volume relation (see, for example Griffin et al. 2007). Others, however, used the market trading screen shown index (e.g. Chen 2012, among others). We follow the second strand of research in selecting the indices under the assumption that the investors in the market are more likely to see the closing value of the index on the trading screen before they trade. Hence, the trading activity on these indices could be more affected by the behavioural bias than their Datastream counterparts. The representative data indices taken from Datastream are as follows: AU (The Austrian Traded Index ATX), AR (S&P/ASX 200), CA (TTOSP60), FR (CAC40), SP (IBEX35I), US (DJIA), UK (FTSE100), SA (FTSE/JSE ALL SHARE), TH (BNGKEST) and TR (Borsa Istanbul 100 Index). Both the stock return and trading volume series are transformed by taking the difference of their log values over two consecutive days. Our raw trading volume proxy represents the number of shares traded[57]. For each country in the sample, we include the weekdays and exclude the weekends. This as Crowley (2007) argued seems to be required before using wavelet decomposition which needs the data to be sampled at equal time intervals. The data missing due to holidays has been carefully examined and assumed to be the same as in previous days.

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[56] Filling the missing trading volume data should bias my estimates from the regression analysis. Yet, I was able to expand the sample by including more emerging countries and missing small size of missing trading volume data in these. Only further graphical analysis has been conducted on the these and the results are reported in

[57] For a more comprehensive review on various definitions of trading volume, see Lo and Wang (2000).

5.3.2 Decomposing trading volume using wavelet transform

In our analysis, we decompose the trading volume using maximum overlap discrete wavelet transform as described in Chapter two.

For the selection of the appropriate filter, this study follows the recommendations of seminal works on wavelet and their applications on time series data. For example, both Daubechies (1992) and Percival and Walden (2000) base their choice for mother wavelet on Daubechies least asymmetric with the length of 8 (D8, hereafter). This filter is asymmetric and has the property of making the wavelet coefficients optimally parallel with the given time series. Hence, our study employs this property in decomposing the trading volume. Kim and In (2010) find that this element is good enough in representing the volatile time series. One important element of the decomposition process to be decided is the number of resolution levels. To meet our objective, we decompose the volume series at six levels (J=6). Scales between 5 and 7 are usually considered appropriate in the task of decomposition irrespective of the frequency of the data at hand. Our selection for the number of time-scales is further confirmed after performing the wavelet variance analysis later in this chapter.

5.3.3 Summary statistics

Table 5.1 presents some descriptive statistics and the correlation matrix between current return ret (0) and the scaled trading volume up to four scales. Panel A of the table reports the basic descriptive statistics for both recent return (the first line) and trading volume series (the second line). Apparently, the value of skewness for trading volume is positive and large for South Africa, Thailand and Turkey compared to other countries in the sample, while it is the largest for Turkey with a value equal to 0.373. For other markets such as the United States the skewness value is negative (-0.291). Analysing the descriptive statistics for the return series, however reveals a different pattern. That is, the skewness value is now negative for South Africa, but positive for the U.S. Kurtosis values for the returns, on the other hand, are largest for the U.S, U.K, and Austria, while the smallest value can be noticed for Turkey. Considering the volume series, kurtosis value appears to be largest for the U.K and smallest for the Thailand. Moreover, the variations in both the return and the volume series are largest for South Africa, with these values being 0.019 and 0.212 respectively. Interestingly, the return and volume series in the U.S. are obviously the least volatile as measured by the standard deviation.

The correlation between variables is given in Panels B which generally shows that the recent returns tend to be significantly and more economically correlated with the trading volume at both the second and third time-scales. There seems to be a positive correlation at these scales for Turkey and Thailand where these markets are emerging. Yet, the most negative relation is shown at the time-scale [16-32] for Australia and the U.S. with the correlation coefficient values of 0.055 and -0.061 respectively.

Table 5.1 Summary Statistics for the data

This table lists the summary statistics of the log difference daily return and volume series for ten markets including: AU (Austria), AR (Australia), FR (France), SP (Spain), the US and the UK, SA (South Africa), (TH) Thailand and TU (Turkey). Time series data are collected from Datastream database. The sample period spans from 1/1/2002 to 31/12/2013 for all markets, except for Canada and South Africa where the starting dates for their samples are 01/05/2003 and 24/06/2003, respectively. Panel A shows the descriptive statistics for the original data series. The correlation between the current stock market return, ret (0) and the trading volume series is shown in panel B. Vol (0) denotes the current trading volume, while at scale t from 1 to 4, the trading volume series is given by Vol (1, 2, 3 or 4). *, ** and *** denote statistical significant at 10%, 5% and 1%, respectively.

Panel A: Descriptive statistics

	AU	AR	CA	FR	SP	US	UK	SA	TH	TU
Mean	0.000	0.001	0.000	0.000	0.000	0.002	0.000	0.001	0.001	0.001
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SD	0.016	0.018	0.015	0.017	0.017	0.012	0.015	0.019	0.015	0.025
	0.122	0.160	0.148	0.136	0.132	0.113	0.119	0.212	0.121	0.135
Skewness	-0.673	-0.066	-0.546	0.229	0.269	0.232	0.120	-0.083	-0.532	-0.055
	-0.583	0.032	-0.033	-0.338	-0.159	-0.291	0.071	0.322	0.203	0.373
Kurtosis	11.492	9.766	13.206	9.206	9.762	12.783	12.249	8.254	10.786	8.139
	7.368	5.490	5.219	8.490	4.886	8.749	11.945	10.503	3.789	9.016
Obs.	3131	3131	2784	3131	3131	3131	3131	2746	3131	3131
Index code	ATXINDX	ASX200I	TTOSP60	FRCAC40	MADRIDI	DJINDUS	FTSE100	JSEOVER	BNGKSET	TRKISTB

Panel B: Correlation between returns and trading volume

	AU	AR	CA	FR	SP	US	UK	SA	TH	TR
	ret (0)	ret (0)	ret (0)	ret (0)	ret (0)	ret (0)	ret (0)	ret (0)	ret (0)	ret (0)
Vol (0)	-0.008	-0.020	-0.014	-0.001	-0.019	-0.008	-0.009	0.027	0.039	0.035
Vol (1)	-0.025	-0.020	-0.019	0.003	-0.009	0.002	0.007	0.002	-0.015	-0.017
Vol (2)	-0.021	-0.007	-0.006	0.000	0.006	-0.033*	-0.003	0.026	-0.021	-0.030
Vol (3)	-0.019	-0.025	0.008	-0.035*	-0.031*	-0.015	-0.007	-0.014	0.043**	0.000
Vol (4)	-0.023	-0.055***	-0.006	-0.041**	-0.029	-0.062***	-0.041**	-0.044**	0.016	0.031*

5.3.4 Methodology

The next section describes the Markov-Switching method as it is employed. Both the baseline linear model and non-linear model which control for bull and bear-market states are described in Sections 5.3.4.2 and 5.3.4.3, respectively.

5.3.4.1 Markov-switching model on stock market return

One of our main aims in this study is to contribute to the related research conducted on the non-linear trading-volume relation. (e.g., Hiemstra and Jones 1994; Chuang and Lee 2006; McMillan

2007; Chen 2012). We use monthly data for the same indexes in the sample and estimated a simple Regime-switching model. The largest numbers of observations are employed for Australia (492) with only 221 observations for South Africa.

The difference in the length of sample between countries is again due to the availability of data. Let R_t the stock market return be the dependent variable in the following two-state simple regime switching model:

$$\varphi(L)R_t = \mu_{St} + e_t, \qquad e_t \sim \text{i.i.d.} N(0, \sigma^2_{St}), \tag{5.1}$$

Where: $\varphi(L) = 1 - L - L^2 - \cdots - L^m$ and L is the corresponding lag operator. Here both μ_{St} and σ^2_{St} represent respectively the mean and the variance of the return R_t. The unobservable state variable in the model is given by the indicator variable S_t equaling 0 or 1 depending on whether the market enters bull or bear-stage. The stock market return here is simply assumed to follow either of the states with a fixed transition probability. Under this assumption, the transition matrix is given by:

$$P = \begin{bmatrix} p^{00} & 1-p^{00} \\ 1-p^{11} & p^{11} \end{bmatrix}, \tag{5.2}$$

Where $p^{00} = P(s_t = 0 | s_{t-1} = 0)$ and $p^{11} = P(s_t = 1 | s_{t-1} = 1)$. The residuals from the model are assumed to be a normally distributed and only one lag of return is selected as suggested by Schwarz's information criterion. We keep our estimation simple without any further modification such as including the trading volume in the right-hand side of the equation since that is not our main interest.

Table 5.2 reports the estimation of parameters from regime-switching model (Panel A) and the defined bull-periods using the smoothing probabilities (Panel B). The results show that the mean value of return is negative in a bear-period for three of the ten markets. For the three emerging markets in the sample (Thailand, South Africa and Turkey) the estimated volatility in a bear-market is high relative to other markets. Using more observations provides better a estimation that is clearly reflected in higher absolute values of information criteria statistics for Australia. It is also obvious from panel A that a bull-market regime persists longer on average relative to a bear-market. This is more evident for the U.K, but less so for Turkey. It is true for all markets that the fixed transition probability during a bull period exhibits slightly larger values relative to those in bear regimes.

Turning to Panel B, we notice that estimated bull periods are reasonable for the markets. This can be observed from the period coincided with the occurrence of the 2008 crisis. For example, it is between 2007:10 and 2009:7 in the U.S. The bear-period defined from the end of 2009 for Austria, France and Canada is expected because of the European debt crisis. The defined bull-period for Spain 2002:12-2007:8 can be explained by what happened during and after that period. In 2002, the four stock Exchanges namely, Iberclear, AAIF, MEFF, SENAF and BME consulting became integrated into the BME Spanish Exchange. In July 2006, an IPO was launched for the new integration. One year later in July 2007, this becomes a listed company and included in the IBEX35 index.[58] The addition of this new component must contribute to the volatility of the index for the period after July 2007. Yet, only two bull-periods for the UK have been defined with the 2008 crisis seemingly positioned between them[59].

5.3.4.2 Bassline models: linear regressions

We first examine the relation between the recent return and the subsequent trading in a linear regression as follows:

$$V(J)_t = \alpha + \beta R_t + e_t \tag{5.3}$$

Where: $V(J)_t$ denotes the trading volume at scale J and day t. R_t is the stock market return defined as the difference of the natural log of the closing price index.

[58] We obtain these details about IBEX35 Spanish market from the Mondovisione Worldwide Exchange Intelligence:
http://www.mondovisione.com/exchanges/sample-exchanges/bolsas-y-mercados-espaoles-bme/.
[59] Obviously, estimating the bull-market states is somewhat subjective. We compare our bull/bear market periods with their daily and ready recession/expansion counterparts. For the U.S. market, we use the NBER's dated periods, while for other markets we collect the data from the OECD database. The data is missing for Thailand. For the U.S., however, the NBER does not report any recession period for the 2011 U.S. government debt crisis, while this period is slightly observed from the regime-switching model. As an additional analysis, we use the recession-based-indictors as available for all countries and that seems to provide similar conclusion on the asymmetric volume-return relation, especially on the first day (time-scale=0). These alternative indictors are used in all the linear and non-linear regressions for both recent return- and the dynamic return-volume relation. The results for those are untabulated, but available upon request.

Table 5.2 Estimation of Markov-switching model

This table shows the estimates from the Markov-switching model with the dependent variable being the monthly stock market return. The linear model is: $\varphi(L)R_t = \mu_{St} + e_t$ Where: μ_{St} and σ^2_{St} denote respectively the mean and the variance of the return R_t in bull/bear-market regimes (St =0/1). ** and *** denote statistical significant at 5% and 1%, respectively.

	AU	AR	CA	FR	SP	US	UK	SA	TH	TU
Panel A: Estimated Parameters										
μ0	0.01***	0.01***	0.01***	0.01***	0.01**	0.01***	0.01**	0.01***	0.01	0.01
μ1	0.00	0.01	-0.01	-0.01	0.00	-0.01	0.01	-0.01	-0.01	0.03
$\sigma^2 0$	0.00***	0.00***	0.00***	0.01***	0.00***	0.00***	0.02***	0.00***	0.01***	0.01***
$\sigma^2 1$	0.02***	0.02***	0.01***	0.01***	0.01***	0.01***	0.01***	0.03***	0.05***	0.04***
p^{oo}	0.97	0.98	0.96	0.98	0.96	0.96	0.99	0.99	0.99	0.90
p^{11}	0.88	0.92	0.82	0.94	0.94	0.88	0.96	0.87	0.94	0.80
Regime 0 persistence	33.71	50.88	23.61	66.64	23.51	24.47	201.63	69.93	98.64	9.52
Regime 1 persistence	8.37	12.62	5.52	17.80	18.12	8.20	24.21	7.95	15.53	4.92
LogLik	391.70	601.54	507.84	431.95	389.66	564.26	514.58	258.97	223.60	122.895
AIC	-771.41	-1191.07	-1003.68	-851.90	-767.32	-1116.52	-1017.16	-485.57	-435.21	-233.791
BIC	-748.540	-1165.90	-980.82	-829.37	-744.67	-1093.65	-994.29	-505.93	-414.45	-213.034
Number of monthly Obs.	334	492	334	316	324	334	334	221	235	235

Panel B: Estimated bull-periods by smoothing probabilities	
AU	2002:1-2008:4, 2009:9-2009:12, 2010:10-2011:6 and 2012:2-2013:12
AR	2002:2-2007:10, 2010:10-2011:7 and 2011:11-2013:12
CA	2003:5-2007:8, 2008:01-2008:05,2009:08-2009:12,2010:03-2011:06, and 2011:11-2013:12
FR	2002:1-2002:4, 2002:11-2007:7, 2008:1-2008:5, 2009:8-2009:12, 2010:3-2011:6 and 2011:11-2013:12
SP	2002:12-2007:8: 2010:6-2011:6, 2013:1-2013:12
US	2003:3-2007:9, 2009:8-2011:5 and 2011:9-2013:12
UK	2002:1-2008:4 and 2010:9-2013:12
SA	2002:6-2008:7, 2009:6-2013:12, 2002:01-2008:7 and 2009:2-2013:12
TH	2002:1-2008:8 and 2009:2-2013:12
TU	2002:1-2002:8, 2003; 1-2003:8, 2004:1-2008:5, 2009:8-2011:12 and 2012:2-2013:12

The second step of analysis involves estimating the dynamic relation between the subsequent return and the trading volume series. By doing that, our analysis can differentiate between the sizes of trading taking place on different time-horizons.

For example, short-term investors in the market who suffer from trading losses might be more willing to leave the market early. The willingness of long-term traders to stay in the market for a long time will instead be motivated by their ability to process private information and use it later to compete with short-term traders.

A similar assumption to that is made and empirically examined by Chinco and Ye (2015) who use the MODWT to decompose the intra-day (one minute) trading volume series of all the NYSE-listed companies. Their analysis shows that the first level short-term trading of one minute exhibits both a higher fraction of trading and variance compared to that at higher time-scales reaching one day of trading.

The study also reveals cross-differences between two stocks that have the same fundamentals. That is, stocks with the most active one-minute trading tend to contribute the most to portfolio's abnormal monthly return than other stocks. As a result, the study found that the excessive one minute-trading looks similar to the idiosyncratic volatility at one month. Furthermore, the variance of their decomposed series shows a fluctuation over time during the period including the 2008 crisis[60]. This cross-sectional variation can also exist in the index level. Hence, motivated by these findings, our new multivariate regression estimates the dynamic return-volume relation:

$$V(J)_t = \alpha + \beta_1 R(J)_t + \beta_2 V_t + e_t \tag{5.4}$$

Where: $R(J)_t$ is the time-scale return at scale $J = 2, 3$ and day t. As shown, the model also controls for the possible lead-lag effect coming from trading volume series itself which to be measured by β_2 .

Accordingly, we clearly examine whether the impact of the main variable of interest in this regression (the time-scaled return) could be incrementally subsumed by that of the recent trading volume factor. Yet, the effect of the later is also expected to explain the subsequent trading especially at short time-scale.

5.3.4.3 Non-linear regression: accounting for bull- and bear-market states

In order to account for the bull and bear-regimes in a non-linear framework, we estimate the following two regression models:

$$V(J)_t = \alpha_t + \beta_{1Bull} R_t + \beta_{2Bear} R_t + e_t \tag{5.5}$$

and

$$V(J)_t = \alpha + \beta_{1Bull} R(J)_t + \beta_{2Bull} V_t + \beta_{1Bear} R(J)_t + \beta_{2Bear} V_t + e_t \tag{5.6}$$

Where β_{1Bull} measures the effect of return in the bull-market period and β_{2Bull} measures the effect during the bear-market regime[61].

[60] In another study, Malagon et al. (2015) decompose the daily return series using wavelet and found that the idiosyncratic buzzle (i.e. negative idiosyncratic risk-expected return relation) is more supported at short-term horizon rather at the long-run.

[61] Shifting the bull/bear estimated series a head to align with the time-scale return series will not change the results. That is, because up to 32 days ahead (the upper limit of fourth time-scale return series), the decision of either bull- or bear-period stays the same.

5.4 Empirical results

Table 5.3 presents the slope estimates, t-statistics and the adjusted R^2 out of equation 5.3 from the analysis being done up to the time-scale [16-32] day-period. That also includes the dynamic relation on the first day. The general observation from the table is that the effect of recent return on the subsequent trading activity is more centered on the higher time-scales of that beyond [4-8] day-period. For four countries in the sample namely Australia, U.S., U.K. and South Africa, the relation is stronger at the time-scale four. For France and Spain, however, this relation is more evident at both the third and fourth time-horizons. In Turkey and U.S., today's return significantly predicts the subsequent trading at the time-scale of [4-8] day-period. With respect to the sign of the beta coefficient, this relation is negative for all countries at the last two time-scales, except for Thailand, and Turkey. Noticeably, these two markets are emerging and the beta coefficients at the third time-scale in their regressions have positive values of of 0.22 (with t-statistic= 2.62) and 0.03 (t-statistic= 0.06), respectively. For the Thai stock market, however, this coefficient value is the largest relative to all of these for other countries. This is also associated with the largest adjusted R^2 of 1.3%. The same can also be observed for all the three emerging markets in the sample where the relation is positive in the first day. It is even significant again for Thailand and Turkey.

The general finding from the table tends to support the notion that depending only on the lagged return to forecast the subsequent trading can be misleading. Hence, the recent return has also some predictive power for subsequent trading activity. Further, the positive sign of relation for two emerging countries can give an indication that overconfidence in these markets is more likely to persist for up to 32 days. The same notion can be true by observing the negative sign for other countries. Here, the investors who are initially moderate or less confident might tend to continue trading in the market for a short-term period while holding the same initial trading beliefs. Yet, relying on the linear regression might be misleading. For example, Griffin et al. (2007), observe that the signs of dynamic trading-volume relations switch from negative to positive for both the U.S and the U.K. during the period from 1992 to 2003.

Next, we estimate the equation 5.4 using the Newey-West estimator and report the associated parameters in Table. 5.4. The main aim of this step of analysis is to examine at which time-scale(s) the dynamic return-volume and recent volume-subsequent relations exist. By looking at the dynamic relation first, we notice a significant β_1 coefficient for all countries at the last two time-scales being used in the analysis. Regardless of the new return variable used here, this seems analogous to the results in Table 5.3.

Table 5.3 Regression of scaled-volume on current return: the baseline model

This table reports the linear regression estimates with using Newey-West (1987) standard error estimator (with the max of 20 lags being selected) of the model:
$V(J)_t = \alpha + \beta\, R_t + e_t$

Where $V(J)_t$ denotes first difference of the natural log of the trading volume at scaled J and day t. R_t is the stock market return defined as the first difference of the natural log of the closing price. The sample period spans from 01/01/2002 to 31/12/2013. The starting dates of the sample for Canada and South Africa are 01/05/2003 and 24/06/2003, respectively. Scales 0, 1, 2, 3 and 4 represent original trading volume series, trading volume at [2-4]. [4-8], [8-16] and at [16-32] day-period. *, ** and *** denote statistical significant at 10%, 5% and 1%, respectively.

Country	Scale	α	t-stat	β	t-stat	Adj. R^2
AU	0	0.00	-0.50	-0.07	0.21	0.000
	1	0.00	0.05	-0.21	-1.33	0.001
	2	0.00	0.27	-0.11	-1.37	0.000
	3	0.00	-0.11	-0.07	-0.99	0.000
	4	0.00	0.09	-0.06	-1.37	0.001
AR	0	0.00	0.20	-0.16	-1.43	0.000
	1	0.00	-0.04	0.16	1.05	0.000
	2	0.00	0.10	-0.03	-0.41	0.000
	3	0.00	-0.13	-0.09	-1.34	0.001
	4	0.00	0.01	-0.14***	-3.23	0.003
CA	0	0.00	-0.08	-0.14	-0.73	0.000
	1	0.00	0.08	-0.18	-1.18	0.000
	2	0.00	0.09	-0.04	-0.35	0.000
	3	0.00	-0.11	0.04	0.42	0.001
	4	0.00	-0.06	-0.02	-0.29	0.000
FR	0	0.00	0.09	-0.01	-0.06	0.000
	1	0.00	0.02	0.03	0.21	0.000
	2	0.00	0.01	0.00	0.03	0.000
	3	0.00	-0.19	-0.14**	-2.23	0.001
	4	0.00	-0.06	-0.13***	-2.72	0.002
SP	0	0.00	0.22	-0.15	-1.09	0.000
	1	0.00	0.06	-0.07	-0.53	0.000
	2	0.00	0.07	0.03	0.33	0.000
	3	0.00	-0.18	-0.10*	-1.67	0.001
	4	0.00	-0.03	-0.07*	1.66	0.010
US	0	0.00	-0.19	-0.08	-0.47	0.000
	1	0.00	0.00	0.01	0.09	0.000
	2	0.00	0.01	-0.21**	-2.00	0.001
	3	0.00	-0.14	-0.06	-0.96	0.000
	4	0.00	-0.02	-0.18***	-3.78	0.004
UK	0	0.00	0.20	-0.07	-0.56	0.000
	1	0.00	0.05	0.06	0.45	0.000
	2	0.00	-0.11	-0.02	-0.22	0.000
	3	0.00	-0.46	-0.04	-0.49	0.000
	4	0.00	-0.14	-0.18***	-2.72	0.002
SA	0	0.00	-0.24	0.31	0.97	0.001
	1	0.00	-0.01	0.02	0.10	0.000
	2	0.00	-0.03	0.14	0.87	0.001
	3	0.00	-0.14	-0.06	-0.69	0.000
	4	0.00	0.03	-0.15**	-2.43	0.002
TH	0	0.00	-0.10	0.32*	1.90	0.002
	1	0.00	0.13	-0.13	-0.71	0.000
	2	0.00	0.08	-0.14	-1.07	0.000
	3	0.00	-0.39	0.22***	2.62	0.013
	4	0.00	-0.06	0.06	0.80	0.000
TU	0	0.00	0.08	0.19*	1.77	0.001
	1	0.00	0.15	-0.09	-0.83	0.000
	2	0.00	0.02	-0.14*	-1.76	0.001
	3	0.00	-0.04	0.03	0.04	0.000
	4	0.00	0.00	0.06*	1.79	0.001

Yet, such a similarity can be noticed again between France and Spain on both the third and fourth time-scales. The dynamic relation is negative, significant and almost equal in absolute value for these countries at either of the two scales. In the Australian market, the highly significant dynamic relation is also at the time-interval [16-32] day (with β_1 =-0.57 and t-statistic= -2.11). Interestingly, the sign of β_1 is again positive and large for Thailand and Turkey compared to other countries in the sample. For instance, it is 1.90 (with t-statistic= 4.97) for the Thai market at third time-scale. This comes in line with our finding from the Table 5.3 of the distinct return-volume relation for these two emerging countries in the sample[62]. Furthermore, Table 5.4 also shows a strong relation at long-term scales for the U.S. and the U.K. with β_1 is large but negative at the time span of 16-32 days.

Having emphasised on the role of the time-scaled return in forecasting the subsequent trading, empirical evidence on predictability coming from the recent volume is also observed. For example β_2 is very significant for France at the first time-scale and t-statistic associated with is also large, namely 6.34 at the first time-scale. Similarly, for Australia the value of β_2 is 0.09 and significant at 1% significant level. This strong relation seems to stay also at the highest time-scales for all countries in the sample, but more at the scale two for Thailand and Turkey.

Surprisingly, a positive correlation between the recent trading volume and the immediate subsequent trading activity is more likely to exist for all markets, except the U.S., U.K. and Turkey. This is followed by a very weak linkage for Austria and the UK with a β_2 equal to zero at the second intermediate horizon. In other words, the recent volume tends to be followed by more subsequent trading at [2-4] time-scale.

This means, at least in the stock markets in our sample, traders who are trading today are more likely to follow their trades for up to four days of trading. In the beginning, they seem to rely

[62] We further examine whether the results for these two countries came by chance or not. To do so, we collect the weekly trading volume and return data from Datastream for all countries in our sample. The trading volume series are then de-trended by taking the log of the dollar volume divided by the one-year back moving average to make the series more smooth and stationary. We then estimate the bivariate VAR model using the data and found that in all countries 1 and 2 lagged returns tend to predict the trading relative to higher lags. Nevertheless, four lagged return seems to significantly predict the trading in 7 out of the 10 countries. Consistent with the literature (e.g. Griffin et al. 2007, among others), the relation is negative in all the developed countries, but positive in the two emerging markets, Thailand and Turkey. We also find very little evidence in all countries that trading volume predicts the return. The results of this analysis are omitted since they are not of our main interest, but available upon request. However, controlling for up to four weeks return in our regressions return does not seem to show a distinct role for any of the 4 weeks lagged-return in predicting the subsequent trading volume. Yet, while the VAR model requires the data to be more stationary, the wavelet transformation is designed to analyse less smooth data. Decomposing the de-trended trading volume turned to be wrong where the variance of the decomposed series continuously increased over scales and did not preserve throughout the analysis.

more on their recent trade to generate the subsequent ones. As the time goes they tend to adjust their trading behavior depending on both the time-scaled return and recent trading activity. We make no assumption on the type of these traders, but our analysis using wavelet can classify between the short-term trading at the time scale [2-4] days and long-term scale of more than four days.

When also considering the overall effect based on the highest Adjusted R^2, several conclusions can be reached. First, the value is now over 1% for all countries, but this is more evident at highest two time-scales up to 32 days. For instance, it is 5 % on average at [16-32] for Australia, France, the UK and South Africa and tends to reach 12% for the U.S. at the same scale. As we exactly found in the Table 5.3, the analysis on Thailand exhibits the largest Adjusted R^2 value at the third scale which is equal to 14%.

Table 5.4 shows that both time-scaled return and the recent volume tend to predict the subsequent trading activity at long-term time-scales where the long-term investors are assumed to focus more. The clear difference we found between the countries in the sample and the two emerging ones namely Thailand and Turkey seems also to exist even with the new predictors being used. Next, we continue doing our analysis by estimating the non-linear relation between the predictors and the subsequent trading volume[63].

In Table 5.5 we account for the bull- and bear-market states as defined from the simple regime-switching model. It can be seen that the recent return continues to predict the subsequent trading at the long term-scales in all countries except Canada[64]. The result from the Wald test shows less evidence of the statistical difference between the defined market periods.

Yet, for Thailand and Turkey again the impact of the recent return is economically more during the bull-periods at the second and the third scales, respectively. Based on the dynamic relation at time-scale=0, the coefficient is positive also for these two countries and Wald's null hypothesis of equality can be rejected.

[63] The inclusion of both the recent return and the time-scaled return together in the same equation will lead to spurious results since both variables are correlated. Recent return should affect the subsequent return under the assumption of autocorrelation. The analysis on that has been done already by Campbell et al. (1992) and Cremers and Pareek (2015), among others. However, when including both variables together, the effect of recent return lost its significance effect.

[64] The choice of the index used (value or equally weighted, the market cap of the companies that are included in, the fraction of the short-term investors and evidence of cross-listed companies…etc.) might also affect the final result. We check the robustness later using Datastream indexes, which exclude the ADRs and the cross-listed companies.

Table 5.4 Regressing time-scaled volume on current volume and time- scaled return: Linear regression

This table reports the beta coefficients and t-statistic using Newey-West (1987) standard error estimator (with the max of 20 lags being selected) for the model:

$$V(J)_t = \alpha + \beta_1 R(J)_t + \beta_2 V_t + e_t$$

Where V_t is the current trading volume and $R(J)_t$ is the scaled nominal return at scale J and day t. Table shows the results for the analysis up to four timescales. Same number of scales is selected for the return. *, ** and *** denote statistical significant at 10%, 5% and 1%, respectively. For the rest of notations, see Table 5.3.

		α	*t*-stat	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2
Country								
AU	1	0.00	0.11	-0.14	-0.69	0.01	0.84	0.001
	2	0.00	-0.01	-0.06	-0.29	-0.02***	-2.86	0.001
	3	0.00	-0.13	-0.82***	-4.12	0.01***	2.61	0.051
	4	0.00	0.08	-0.38**	-2.11	0.01***	4.21	0.018
AR	1	0.00	0.06	-0.09	-0.46	0.09***	4.53	0.008
	2	0.00	0.08	-0.15	-0.92	0.00	0.07	0.001
	3	0.00	-0.17	-0.22	-1.52	0.01***	3.14	0.005
	4	0.00	-0.03	-0.57***	-3.62	0.01***	3.40	0.048
CA	1	0.00	-0.05	-0.14	-1.99	0.04	0.46	0.010
	2	0.00	0.07	0.44**	2.24	0.00	-0.11	0.005
	3	0.00	-0.09	0.13	0.65	0.02***	4.30	0.025
	4	0.00	-0.06	0.12	0.63	0.00	0.67	0.054
FR	1	0.00	0.02	0.08	0.37	0.11***	6.34	0.010
	2	0.00	0.01	-0.33	-1.64	-0.01	-1.63	0.005
	3	0.00	-0.21	-0.71***	-3.13	0.02***	3.88	0.025
	4	0.00	-0.08	-0.88***	-4.28	0.01***	3.85	0.054
SP	1	0.00	0.02	0.06	0.28	0.03*	1.97	0.001
	2	0.00	0.09	-0.24	-1.25	-0.01	-1.59	0.003
	3	0.00	-0.18	-0.94***	-5.90	0.01**	1.82	0.074
	4	0.00	-0.06	-0.75***	-5.35	0.01***	4.10	0.072
US	1	0.00	0.02	0.05	0.21	-0.03	-1.52	0.001
	2	0.00	-0.08	-0.63**	-2.22	-0.02***	-2.85	0.010
	3	0.00	-0.16	-1.01***	-4.14	0.02***	4.37	0.044
	4	0.00	-0.07	-1.20***	-6.38	0.01***	3.04	0.127
UK	1	0.00	-0.01	0.14	-0.20	-0.04***	5.79	0.015
	2	0.00	-0.12	-0.21	0.29	0.00	-1.03	0.002
	3	0.00	-0.48	-0.44***	4.79	0.04	-1.36	0.009
	4	0.00	-0.16	-1.32***	-4.99	0.02***	3.07	0.057
SA	1	0.00	0.01	0.43	1.28	0.05	1.39	0.015
	2	0.00	0.05	-0.05	-0.24	-0.01**	-2.11	0.002
	3	0.00	-0.18	-0.50***	-2.61	0.01***	2.73	0.009
	4	0.00	-0.01	-0.86***	-4.07	0.01***	2.78	0.057
TH	1	0.00	0.00	0.36	1.18	0.03	1.10	0.002
	2	0.00	-0.02	1.71***	4.97	-0.02***	-2.15	0.075
	3	0.00	-0.24	1.90***	7.69	0.03***	4.40	0.141
	4	0.00	-0.04	1.13***	5.49	0.02***	4.02	0.101
TU	1	0.00	0.07	0.93***	6.11	-0.04	-1.51	0.029
	2	0.00	-0.05	1.19**	-1.89	-0.02***	4.86	0.079
	3	0.00	0.01	0.66***	2.81	0.02***	2.47	0.043
	4	0.00	0.02	**0.28***	1.80	0.01***	4.19	0.019

Due to the little evidence of asymmetry from Table 5.5, we focus next on the estimation of equation 5.6 where explaining dynamic return-volume relation became the main interest. Table 5.6 shows the news results and it is obvious that more evidence of the strong relation is found during the bull relative to bear-market states. Our observation for a stronger relation is the most again for Thailand and Turkey. For example, the value of β_{1bull} is 1.26 (t-statistic= 6.39) at the fourth time-scale against β_{1bear} = -0.17 (t-statistic=-0.27).

Noticeably, the Wald test's null hypothesis is rejected more times now at 1% level (or higher). That is, no equality is found across the market states at the fourth-time scale in Austria, Spain, the U.S., the U.K., Thailand and Turkey and at the scale [8-16] days for Australia, France and South Africa.

On the other hand, the impact coming from the recent trading volume seems to be similar to that reported in Table 5.4. Here today's trading continues to have a positive relation with the near-term trading, but in bull-market periods. This is shown at the first-time scale in all the ten markets except Canada, the U.S. and Turkey. Out of this general evidence, the Wald hypothesis is rejected for Austria, the U.S., the U.K. and South Africa. Apparently, recent volume still shows a statistical and economical predictability for the subsequent trading at the last two time-scales in all countries. Again, this evidence appears only in the bull-market periods.

To summarise, our general finding drawn from Table 5.6 on the asymmetric relation seems in line with that of Chuang and Lee (2006) and Chen (2012). Both studies document that the relation is stronger during bull period using the lagged return. Our result, however, is based on the subsequent return-volume and recent volume-subsequent trading relations, with more evidence on the former relation is found relative to the later.

5.5 Robustness checks

Multiple checks of the robustness of the main results were carried out. We examine whether with the new analysis both recent trading volume and the time-scaled return explain the subsequent trading and most at the long-term horizon. Furthermore, we continue examining the difference in the results for Thailand and Turkey and other markets in the sample. The next section discusses the results on a linear regression when two different sub-periods are decided according to the 2008-2009 crisis. Section 5.5.2, describes the results from the regressions when the Datastream indexes are used. The results are only reported for Section 5.5.1, for brevity Section 5.5.2 results are omitted, but available upon request.

Table 5.5 Current returns and the near-term trading volume relation in a state-dependent regression

This table reports the non-linear regression estimates for the following model using the Newey-West estimator:

$V(J)_t = \alpha_t + \beta_1 R_t + \beta_2 R_t + \ + e_t$

Where $V(J)_t$ denotes the trading volume at scaled J and day t. R_t is the stock market return defined as the first difference of the natural log of the closing price. β_1 measures the effect of return in the bull-market period and β_2 measures the effect during the bear period. The sample period spans from 01/01/2002 to 31/12/2013. The starting dates of the sample for Canada and South Africa are 01/05/2003 and 24/06/2003, respectively. Scales 0, 1, 2, 3 and 4 represent original trading volume series, trading volume at [2-4]. [4-8], [8-16] and at [16-32] day-period. Figures in bold belong to the variable for which the null hypothesis of the equality ($\beta_1 = \beta_2$) from the Wald test has been rejected at 1% or higher significance level *, ** and *** denote statistical significant at 10%, 5% and 1%, respectively.

Country	Scale	α	t-stat	β_1	t-stat	β_2	t-stat	Adj. R^2
AU	0	0.00	0.20	-0.07	-0.27	-0.07	-0.44	0.000
	1	0.00	-0.31	0.12	0.51	-0.43**	-2.19	0.001
	2	0.00	0.12	-0.18	-1.16	-0.06	-0.69	0.000
	3	0.00	-0.23	0.08	0.85	**-0.17***	-1.78	0.001
	4	0.00	0.11	-0.10	-1.26	-0.03	0.61	0.000
AR	0	0.00	0.24	-0.21	-0.97	-0.13	-1.01	0.000
	1	0.00	-0.39	**0.54****	2.09	-0.04	-0.25	0.000
	2	0.00	0.18	-0.15	-1.08	0.03	0.31	0.000
	3	0.00	-0.92	-0.11	-0.93	-0.08	-0.97	0.000
	4	0.00	0.01	-0.14**	-2.11	-0.14***	-2.53	0.002
CA	0	0.00	0.08	-0.14	-0.48	-0.14	-0.56	0.000
	1	0.00	0.14	-0.26	-0.96	-0.13	-0.71	0.000
	2	0.00	0.08	-0.02	-0.10	-0.05	-0.43	0.000
	3	0.00	-0.19	0.19	1.01	-0.07	-0.96	0.000
	4	0.00	-0.09	0.08	0.90	-0.09	-1.28	0.000
FR	0	0.00	0.02	0.11	0.38	-0.05	-0.36	0.000
	1	0.00	-0.02	0.08	0.32	0.00	0.03	0.000
	2	0.00	-0.07	0.15	1.21	-0.05	-0.46	0.000
	3	0.00	-0.13	-0.28***	-2.65	-0.09	-1.14	0.001
	4	0.00	-0.05	-0.14**	-1.91	-0.12***	-2.15	0.001
SP	0	0.00	0.15	-0.01	-0.02	-0.17	-1.16	0.000
	1	0.00	-0.24	0.44	1.29	-0.15	-1.02	0.000
	2	0.00	0.15	-0.12	-0.51	0.05	0.58	0.000
	3	0.00	-0.16	-0.15	-0.95	-0.09	-1.43	0.000
	4	0.00	-0.05	-0.01	-0.09	-0.08*	-1.79	0.001
US	0	0.00	-0.03	-0.27	-0.91	0.02	0.10	0.000
	1	0.00	0.07	-0.06	-0.20	0.05	0.28	0.000
	2	0.00	0.12	-0.36**	-2.15	-0.13	-0.96	0.001
	3	0.00	-0.19	0.02	0.13	-0.10	1.36	0.000
	4	0.00	-0.02	-0.18***	-2.65	-0.18***	-2.92	0.003
UK	0	0.00	0.22	-0.13	-0.71	-0.01	-0.03	0.000
	1	0.00	-0.02	0.09	0.43	0.02	0.17	0.000
	2	0.00	-0.12	0.02	0.13	-0.05	-0.51	0.000
	3	0.00	-0.48	0.02	0.17	-0.11	-1.09	0.000
	4	0.00	-0.13	-0.25***	-2.59	-0.11	-1.21	0.001
SA	0	0.00	0.00	-0.07	-0.30	1.05	1.24	0.002
	1	0.00	-0.23	0.31	1.97	-0.57	-2.01	0.001
	2	0.00	0.06	0.00	-0.03	0.43	0.96	0.001
	3	0.00	-0.19	0.03	0.37	-0.24	-1.43	0.000
	4	0.00	0.02	-0.11*	-1.76	-0.21*	-1.71	0.001
TH	0	0.00	-0.18	**0.36****	1.94	0.06	0.24	0.001
	1	0.00	0.34	-0.21	-1.03	0.37	1.54	0.000
	2	0.00	-0.09	-0.03	-0.29	-0.80**	-2.30	0.001
	3	0.00	-0.40	0.23***	2.52	0.18	0.79	0.001
	4	0.00	-0.09	0.09	1.47	-0.14	-0.49	0.000
TU	0	0.00	0.03	**0.04**	0.38	0.55	2.22	0.001
	1	0.00	0.16	-0.06	-0.49	-0.17	-0.72	0.000
	2	0.00	0.04	-0.05	-0.62	-0.34**	-1.97	0.001
	3	0.00	-0.02	0.07	0.94	-0.17	-1.06	0.001
	4	0.00	-0.01	0.10***	2.49	0.00	0.03	0.000

Table 5.6 Regressing time-scaled volume on current volume and time- scaled return: State-dependent regression

This table reports the beta coefficients and t-statistic using Newey-West (1987) standard error estimator (with the max of 20 lags being selected) for the model:

$$V(J)_t = \alpha + \beta_{1Bull}\, R(J)_t + \beta_{2Bull}\, V_t + \beta_{1Bear}\, R(J)_t + \beta_{2Bear}\, V_t + e_t$$

Where V_t is the current trading volume and $R(J)_t$ is the scaled nominal return at scale J and day t. β_{Bull} measures the effect of return in the bull-market period and β_{Bear} measures the effect during the bear period. The Table shows the results for the analysis up to four timescales. Same number of scales is selected for the return. *, ** and *** denote statistical significant at 10%, 5% and 1%, respectively. Figures in bold belong to the variable for which the null hypothesis of the equality ($\beta_1 = \beta_2$) from the Wald test has been rejected at 1% or higher significance level. For other notations, see Table 5.3.

		α	t-stat	β_{1Bull}	t-stat	β_{2Bull}	t-stat	β_{2Bear}	t-stat	β_{2Bear}	t-stat	Adj. R^2
Country												
AU	1	0.00	0.10	**-0.64**	-1.55	0.01	0.87	0.14	0.63	0.02	0.13	0.001
	2	0.00	-0.01	-0.05	-0.15	-0.02***	-2.75	-0.06	-0.25	-0.01	-0.80	0.000
	3	0.00	-0.12	-0.99***	-4.23	0.01***	2.60	-0.68**	-2.40	0.01	0.65	0.051
	4	0.00	0.09	**-0.66****	-2.31	0.01***	3.23	-0.09	-0.52	-0.01***	2.72	0.026
AR	1	0.00	0.09	-0.34	-0.83	**0.11*****	4.74	0.04	0.24	0.02	0.66	0.009
	2	0.00	0.03	-0.47	-1.65	0.00	-0.14	0.05	0.23	0.00	0.29	0.003
	3	0.00	-0.17	**-0.52****	-2.01	0.01***	2.93	-0.08	-0.45	0.01	1.22	0.007
	4	0.00	0.00	-0.71***	-3.61	0.01***	2.59	-0.46**	-1.96	0.01**	2.19	0.050
CA	1	0.00	-0.05	**0.94****	2.01	-0.03	-1.51	-0.40	-1.17	-0.08	-1.34	0.005
	2	0.00	0.07	0.60*	1.66	0.00	-0.45	0.31	1.56	0.02	1.29	0.006
	3	0.00	-0.16	-0.19	-0.61	0.02***	4.08	0.38	1.48	0.01	1.47	0.005
	4	0.00	-0.06	0.30	1.22	0.00	0.77	-0.01	-0.05	0.00	-0.13	0.002
FR	1	0.00	0.02	0.21	0.45	0.13***	5.99	0.03	0.15	0.08	2.76	0.010
	2	0.00	0.01	0.08	0.21	-0.01	-0.58	-0.48**	-2.04	-0.02*	-1.76	0.006
	3	0.00	-0.17	**-1.41*****	-3.43	0.02***	3.14	-0.45*	-1.68	0.02***	2.48	0.033
	4	0.00	-0.08	-0.78**	-2.13	0.01**	2.36	-0.91***	-3.76	0.02***	3.19	0.053
SP	1	0.00	0.01	-0.23	-0.39	0.06**	2.04	0.10	0.44	0.01	0.53	0.001
	2	0.00	0.09	-0.40	-0.68	-0.01	-0.72	-0.22	-1.06	-0.01	-1.43	0.002
	3	0.00	-0.19	-1.22***	-3.00	0.01	1.43	-0.89***	-5.14	0.01	1.18	0.074
	4	0.00	-0.08	**-1.41*****	-2.94	0.01***	3.34	-0.63***	-4.58	0.01***	2.58	0.082
US	1	0.00	0.02	-0.37	-0.80	**-0.01**	-0.41	0.27	0.94	-0.08***	-2.53	0.020
	2	0.00	-0.07	-0.99**	-2.05	-0.02***	-2.53	-0.42	-1.20	-0.03	-1.39	0.011
	3	0.00	-0.14	-1.22***	-4.01	0.02***	5.14	-0.89***	-2.56	0.01	0.77	0.044
	4	0.00	-0.07	**-1.09*****	-5.39	0.00	1.50	-1.26***	-4.65	0.02***	3.04	0.127
UK	1	0.00	-0.02	0.23	0.75	**0.17*****	7.71	-0.31	-1.28	0.00	-0.05	0.019
	2	0.00	-0.12	-0.26	-0.82	0.00	-0.04	-0.16	-0.64	0.02	0.70	0.000
	3	0.00	-0.47	-0.77*	-1.88	0.04***	4.51	-0.12	-0.26	0.03*	1.77	0.010
	4	0.00	-0.15	**-1.86*****	-5.93	0.02**	2.42	-0.59	-1.38	0.02**	2.31	0.070
SA	1	0.00	0.00	0.48	1.38	**0.09*****	3.38	0.08	0.20	-0.06***	-2.45	0.020
	2	0.00	0.06	**-0.36***	-1.71	-0.01*	-1.82	0.53	1.45	-0.01	-0.78	0.006
	3	0.00	-0.20	**-0.80*****	-3.87	0.02***	2.71	0.01	0.04	0.01	1.11	0.022
	4	0.00	-0.01	-0.83***	-3.74	0.01***	2.87	-0.93*	-1.90	0.01	1.06	0.050
TH	1	0.00	-0.01	0.34	1.06	0.03	1.38	0.57	0.71	-0.12	-1.57	0.002
	2	0.00	-0.04	**2.01*****	6.02	-0.02*	-1.88	0.41	1.01	-0.03	-0.80	0.084
	3	0.00	-0.25	2.03***	7.83	0.03***	4.51	1.21**	1.95	-0.01	-0.31	0.145
	4	0.00	-0.03	**1.26*****	6.39	0.01***	3.88	-0.17	-0.27	0.03	1.21	0.114
TU	1	0.00	0.07	0.84***	4.84	-0.04	1.59	1.12***	3.62	-0.01	-0.27	0.028
	2	0.00	-0.08	0.98***	3.94	-0.01	-0.81	1.60***	3.07	-0.06**	-2.01	0.083
	3	0.00	0.04	0.79***	3.54	0.01**	1.77	0.42	0.92	0.03	1.56	0.045
	4	0.00	0.06	**0.43****	2.39	0.01***	4.25	-0.18	-0.82	0.01	1.59	0.033

5.5.1 Sub-periods: pre-crisis and crisis-included periods

In Table 5.7, the relation is examined in a linear regression for pre-crisis and 2008 crisis included sub-periods. For our definition the crisis starts on 15/09/2008. It turns out that on the higher scales namely third and second, the effect of the time-scaled return tends to be stronger (in absolute value) in the pre-crisis period relative to the crisis-period itself. This is more evident for most of the countries. For example, this evidence is clear at the time-horizon [16-32] for Austria, Canada, France, the U.K., South Africa and Thailand. An exception is for Turkey where this impact is economically and statistically stronger at the first three time-scales before the crisis but not throughout.

Two more interesting findings emerged from the table. The first one is shown on the analysis at the first time-scale. That is, the sign of β_1 before the crisis is always positive for all countries and even significant for Austria, France, South Africa, Thailand and Turkey. Second, among all countries, the impact in the U.S is stronger over the second sub-period. This is also associated with high Adjusted R^2 of approximately 15% and 5% at the third and fourth scales, respectively. In contrast, and in terms of the overall effect at the long-term horizons, stronger impact is also observed in the first sub-period at the longest horizon for Austria (Adjusted R^2= 2%), for Spain (10.6%), for the U.K. (10.9%) and the mostly observed for Thailand (13.6%).

The reverse relation for the U.S. can be explained where the rational investors in the U.S. may tend to learn more from the trading mistakes they made before the crisis, and hence to heavily rely on time-scaled return to generate the short-term trading. In other words, the stock market seems to be more efficient in the U.S., yet less in other countries after the crisis. To sum up, Table 5.7 shows that the dynamic relation at the higher timescales can still be observed after conducting the analysis on sub-periods, which is consistent with our more main findings. Yet, further analysis must be done where the variance and covariance could also change as we move from one scale to another. We check this further in Section 5.6.2.

5.5.2 Analysis on Datastream indexes[65]

To check whether the selection of the index will alter the results, we conduct the analysis on Datastream indexes. We collect return and trading volume data for the countries in the sample

[65] The results are untabulated, but available upon request and the analysis used the expansion/recession indicators for all countries, but not for Thailand where the bull/bear defined later in this paper are employed, instead.

Table 5.7 Regressing time-scaled volume on current volume and time- scaled return: Sub-periods

This table reports the non-linear regression estimates using Newey-West (1987) standard error estimator (with the max of 20 lags being selected) for the model:

$$V(J)_t = \alpha_t + \beta_1 R(J)_t + \beta_2 V_t + e_t$$

Where V_t is the current trading volume and $R(J)_t$ is the scaled nominal return at scale J and day t. The linear model is estimated before the 2008-2009 crisis for the sub-period covers the crisis period and after until 31/12/2013. The crisis period is defined to start from 15/09/2008. *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively. For the rest of notations, see Table 5.3.

		Pre-crisis period					Crisis period				
		β_1	*t*-stat	β_2	*t*-stat	R^2	β_1	*t*-stat	β_2	*t*-stat	R^2
	Scale										
AU	1	0.03*	1.86	0.08	0.17	0.001	-0.20	-0.92	-0.02	-0.78	0.002
	2	0.23***	0.78	-0.02***	-2.55	0.003	-0.17	-0.67	-0.01	-1.34	0.003
	3	-0.99***	-3.84	0.01***	2.92	0.045	-0.73***	-2.78	0.00	0.39	0.061
	4	-0.59*	-1.78	0.01***	3.21	0.025	-0.25	-1.22	0.01***	2.74	0.014
AR	1	0.14	-0.37	0.11***	3.91	0.012	-0.05	-0.27	0.06**	2.33	0.003
	2	-0.43	-1.42	0.00	-0.23	0.006	0.00	0.02	0.00	0.42	0.000
	3	-0.42	-1.61	0.02***	2.69	0.010	-0.10	-0.56	0.01	1.56	0.002
	4	-0.60**	-2.19	0.01**	2.27	0.039	-0.55***	-2.91	0.01***	2.62	0.058
CA	1	0.28	0.45	-0.04	-1.29	0.002	0.09	0.25	-0.04	-1.62	0.001
	2	0.18	0.43	0.00	0.26	0.001	0.54**	2.43	0.00	-0.48	0.014
	3	-0.37	-1.06	0.02***	2.93	0.005	0.42*	1.71	0.02***	3.01	0.015
	4	0.19***	2.22	0.00	0.15	0.002	0.07	0.30	0.00	0.59	0.010
FR	1	0.71***	2.29	0.13***	5.89	0.022	-0.24	-0.94	0.07***	2.88	0.005
	2	-0.26	-0.79	0.01	-0.90	0.002	-0.38	-1.50	-0.02	-1.40	0.009
	3	-0.83**	-2.21	0.02***	2.99	0.023	-0.64**	-2.27	0.02**	2.41	0.029
	4	-1.03***	-3.10	0.01***	3.11	0.054	-0.77***	-2.93	0.01**	2.30	0.056
SP	1	0.17	0.48	0.05**	2.03	0.003	0.01	0.06	0.01	0.35	0.000
	2	-0.14	-0.37	-0.01	-1.38	0.001	-0.28	-1.26	-0.01	-0.87	0.006
	3	-1.32***	-5.27	0.01*	1.68	0.085	-0.78***	-3.99	0.00	0.74	0.073
	4	-1.16***	-4.12	0.01***	3.68	0.106	-0.53***	-3.39	0.01**	2.05	0.053
US	1	0.53	1.49	0.00	0.20	0.003	-0.32	-0.95	-0.05*	-1.87	0.004
	2	-0.77**	-2.41	-0.02**	-2.13	0.015	-0.52	-1.19	-0.03**	-2.12	0.007
	3	-1.01***	-2.52	0.02***	3.87	0.042	-1.02***	-3.52	0.01***	2.47	0.046
	4	-1.11***	-3.75	0.01***	2.91	0.104	-1.28***	-5.57	0.00	1.47	0.155
UK	1	0.38	1.15	0.20***	6.38	0.033	-0.27	-1.11	0.07**	2.01	0.006
	2	-0.07	-0.22	0.01	0.93	0.000	-0.31	-1.09	-0.01	-0.38	0.003
	3	-0.74	-1.63	0.04***	3.90	0.014	-0.29	-0.68	0.04***	2.83	0.006
	4	-1.88***	-4.58	0.03***	2.51	0.109	-0.93***	-2.77	0.01*	1.81	0.029
SA	1	0.91*	1.74	0.09***	2.74	0.018	-0.30	-1.17	0.10***	2.72	0.010
	2	0.03	0.08	-0.01	-1.43	0.001	-0.21	-0.98	-0.01	-1.28	0.004
	3	-0.98***	-4.16	0.01*	1.90	0.039	-0.03	-0.10	0.03***	3.86	0.004
	4	-0.82***	-2.78	0.01**	2.17	0.039	-0.55**	-2.15	0.01***	2.88	0.031
TH	1	1.44***	3.95	0.04	1.11	0.022	-0.82**	-2.08	0.00	0.08	0.011
	2	2.71***	6.27	-0.01	-1.19	0.142	0.70*	1.89	-0.02*	-1.68	0.019
	3	1.98***	5.21	0.04***	3.93	0.135	1.80***	6.16	0.02*	1.85	0.015
	4	1.34***	4.80	0.01***	2.88	0.136	0.81***	3.07	0.02***	3.03	0.057
TU	1	1.58***	3.64	-0.03	-1.01	0.021	0.23	0.98	-0.05	-1.24	0.005
	2	1.12**	2.29	-0.02	-1.24	0.021	0.39	1.16	-0.04*	-1.84	0.010
	3	0.84**	2.05	0.01*	1.80	0.022	0.16	0.70	0.02	1.52	0.004
	4	-0.11	-0.52	0.01***	2.97	0.002	-0.34	-1.42	0.02***	3.59	0.019

from Datastream database. Our unreported analysis continues to broadly generate similar findings that the time-scaled return and recent trading significantly predict the subsequent trading at the longer time-horizons of namely [8-16] and [16-32] day periods.Moreover, we continue observing a positive dynamic relation for Turkey and Thailand. Yet, two exceptions are found in this analysis. Those are the significant dynamic relation at the long-horizons for Canada during the market advancing stage and at all time-scales for the U.S. during the expansion period, yet the strongest at the longest time-horizon.

In terms of the overall impact, the adjusted R^2 is the highest again at the time period [16-32] for Austria (equals to 1.5%), for Australia (5%), for Canada (1.9%), for France (2.3%), for the U.S. (10.8%), for the U.K (3.1%) and for Thailand (6%). A more pronounced relation is found, but at the third scale for Spain and Turkey with the the adjusted R^2s being equal to 6% and 6.6% respectively.

On the other hand, the null hypothesis from the Wald test of that β_{1bull} =β_{1bear} is rejected at 1% significance level or higher at the last two time-scales for Austria and Canada. At the third and first scales for Spain and the U.K. respectively. While for two of the emerging countries in the sample, namely Thailand and Turkey, the rejection is more evident. For example, it is now at the intermediate and the long-time horizons for turkey and at the intermediate and the last scales for Thailand. One more finding from the analysis is the positive statistical effect of the recent trading volume at the short-time horizon [2-4] day period. The associated coefficient β_{2bull} is clearly positive all countries and even highly significant in all, but not in Thailand, Austria and Spain.

This observation again supports our main results and the argument we made before on how the investor update their beliefs over time. This is also consistent with the recent study by Chinco and Ye (2016) that used the wavelet variance estimator to decompose the one-minute trading volume on scales and introduced the notion of "correlation across horizons". By considering the one-minute scale as a measure for the short-time horizon, they argue that:

"*Stocks with the largest fraction of trading activity at the one minute-horizon will tend to have less trading activity at all longer horizons. But the relationship between any pairs is not mechanical… Therefore, a stock might have a large fraction of its trading activity at the one minute horizon, a moderate fraction of its trading activity at the one-day horizon, and very little activity at all horizons between".* Chinco and Ye (2016, page 14)

Yet, they empirically confirm that where the stocks with the largest fraction of trading at one horizon are observed to have less trading at the one-day horizon. With our analysis being conducted on the index level and with the daily data, a similar notion can hold[66]. To get a better insight on this relation and the dynamic return-volume relation at higher time-scales, we rely more on wavelet variance, covariance and correlation analysis in Section 5.6.2, so our results can be more comparable with Chinco and Ye (2016), since they also depend on the wavelet- variance estimator to reach their finding.

5.6 Additional analysis

5.6.1 The relation between recent volatility and subsequent trading volume

The relation between the overconfidence and the stock market volatility is already examined. For example, Odean (1998b) argues that there should be a positive relation between the overconfidence and volatility depending on who is overconfident in the market. Chuang and Lee (2006) find that more trading as associated with the overconfidence behaviour generates excess volatility in the market. When incorporating the stock market volatility estimates directly in the relation, Griffin et al. (2007) document that turnover-return relation tends even to be stronger. Based on this area of literature, we ask whether the stock market volatility also predicts the trading volume at time-scales beyond the first day. For the new analysis, we consider the following regression:

$$V(J)_t = \alpha_t + \beta_1\, 1000\sigma_t^2 + \beta_2\, 1000\sigma_t^2 + e_t \qquad (5.7)$$

Where: $V(J)_t$ denotes the trading volume at timescales J=1…4 and day *t*. σ_t^2 is the conditional volatility estimates from an EGARCH (1,1) model[67]. β_1 measures the effect of volatility in the bull-market period and β_2 measures the effect during the bear period.

[66] To match our results further with Chinco and Ye (2016), we run a separate regression and regress the subsequent trading in each country on its previous trading activity with the main independend variable being the time-scaled trading volume up to four scales. Our result using the stock index series, show that only at trading volume at the horizon [2-4] day-period significantly predicts the trading activity at the next scale [4-8] day-period in all countries but not Austria, Canada, Thailand and Turkey. For the latter two countries, however, a significant relation is observed instead between the trading at [4-8] as a predictor and the subsequent trading at the [8-16] day-period. The coefficient values in all these cases are negative and at the significance level of always 5% or lower, while this is more evident for Australia, Spain and the U.K. with the significance level equals to 1%. The results for those are untabulated, but available upon request. The cross differences between countries require further investigation on the fraction of short-term trading or more specifically on individuals versus institutional trading activity in each country and examining how that changes over time. This is beyond the scope of this paper.

[67] The model is estimated for all countries under the assumption that the error term follows a normal distribution.

We end up with a major finding based on correlation matrix (Table 5.8) and the regression estimates (Table 5.9). That is, more stock market volatility today tends to be followed by the more subsequent trading in the next day and up to four days before this relation reversed again at the higher subsequent time-scales. Therefore, both Tables show that as the time goes on the effect of volatility on the subsequent trading tends to economically diminish but to become the most significant at the fourth time-horizon.

Table 5.8 Correlation matrix: the scaled volume and volatility

This table repots the correlation matrix the stock market volatility and the volume on scales Volatility estimates are from an EGARCH (1, 1) specification estimated under the assumption the error distribution being normally distributed. The sample period spans from 01/01/2002 to 31/12/2013. The starting dates of the sample for Canada and South Africa are 01/05/2003 and 24/06/2003, respectively. Scales 1, 2, 3 and 4 represent the trading activity at [2-4]. [4-8], [8-16] and at [16-32] day-period.*, ** and *** denote statistical significant at 10%, 5% and 1%, respectively.

	AU	AR	CA	FR	SP	US	UK	SA	TH	TU
Vol (1)	0.000	0.001	-0.001	0.001	0.004	-0.001	0.002	0.004	0.019	0.014
Vol (2)	-0.018	-0.012	-0.007	-0.019	0.003	-0.023	-0.016	-0.012	-0.037**	-0.054
Vol (3)	-0.026	-0.003	0.010	-0.031*	-0.010	-0.030*	-0.025	-0.005	-0.018	-0.034***
Vol (4)	-0.039**	-0.027	-0.027	-0.050***	-0.042**	-0.062***	-0.054***	-0.045*	-0.047***	-0.017*

As shown in Table 5.8. The correlation becomes large and significant at the scale [16-32] days for all countries except for Australia, Canada. Table 5.8 further indicates that most of the significant relation is observed at the intermediate and the highest timescale and specifically during the bull periods. However, the hypothesis of equality is rejected only for Austria, Thailand, and Turkey at [2-4] day-horizon. Overall, the new analysis here showed that the impact of volatility on trading activity also switches from being positive and less significant at the short-term investment horizon to significant but negative at higher horizons. One possible explanation for that is decreasing of the variance level of trading volume over time. It is the most in the first time-scale, but less afterwards. This is confirmed in the next section and hence should be reflected on trading volume-volatility relation.

5.6.2 the results from wavelet variance, co-variance and correlation analysis[68]

In this section, we perform the wavelet variance, covariance and correlation graphical analysis using the equations described in Section 2.5.4. Figure 5.1 depicts the changes in the variance of the return series over time-horizons and up to the sixth scale. In all countries in the sample, the

[68] For the full details, refer to section 2.4.4 in this thesis.

analysis shows that the variance deteriorates over time as the time-scale increases. This pattern implies that the short run-investor tends to bear more risk while trading at the short investment

Table 5.9 Today's stock market volatility-subsequent trading volume relation

This table reports the non-linear regression estimates using Newey-West (1987) standard error estimator (with the max of 20 lags being selected) for the model:

$$V(J)_t = \alpha_t + \beta_1\,1000\sigma_t^2 + \beta_2\,1000\sigma_t^2 + e_t$$

Where $V(J)_t$ denotes the trading volume at scaled J and day t. σ_t^2 is the volatility estimate from an EGARCH (1,1) model. β_1 measures the effect of volatility in the bull-market period and β_2 measures the effect during the bear period. The sample period spans from 01/01/2002 to 31/12/2013. Figures in bold belong to the variable for which the null hypothesis of the equality ($\beta_1 = \beta_2$) from the Wald test has been rejected at 1% or higher significant level. *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively.

Country	Scale	α	*t*-stat	β_1	*t*-stat	β_2	*t*-stat	Adj. R^2
AU	1	0.00	-0.78	0.01	1.15	0.00	0.14	0.000
	2	0.00**	2.24	-0.02***	-2.50	-0.01**	-2.07	0.000
	3	0.00*	1.74	-0.02**	-1.94	-0.01*	-1.69	0.001
	4	0.00	1.29	-0.03	-1.50	-0.01	-0.93	0.005
AR	1	0.00	-1.36	**0.01***	1.68	0.00	0.76	0.000
	2	0.00	1.07	-0.01	-1.08	-0.01	-1.07	0.000
	3	0.00	-0.26	0.00	0.27	-0.01	-0.05	0.000
	4	0.00	1.54	-0.04**	-1.97	-0.01	-1.09	0.010
CA	1	0.00	-0.10	0.00	-0.14	0.00	-0.12	0.000
	2	0.00	1.26	-0.02	-1.33	0.00	-0.76	0.000
	3	0.00	-0.37	-0.02	0.30	0.00	0.41	0.000
	4	0.00	0.17	0.00	-0.13	0.00	-0.38	0.001
FR	1	-0.00	-0.62	0.01	0.94	0.00	0.32	0.000
	2	0.00	1.45	-0.01	-1.55	-0.01	-1.53	0.000
	3	-0.03	1.41	-0.01*	-1.78	-0.01	-1.39	0.001
	4	0.00	0.50	-0.01	-0.40	-0.01	-0.74	0.002
SP	1	-0.01	-1.24	0.02	1.31	0.00	1.30	0.000
	2	0.00	0.47	-0.01	-0.75	-0.01	-0.08	0.000
	3	0.00	1.25	-0.03	1.53	-0.01	-1.21	0.000
	4	0.01*	1.75	-0.06**	-2.08	-0.01*	-1.67	0.012
US	1	0.00	-0.91	0.02	1.33	0.00	-0.02	0.000
	2	0.00*	1.71	-0.03*	-1.68	-0.01*	-1.71	0.000
	3	0.00	-1.46	-0.03*	-1.76	-0.01	-1.32	0.001
	4	0.00	0.95	-0.03	-1.17	-0.01	-0.69	0.005
UK	1	0.00	-0.36	0.01	0.43	0.00	0.28	0.000
	2	0.00	1.21	-0.01	-1.62	-0.01	-1.14	0.000
	3	0.00	1.18	-0.03**	-2.08	0.00	-1.02	0.001
	4	0.00	0.61	-0.02	-0.91	-0.02	-0.74	0.003
SA	1	-0.00	-0.52	0.00	0.62	0.00	0.45	0.000
	2	0.00	1.34	-0.01	-1.64	0.00	-0.68	0.000
	3	0.00	0.26	0.00	-0.40	0.00	-0.12	0.000
	4	0.00	0.00	-0.01	-0.01	0.00	-0.01	0.001
TH	1	0.00**	-2.38	**0.02*****	2.68	0.00	0.10	0.010
	2	0.00**	2.13	-0.02**	-2.39	-0.01	-1.46	0.001
	3	0.00	0.46	-0.01	-0.63	0.00	-0.37	0.000
	4	0.00	1.10	-0.01*	-1.90	0.00	-0.09	0.004
TU	1	0.00*	-1.79	**0.01***	1.83	0.00	1.50	0.000
	2	0.00***	3.28	-0.01***	-3.61	-0.01***	-2.12	0.003
	3	0.00	1.46	-0.01*	-1.84	0.00	-0.38	0.001
	4	0.00	0.17	0.00	-0.07	0.00	-0.47	0.000

horizon. More conservative investor with a long run horizon focuses at the long horizon where the market is less volatile.

This observation here applies in all countries with some difference between them. For example, Canada, the U.K. and the U.S. show less variation than others in the sample, while it is the least for the U.S. It is also clear from the Figure how the first four scales contribute more to the variation in the return during the month. The last two scales exhibit very small variation that reaches the zero level. For three countries in the sample where the markets namely Austria, Thailand, and Turkey, this evident appears less. The reason for these little differences across the markets can be explained by the market size, where the small market such as Thailand can be more volatile than the U.S. market.

Next, we aim to gain a better insight about the different return-volume relation across sub periods that which is already examined in Table 5.7. In order to do so, wavelet variance estimator is applied twice on both sub periods as defined previously before 15/09/2008 for the first and from that data and beyond for the second period. The variance at each scale for the non-crisis period is subtracted from that during the crisis and the pattern over the time horizons for each country is plotted in Figure 5.2. Interestingly, among all countries in the sample, only Canada, the U.K. and the U.S show more variation in the trading volume during the crisis period over the period before.

For the analysis in other countries, Figure 5.2 illustrates also how the difference in variance throughout the crisis sub-period is negative in the shortest time-horizon, but not at the second and third scales. The variations in Austria, Spain, Turkey and Thailand are similar and show more persistence up to the third scale. The analysis here shows an exception for the Thai stock market, where the negative difference continues to appear up to the forth investment horizon. The same observation also applies but less for Spain and the U.K. This new finding here is in line with that in Table 5.7 where the Adjusted R^2 for the Spain, U.K. and Thailand at the forth scale are found to be the most relative to that in other countries before the crisis. Those values are again 10.6%, 10.9% and 13.6% for the three countries respectively (see Table 5.7).

The trading activity in U.S. market, however, seems to be more volatile up to the fourth scale than any other country in the sample. This distinct observation explains our results in Table 5.7 regarding the more dynamic return-volume relation for the U.S. at higher scales and in the second sub-period.

Moreover, the last general observation from Figure 5.2 shows that at the long fifth and sixth time

Figure 5.1 Estimated wavelet variance of return series using the full-sample period.

The analysis is carried out based on MODWT wavelet transformation with Db8 wavelet filter and up to the sixth time-scale. The solid line shows the unbiased wavelet variance, while the upper and lower lines represent the 95% upper and lower confidence intervals, respectively.

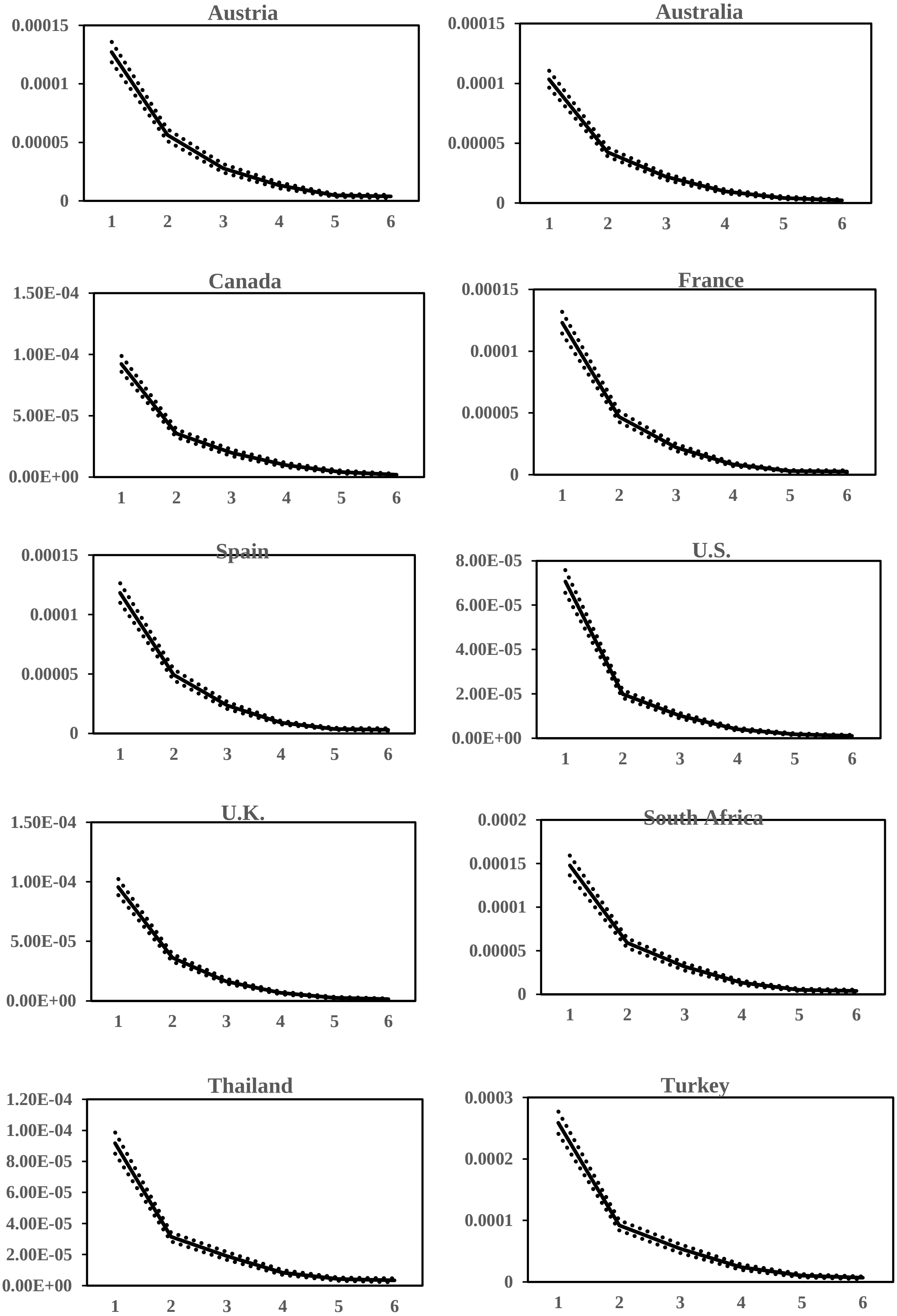
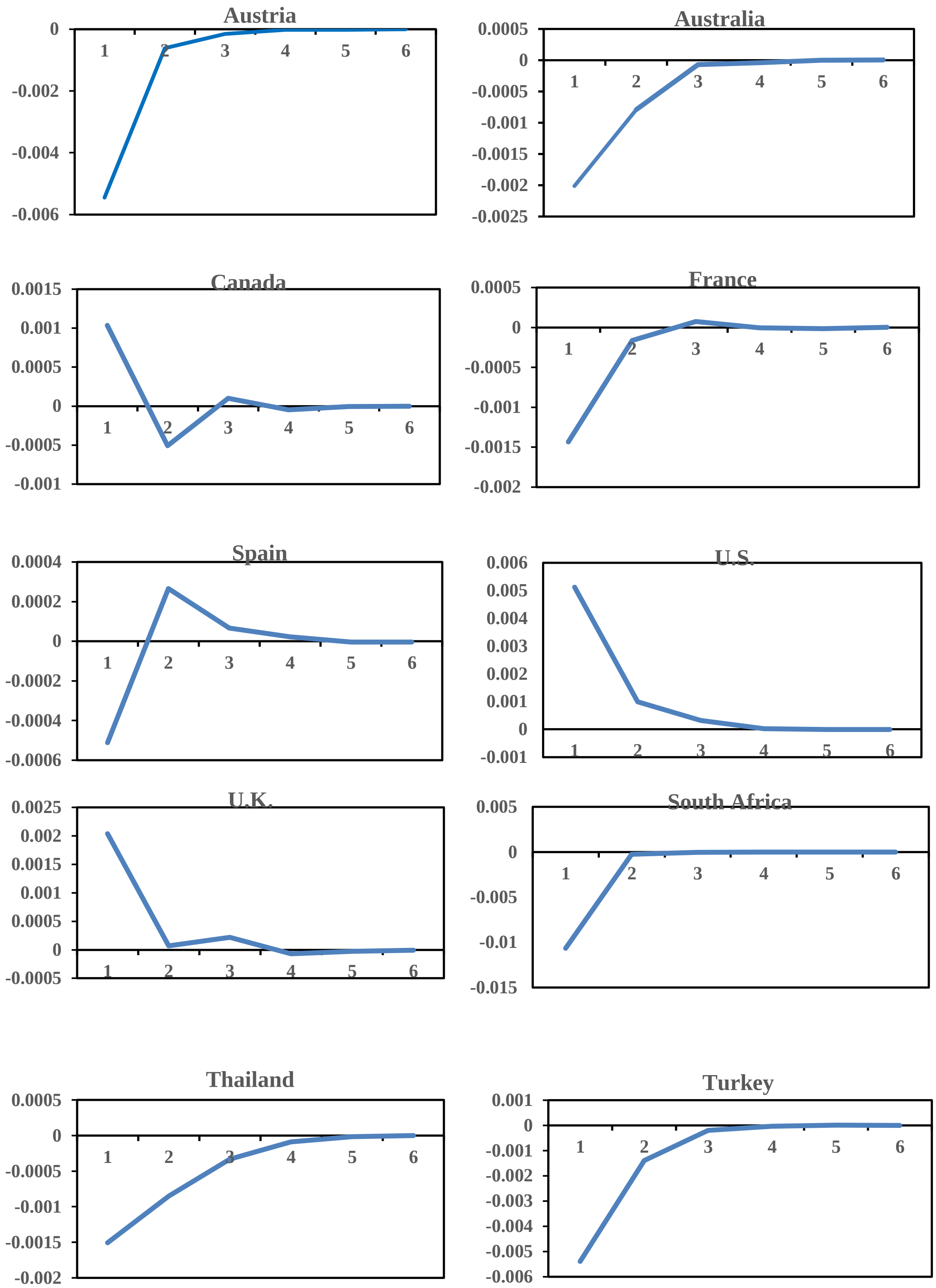


Figure 5.2 the difference in wavelet variance of trading volume between the crisis and non-crisis sub-periods

See notes on Figure 5.1.



horizons, the differences in trading activities across sub-periods disappears. Our findings indicate that investors in the markets are updating their beliefs over time, especially if the trading volume is considered as a liquidity proxy of which its measurement changes across the investment horizons. The return-trading volume relation is further examined by analyzing the covariance and the correlation in Figures 5.3 and 5.4, respectively.

Figure 5.3 continues to support our previous findings on the similarity between the analyses on Canada, the U.K. and the U.S. and that for Thailand and Turkey on the other sides. As it is shown, negative covariance is observed between the scales two and four for the first group of countries indicated here. Yet, the completely reversed relation is shown for Turkey and Thailand over the same horizons. Other countries including Austria, France and South Africa show a positive covariance in the shortest time-scale [2-4] days. Considering the covariance at the long fifth and sixth horizons, Thailand still behaves as an exception with the value for is still positive at the long time-horizon, while it is either less negative or approaching the zero point for other countries.

By analysing the new estimates in Figure 5.4, we observe the following. First, the correlation between the trading activity and the return in each country seems to start changing from the second-time scale. That is, more similarity is found here for all countries in the sample except for Thailand and Turkey. To notice again, these two countries are emerging and the correlation for them increases as the wavelet horizon increases. It evens stays positive and does not exhibit any decrease up to the fifth scale. Second, for most of the countries in the sample, the break in correlation is shown at fourth scale. This is the most observed for example for Austria, Spain, the U.K. and Thailand, but less for Canada. However, this seems not to be for France, the U.S and South Africa, where the correlation is continuously decreasing after the second scale.

In sum, the graphical analysis here (from Figure 5.1 to 5.4) confirms our finding that the stock market return mostly explains the subsequent trading at the long-run horizon. The relation is negative for all countries, but not for Thailand and Turkey. Although the South African market is included in the sample to represent an emerging one, the index selected for it which is FTSE/JSE all share can partially explain why the result is not as we expected to be for an emerging market. One further explanation for the similarity between Thailand and Turkey can be the nearly geographic location, where the Turkish market is almost located in the Asian continent[69].

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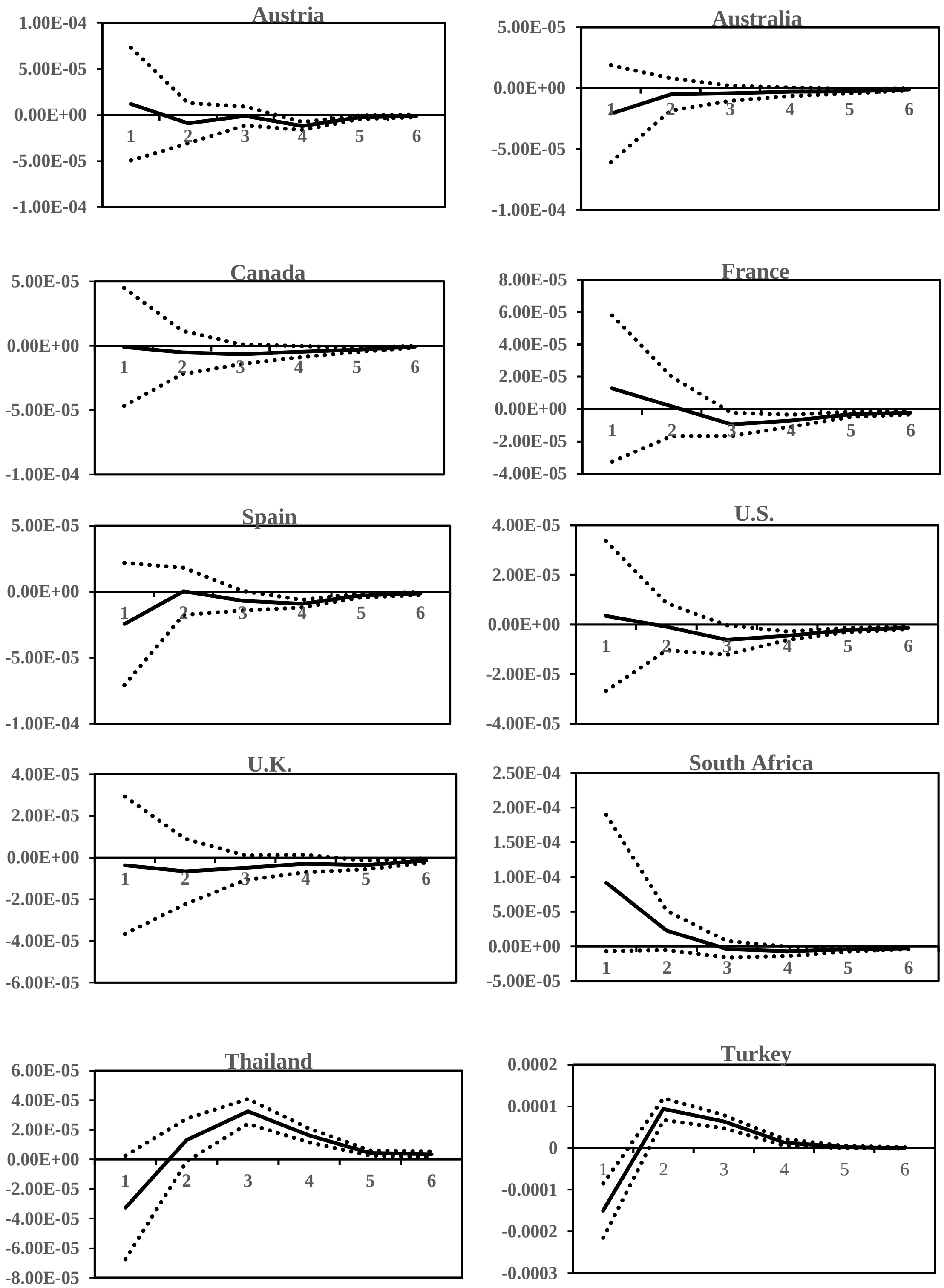
[69] In order to build on this argument, we expanded the sample by doing the analysis on three more emerging stock market indexes from India, Mexico and Sweden. Among these, in India only the stock market return positively explains subsequent trading at the third and fourth horizon. In the other two countries, this evidence is less and the sign of coefficient is negative. From the non-linear return-trading regressions using the defined bull/bear regimes and at the forth scale for India, the adjusted R^2 is 18%. The results are

Figure 5.3 Estimated unbiased wavelet covariance between return and volume series using the full-sample period

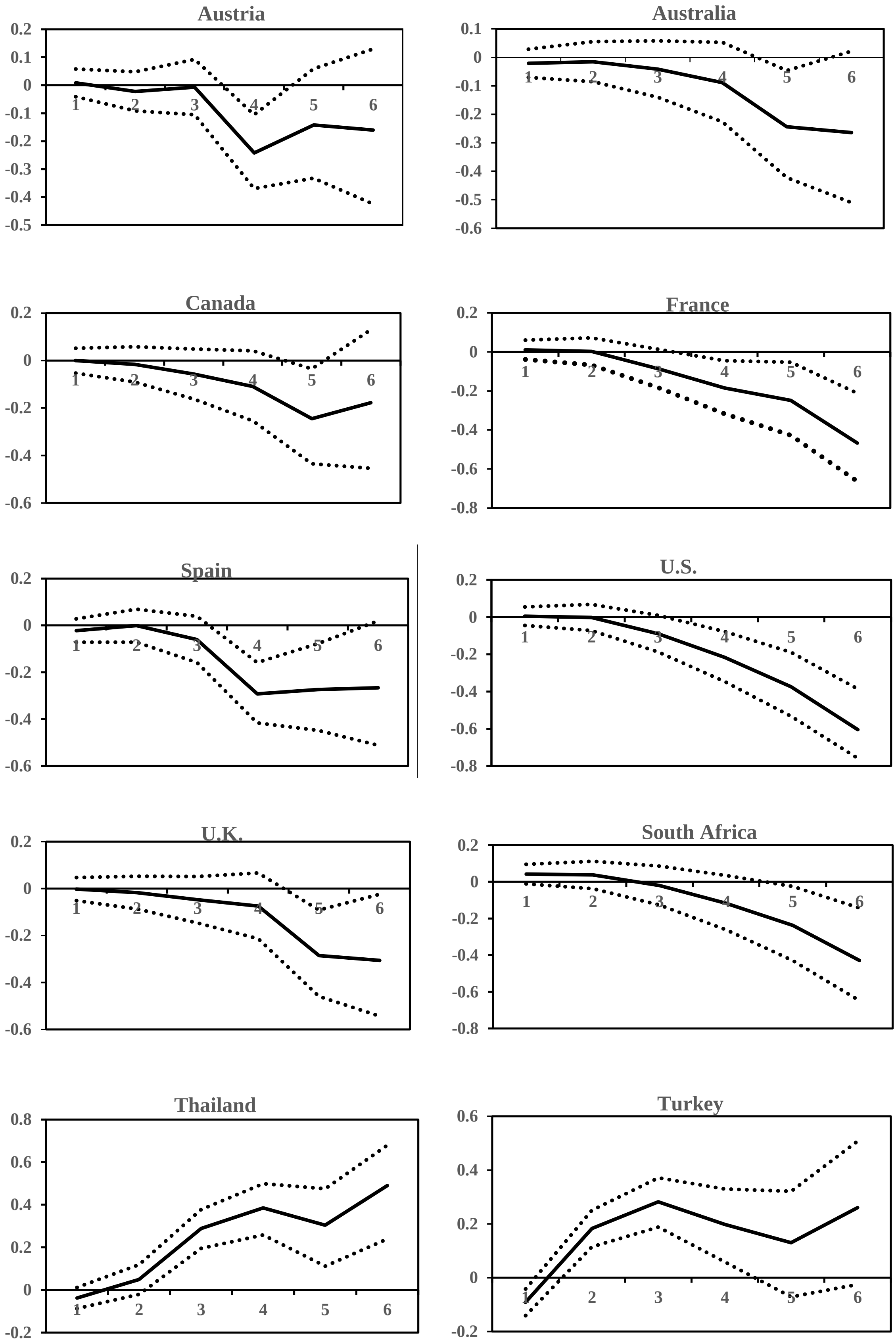
See notes on Figure 5.1.



untabulated, but available upon request. The result here suggests doing more analysis on the possibility of herding behavior between the markets within the same geographic region. A study on that can be a development over Chinco and Ye (2016) who used the wavelet variance estimator to examine the trading volume spillover across time-scales, but not between markets.

Figure 5.4 Estimated unbiased wavelet correlation between return the trading volume series

See notes on Figure 5.1.



5.6.3 Expanding the sample: more Emerging Datastream indexes

In this section, we collected the daily trading volume and closing price for eight more emerging countries using the Datastream indexes. The sample period is again from 01/01/2002 to 31/12/2013 with the countries selected being Indonesia, India, Korea, Malaysia, Taiwan, Philippines, Brazil and Greece. Our focus on the emerging markets is to ensure the balance in our sample. The focus on the emerging markets, however, is to shed more light on previous assumption that the trading behaviour for the emerging the same region can be a result of herding and on the subsequent investment horizons. The estimates from the wavelet-based correlation analysis are plotted in Figure 5.5 Again, the positive volume-return subsequent relation is evidence for all the new selected markets at the higher time scales. Yet, this seems less obvious for the markets located outside the Asian continent (see the relations in Brazil and Greece).

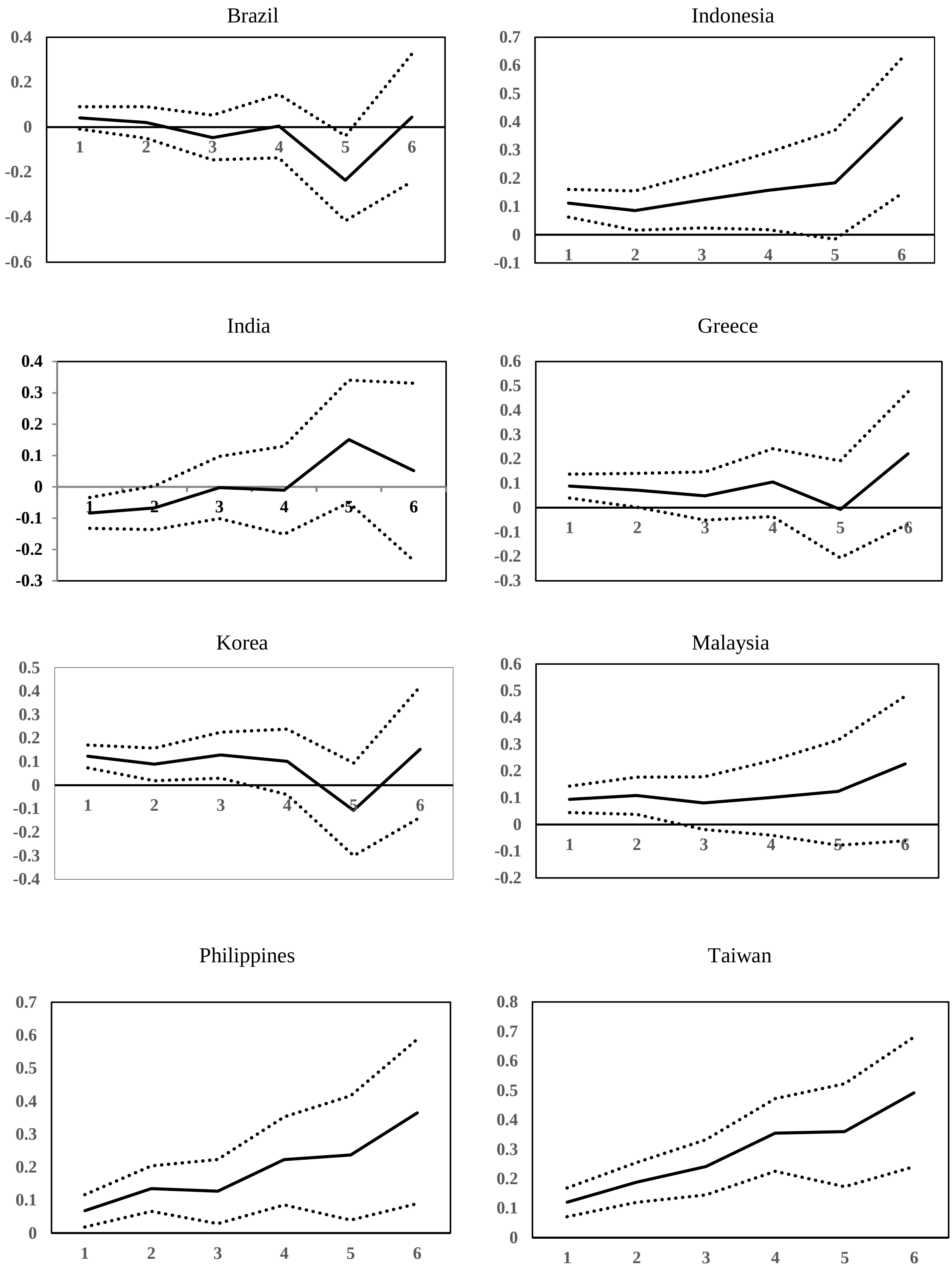
5.7 Discussion and interoperation

The main question from the literature we aimed to answer is: what explains the subsequent trading volume? We find evidence from ten markets that the time-scaled return is an important factor that is statistically correlated with the subsequent trading activity. Most of this relation is centred at the long time-horizons of [8-16] and [16-32] day-period, respectively. Furthermore, the study finds that this subsequent dynamic link between the return and the trading activity is mostly observed in bull-market periods. Of all countries, however, the relation is only positive always for two emerging countries, those are Thailand and Turkey.

We can clearly link that to the early finding by Tauchen and Pitts (1983) who examine how the joint distribution of the changes in price and volume vary within a day interval, as more active traders enter or exist a speculative market. In their study, both the variance of the daily changes in price and the mean of trading volume are theoretically assumed to change over time. Hence and according to their study that should be reflected on the joint distribution and the dynamic volume-price changes relation. Tauchen and Pitts emphasise on the role of a trend in the trading volume and how that can conceal the price-changes relation over time.

Our wavelet-variance estimation also supports Tauchen and Pitts's (1983) argument, where we find that the variance of return and trading volume are decreasing as the time-scale increases. Considering the reverse lead-lag relation from the trading volume to return, Gervais et al. (2001) give rise to what they called "the high volume-return premium" hypothesis.

Figure 5.5 Expanding the sample with the unbiased wavelet correlation between return the trading volume series.



They empirically find that a given shock in an individual trader's interest of a specific stock is supposed to support this hypothesis. More specifically, high (low) unusual trading of an individual investor in a short time period of a day or week tends to be followed by large (small) return over the next month. This relation can hold in the emerging markets with more individual trading being exist. Here we can expect the more return by the end of the month to generate a subsequent return in the same direction next month due to the autocorrelation in the return. As a result, the trading volume will increase as well based on the positive dynamic return-volume relation usually observed in the literature (See, for example, Karpoff, 1987). In line with this argument, Kaniel et al. (2008) find that individual investors tend to buy more stocks following the decline in price in the previous month and sell more otherwise. Consequently, the study documented excess return as positive following intense buying and negative if the previous month's selling is more.

One more question emerges after an examination of our findings; why is the subsequent return-volume relation on the long-term third and fourth investment horizon? The answer is that the moderate return and volume variances at these scales and this is what we found using the wavelet-based variance estimator. The results from the wavelet correlation analysis between the subsequent return and trading are also in line with those numerically obtained from regression models. For example, with the analysis conducted on sub-periods, the subsequent dynamic trading-return relation is found to be stronger during the crisis period. At the same time, we find that the difference in wavelet-variance between the crisis and non-crisis periods is the largest in the U.S. relative to other countries over the subsequent trading periods. This evidence is stronger at the time-scales span up to 16 days. Finally, more evidence has been identified of the subsequent relation during the bull-market period is consistent with Chuang and Lee (2006) on the asymmetric trading based on the overconfidence hypothesis and with Chen (2012) who examines both the dynamic and the lead-lag volume relations.

During the bull-period, the investor might update his beliefs in either direction before deciding whether to trade. As time goes by, investor overconfidence may diminish the most in the emerging markets. Hence, a heavy reliance on the subsequent return to generate the future trading can be seen as a normal process. However, how this later behavioural explanation is related to overconfidence needs to be further supported with technical evidence.

5.8 Summary and conclusion

Examination of the overconfidence theory has received considerable attention in the literature. Yet, studies conducted on that theory tend to ignore the role of factors rather the lagged return in predicting the subsequent trading. In order to add to the literature, we specifically examine whether the recent return, the time-scaled return can predict subsequent trading. In our analysis, we first decompose the trading volume on time-scales up to 32 days. Then we regress the subsequent trading volume on the recent return in one model and the subsequent return along with recent trading volume in another. We address our research question based on both the linear and non-linear regression and the wavelet-variance estimator. We conduct our study on ten stock markets and focus more on the asymmetric relation using the defined bull and bear regimes. We find little evidence that recent return does predict the subsequent trading, though this predictability is observed more at the long-run horizon. On the other hand, the study finds that subsequent trading and return relation are more statistically related to each other at the long-time investment horizons of [8-16] and [16-32] day periods. Yet, this relation has mostly a negative sign, but positive for two developing countries. Yet, it tends to be economically stronger during the bull periods. This last result is robust using the pre-crisis (crisis included) sub-periods and to alternative selection of the stock market indexes. We also find that stock market volatility tends to be significantly correlated with recent trading and at the timescale [16-32] day period. We support our evidence on the positive subsequent volume-return dynamic relation after performing the wavelet-correlation analysis and expanding the sample with more emerging markets.

All in all, by doing our analysis, we allow the participants in the stock markets as well as the regulators to better understand how trading in financial markets takes place over time. Our study differentiates between short-term and long-term horizon investors, where the risk and liquidity factors are assumed to contribute differently to the asset pricing process across different time-scales.

CHAPTER SIX

Summary & Conclusion

6.1 Summary

The previous chapters describe the wavelet theory and introduce three new applications for it to uncover the hidden relations and information in financial time series data.

The first empirical study in this thesis (**Chapter three**) investigates whether the wavelet de-noising improves the volatility forecasting and provides economic benefits for the risk management decisions. Using wavelets, the chapter de-noise the daily return data sets for eight international stock markets over the sample period from 01/ 01/1998 to 31/12/2013. For de-noising, the study employs one of the most common shrinking approaches, namely soft thresholding. More specifically, the study employs MODWT as a pre-processing technique to decompose return series data over six time-scales, with the order to be selected based on the literature and the variance of the return series in each market. In order to properly de-noise the data, the analysis considers the threshold limit dependence at each time-scale, given that the approximation components are not de-noised at all. Next, the forecasting exercise uses both the raw return series data and the de-noised data as obtained from the first step. The analysis here involves forecasting the volatility using a group of symmetric, asymmetric and long-memory models belonging to the GARCH family. Further, this analysis performs one step-ahead volatility forecasting.

The study finds that not only does the wavelet de-noising improve the forecasting performances of the GARCH models considered, but it also changes the ranking of the models. That is, the asymmetric models become the best performers after de-noising with respect to the accuracy of the statistical forecasting. Similar evidence is obtained with the superior equal predictive accuracy tests. The results here contribute to the finance literature that employs different factors, such as the error distribution assumption or the frequency of the data to judge the best model for forecasting. Moreover, the in-sample rolling regression exercise for the GARCH and EGARCH models, shows that the wavelet de-noising affects the suitability of the model parameters.

The results in chapter three also show that with the statistical forecast error measures, wavelet-based forecasts can generally be improved over raw returns-based forecasts across the range of models employed. Moreover, the study finds that removing noise enables the detection of some of the similarities between the stock markets considered with this being more pronounced around the major crisis periods. The contribution here is on how the noise itself (as defined in the study) changes the contributions of the parameters to the conditional volatility process over the full-sample period and around several turmoil periods.

Finally, and most importantly, this study also provides evidence on the importance of de-noising to gain more accurate Value-at-Risk estimate. In order to do that, the backtesting analysis considers both 95% and 99% confidence interval. The study, then, comes up with interesting findings. First, no significant changes after de-noising can be documented at the 5%. Second, at the 99% VaR, models are more likely to pass the three tests of coverage considered. However, this result becomes more obvious after de-noising the data.

Chapter four examines, for the first time in the finance literature, up to many days the effect of fourteen macroeconomic news persists on the stock-bond dynamic correlation in the U.S. The analysis mainly concerns the effect of macroeconomic news throughout and around the crisis periods. The crisis periods are the 2008 crisis the 2001 Dot-com and the 2011 U.S government debt ceiling dispute periods. In order to match my results with the literature, I construct macroeconomic surprises series by subtracting the analyst's median expectations from the actual (released) figures. I then standardise the surprises series for each macroeconomic indicator, to allow for comparison between the effects of different macroeconomic news with different units of measurements.

The study employs daily closing indexes for the DJIA, the 2-year and the 30-year maturity benchmark government bonds from Datastream database and for the sample period from January 3, 2000-Decmber 25, 2013.

The modelling process involves four main stages. First, I decompose the equity series data up to six time-scales by the MODWT wavelet transform. Second, I estimate the dynamic correlations between the stock return and each bond return series using the diagonal version of the asymmetric DCC-GARCH model of Cappiello et al. (2006). Third, the study feeds the decomposed series (only the low-frequency detailed components) into the ADCC model to estimate the correlation on scales. In the last stage, the study regresses the decomposed-based correlations on each macro surprises series separately. In this stage, however, I use both linear and non-linear regressions to account for the impact of news during the crisis period. To do this, all the regressions employ only the raw dynamic correlation series and those based on the first three investment horizons of [2-4], [4-8] and [8-16] day-period. The idea of using fewer time-scales in the analysis stems from the finding of the literature on the quick reaction of the individual equity series to the macroeconomic news. The literature here also documents stronger and quicker reactions during the crisis than the non-crises time periods. Yet, the related research finds nothing regarding the speed of reaction of correlation between equities to the news. Due to this, it was essential to conducts a study that accounts for differing crisis periods. This is because, during different episodes, the reaction to the news should be affected by sentiment and uncertainty. While, the role these factors play in the trading behaviour should be different across the crisis periods. This should then generate different reactions to the macroeconomic news.

Furthermore, more recent studies document that the correlation between equities are different across the decomposed wavelet-based series, (see, for example, Kim and In 2007; Graham and Nikkinen, 2011; Lehkonen and Heimonen, 2014). Hence, I find that it is also interesting to fill the gap by combining the two strands of research (i.e. the reaction during the crisis and different correlation patterns over time).

The results from the second study can be summarised as follows. First, little significant economic effects of the macroeconomic news are found on the correlations over the full sample periods. On the other hand, accounting for the crisis periods generated new findings. That is, most of the announcements show significant impact during the 2008 crisis period, with their effects tending to persist even beyond the announcement days. This changed after replacing the 2008 global crisis period with the 2001 and the 2011 periods. Here, the non-linear regressions show fewer effects of most of the surprises during the new episodes we controlled for. Yet, the general finding from this analysis confirmed the significant impact of both the housing starts and the CPI factors outside all the crisis periods considered. Second and interestingly, a link is observed between the speed of the reaction to news surprises and the timing of macroeconomic news release. Notably, news released early in the day and in the month, shows slower effects on the dynamic correlation than news released later in the day or later in the month. This conclusion is reached when the 2008 crisis period is used.

Overall, the second study contributes to the related literature in three ways. First, by providing new evidence on the slow reaction of the dynamic correlation to news. Second, on the role of the crisis itself in generating the reaction, with this being different across the crises periods. Finally, a part of the results introduces the basic for the “correlation reaction to news-release time” relation. This later evidence, however, requires further investigation.

Chapter four then suggested considering the time-scaling procedures, while examining the reaction to the macroeconomic news during and around the crises periods. Our findings on the

U.S. market and more on other markets should enhance understanding of the link between financial markets and the macroeconomic level.

Chapter five examines the predictability of the subsequent trading in stock markets using the recent return and the subsequent return. To do this, the MODWT is used again to decompose the trading volume and return series data for up to sixth investment horizons. The sample comprises both the daily return and trading volume series for ten stock market indexes and for the period from 1/1/2002 to 31/12/2013.

However, no results have been documented about what generates the subsequent trading. Hence, the two variables selected in trying to explain the future trading are the recent and the subsequent returns. Following the analysis in the beginning of the chapter, we examined up to how many days the predictability holds. The analysis in the chapter employs the linear and the non-linear regressions. In both cases, the decomposed trading volume series are regressed on the predictors. The first equation estimates the effect of the recent return, while the second employs both the decomposed return along with recent trading volume. The non-linear regressions, however, account for the bull and bear-market regimes as estimated by a simple Markov-switching model. In order to define the regimes, the study employs the monthly return series. Controlling for the market states, while examining the dynamic (lead-lag) trading volume-return relations are also justified by the findings of literature. For example, Chuang and Lee (2006), among others, document more statistical dynamic relations during the bull-periods than during the bear-periods.

The regression analysis undertaken documents very little statistical evidence that the recent return predicts the subsequent trading at the long-run investment horizons of [8-16] and [16-32]. More significant dynamic return-volume relations are also documented at the same higher time- scales. The second finding from the research is that, both of our predictors selected tend to have a negative impact in the developed markets, but positive in two emerging markets, namely, Thailand and Turkey. Further analysis employs the wavelet variance, covariance and correlation estimators. Here I find that among the ten countries in the sample, the trading volume-return relation continues to increase at higher time-scales for only Thailand and turkey. Last, from the nonlinear estimation, the greatest economic impact for the return series predictors is observed during the defined bull-periods.

Overall, the analysis in the last chapter certainly supports the view that the performance of investors in the stock markets change over the time horizons. Related studies in the literature reach the same finding when the wavelet is used to examine the relations between finance (economic) variables (e.g. Kim and In, 2005; Gallegati et al., 2011).

6.2 Conclusion

This thesis applies the wavelet analysis to uncover the information and hidden relations in the time series data. More specifically, it presents the advantage of the time scaling property that wavelet relates to investment horizon to provide new insights in finance.

These studies conducted with wavelet principally aim to either de-noise the data or even decompose them on specific time scales. Doing that with wavelet methods allows the investors to understand the dynamicity of the data at hand. Yet, relying on the aggregate data or the frequency domain procedures presents an obstacle to gaining more details from the data over time. In finance literature, subjects such as the volatility forecasting or the dynamic relations between variables require further investigation. Within this, the theories of "noise trader hypothesis" or "the noisy market hypothesis" already debate the role of noise in trading and the bad consequences from noise trading. Furthermore, studies in the literature seem to either empirically ignore the effect of noise in forecasting the volatility or using the frequency-based approaches. Examples on these filtering procedures include the standard Fourier or the Kalman filters. Applying the wavelet methods, instead, aims to decompose the time series into high and low-frequency components. Wavelet analysis then continues by isolating more detailed information from noise when both components are located in high-frequency components. The analysis here with wavelets considers the variance of the return series on different time scales, and sets a threshold limit based on that to de-noise the data. Applications on that include, for example, Capobianco (2002) and Herwartz and Schlüter (2016).

The analysis in **Chapter three** documents that both the forecasting performance for one day-ahead and using the GARCH models can be statistically improved after de-noising the return. More interestingly, the study reveals that the ranking of the model itself has been changed after removing the noise. Specifically, here, the asymmetric GARCH models became the best performers, thought this is not universal. Furthermore, the suitability of the wavelet de-noising for the economic performance has been proved under 99 % VaR requirement compared to the 95%. Chapter three then enters new debate to answer the question why the asymmetric GARCH models became mostly the best after de-noising. The answer to this question is that de-noising the data helps to uncover stronger asymmetry in the volatility compared to that detected before de-noising.

On the other hand, the interactions between the financial markets and the financial (economic) variables in the markets continually change depending on investor decisions and the market's regime. In these dynamic environments, the wavelet decomposition again appears as an appropriate methodology to decompose the data on time-scales, before understanding how these relations vary over time, (see, e.g. In and Kim, 2013; Gallegati and Semmler, 2014).

In order to build upon this lineage of research, I use MODWT again in two more studies and the new dynamic relations have been detected. In **Chapter four**, and for the first time, I examine how stock-bond dynamic correlation in the U.S. tends to change on the same day as a macroeconomic news announcement and some days afterwards. The study here reveals that reaction to the news can be merely determined by the state of the market and the time of the release. Specifically, it is found that the reaction to the news tends to slow down during the recent 2008 crisis and this pattern ends to be slightly different after accounting for other crisis periods. Interestingly, a link is also observed between the speed of the reaction to the news and the exact time of release. More specifically, there is a slower reaction to early time releases. The findings in this chapter seems to support the general idea that, first it is important for the future research to account for the reaction to the macroeconomic news on time-scales basis and different market conditions. In other words, such a reaction can be continuously revealed over the subsequent investment horizons. That speed of reaction and how quick the investor in the market is in adjusting their portfolio tend depend on a specific crisis and not the whole bear (recession) market period. Generally, the findings in this study supports the general view of the researchers that investors over-react to private news, but under-react to public news.

Finally, **Chapter five** examines whether the recent and the subsequent stock market return generate the subsequent trading activity in the market. Using MODWT again and with daily data, I find that the more trading on the distant investment horizons [8-16] and [16-32], is statistically related to the return at the same horizons. Allowing for market classification, however, reveals that the sign of relation is mostly positive (negative) for the developing (developed) countries in the sample. This finding has been further supported in the study by expanding the sample, while doing the wavelet correlation-based graphical analysis between the daily return and trading activity.

6.3 Limitations of the thesis and recommendations for future research

6.3.1 Limitations of the thesis

The samples and the methods employed in the thesis have both advantages and drawbacks. These can be described as follows.

In the first study, the data is restricted to the developed markets, with no emerging market being selected at all. Although, doing the analysis in the developed countries should partially isolate the effect of investor sentiment and market uncertainty, which affect emerging markets the most. This requires controlling for these factors while removing the noise from the return data. However, there is almost no data available for either of these psychological variables in emerging markets.

On the other hand, sentiment proxies such as consumer confidence, business surveys and uncertainty variables (e.g. implied volatility index) are all well developed in the literature; hence they can be easily collected for the developed markets. In addition, the complexity of the wavelet de-noising approach should suit more informed investors in developed markets. Investors in these markets are more able to use advanced pre-processing methods compared to traders in developing markets. In contrast, forecasting the volatility in emerging markets can be accurately done using the simple models, such as the RiskMetrics (e.g. McMillan and Kambouroudis, 2009). In other words, there is a trade-off between the complexity of the wavelet de-noising methodology and the outcomes from the analysis. Therefore, it seems important to compare the performance of the frequency-based simple methods, such as the Fourier method and the wavelet approach. The applicability of one method might depends on the classification of the market itself (i.e. emerging or developed).

Furthermore, the second study is conducted in the U.S market only. Further analysis by expanding the sample to include European countries, for example, might be of interest. A study here could examine the effect of the macroeconomic surprises in the Euro area on stock-bond dynamic correlation during and around the 2011 Euro crisis.

The last empirical study focuses on the predictability of the subsequent trading mainly using two variables, the recent and the subsequent returns. These two factors, however, are relevant to short-term investors in the markets who update their beliefs over time. Controlling for more variables, such as transaction costs, the type of investors in the market and investor sentiment should explain our finding. Incorporating these factors, or others, might explain the positive difference in trading volume between the 2008 crisis and non-crisis period in the U.K., U.S. and Canada. This, again, is what the study found on the first decomposition level, [2-4] day-period, while using the wavelet- variance estimator.

Finally, the sample in chapter five also mostly covers the developed markets. Yet, this is due to the availability of trading volume data in the emerging markets. For other markets not included in the sample, the data is either available only after 2005, and/or has a very large amount of missing observations after that.

6.3.2 Recommendations for future research

Several possible applications of wavelet in finance can be explored further. For example, a study can be conducted to examine the herding behaviour on time-scale basis within and across countries. Moreover, a comprehensive study on a large sample of countries must analyse how the stock-bond correlation tends to change throughout and outside several crisis periods. Finally, an interesting study can again apply wavelet de-noising method and examine how the noise moves from one financial market to another. The study here can also be extended to examine the noise spillover/contagion under different conditions whether, for example, the weaknesses of market regulations and proportion of the irrational investors in the market should enforce the noise trading behaviour across markets at one time. I am working now on some of these suggested ideas and the research is ongoing.

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APPENDIX

Appendix (A) to Chapter three

Table A.1 Pairwise correlation between the original and de-noised return series for the same index.

*** denotes to a significant relation at 1% significance level.

Index	Correlation
AEX	0.881***
DAX	0.910***
CAC	0.916***
DJIA	0.930***
IBEX	0.920***
FTSE	0.915***
NASDAQ	0.932***
NIKKEI	0.870***

Table A.2 Test of ARCH effect under Ho: No ARCH effects with one lag.

The result reported in the Table for either rejection of the null hypothesis (N) or acceptance (Y) at 1% significance level.

Index/Model	GA	EG	TG	AP	CG	FI	HY
Panel A: Using the contaminated return series							
AEX	Y	N	**Y**	**Y**	N	N	N
DAX	**Y**	**Y**	**Y**	**Y**	N	N	N
CAC	N	N	N	N	N	N	N
DJIA	N	N	N	N	N	N	N
IBEX	N	N	N	N	N	N	N
FTSE	N	N	N	N	N	N	N
NASDAQ	N	N	N	N	N	N	N
NIKKEI	**Y**	**Y**	**Y**	**Y**	N	N	N
Panel B: Using the de-noised return series							
AEX	N	N	N	N	N	N	N
DAX	**Y**	**Y**	**Y**	**Y**	N	N	N
CAC	N	N	N	N	N	N	N
DJIA	N	N	N	N	N	N	N
IBEX	N	N	N	N	N	N	N
FTSE	N	N	N	N	N	N	N
NASDAQ	N	N	N	N	N	N	N
NIKKEI	N	N	N	N	N	N	N

Table A.3 Test of autocorrelation at squared standardised residual with one lag. Ho: No autocorrelation.

The result reported in the Table for either rejection of the null hypothesis (N) or acceptance (Y) at 1% or higher.

Index/Model	**GA**	**EG**	**TG**	**AP**	**CG**	**FI**	**HY**
Panel A: Using the contaminated return series							
AEX	**Y**	N	N	N	N	N	N
DAX	**Y**	**Y**	**Y**	**Y**	N	N	N
CAC	N	N	N	N	N	N	N
DJIA	N	N	N	N	N	N	N
IBEX	N	N	N	N	N	N	N
FTSE	N	N	N	N	N	N	N
NASDAQ	**Y**	**Y**	**Y**	**Y**	N	N	N
NIKKEI	**Y**	**Y**	**Y**	**Y**	N	N	N
Panel B: Using the de-noised return series							
AEX	N	N	N	N	N	N	N
DAX	**Y**	**Y**	**Y**	**Y**	N	N	N
CAC	N	N	N	N	N	N	N
DJIA	N	N	N	N	N	N	N
IBEX	N	N	N	N	N	N	N
FTSE	N	N	N	N	N	N	N
NASDAQ	N	N	N	N	N	N	N
NIKKEI	N	N	N	N	N	N	N

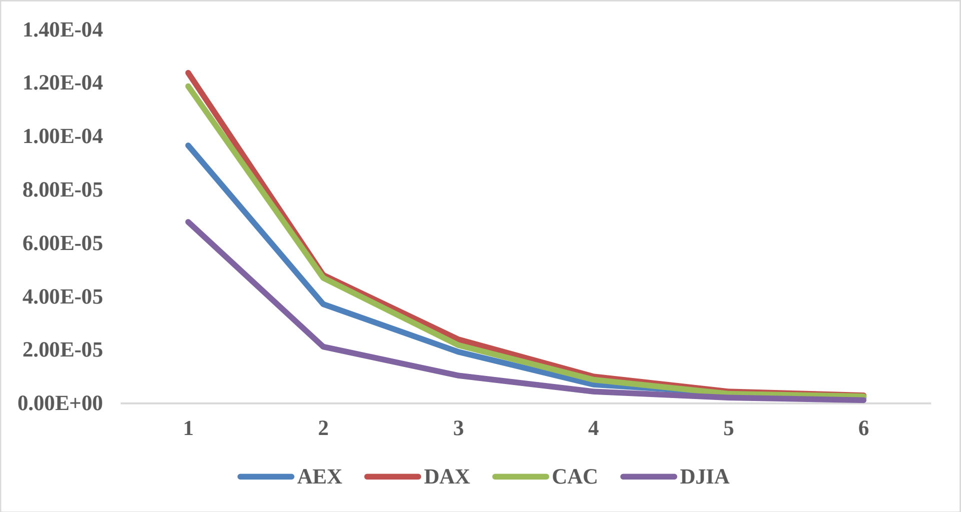
Table A.4 Graphical representation for the wavelet-variance estimates at the investment horizons.

The analysis used the Matlab codes as applied by Percival and Walden (2000) with Circular boundary condition and the 95% unbiased confidence interval estimator. The variance at each scale is calculated as follows:

$$\nu_S^2(\tau_j) = \frac{1}{\tilde{n}_j} \sum_{t=L_j}^{n} \left[\tilde{D}^S_{j,t} \right]^2$$

Where: S is the return series at hand. τ_j = is the time scale, t= time period, D= detailed series component, and n= total number of observations in the original time series.

Panel A: The variance decomposition for AEX, DAX, CAC and DJIA.



Panel B: The variance decomposition for IBEX, FTSE, NASDAQ and NIKKEI.

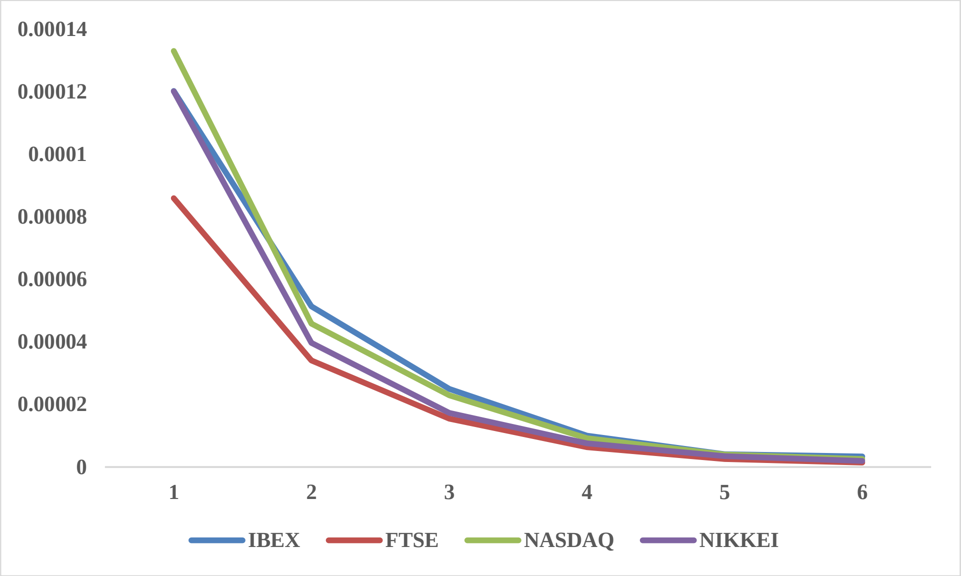


Table A.5 the estimates of the threshold limites at the investment horizons. The estimates are obtained after minimizing the Stien's unbiased risk estimator.

	Threshold limit at the time scale =					
	1	2	3	4	5	6
AEX	0.016	0.014	0.014	0.017	0.009	0.008
DAX	0.017	0.019	0.018	0.021	0.018	0.013
CAC	0.017	0.015	0.016	0.018	0.016	0.022
DJIA	0.012	0.012	0.011	0.011	0.010	0.010
IBEX	0.016	0.015	0.015	0.021	0.019	0.025
FTSE	0.016	0.015	0.010	0.011	0.016	0.017
NASDAQ	0.014	0.016	0.017	0.014	0.014	0.019
NIKKEI	0.020	0.027	0.018	0.020	0.021	0.020

Appendix (A) to Chapter Four

Table A.1 The description of some macroeconomic news in the sample and the importance to investors. Source: the 2017 Bloomberg Economic Calendar.

Macroeconomic event	Event definition	Why investors care?
CPI	It is a chain-weighted index that measures a variable basket of goods and services whereas the regular CPI-U and CPI-W measure a fixed basket of goods and services. That is the index shows the change in price levels since the index base period, currently 1982-84 = 100. Monthly changes in the CPI represent the rate of inflation.	The effect ripples across stocks, bonds, commodities, and your portfolio, often in a dramatic fashion. The bond market will rally (fall) when increases in the CPI are small (large). The equity market rallies with the bond market because low inflation promises low interest rates and is good for profits.
Consumer Credit	The dollar value of consumer installment credit outstanding. Changes in consumer credit indicate the state of consumer finances and portend future spending patterns.	Financial market players focus less attention on this indicator because it is reported with a long lag relative to other consumer information. Long term investors who do pay attention to this report will have a greater understanding of consumer spending ability. This will give them a lead on investment alternatives. Also, during times of distress in credit markets, consumer credit can give an idea about how willing banks are to lend.
Factory goods orders	The dollar level of new orders for both durable and nondurable goods.	Investors want to keep their fingers on the pulse of the economy because it usually dictates how various types of investments will perform. The stock market likes to see healthy economic growth because that translates to higher corporate profits. The bond market prefers more moderate growth which is less likely to cause inflationary pressures. By tracking economic data like factory orders, investors will know what the economic backdrop is for these markets and their portfolios.
Housing starts	The start of construction of a new building intended primarily as a residential building.	The bond market will rally when housing starts decrease, but bond prices will fall when housing starts post healthy gains. A

		strong housing market is bullish for the stock market because the ripple effect of housing to (other) consumer durable purchases spurs corporate profits. In turn, low interest rates encourage housing construction.
Industrial production	It measures the real output and is expressed as a percentage of real output in 2007.	The bond market will rally (fall) when the industrial production is low (high) and the reverse is true for the relation with the stock market.
New single-house sales	The number of newly constructed homes with a committed sale during the month.	There is a direct bearing on stocks, bonds and commodities. Trends in the new-house sales data carry valuable clues for the stocks of home builders, mortgage lenders and home furnishings companies.