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Global financial crisis and multiscale systematic risk: Evidence from selected European stock markets

A. K. Alexandridis*,[1] and M. S. Hasan[1]

[1]University of Kent, Kent Business School, Canterbury, Kent, CT2 7PE, UK

Abstract - In this paper, we have investigated the impact of the global financial crisis on the multi-horizon nature of systematic risk and market risk using daily data of eight major European equity markets over the period of 2005-2018. The method is based on a wavelet multiscale approach within the framework of a capital asset pricing model. Empirical results demonstrate that beta coefficients have a multiscale tendency and betas tend to increase at higher scales (lower frequencies). In addition, the size of betas and R^2s tend to increase during the crisis period compared with the pre-crisis period. The multiscale nature of the betas is consistent with the fact that stock market investors have different time horizons due to different trading strategies. Our results based on scale dependent value-at-risk (*VaR*) suggest that market risk tends to be more concentrated at lower time scales (higher frequencies) of the data. Moreover, the scale-by-scale estimates of *VaR* have increased almost three fold for every market during the crisis period compared with the pre-crisis period. Finally, our approach allows for accurately forecasting time-dependent betas and *VaR*.

Keywords: Global Financial Crisis; Multiscale Systematic Risk; Wavelet Analysis; Wavelet Networks; CAPM

JEL Classification: C22; G15

1 Introduction

In this paper, we investigate the impact of the global financial crisis on the multi-horizon nature of systematic risk and market risk. We use daily data from eight major European equity markets. Our method is based on a recent and powerful method to estimate both the market risk and the systematic risk within the framework of the Capital Asset Pricing Model (CAPM) using wavelet analysis (WA).

Although the major financial US institutions, such as New Century Financial, US holding of HSBC, and the world's top five investment banks suffered huge losses in the subprime mortgage and collateralized debt obligation (CDO) transactions by Summer 2007, the world financial system observed a period of relative calm with some optimism regarding the outcome of the ongoing crisis until the eight months of 2008[1,2]. Figure 1 presents a cursory example of several major banks' exposures to AIG during the time of financial crisis for readers to

* Corresponding author. Email: A.Alexandridis@kent.ac.uk

[1] For example, see the interim report title, "Assessing the impact of the current financial and economic crisis on global FDI flows", UNCTAD, January 2009.

[2] Dowd (2009) noted that the size of the collateralized debt obligations (CDO) market in 2007 was around \$500 billion, and then notional principal of the Credit Default Swaps (CDS) market by the end of 2007 was around \$60 trillion.

understand the magnitude and extent of the problem inherent in the systemic risks associated with the financial system and institutions.

The subprime mortgage crisis eventually erupted when first, major US financial firms, such as Lehman Brothers and AIG, and then European financial institutions, such as Northern Rock, Fortis, Dexia, and a number of Icelandic banks, showed signs of insolvency.[3] The crisis exposed the inherent vulnerabilities, systemic risks and a catalogue of regulatory failures in the global financial services industries. The meltdown of the subprime crisis of 2007 exerted a meteor shower effect across the world's stock market by the fourth quarter of the 2008. In the last quarter of 2008, the stock markets of both developed and emerging economies experienced large decline in prices of securities.[4] Figure 2 presents movements of stock market indices in USA and five European countries namely, Netherlands, United Kingdom, Germany, Greece and Spain, during the period of 2005-2012 which uniformly demonstrates a sharp decline of share prices during the period of September-November, 2008 for all countries. Although the stock markets of United Kingdom, Netherlands and Germany exhibit an upward trend after November 2008, the stock markets of Greece and Spain show a persistent downward trend in their share prices. It is clearly evident that the Global financial crisis exerts an adverse impact on both systematic and market risks for these countries.

Eichengreen *et al.* (2012) investigated the impact of subprime crisis on the global banking system using a dynamic factor model. The study employed principal components analysis to identify common factors in the movement of banks' credit default swap spread (CDS). The study found that the share of the variance accounted by common factors rose steadily to exceptional level from the outbreak of the subprime crisis which reflected the heightened funding and counterparty risks coupled with the deterioration of banks' loan portfolio. Vo (2014) utilized co-exceedance approach to examine financial contagion in Euro Area and South Asian markets using a framework of multinomial logit regression model and daily data spanning the period January 2007 to March 2013. Exceedances are defined as extreme negative returns that are below a certain threshold (i.e., 5% bottom tail) in one country, whereas co-exceedances refer to the joint occurrences of exceedances in two or more markets. The study documented evidence of co-exceedances during global financial crisis and Eurozone crisis. Choudhry and Jayasekera (2015) reported that during the turbulent period of global financial crisis, betas increased for most firms in the UK from the pre-crisis to the crisis period and the level of market efficiency declined significantly from the pre-crisis to crisis period. Asgharian *et al.* (2017) examined the long-run and short-run components of factor betas using a framework of component GARCH model. They have applied an augmented Fama-French asset pricing model to industry portfolios using market, SMB and HML as risk factors. The study reported that the cross-sectional average and dispersion of the short-run component of betas increase in bad states of the economy. Given the anecdotal evidence of significant deterioration of systematic risk and market risk, the findings from these studies indicate that the extent of co-movement in stock markets points to tendencies of the degree to which the global financial system is perceived to be tied to common factors. Consequently, CAPM and International CAPM (ICAPM) provide an appropriate methodological framework to approximate the heightened systematic risk underlying the deterioration of common factor in such turbulent market conditions.

[3] In a revised estimate of the International Monetary Fund, large US and European banks are expected to lose nearly 2.6 trillion from 2007 to 2010 where the US banks' forecasted loss tends to reach $1 trillion and the European banks losses were expected to hit $1.6 trillion (see Choudhry and Jayasekera (2012)).

[4] Bartram and Bodnar (2009) noted that the global equity market which stood at an all-time high of $51 trillion in October 2007, dropped to $22 trillion by the end of February 2009.

One recent research strand of CAPM has built an empirical modelling strategy centering on the issue of the multiscale nature of the systematic risk using a framework of WA, Fernandez (2006), Gençay *et al.* (2005), Masih *et al.* (2010), Norsworthy *et al.* (2000), and Rua and Nunes (2012). WA is often regarded as a "microscope" in mathematics and provides a powerful tool to represent nonlinearities and to decompose time-series data into orthogonal components with different frequencies and the method can accommodate structural changes, discontinuities and regime shifts often found in financial data. Empirical characteristics of financial time-series vary depending on the time horizon. As In and Kim (2006) contended, the security markets consists of thousands of traders and investors with different time horizons and strategies in their mind regarding the investment decision.[5] Furthermore, Kamara *et al.* (2016) argued that investors' view of systematic risk for a given asset is horizon dependent which leads to a clientele effect and a phenomenon of horizon pricing. Under this thesis, investors with a preference of one horizon clientele underweights certain asset which cause another clientele to overweight those assets. For instance, highly leveraged hedge funds are concerned with short-term liquidity shocks while long-term investors, such as pension funds, endowments, close-end mutual funds, long-run individual investors are capable of investing in high-yield but less liquid assets.[6] Given the different pricing kernel and different horizon clienteles, it is important to measure both systematic and market risks at different horizons for investors and financial practitioners with varying risks and investment preferences. If investors use a shorter time horizon than the true one the beta estimates of the CAPM will be biased, Gençay *et al.* (2005), Levhari and Levy (1977). Hence, WA is ideal for studying the multi-horizon properties of time-series as they can be used to decompose a signal into different time horizon or frequency components. Furthermore, the wavelet approach overcomes the data reduction problem generally found for low-frequency data, capturing information associated with all available data, Conlon *et al.* (2016). Ramsey (1999) contends that WA has the ability to represent highly complex structures without knowing the underlying functional form, which is of great benefit in economic and financial research.

Therefore, in this paper, we are investigating the impact of the global financial crisis on the stock markets of eight major European equity markets, such as France, Germany, Greece, Italy, Netherlands, Portugal, Spain and the United Kingdom within the framework of CAPM using daily data over the period of 2005-2018. The stock exchanges of these countries represent major exchanges within the European Union (EU) in terms of both market capitalisation and trading volume[7].

We contribute to the relative literature in the following ways. First, we assess the impact of the global financial crisis and contagion by investigating the stock markets' responses in terms of their effects both on systematic and market risk in highly correlated markets linked with trade and investment. Second, we study the multi-horizon behavior of the systematic and

[5] For example, within the speculator group, there are scalpers, day traders and position trader who act in the markets ranging from minute by minute, hour by hour, day by day, even month by month. Even within the three different types of participants, i.e., hedgers, speculators and arbitrageurs, in the derivative markets, there are long-horizon traders who concentrate on long-run price fundamental and there are short-term traders who respond to information within a short-term horizon [see, Connor and Rossiter (2005) and Fernandez (2008)].

[6] Kamara *et al.* (2016) noted that in a well-segmented market, as assets are held by different horizon clienteles, different assets are priced with different pricing kernel. They find that liquidity risk is priced over short horizons while value risk is priced over intermediate horizons; long horizon investors focus on investing in less liquid but high return assets.

[7] Furthermore, the US and European investors hold a large amount of financial assets in their portfolios by investing in ADR, GDR, country fund and direct participation in both markets. Given this closer relationship, investors and financial institutions from a number of European countries suffered huge losses in the US real estate market.

market risks in different time-periods and market conditions. The behaviour and performance of the CAPM during the pre-crisis, crisis, Euro-crisis and post-crisis periods provides a convenient and powerful framework for an empirical assessment of the impact of the crisis on the European stock markets. Third, we study the positions of the wavelets of the decomposed signal and we identify features of the return series which we match with various economic and socio-political events. Finally, we investigate whether we can model the decomposed parts of each return signal using a nonlinear nonparametric Wavelet Network (WN) and whether this approach can lead to enhanced forecasts for both the systematic risk and market risk.

In our analysis, we first investigate for possible contagion effects of the U.S. crisis to the European stock markets and then we perform a local analysis of each European stock market separately by applying a national CAPM. Our results indicate that the correlation between the markets increased during the crisis period but significantly decreased when the U.S. market started to recover, and correlation increased again when the crisis moved to the Eurozone. Our results suggest that the beta coefficients have a multiscale dependency and tend to increase at mid to higher scales making CAPM predictions more meaningful for investment horizons of 8-16 days. In our analysis, the results from the Euro-crisis and post-crisis samples indicate that changes of both betas and R^2 varies between the two groups of the European markets. The market risk tends to be concentrated at lower time scales. In addition, Value-at-Risk (*VaR*) estimates tend to increase threefold almost for every country during the global financial crisis period relative to the pre-crisis period. The evidence of multiscale nature of systematic risk and market risk has important policy implications for financial practitioners, fund managers, researchers and policy-makers. It is essential for investors to assess market and systematic risk at scale level and match it with their investment horizon. Finally, our results indicate that WNs constitute an accurate tool for forecasting the systematic and market risks by capturing their dynamics and their multiscale nature.

The rest of the paper is organised as follows. Theoretical underpinning and implications are discussed in section 2. The proposed methodology is presented in section 3 while the data are described in section 4. Our empirical results regarding the multiscale systematic risk and the multiscale market risk are discussed in section 5. Finally, in section 6 we conclude.

2 Literature review

2.1 Theoretical underpinning and implication

The concept and importance of equity market linkage, crisis, contagion and spillovers has stimulated substantial research at both a theoretical and an empirical level that extends over almost three decades following financial market liberalisation, globalisation and advances in communication and information technology.[8] One of the main explanations for stock market propagation is that, as world equity markets are becoming more integrated, individual stock prices share common stochastic trend(s) – a phenomenon which is known as cointegration. The long-run co-trending properties of stock indices across markets indicate that stock price behaviour in these markets is founded upon the same economic growth factors that underlie earnings and dividends. The application of the ICAPM generates theoretical predictions which are in accordance with common trend(s). The latent factor model and the recent dynamic factor model maintain that stock prices are determined by world and regional factors, as well as a

[8] For example, see Masih and Masih (2002) and a list of references therein for research on stock market interdependence, see Engle *et al.* (2012), Engle *et al.* (1990) and a list of references therein, and Theodossiou and Lee (1993) for research on mean and volatility spillovers across markets, see Claessens and Forbes (2001), Forbes and Rigobon (2002) and Dungey and Martin (2007) for research issues of crisis and contagion.

local factor representing idiosyncratic risk. A special type of cointegration is contagion where markets become excessively aligned. Bekaert *et al.* (2005) defined contagion as correlation which is stronger than that based merely upon market fundamentals. A distinction is drawn between two factors underpinning a stock return: the US equity market return; and the regional equity market return. Within this context, the size and structure of correlations are examined, subject to a change in the volatility factor and factor sensitivities.

[Insert Figure 1]

[Insert Figure 2]

Engle *et al.* (1990) proposed two hypotheses as to how volatility might manifest itself across trading centers. The 'heat wave' hypothesis asserts that volatility has only location-specific autocorrelation, such that a volatile day in New York, for example, would be followed by another volatile day in New York. The 'meteor shower' hypothesis asserts that intraday volatility extends from one trading center to another, so that a volatile day in New York, for example, would be followed by a volatile day in London. Engle *et al.* (1990) described the meteor showers in the context of complete access to world-wide news in a market which allows for continuous trading. In this model, terrestrial geography plays no role in determining the impact of news on the volatility of financial markets. In such a market, volatility spillovers occur when uninformed liquidity traders and investors with heterogeneous priors cannot efficiently absorb private information in the price formation of securities.

Given the theoretical foundation and consequences for efficiency, an appreciation of the phenomenon of stock market propagation is essential for several reasons. First, recognising the existence of stock market propagation is critical to the investors and financial practitioners for the purpose of valuing securities, implementing hedging strategies and deciding upon the distribution of assets. Second, an awareness of stock market propagation and volatility is required by financial sector regulators for the calculation of Minimum Capital Risk Requirement (MCRR), and performing stress tests and scenario analysis, founded upon value at risk and/or extreme value models. Also, such information is of particular relevance for policy-makers with the potential to intervene in financial markets and regulate the operation of equity markets.

2.2 Empirical studies on contagion

There is a wealth of literature on financial contagion, which has accumulated over the past three decades, founded on several financial crises (see, for example, Allen and Gale (2000), Chiang *et al.* (2007), Fry-McKibbin and Hsiao (2014), Gallegati (2012), and Kenourgios *et al.* (2011), and references therein).[9] Bekaert *et al.* (2014) note six channels of contagion. First, as the recent global financial crisis originated in the banking sector, the international banking sector links transmit shocks from one country to another. Second, as a consequence of the implementation of various financial policies (through debt and deposit guarantees and capital injection) across countries in order to protect the domestic financial sector.[10] Third, in

[9] The bulk of the research on contagion is data driven, relying on various types of time series models, such as a testing scheme based on changes in correlation coefficients (King and Wadhwani 1990), ARCH and GARCH models (Engle *et al.* 1990), cointegration relationships (Chouliaras *et al.* 2012), probit/logit models (Eichengreen *et al.* 1996, Kaminsky and Reinhart 2000), regime switching (Boyer *et al.* 2006, Rodriquez 2007), the factor model (Bekeart *et al.* 2014), the Copula approach (Rodriquez 2007) and the higher moments of probability distributions (Fry *et al.* 2010).

[10] For example, see Federal Reserve Bank of St Louis' Financial Crisis Timeline (2009).

accordance with the globalization hypothesis, in highly integrated international economies, contagion occurs through trade and financial linkages. Fourth, during economic crises, information asymmetries decrease as investors focus more on publicly available information, which may lead to an increase in correlation. Fifth, under the 'wake-up call hypothesis', a crisis in one market segment or country furnishes new information that motivates investors to reassess the vulnerability of other market segments or countries. Finally, there is the potential for herding behavior or investors' risk appetite.

Bekaert *et al.* (2014) develop a three-factor model for the pricing of 415 country-sector equity portfolios across 55 countries: a U.S.-specific factor; a global financial factor; and a domestic factor. The labels which they attach to these are respectively: 'U.S. contagion'; 'global contagion'; and 'domestic contagion'. The study finds evidence of: modest contagion from the US and global financial sector; yet substantial contagion from domestic markets to individual domestic portfolios.

Tabak *et al.* (2016) investigate contagion in the context of Credit Default Swaps and banking and equity markets over the period, January 2006 to August 2013. The study finds evidence of strong contagion in these markets in several cases. In particular, it reports widespread contagion during the Global Financial Crisis and Eurozone Sovereign debt crisis.

Fry *et al.* (2010) proposed a coskewness-based test of contagion to identify transmission channels of financial market crises using data on real estate and equity markets following the Hong Kong crisis in 1997-1998 and the US subprime crisis in 2007. The results of these tests showed linkages across markets that correlation based measure of contagion were unable to detect. Fry-McKibbin and Hsiao (2014) examine the issue of contagion during the nine crises ranging from Asian crisis in 1997-98 to the recent European debt crisis of 2010-2013. They employ a regime-switching model to identify the crises' dates and a framework of correlation, coskewness and covolatility to examine the dependence structure of the equity markets. Their empirical results show that finance linkages are more important than trade in crisis transmission; emerging market crises were transferred to developed markets and the Great Recession is a truly global financial crisis.

Baur (2012) investigates the issue of financial contagion and the real economy using data on ten sectors in 25 major developed and emerging stock markets over the period of Global Financial Crisis, 2007-2009. The study finds that the crisis led to an increased co-movement of returns among financial sector stocks across countries and between financial sector stocks and real economy stocks.

Interested readers may consult a series of papers, which have documented experience of contagion based on other non-European countries. For example, Chiang *et al.* (2007) examine the issue of financial contagion in nine Asian markets using a dynamic conditional-correlation model over the period, 1990 to 2003. The study finds evidence of a contagion effect and identify two phases of Asian crisis. The first stage demonstrates an increase in correlation (contagion), while the second shows a continued high correlation (herding). Samarakoon (2011) investigates the transmission of shocks between the US and the emerging and frontier markets to delineate interdependence from contagion. The study indicates that interdependence is driven more by U.S. shocks, while contagion stems from emerging market shocks.

Aloui *et al.* (2011) investigate the extent of the current global financial crisis and the contagion effect to examine the extreme financial interdependences using daily return data from Brazil, Russia, India and China (BRIC) and the U.S. during the period, 2004-2009. Their results, which are based on a multivariate copula approach, show evidence of time-varying dependence between each of the BRIC markets and the US market. Kenourgios *et al.* (2011) examine financial crises and stock market contagion among the BRIC markets and two developed markets (U.S. and U.K.) during the period, 1995-2006 (which covers five recent financial crises). The study also demonstrates that emerging markets are more prone to financial contagion and an industry-specific shock has a larger impact than country-specific crises.

2.3 Empirical studies on global financial crisis

In the case of the recent global financial crisis, the problem is considered to have emanated from the toxic securitized markets, with consequent spillovers to the derivative markets, via, for example, CDS, and to equity markets, by virtue of the meteor showers on the global financial markets. Consequently, a large body of empirical literature has accumulated in recent years regarding the causes and consequences of the global financial crisis on the global financial markets.[11] The literature review which follows here constitutes merely a few representative sample of research that has been focused on the financial markets regarding the causes and consequences of the global financial crisis.

Dorn (2009) contended that U.S. housing policy, along with securitization and easy money contributed to the asset price bubble in the housing market.[12] The role of government-sponsored enterprises, flawed financial-risk models, lax regulatory framework, inadequate credit rating and innovations that allowed banks to overleverage-all these factors in a body contributed to the sub-prime crisis. Schwartz (2009) argued that the process of asset securitization produced products that were difficult to price. Calomiris (2009) argued that inadequate or inappropriate regulation contributed to the subprime crisis by allowing banks to maintain insufficient amounts of equity capital per unit of risk undertaken in their subprime holdings. Banti *et al.* (2012) using proprietary data from a large investment bank reported that the magnitude of liquidity risk premium increased substantially after the collapse of Lehman Brothers during the period of financial crisis.

In recent studies Choudhry and Jayasekera (2015) investigated the anomalous behaviour of stock prices and asymmetric response of time-varying beta using the data from US-UK bank stocks and UK stock markets during the period of global financial crisis, respectively. Their empirical results reported that the level of market efficiency declined and the time-varying betas for individual firms increased significantly during the crisis period. They rationalized the anomalous behaviour of stock prices in terms of two competing hypotheses, i.e., market efficiency hypothesis and behavioural finance based explanation. The market efficiency hypothesis (EMH) predicts that beta of individual stock rises (fall) in response to abnormally negative (positive) returns as an asymmetric response to good and bad news. Regarding the behavioural finance explanation, there exists plethora of literature which presents evidence of over/under reaction of stock prices to new information.[13]

There is a rich array of literature on the asymmetric effect of good and bad news on stock prices. For example, see Black (1976), Cho and Engle (1999), Christie (1982), Glosten *et al.* (1993). The explanation of asymmetric effect on time-varying beta emanates from two plausible sources, such as leverage based explanation and volatility based explanation. The leverage effect is due to the reduction in the equity value, which would raise the debt-equity

[11] Interested readers are referred to samples of few articles from special issues of the following journals on this topic: Applied Financial Economics, Vol. 20, Issue 1-2, 2010, Cato Journal, Vol 29, Issue 1, Winter 2009, Journal of International Money and Finance, Vol. 49, Part B, December 2014, Multinational Finance Journal, Vol. 18, Issue 3 & 4, 2014, pp. 169-336, Journal of International Money and Finance, Vol. 28, Issue 8, December 2009, pp. 1243-1472.

[12] Calomiris (2009) noted that total subprime and Alt-A originations grew from $395 billion in 2003 to $715 in 2004 and increased to $1,005 billion in 2008.

[13] For example, see Dharan and Ikenberry (1995), Frazzini (2006), Loughran and Ritter (1995).

ratio, hence raising the riskiness of the firm as a result of an increase in future volatility.[14] The volatility based explanation posits a positive relation between volatility and expected risk premium.[15] An increase in volatility raises the expected return by lowering the stock prices which in turn contributes to the asymmetric effect in volatility. Consequently, this effect in volatility is impacted upon the beta through an asymmetric effect. In a recent study Iqbal and Kume (2014) investigated the impact of the recent financial crisis on the capital structure decision of UK, French and German firms. Their results indicate that overall leverage ratios increased from pre-crisis (2006 and 2007) to crisis (2008 and 2009) period and then decreased in the post-crisis (2010 and 2011) period.

2.4 Empirical studies on CAPM

Since the seminal contribution made by Sharpe (1964) and Lintner (1965), the notion and significance of the CAPM has spawned considerable research at both theoretical and empirical levels that spans almost six decades. According to CAPM, in a perfect capital market, the excess return of a stock or a portfolio of stocks (return over the riskless rate of return) should move in proportion to the market premium (market return over the riskless rate of return). The proportionality factor known as 'beta' (β) captures the 'systematic risk' of the market.

Previous studies suggest that the empirical validity of CAPM appears to depend on the return interval chosen albeit with mixed results. For example, studies of Kothari *et al.* (1995), and Handa *et al.* (1993) show that βs from annual returns produce stronger relation between beta and average return than βs from monthly return. Frankfurter *et al.* (1994) contend that the mean and variance of β increases from daily returns to yearly returns. A study by Brailsford and Faff (1997) suggests that CAPM is rejected when daily returns data is used, while CAPM is accepted when weekly returns data is used. In contrast, Fama and French (1996) show that annual and monthly βs produce the same inference about the β premium.[16]

Given the mixed results regarding the inference about the CAPM and βs, and the multiscale nature of the systematic risk (see, Gencay et al. 2005 and others), in this paper, we have employed a powerful method to estimate the systematic risk of CAPM using WA to examine the meteor shower effects of the global financial crisis on selected European stock markets.

2.5 Empirical studies using wavelet analysis

The wavelet technique is currently being used in the field of Finance for the purpose of analysing rapidly changing transient signals; in addition, it is a powerful tool for representing nonlinearities (Fang and Chow, 2006).[17] For example, wavelet technology has been applied in order to estimate both the hedge ratio (In and Kim (2006)) and the international CAPM (In and Kim (2007)). The estimation of systematic risk is studied in Gençay *et al.* (2002, 2005), Masih

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[14] For example, see Black (1976), Cho and Engle (1999), Christie (1982), Glosten *et al.* (1993).

[15] For example, see Bollerslev *et al.* (1988), Poterba and Summers (1984).

[16] Several explanations are offered for the interval bias of systematic risk, such as infrequent trading, delays in information processing, increase of standard error of the beta as the return interval is lengthened, disproportionate move of covariance relative to the variance estimate in the measurement of beta, and seasonality. Masih *et al.* (2010) furnished a good discussion on the issue.

[17] Alexandridis and Zapranis (2013, 2014), Fernandez (2006), Gencay *et al.*(2003, 2005), In and Kim (2006, 2007), Kim and In (2005, 2007), Maharaj *et al.* (2011), Masih *et al.* (2010), Norsworthy *et al.* (2000), Ramsey (1999), and Rua and Nunes (2012) are a small sample of papers which have adopted the wavelet approach towards analysing financial time series.

et al. (2010) and Rabeh and Mohamed (2011). In Maharaj *et al.* (2011), a comparison is made of developed and emerging equity market return volatility at different time scales. In Kim and In (2007), consideration is given to the relationship between changes in stock prices and bond yields in the G7 countries. Finally, in Kim and In (2005), the connection is examined between stock returns and inflation.

Kim and In (2010) investigate portfolio allocation over various time scales using monthly nominal stock, long-term government bond and Treasury bill returns for the US spanning the period January 1926 to December 2003. The study finds that stocks are less risky than bonds and Treasury bills at longer time scales, relative to shorter time horizons. Gallegati (2012) employed a wavelet-based approach to test for financial contagion in G7 countries, Brazil and Hong Kong during the US subprime crisis of 2007. The study shows that all stock markets have been affected by this event. Results further indicate that contagion occurred at lower scales (higher frequencies) and interdependence happened at higher scales (lower frequencies) for all markets except Brazil and Japan. In the case of both Brazil and Japan, contagion is observed at all scales. Mensi et al. (2017) investigate the portfolio risk and the co-movement between each of the BRIC emerging and South Asian frontier stock markets and each of the major developed stock markets (U.S., U.K. and Japan) using the wavelet squared coherence approach as well as the wavelet-based Value at Risk (VaR) method. Their results demonstrate that the co-movements and diversification benefits between markets vary over time and across frequencies. Furthermore, the co-movements are intensified in the wake of the recent global financial crisis and the Eurozone crisis.

Fernandaz-Macho (2012) investigates the level of integration of eleven countries of Eurozone stock markets using wavelet correlation and cross-correlations. The study finds evidence of perfect integration of these Eurozone stock markets at the longest time scales. Wang *et al.* (2017a) empirically examine the interaction of 457 stocks in 12 clusters in the US market in various time horizons from a network perspective using wavelet and topological methods of minimum spanning tree (MST) and planner maximum filtered graph (PMFG) over the period 2005-2012. They find that 1) the topological structure and properties of networks vary across time horizons, 2) there is a sectoral clustering effect in the networks at small time scales. Wang *et al.* (2017b) empirically examine the stock market contagion during the global financial crisis from the US to other six G7 and BRIC countries using wavelet approach. The study finds that stock market contagion depends on both the recipient country and the time scale. The study also reports that contagion from the US to Japan, China and Brazil occurs at a time scales longer than 50 days or more.

3 Methodology

3.1 The Capital Asset Pricing Model

The widely presented testing equation for the CAPM is given by:

$$E\left[r_{i,t}\right] = r_{f,t} + \beta_i \left(E\left[r_{m,t}\right] - r_{f,t}\right) + \varepsilon_{i,t} \tag{1}$$

where $r_{i,t}$, $r_{f,t}$ and $r_{m,t}$ signify rates of return on *i*-th risky asset, risk-free asset and market portfolio, respectively. The CAPM predicts that the return to individual stock is a direct and linear function of the investments' systematic risk and market risk premium. The beta is defined as:

$$\beta_i = \frac{Cov(r_{i,t}, r_{m,t})}{Var(r_{m,t})} \tag{2}$$

where $Cov(r_{i,t}, r_{m,t})$ signifies the covariance between the return on asset *i* and the return on the market portfolio and $Var(r_{m,t})$ denotes the variance of the portfolio return. When beta is found to be more than unity, this suggests that the firm under study is perceived more risky than the market. Alternatively, if beta is greater than 1, the security is termed to be aggressive, and if it is less than 1, it is said to be defensive.

3.2 Wavelet Analysis

WA is an extension of Fourier analysis. The fundamental idea behind wavelets is to analyse according to scale. Low scale represents high frequency while high scales represent low frequency. The wavelet transform (WT) not only is localized in both time and frequency but also overcomes the fixed time-frequency partitioning. This means that the WT has good frequency resolution for low-frequency events and good time resolution for high-frequency events. Hence, the WT can be used to analyse time series that contain no stationary dynamics at many different frequencies.

In this study we use the Maximal Overlap Discrete WT (MODWT). The MODWT has many desirable properties, Percival and Walden (2000)[18]. The MODWT can handle any sample size of the data and does not suffer from sensitivity to the choice of a starting point for a time series. The detail and smooth coefficients of a MODWT multi-resolution analysis (MRA) are associated with zero phase filters and the wavelet variance estimator is asymptotically more efficient than the same estimator based on the DWT[19].

A time-series $f(t)$ can be written as a linear combination of wavelet functions as follows:

$$f(t) \approx \sum_k s_{J,k}\varphi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t) \qquad (3)$$

where J is the number of scales and k indicates the k^{th} coefficient. The wavelet transformed coefficients $s_{J,k}, d_{J,k}, ..., d_{1,k}$ can be approximated by the following integrals: $s_{J,k} \approx \int \varphi_{J,k}(t) f(t)dt$ and $d_{J,k} \approx \int \psi_{J,k}(t) f(t)dt$ where $j = 1,2,...,J$. The functions $\varphi_{j,k}$ and $\psi_{j,k}$ are the approximating wavelet functions. By setting $S_J(t) = \sum_k s_{J,k}(t)\varphi_{J,k}(t)$ and $D_J(t) = \sum_k d_{J,k}(t)\psi_{J,k}(t)$ the original time-series can be reconstructed:

$$f(t) \approx S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_1(t) \qquad (4)$$

This reconstruction is known as multi-resolution analysis (MRA) and is applied in order to reconstruct the original time-series from the wavelet and scaling coefficients. The elements of S_J are related to the scaling coefficients at the maximal scale and therefore represent the smooth components of $f(t)$. The elements of D_j are the detail (or rough) coefficients of $f(t)$ at scale j.

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[18]So far, the MODWT was successfully applied in many studies in finance. For example, see In and Kim (2006), In and Kim (2007), Gençay *et al.* (2002, 2005), Masih *et al.* (2010), Rabeh and Mohamed (2011) and In Maharaj *et al.* (2011).

[19] In this study the LA8 (Least Asymmetric of length 8) wavelet transform filter is used. Our analysis is performed in 5 levels of the decomposition and the reflection method was used for the boundary conditions.

3.3 Computation of Wavelet Variance and Wavelet Covariance

WA allows us to decompose the variance of a financial time-series into various parts, each one representing the variance at each scale. This wavelet-variance analysis shows us which scales are contributing significantly to the overall variability of the time-series, see Percival and Walden (2000). For a stationary process X, the variance σ_X^2 is given by:

$$\sigma_X^2 = \sum_{j=1}^{\infty} \upsilon_x^2\left(\tau_j\right) \tag{5}$$

where $\upsilon_x^2\left(\tau_j\right)$ is the wavelet variance for scale τ_j. Equation (5) is analogous to the relationship between the variance of a stationary process and its spectral density function. An unbiased estimator of the wavelet variance is given by:

$$\hat{\upsilon}_X^2\left(\tau_j\right) = \frac{1}{\tilde{N}_j} \sum_{t=L_j-1}^{N-1} \tilde{d}_{j,t}^2 \tag{6}$$

where $\tilde{d}_{j,t}^2$ is the MODWT wavelet coefficients at scale τ_j, n is the sample size, L_j is the length of the scale τ_j wavelet filter and $\tilde{N}_j$ is the number of the MODWT coefficients unaffected by the boundary.

Similarly, an unbiased estimator of the wavelet-covariance between two time-series X and Y is given by:

$$\hat{\upsilon}_{XY}^2\left(\tau_j\right) = \frac{1}{\tilde{N}_j} \sum_{t=L_j-1}^{N-1} \tilde{d}_{j,t}^{(X)} \tilde{d}_{j,t}^{(Y)} \tag{7}$$

3.3.1 A Wavelet Beta Estimator

Under the CAPM the wavelet beta estimator for asset i at scale j is defined as:

$$\hat{\beta}_i\left(\tau_j\right) = \frac{\hat{\upsilon}_{r_i r_m}^2\left(\tau_j\right)}{\hat{\upsilon}_{r_m}^2\left(\tau_j\right)} \tag{8}$$

where $\hat{\upsilon}_{r_i r_m}^2\left(\tau_j\right)$ is the wavelet covariance of asset i and the market portfolio at scale j, and $\hat{\upsilon}_{r_m}^2\left(\tau_j\right)$ is the wavelet variance of the market portfolio at scale j. Furthermore, according to Gençay *et al.* (2003) a wavelet R^2 estimator for asset i at scale j is computed by:

$$R_i^2\left(\tau_j\right) = \hat{\beta}_i^2\left(\tau_j\right) \frac{\hat{\upsilon}_{r_m}^2\left(\tau_j\right)}{\hat{\upsilon}_{r_i}^2\left(\tau_j\right)} \tag{9}$$

3.3.2 Scale Specific Value at Risk

VaR is a very popular measure that describes the market risk. *VaR* measures the amount that an investor can lose with a given probability over a certain time horizon. We construct a portfolio where individual company stocks within each country constitute the portfolio. For simplicity we assume an equally weighted portfolio of k assets where ω is vector that contains the portfolio weights, i.e. a $k \times 1$ vector which each element is $1/k$. Then, the ratio:

$$\frac{\sigma_m^2\left(\tau_j\right)\left(\sum_{i=1}^{k}\beta_i\left(\tau_j\right)/k\right)^2+\frac{1}{k^2}\sum_{i=1}^{k}\sigma_{\varepsilon_i}^2\left(\tau_j\right)}{\sigma_m^2\left(\sum_{i=1}^{k}\beta_i/k\right)^2+\frac{1}{k^2}\sum_{i=1}^{k}\sigma_{\varepsilon_i}^2} \tag{10}$$

is an estimate of the contribution of scale *j* to total *VaR* of an equally weighted portfolio, where

$$\sigma_\varepsilon^2\left(\tau_j\right)=\sigma_i^2\left(\tau_j\right)-\beta_i^2\left(\tau_j\right)\sigma_m^2\left(\tau_j\right) \tag{11}$$

and $\sigma_i^2\left(\tau_j\right)$ is the variance of stock *i* at scale *j*, $\beta_i\left(\tau_j\right)$ is the beta of stock *i* return at scale *j* and the variance of the market portfolio at scale *j* is given by $\sigma_m^2\left(\tau_j\right)$, see Fernandez (2006).

3.4 Forecasting using Wavelet Networks

The final objective of this paper is to examine whether the decomposed returns produced by WA can lead to accurate forecasts of the multiscale systematic risk. In order to do so, we will employ non-linear non-parametric WNs. More precisely, WNs will be used in order to capture and forecast the dynamics and the multiscale nature of the systematic risk.[20]

We will use one period of our dataset for in-sample training and one period for out-of-sample forecasting. In order to do so, the third data set that represents the period of Eurozone crisis is used to train artificial WNs. Then the trained WNs will be used in order to forecast the betas in the out-of-sample period which is the fourth data set ranging from January 1, 2014 to August 28, 2018 and represents the post-crisis period. A rolling window with one-step-ahead forecasting scheme is applied.

4 Data description

We are investigating the impact of the crisis on the stock markets of eight European markets. The selected markets are distinguished in two groups. The first group consists of four countries that at the moment face much European uncertainty and are under a rescue program and under the supervision of the International Monetary Fund (IMF) and/or the European Central Bank (ECB). These countries are: Portugal, Italy, Greece and Spain. On the other hand, the second group consists of four countries whose economies are traditionally considered strong and stable. These countries are: Germany, Netherlands, UK and France. The selected countries represent major exchanges within the EU in terms of both market capitalization and trading volume.[21]

Our data set includes the daily values of the main stock index in each country from June 1, 2005 to August 28, 2018 as well as the daily stock prices of the stocks that constitute each

[20] In order to reduce the size of this paper we avoid to present analytically any technical details on WNs. The basic mathematical aspects and construction procedures as well as additional information on training and forecasting of the WNs are presented in Appendix A. For an analytical treatment of WNs we refer the interested reader to Alexandridis and Zapranis (2013), (2014).

[21] The value of stock market capitalization for markets of the United Kingdom, France, Germany, Netherlands, Spain, Italy, Portugal and Greece in 2012 were 3019, 1823, 1486, 651, 995, 480, 66 and 45 billion US dollars, respectively.

index.[22] In this study, we estimate the beta of a risky asset at different time-frequencies and in different time-periods in order to obtain an estimate of the impact of the U.S. crisis in the systematic risk in these markets.

Narayan and Sharma (2015) and Narayan et al. (2015) suggest that hypotheses tests can be data frequency dependent. There are four reasons behind our motivation to use daily data. First, daily data contain richer information than weekly or monthly data, Bannigidadmath and Narayan (2016). Second, daily data give us a sufficient number of observations both when we consider the whole sample and when we consider the four sub-periods. Third, in hedging and investment decisions, one needs to match the frequency of the data or the differencing interval with the hedging horizon. For example, one needs to use weekly, monthly and annual data to obtain hedge ratios, consistent with weekly, monthly and annual investment horizons, respectively (Lien and Shrestha (2007)). Alternatively, for a *k*-period hedging horizon, one should use a *k*-period differencing. This method results in a substantial reduction of the sample size when a long-horizon period is assumed.[23] Hence, the third reason for using daily data arises from the fact that a potential advantage of using wavelet analysis is that it alleviates the sample reduction problem. Finally, high frequency data provide additional information (Bollerslev and Wright 2001) and high frequency data improve volatility and return forecasts (see Anderson *et al*. 1999, and Maheu and McCurdy, 2011).

In order to identify periods of turmoil we follow the timelines provided by the Bank of International Settlements (BIS (2010)) and the Federal Reserve of St. Louis (2009). This approach was followed by Baur (2012).[24] Hence, we split our dataset in four periods. The first sample corresponds to the pre-crisis period and includes daily stock values from June 1, 2005 to July 31, 2007. The second sample represents the crisis period and it ranges from August 1, 2007 to November 4, 2009. The third sample represents the Euro-crisis and it ranges from November 5, 2009 to December 31, 2013. Finally, there is a fourth sample from January 1, 2014 to August 28, 2018 that represents the post-crisis period, specifically a period of moderation and restoration.

In order to avoid survivorship bias only the stocks that survive for each sample period are examined.[25] Daily return series for each stock as well as the market index were collected from each stock market. This resulted in 564 values for the first sample, 591 for the second, 1,084 for the third, 1,216 for the fourth, giving a total of 3,455 values. The logarithmic returns of the stocks, $r_{i,t}$, and of the market index, $r_{m,t}$, were computed.

For the estimation of model (1) the risk-free rate of return is proxied by the daily rate of return from 1-month Euribor offer rate for all countries with an exception in the case of the U.K. where it is represented by the daily rate of return from the 1-month U.K. Treasury bill rate.

[22] The eight indices are the following: AEX25 from Netherlands, FTSE/ATHEX 20 from Greece, CAC 40 from France, DAX 30 from Germany, FTSE 100 from UK, IBEX 35 from Spain, MIB 40 from Italy and PSI 20 from Portugal.

[23] As Lien and Shrestha (2007, p. 129) noted, one needs to compute approximately 1,000 daily returns or 208 weekly returns, or 3 annual returns of non-overlapping periods using with 4 years worth of data.

[24] Alternatively, many studies use Markov regime switching model to identify the crisis periods endogenously, e.g. Boyer *et al.* (2006), while other use both statistical and economic approaches, e.g. Baur (2012), Dimitriou *et al.* (2013), Kenourgios (2014).

[25] Pre-crisis: Netherlands: 20, Greece: 20, France: 37, Germany: 27, UK: 83, Spain: 24, Italy: 31, Portugal: 12. In-crisis: Netherlands: 20, Greece: 22, France: 39, Germany: 27, UK: 90, Spain: 27, Italy: 35, Portugal: 14. Euro-crisis: Netherlands: 20, Greece: 23, France: 39, Germany: 27, UK: 91, Spain: 28, Italy: 37, Portugal: 17. Post-crisis: Netherlands: 20, Greece: 24, France: 39, Germany: 28, UK: 99, Spain: 32, Italy: 40, Portugal: 18.

5 Empirical results

5.1 Preliminary analysis

In this section we present a preliminary analysis. First, we split the data into four periods and then perform a separate WA in each sub-sample. There are two main reasons. First, the aim is to study how the beta and *VaR* estimates changes across periods. Second, we want to examine whether the wavelet based estimates of the betas and *VaR*'s can provide useful information to investor regarding the future performance of the European markets. In other words the investor has only the information included in the period under consideration and tries to devise his strategy based on the estimates of betas and *VaR*'s at different time-scales and frequencies. If the complete time-series is used the beta estimates will be distorted through the way the wavelet transform operates essentially using information of future values (outside the specific period into consideration).

A quick inspection of Figure 2 reveals that co-movements of the U.S and the European markets are evident although Greece and Spain have a declining course even after the recovery of the U.S. market. As a part of the preliminary analysis, we have conducted a correlation analysis across sub-periods. In this paper, we have assumed 'pure' contagion which refers to the transmission of shocks from one country to another country in excess of what should be expected after controlling for fundamental factors (see Bae *et al*. (2003) and Kumar and Persaud (2001)). This is generally related to investors' behaviour, such as herding, financial panic, loss of confidence, etc., and leads to excessive co-movements (Gallegati 2012, p. 3491-3492). Also, Acharya and Pederson (2005) contend that contagion operates through a time-varying risk-premium channel, where negative returns in the distressed market affect subsequent returns in other markets. In Table 1 the correlation between the returns of the S&P 500 and the selected European stock markets under study is presented. It is clear that the correlation coefficients increase as we move from the pre-crisis to the in-crisis period. During the Eurozone crisis where the U.S. economy started its recovery it is evident that the correlation was further increased for all countries except Greece. The highest values are observed in the group of countries with strong economies while lower values are observed for Greece, Spain, Italy and Portugal. Finally, focusing on the post-crisis period the correlation decreased. As it can be seen, correlation coefficients show significant instability over the sub-periods.[26]

In Figure 3 the wavelet decomposition of the index returns in Greece and Germany is presented. The wavelet decomposition was performed at 5 levels for the entire dataset. The red vertical lines indicate the different subperiods. It is evident that the volatility of daily stock index returns changes over time and over frequency. First, the volatility is concentrated at high frequencies. Second, a closer inspection of Figure 3 reveals that the variability of the returns is relatively small for both countries in the pre-crisis period with an exception of early 2006. The variability has significantly increased during the financial crisis periods. Furthermore, a large spike is observed in mid-2008 indicating the start of the global financial crisis. The Eurozone crisis and the post-crisis periods are different for the two countries. In Greece, a further increase in the variability is observed. A closer inspection of d_2 reveals that large spikes are aligned with various events that affected the trust of the investors in the Greek economy[27]. On the other hand, inspecting the wavelet decomposition of the returns of the German index, a significant

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[26] A two-sample Kolmogorov-Smirnov goodness-of-fit is performed to test the null hypothesis that the returns of two different periods come from the same distribution. The null hypothesis is rejected almost always, in 804 out of 834 cases.

[27] Indicatively, we mention the following events: the three government elections that took place in 10/2009, 5/2012 and 6/2012. Also, a large spike is evident before the debt-restructuring deal in 2/2012 and the call for referendum from the Greek prime minster in 10/2012 that also led him to resign few days later.

decrease in the variability is evident for the last two periods. A period of uncertainty is evident in late 2011 following the events in Greece discussed previously. In the fourth period a further decrease in the volatility of the returns is observed indicating the trust of the investors in the German economy.

[Insert Table 1]

[Insert Figure 3]

It is worth to mention that the results from the U.K., Netherlands, France and Germany are similar, while Spain, Italy and Portugal follow the pattern of Greece. However, it is worth mentioning that in Portugal the variability has been significantly decreased after mid-2011. Again, the remaining results are available from the authors upon request.

Finally, following Whitcher *et al.* (2002) we apply a test for homogeneity of variance on a scale-by-scale basis. The test is rejected for all time-series indicating a sudden shift in the variance.[28]

5.2 Multiscale analysis of betas

In this section we will focus on the local CAPM of each country. The results for each country are presented in Table 2 to Table 5. More precisely, the beta and R^2 at each scale j are presented while in the last two columns the beta and R^2 from the classic linear CAPM are presented. Analytical tables for each stock are available upon request. Our analysis was performed in a depth of 5 scales. Scale 1 corresponds to periods of 2-4 days, scale 2 to 4-8 days, scale 3 to 8-16 days, scale 4 to 16-32 days and scale 5 to 32-64 days.

Focusing on the pre-crisis period, Table 2 reveals that the linear relationship between an individual stock and the market portfolio becomes stronger as the scale increases, while usually a slight decrease is observed at scale 5. In other words the maximum values of beta and R^2 are observed in scales 3 and 4. Our results accord well with Gençay *et al.* (2005) and Fernandez (2006). We also observe that the systematic risk of almost all stocks and proposed portfolios is less than one in the markets of Greece, Netherlands, Germany and Portugal for 2-64 days horizon.[29] This suggests that the benchmark market indices have a reduced impact on assets in these markets in the short to intermediate-run horizons. The R^2 ranges from 0.12 at scale 2 for Portugal to 0.41 at scale 5 for Spain. The lower values of R^2 are observed in Portugal, Netherlands and Italy while the highest values are observed in Spain, Germany and France.

During the crisis betas have increased for the stock markets of France, Germany and Portugal as it is shown in Table 3. The increased magnitudes of betas reflect heightened sensitivity of financial market to the whole range of economic and financial variables, and incomplete knowledge regarding the magnitudes to toxic asset positions in the early stage of the crisis. The evidence of increased betas during the financial crisis era is consistent with the findings of Choudhry and Jayasekera (2015), Asgharian *et al.* (2017) and others.[30]

[28] More precisely, the test is rejected for all scales for Netherlands and Greece and it is rejected for scales 1, 2, 3 and 4 for the remaining countries.

[29] Kamara *et al.* (2016) note that long-horizon institutional investors overweight asset with high short-horizon liquidity risk and high intermediate horizon HML risk. However, they appear to be the natural bearers of systematic risk.

[30] Rua and Nunes (2012) noted that beta tends to rise during crises period, such as the Mexican crisis in 1994, Emerging market crisis in 1998, Turkish crisis in 2006 and recent global financial crisis.

During the crisis period, negative information led to a freeze in several markets which may have led to decrease in magnitudes of betas in other markets, i.e., the markets for Greece, Italy, Spain and the UK. On the other hand, the R^2 has increased for all countries. The lower values of R^2 observed in UK (0.35) and Portugal (0.34) while the highest one in France (0.50). In addition, in contrast to the remaining countries, the beta for Greece fluctuates between 0.77 and 0.74 for the first three scales and then increases to 0.86 in the last scale. For the remaining countries the maximum beta is observed at scales 3 and 4 while the minimum, usually, at scale 1.

[Insert Table 2]

[Insert Table 3]

[Insert Table 4]

[Insert Table 5]

As Table 4 depicts, during the Eurozone crisis the betas are almost 1 for each scale, although a slight increase is observed at higher scales, for all countries in the "strong" group, i.e. Netherlands, France, Germany and UK. For the reaming countries the betas are around 0.85. The increased sizes of the betas again indicate the heightened sensitivities induced by the uncertainty of the Eurozone crisis in these markets. For all countries the R^2 has increased with an upward trend from scale 1 to scale 3 and then a downward trend until scale 5.

Table 5 depicts the results from the post-crisis period. An increase is observed in the beta values of Greece, Spain and Portugal while betas slightly decreased for the remaining countries. Similarly R^2 increased for Greece and Portugal while it decreased in all other countries.

In summary, WA provides indication of financial instability that is clear only in a frequency analysis. We observe a different behaviour of betas for Greece, Portugal and Spain than the betas for UK, Germany and France. Overall, beta coefficients show a multiscale tendency. The values of betas have increased at low frequencies (higher scale) across periods and markets. This result may arise from the fact that long-term investors are more exposed to systematic risk than short-term investors. Values of betas have changed during global financial crisis period relatively to the pre-crisis period. During the period of Eurozone debt crisis, values of betas have increased for the majority of the sample Eurozone countries. The increase of multi-scale betas during periods of global financial crisis and Eurozone crisis may be induced by a combination of leverage effect and asymmetric response of the market to bad news. In addition, a rich array of literature in behavioural finance presented evidence of under/over reaction of stock prices to information in such turbulent market condition. The evidence of asymmetric effect in time-varying beta is consistent with the findings of Choudhry and Jayasekera (2015) and the evidence of leverage effect accords well with the finding of Iqbal and Kume (2014) in their study of markets from the UK, France and Germany. Furthermore, as Braun *et al.* (1995) and Ball and Kothari (1989) contended that an increase (decrease) in market shocks to the firm increase (decrease) the beta and lead to a rise (fall) in expected return in market. Therefore, asymmetry in volatility in these markets during the crises periods led to asymmetry in time-varying beta.

Chiang *et al.* (2007) and Syllignakis and Kouretas (2011) provide the evidence of financial contagion due to herding behavior during the financial crisis.[31] In normal market conditions, investors and traders use on some occasions technical analysis such as momentum trading to generate above average market return. However, during the crisis, negative information led to a freeze in several markets or may have led to a disposition effect. As mean betas in each scale are around 1 or slightly above 1 and increase in higher scales, investors and traders should employ a contrarian trading strategy across scales. The long-term investors may utilize a buy and hold strategy in such a bearish market. Once the market rebound to their long-run mean values, the investors may resort to momentum trading strategy.

5.3 Value-at-Risk at different time-scales.

In Table 6 the $VaR(a)$ at different time scales for an equally weighted portfolio is presented for the four different time periods for all countries. The initial value of the portfolio is 1 unit of the specific market's currency invested in 1-day horizon at the 95% confidence interval.

As we can see from Table 6 the $VaR(a)$ declines monotonically as we move to higher scales. In other words, the $VaR(a)$ is higher at lower scales. Similarly, the contribution of the $VaR(a)$ is higher at lower scales and decreases as we move to higher scales. The observation that the risk is higher at lower scales appears to be an echo of the property stating that under the random walk assumption about logarithmic prices, the wavelet variance for log returns decreases exponentially as the scale parameter increases.

[Insert Table 6]

A closer inspection of Table 6 during the pre-crisis period reveals that the total $VaR(a)$ is relatively low for all countries. More precisely, the lower value is observed in Portugal (0.009) while the higher value in Greece (0.0158). On the other hand the $VaR(a)$ for Netherlands, France, Germany, UK and Spain ranges from 0.0121 to 0.0136. During the crisis time-period the $VaR(a)$ has grown threefold almost for every country. The effects of the European crisis can be found in the estimation of $VaR(a)$ in Greece, which was further increased. On the contrary, the $VaR(a)$ from the remaining countries was decreased. During the post-crisis period, Greece and Portugal was facing financial problems while Greece was under strong political instability. This can be reflected from the estimated $VaR(a)$ in each country. For both countries the $VaR(a)$ is on almost the same as during the Eurozone crisis. For the reaming countries a significant decrease in VaR is observed and the estimated VaRs, although higher, are very close to values estimated in the pre-crisis periods.

A potential loss of the portfolio is higher when we focus on lower scales. Hence, for investors with one day position, mean VaR for one-day investment is higher than the mean VaR for investors with one-month investment horizon. Finally, we can observe that the $VaR(a)$ estimated using the CAPM to compute the betas on the original returns and the total $VaR(a)$ estimated from the recomposed returns are very close. Our results suggest that risk is concentrated at the lower scale of the data. In all time samples, scale 1 contributes with more that 42% to the total $VaR(a)$ while in some cases reaches up to 55%. As Maharaj *et al.* (2011)

[31] Using the example of US stock market crash of October 1987, Lin *et al.* (1994) argued that price movements driven by fads and herd instinct have the capability of being transmitted across borders when speculative trading and noise trading occur in international financial markets.

noted, the lower scales capture the activity of speculative traders and the higher scales reflect the sentiments of investor with medium to long-term investment horizons. This finding has important implications for scalpers, day traders and position traders.

As Bae *et al.* (2003) noted, extreme returns occur more frequently in crisis period, information is therefore important for all groups of traders, such as hedgers, speculators and arbitragers in both cash and derivative markets. The evidence is also consistent with the findings of Vo (2014).

Overall, period specific *VaR* analysis provides a more detailed breakdown of the market risk compared to the whole period. *VaR* has grown threefold almost for every country during the period of global financial crisis. *VaR*s in debt-ridden countries are larger during Eurozone crisis period relatively to pre-global financial crisis period, with the exception of Portugal.

5.4 Forecasting the Multiscale Nature of Systematic Risk

In Table 7 we present the forecasted values of the average betas and R^2 for each market for each scale as well as the values obtained from the CAPM from the original data. The standard deviation, the skewness and the kurtosis are also reported. Comparing the forecasted values from Table 7 against the estimated ones presented in Table 5 we can conclude that the WN has the ability to forecast accurately both the betas and the R^2. The multiresolution analysis of the systematic risk allowed the WN to be efficiently trained. Next, comparing the real and forecasted *VaR* at different timescales in Table 8 and the post-crisis panel of Table 6 we can observe that the WN slightly underestimates the *VaR* for all countries. However, the basic dynamics of the *VaR(s)* and the changes of the *VaR(s)* according to scale were successfully captured. Note that the last raw of Table 8 referrers to the *VaR* computed using the betas that were estimated using the CAPM on the forecasted raw (undecomposed) returns.

[Insert Table 7]

[Insert Table 8]

In Figure 4, the 1-period ahead forecast of excess returns of the AEX index is presented. The forecasts were based on the multiscale analysis of the WA. Then, WNs were used to learn the dynamics of the returns in each scale. The trained networks were used to forecast the decomposed excess returns. A one-day-ahead rolling window forecast scheme is used. A closer inspection of Figure 4 reveals that the proposed method can track the excess returns. More analytically, the normalized mean square error is 0.148 while the mean and maximum absolute error is only 0.002 and 0.034 respectively. Due to space limitations we present the results only for the AEX index. The results for the remaining countries and stocks are similar and are available upon request from the authors.

[Insert Figure 4]

Finally we evaluate the forecasting performance of the proposed method. We use two benchmark forecasting model. The first one is the simple CAPM where betas are obtained using a rolling window (denoted as CAPM). The size of the rolling window and the forecasting period is the same as in the case of the WN. The second benchmark model is the CAPM were we estimate multiscale betas as in section 5 (denoted as CAPM Multiscale). Again a rolling window is used in order to estimate the multiscale betas and forecast one day ahead.

We use the Campbell and Thompson (2007) out-of-sample R^2, denoted as R^2_{OOS}. To measure the performance of a candidate model relative to the benchmark model we use the following formula:

$$R^2_{OOS} = 1 - \frac{MSFE_h}{MSFE_b} \tag{12}$$

R^2_{OOS} measures the proportional reduction in the Mean Square Forecast Error (MSFE) of model *h* against the MSFE of the benchmark, *b*. Hence, a positive R^2_{OOS} indicates that the competing model outperforms the benchmark. The statistical significance of outperformance is assessed by the $MSFE_{adj}$ proposed by Clark and West (2007) and it is given by

$$MSFE_{adj} = \frac{1}{P}\left\{\sum_{t=R+1}^{T-1}\left\{\left(r_{t+1} - \hat{f}^{\,b}_{t+1}\right)^2 - \left[\left(r_{t+1} - \hat{f}^{\,h}_{t+1}\right)^2 - \left(\hat{f}^{\,b}_{t+1} - \hat{f}^{\,h}_{t+1}\right)^2\right]\right\}\right\}$$

where P is the number of the out-of-sample observations (P=1215), T is the number of the total sample (T=2999), r_{t+1} is the actual return, $\hat{f}^{\,b}_{t+1}$ is the forecast from the benchmark model and $\hat{f}^{\,h}_{t+1}$ is the forecast of the candidate model.

In Table 9 a summary of results is presented. More precisely, Table 9 depicts the number of time the candidate model outperform the benchmark in term of R^2_{OOS}. It is clear that the forecasts obtained from the proposed WN clearly outperforms both benchmarks. The WN outperforms the CAPM 265 times out of 290 cases and the CAPM Multiscale 264 times.[32]

[Insert Table 8]

6 Conclusions

The US subprime loan crisis unleashed a series of negative effects on the global economy ranging from the stock market collapse, financial institutions failure and global recession. The meltdown of the subprime crisis of 2007 exerted a meteor shower effect across the world's stock market by the fourth quarter of 2008. In the last quarter of 2008, the stock markets of both developed and emerging economies experienced large decline in prices of securities. In this paper, we have investigated the impact of the global financial crisis on the systematic and market risks in eight European markets: France, Germany, Greece, Italy, Netherlands, Portugal, Spain and the UK using the framework of a capital asset pricing model.

It is essential for investors to assess market and systematic risk at scale level and match it with their investment horizon. In this study we provide the tools to do so. In our analysis we first investigated whether the U.S. crisis affected the European stock markets by studying the relationship between the U.S market and the eight different European countries. Our results indicate that the correlation between the markets increased during the crisis period but significantly decreased when the U.S. market started to recover, and correlation increased again when the crisis moved to the Eurozone. Our dataset was split in four different sub-periods.

Next, we have studied the multiscale systematic risk locally by applying a national CAPM. Our empirical results indicate that average beta coefficients have a multiscale tendency and betas tend to increase at mid to higher scales for the whole period supporting the CAPM at

[32] Note that the analysis presented in section 5 was repeated for the period 2005-2012. In this scenario we split the data in 4 subperiods: 1) June 1, 2005 to July 31, 2007, 2) August 1, 2007 to September 30, 2009, 3) October 1, 2009 to November 30, 2011 and 4) December 1, 2011 to September 10, 2012. Regardless the change in the sample and the selection of the sub-periods our findings are consistent showing the robustness of our results.

medium time horizons. This result may arise from the fact that long-term investors are more exposed to systematic risk than short-term investors.

During the sub period of financial crisis, the size of betas tends to increase for some countries and R^2s increase for every country relatively to the pre-crisis period. The increased magnitudes of betas reflect heightened sensitivity of financial market to the whole range of economic and financial variables, and incomplete knowledge regarding the magnitudes to toxic asset positions in the early stage of the crisis. During the crisis period, negative information led to a freeze in several markets which may have led to decrease in magnitudes of betas in other markets, i.e., the markets for Greece, Italy, Spain and the UK. The increase of multi-scale betas during periods of global financial crisis and Eurozone crisis has been induced by a combination of leverage effect and asymmetric response of the market to bad news. Moreover, in our analysis, the results from the Euro-crisis and post crisis periods, indicate that changes of both betas and R^2 varies between the two groups of the European markets. From financial practitioners and investors point of view, as there are heterogeneous groups of investors, traders and the levels of investment horizon and risk appetites vary across them, the relative choice of beta depends on investors' horizon preference. However, as betas are slightly unstable at lower scales and stabilises at higher scale, a number of investors may prefer higher scale betas.

The scale dependent *VaR* results suggest that risk is concentrated at the lower scale of the data. *VaR* estimates tend to increase threefold almost for every country during the global financial crisis period relative to the pre-crisis period. Therefore, a potential loss of portfolio is higher at lower scales; furthermore, a potential loss of portfolio across scales is far higher during the crisis period. *VaR* has grown threefold almost for every country during the period of global financial crisis. *VaR*s in debt-ridden countries are larger during Eurozone crisis period relatively to pre-global financial crisis period, with the exception of Portugal.

Finally, WNs were employed in order to capture the dynamics of the multiscale systematic risk. Our results indicate that WNs can accurately forecast both the betas and the *VaR*s. Overall, beta has in sample and out-of-sample predictive content regarding the state of the financial markets. Based on analysis of the multi-scale betas and *VaR*s, the strong and stable markets, such as the UK, France, Germany and Netherland show more resilience for portfolio invertors' destination.

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Appendix A: Wavelet Neural Networks

WNs are a new class of networks that combine the classic sigmoid neural networks and the WA. WNs have been used with great success in a wide range of applications. For a complete theoretical background and a concise treatment of WNs, readers are referred to Alexandridis and Zapranis (2014).

A WN usually has the form of a three layer network. In the input layer the explanatory variables, $\mathbf{x}=\{x_1,..,x_m\}$, are introduced to the WN. The hidden layer consists of the hidden units (HUs),

$$\Psi_j(\mathbf{x})=\prod_{i=1}^{m}\psi\left(\frac{x_i-w_{(\xi)ij}^{[1]}}{w_{(\zeta)ij}^{[1]}}\right)$$

In the hidden layer the input variables are transformed to dilated and translated version of the mother wavelet. Finally, in the output layer, the approximation of the target values, $\hat{y}(\mathbf{x})$, is estimated. The structure of a single hidden-layer feed forward WN is given in Figure 5 at the end of Appendix B. The network output is given by the following expression:

$$g_\lambda(\mathbf{x};\mathbf{w})=\hat{y}(\mathbf{x})=w_{\lambda+1}^{[2]}+\sum_{j=1}^{\lambda}w_j^{[2]}\cdot\Psi_j(\mathbf{x})+\sum_{i=1}^{m}w_i^{[0]}\cdot x_i\ .$$

[Insert Figure 5]

In that expression, $\mathbf{x}$ is the input vector, m is the number of network inputs λ is the number of HUs and w stands for a network weight. Finally, $\Psi_j(\mathbf{x})$ is a multidimensional wavelet which is constructed by the product of m scalar wavelets. In this study the second derivative of the Gaussian, the so-called "Mexican Hat" wavelet is used.

The complete vector of the network parameters comprises: $w=\left(w_i^{[0]},w_j^{[2]},w_{\lambda+1}^{[2]},w_{(\xi)ij}^{[1]},w_{(\zeta)ij}^{[1]}\right)$. These parameters are adjusted during the training phase.

A.1. Training and Forecasting

First, the WNs, $g_\lambda(\mathbf{x};\mathbf{w})$, had to be trained. For each stock, wavelet networks were trained for each scale for both the detail D_j and the smooth components S_j. In order to determine the lag series of the training patterns and the network topology, i.e. the number of the HUs, the model identification algorithm described in Alexandridis and Zapranis (2014) was followed[33]. The WNs were trained using the data from the first post-crisis period. The training pairs consist of the input values and the target values. More precisely, in order to train the wavelet network on a particular detail D_j we use as input values the vector $\mathbf{x} = \{D_{j,t-m}, D_{j,t-m+1}, ..., D_{j,t-1}\}$ and the target values are given by $\mathbf{y} = D_{j,t}$. A similar approached was followed for the remaining details and the smooth components. The WNs were trained using the backpropagation algorithm as it is described in Alexandridis and Zapranis (2014).

In order to evaluate the performance of the WNs in predicting the dynamics of the multiscale betas the 1-period-ahead forecasting method has been employed. More precisely the WNs were trained on the decomposed data of the first post-crisis period in order to forecast the values of the beta on the second post-crisis period. Note, that the data from the second post-crisis period have not been used for training or calibration of the WNs. Hence, we produced recursively using a rolling window of 203 out-of-sample one-period-ahead forecasts.

[33] The model identification algorithm is a two-component procedure that consists of the model selection algorithm (number of HUs) and the variable selection algorithm (statistical significant variables that will be used for the training of the wavelet network, i.e. the number of lags). The algorithm and every aspect of the wavelet networks are described in detail in Alexandridis and Zapranis (2014).

Table 1. Correlation between the S&P 500 and the European stock markets in different time-periods.

		AEX	ATHEX	CAC 40	DAX 30	FTSE 100	IEX 35	MIB	PSI-20
Pre-crisis	S&P 500	0.48	0.26	0.50	0.50	0.48	0.48	0.48	0.29
In crisis		0.59	0.34	0.59	0.64	0.56	0.56	0.55	0.42
Euro crisis		0.68	0.27	0.69	0.69	0.67	0.60	0.63	0.52
Post crisis		0.55	0.25	0.55	0.52	0.53	0.50	0.49	0.46
Whole		0.60	0.26	0.60	0.61	0.58	0.54	0.54	0.44

Table 2. Beta and R^2 computed from recomposed crystals of each index. Pre-crisis period

	Beta at each scale					R^2 at each scale					CAPM	
	1	2	3	4	5	1	2	3	4	5	Beta	R^2
AEX												
Mean	0.90	0.95	0.90	0.96	0.90	0.28	0.29	0.32	0.33	0.25	0.92	0.30
SD	0.25	0.26	0.32	0.33	0.33	0.18	0.17	0.18	0.18	0.17	0.24	0.17
Skew.	0.39	0.03	-0.29	0.30	0.19	1.22	1.20	1.00	0.55	1.29	0.08	1.19
Kurtosis	2.44	1.90	2.63	2.57	3.29	3.47	3.75	3.85	2.69	4.62	2.07	3.74
ATHEX												
Mean	0.86	0.82	0.92	0.94	0.99	0.27	0.28	0.34	0.36	0.36	0.87	0.30
SD	0.25	0.22	0.26	0.29	0.49	0.17	0.16	0.17	0.18	0.22	0.22	0.16
Skew.	0.91	1.34	0.22	0.45	-0.05	1.31	1.26	0.63	0.75	0.18	0.89	1.35
Kurtosis	2.98	5.77	2.37	2.20	2.21	4.08	4.08	2.76	2.91	2.49	3.17	4.19
CAC 40												
Mean	0.93	0.96	0.96	1.01	0.99	0.37	0.36	0.39	0.39	0.32	0.95	0.37
SD	0.23	0.21	0.24	0.28	0.33	0.16	0.14	0.16	0.16	0.16	0.20	0.15
Skew.	-0.01	-0.03	-0.05	0.69	-0.42	0.69	0.51	0.41	0.41	0.01	-0.02	0.73
Kurtosis	2.11	2.38	2.87	3.60	2.64	2.69	2.79	2.58	2.08	2.02	2.00	2.66
DAX 30												
Mean	0.83	0.88	0.90	0.96	0.96	0.32	0.34	0.41	0.40	0.36	0.87	0.35
SD	0.17	0.17	0.23	0.23	0.25	0.12	0.14	0.17	0.15	0.17	0.16	0.13
Skew.	0.04	-0.08	-0.23	0.05	0.00	0.65	0.82	0.15	0.15	0.35	-0.01	0.63
Kurtosis	2.15	2.14	2.35	2.42	2.06	3.27	3.71	2.23	2.31	2.31	1.97	2.96
FTSE 100												
Mean	0.95	1.00	1.09	1.05	0.91	0.28	0.28	0.33	0.33	0.28	0.98	0.29
SD	0.36	0.32	0.41	0.38	0.50	0.14	0.13	0.16	0.16	0.19	0.32	0.13
Skew.	1.11	1.09	0.72	0.26	0.74	0.25	0.23	0.32	0.39	0.46	1.19	0.23
Kurtosis	4.84	4.33	3.13	2.53	4.31	2.39	2.56	2.38	2.98	2.72	4.63	2.53
IBEX 35												
Mean	0.98	0.95	0.99	1.02	0.98	0.37	0.35	0.36	0.39	0.41	0.97	0.37
SD	0.28	0.22	0.25	0.27	0.36	0.18	0.18	0.19	0.18	0.19	0.21	0.18
Skew.	1.42	0.22	-0.11	-0.13	0.60	0.64	0.27	0.04	-0.12	-0.25	0.34	0.37
Kurtosis	5.52	2.63	2.91	3.29	3.74	2.90	2.96	2.27	2.67	2.71	2.33	2.83
MIB												
Mean	0.85	0.86	0.88	0.95	1.04	0.28	0.24	0.27	0.28	0.33	0.87	0.28
SD	0.35	0.35	0.44	0.43	0.46	0.17	0.13	0.15	0.15	0.16	0.34	0.15
Skew.	-0.39	-0.87	-0.57	0.49	0.97	0.21	0.15	0.39	0.20	-0.14	-0.54	0.16
Kurtosis	3.04	3.16	3.48	4.32	5.96	2.66	2.75	3.21	2.13	2.31	2.75	2.84
PSI-20												
Mean	0.73	0.71	0.79	0.88	0.90	0.13	0.12	0.17	0.25	0.22	0.76	0.16
SD	0.44	0.51	0.34	0.45	0.60	0.13	0.14	0.15	0.18	0.17	0.37	0.14
Skew.	0.10	0.34	0.89	0.31	-0.08	0.90	0.90	1.08	-0.05	-0.06	0.21	0.79

Kurtosis	1.98	1.64	2.82	2.13	1.86	2.10	2.26	2.81	1.30	1.36	2.11	2.05

Table 3. Beta and R^2 computed from recomposed crystals of each index. In-crisis period

	Beta at each scale					R^2 at each scale					CAPM	
	1	2	3	4	5	1	2	3	4	5	Beta	R^2
AEX												
Mean	0.87	0.90	0.96	0.98	0.96	0.43	0.44	0.42	0.39	0.49	0.90	0.43
SD	0.41	0.46	0.53	0.57	0.44	0.16	0.17	0.17	0.19	0.13	0.44	0.15
Skew.	1.26	1.10	0.90	0.72	0.99	-0.19	-0.25	-0.33	-0.07	-0.04	1.18	-0.20
Kurtosis	3.53	3.28	2.84	2.49	2.79	2.74	2.14	1.88	1.61	1.45	3.31	2.29
ATHEX												
Mean	0.76	0.77	0.74	0.80	0.86	0.37	0.37	0.34	0.44	0.44	0.77	0.38
SD	0.28	0.30	0.30	0.35	0.31	0.20	0.20	0.20	0.21	0.21	0.29	0.19
Skew.	0.89	0.80	0.58	0.68	0.33	0.97	0.90	0.86	0.47	0.56	0.84	0.99
Kurtosis	3.06	3.05	3.04	3.04	1.74	2.89	2.75	3.04	2.77	2.46	3.02	2.97
CAC 40												
Mean	0.96	1.01	1.08	1.09	1.10	0.51	0.52	0.46	0.47	0.44	1.00	0.50
SD	0.29	0.32	0.42	0.46	0.36	0.14	0.14	0.15	0.17	0.13	0.31	0.13
Skew.	0.72	0.30	0.25	0.26	0.22	0.32	-0.08	-0.61	-0.47	-0.65	0.50	0.20
Kurtosis	2.74	2.42	2.25	2.37	3.47	2.28	2.52	2.71	2.40	4.38	2.50	2.43
DAX 30												
Mean	0.84	0.85	1.02	0.93	0.92	0.35	0.36	0.38	0.41	0.41	0.88	0.37
SD	0.28	0.31	0.40	0.45	0.43	0.14	0.17	0.17	0.20	0.21	0.31	0.15
Skew.	-0.01	0.03	-0.11	0.05	0.12	-0.22	0.06	0.01	-0.22	-0.31	-0.01	-0.11
Kurtosis	2.29	2.04	2.32	2.33	2.41	1.98	2.02	2.52	2.41	2.09	2.16	2.03
FTSE 100												
Mean	0.92	0.94	1.01	1.06	0.96	0.36	0.37	0.32	0.31	0.31	0.95	0.35
SD	0.34	0.35	0.45	0.62	0.48	0.14	0.15	0.14	0.15	0.17	0.35	0.13
Skew.	1.00	1.03	0.66	1.55	0.78	0.12	0.17	0.28	0.32	0.53	0.96	0.24
Kurtosis	3.40	3.72	3.43	7.55	3.69	2.80	2.56	2.75	2.50	3.13	3.27	2.84
IBEX 35												
Mean	0.90	0.88	0.87	0.87	0.94	0.48	0.44	0.44	0.39	0.33	0.90	0.45
SD	0.30	0.34	0.37	0.42	0.55	0.22	0.22	0.22	0.22	0.24	0.32	0.21
Skew.	0.11	0.24	0.37	0.37	0.55	0.00	0.17	0.14	0.22	0.28	0.18	0.09
Kurtosis	2.41	2.00	2.10	2.22	2.93	2.59	2.16	2.22	2.60	2.10	2.13	2.47
MIB												
Mean	0.76	0.76	0.84	0.89	0.90	0.37	0.38	0.39	0.40	0.44	0.79	0.38
SD	0.33	0.34	0.41	0.38	0.41	0.19	0.20	0.19	0.19	0.20	0.34	0.19
Skew.	-0.01	-0.04	-0.06	-0.29	0.38	0.09	0.05	-0.33	-0.26	-0.24	-0.17	-0.10
Kurtosis	3.27	3.16	2.82	3.08	4.06	2.39	2.56	2.63	2.38	2.48	3.29	2.57
PSI-20												
Mean	0.87	0.90	0.91	0.88	1.01	0.38	0.35	0.39	0.34	0.35	0.90	0.38
SD	0.30	0.31	0.35	0.30	0.38	0.17	0.17	0.16	0.14	0.13	0.29	0.15
Skew.	-0.32	-0.35	-0.67	-0.32	0.67	-0.61	0.00	-0.93	-0.62	0.22	-0.31	-0.60

Kurtosis	2.14	1.97	2.08	1.62	1.95	2.48	2.82	3.00	1.99	3.40	1.91	2.88

Table 4. Beta and R^2 computed from recomposed crystals of each index. Eurozone crisis period

	Beta at each scale					R^2 at each scale					CAPM	
	1	2	3	4	5	1	2	3	4	5	Beta	R^2
AEX												
Mean	0.98	0.99	1.03	1.01	0.96	0.41	0.46	0.51	0.44	0.46	0.99	0.45
SD	0.47	0.43	0.44	0.41	0.34	0.18	0.17	0.19	0.18	0.20	0.42	0.17
Skew.	1.13	1.21	0.93	0.79	0.84	-0.20	-0.56	-0.72	-0.50	-0.63	1.11	-0.57
Kurtosis	3.60	3.83	2.97	2.47	2.98	2.25	2.63	2.58	2.15	2.67	3.45	2.51
ATHEX												
Mean	0.79	0.80	0.79	0.86	0.87	0.34	0.36	0.35	0.34	0.43	0.81	0.36
SD	0.49	0.50	0.48	0.52	0.43	0.19	0.18	0.17	0.16	0.16	0.49	0.18
Skew.	1.07	1.06	1.03	1.03	0.63	0.15	0.09	-0.03	0.13	-0.12	1.06	0.06
Kurtosis	2.99	2.88	2.88	2.98	2.42	2.12	2.23	2.10	1.98	2.21	2.95	2.17
CAC 40												
Mean	0.97	1.01	1.04	1.01	1.01	0.51	0.55	0.57	0.50	0.51	1.00	0.54
SD	0.32	0.34	0.38	0.40	0.35	0.15	0.13	0.14	0.16	0.16	0.32	0.14
Skew.	0.63	0.85	0.56	0.72	0.35	-0.18	-0.04	-0.25	-0.29	-0.30	0.68	-0.18
Kurtosis	3.25	3.22	2.70	3.12	2.50	2.63	2.54	2.55	2.29	2.93	3.10	2.76
DAX 30												
Mean	0.90	0.95	0.96	0.94	0.94	0.41	0.51	0.54	0.43	0.46	0.93	0.47
SD	0.30	0.30	0.34	0.33	0.29	0.15	0.15	0.17	0.16	0.17	0.29	0.15
Skew.	-0.31	-0.28	-0.17	-0.12	0.00	-0.46	-0.56	-0.53	0.00	-0.24	-0.29	-0.43
Kurtosis	2.29	2.35	1.91	1.96	2.16	2.57	3.00	2.20	2.20	2.30	2.13	2.59
FTSE 100												
Mean	0.97	1.01	1.05	1.00	0.97	0.36	0.41	0.43	0.37	0.42	0.99	0.40
SD	0.36	0.38	0.43	0.38	0.35	0.14	0.14	0.16	0.15	0.16	0.34	0.13
Skew.	0.57	0.29	0.42	0.33	0.30	0.13	-0.24	-0.25	0.03	-0.13	0.43	-0.07
Kurtosis	3.34	3.17	2.42	2.25	2.53	2.85	3.07	2.59	2.40	2.80	2.99	3.12
IBEX 35												
Mean	0.81	0.85	0.90	0.87	0.90	0.44	0.51	0.54	0.46	0.50	0.85	0.48
SD	0.28	0.28	0.28	0.31	0.31	0.23	0.22	0.21	0.22	0.22	0.27	0.22
Skew.	-0.12	-0.15	-0.26	-0.25	-0.24	0.42	0.05	-0.28	0.15	-0.19	-0.23	0.18
Kurtosis	3.03	2.98	2.87	2.70	2.62	2.84	2.74	2.96	2.60	2.38	3.04	2.81
MIB												
Mean	0.85	0.86	0.90	0.84	0.86	0.44	0.46	0.48	0.40	0.36	0.86	0.45
SD	0.39	0.39	0.41	0.37	0.42	0.20	0.20	0.20	0.20	0.20	0.38	0.20
Skew.	-0.04	-0.15	-0.14	-0.27	0.12	-0.23	-0.37	-0.47	-0.05	-0.05	-0.11	-0.31
Kurtosis	2.80	2.99	2.82	3.00	2.27	2.88	2.86	2.79	2.72	2.07	2.86	2.92
PSI-20												
Mean	0.77	0.78	0.78	0.79	0.80	0.29	0.34	0.35	0.34	0.34	0.79	0.32
SD	0.34	0.33	0.33	0.30	0.34	0.17	0.18	0.19	0.16	0.17	0.31	0.17
Skew.	0.12	0.27	-0.32	-0.43	0.02	-0.53	-0.65	-0.61	-0.70	-0.34	0.02	-0.71

Kurtosis	3.22	2.85	2.07	2.62	1.84	2.09	2.03	1.92	2.56	1.82	2.88	2.15

Table 5. Beta and R^2 computed from recomposed crystals of each index. Post crisis period

	Beta at each scale					R^2 at each scale					CAPM	
	1	2	3	4	5	1	2	3	4	5	Beta	R^2
AEX												
Mean	0.94	0.98	1.00	0.97	0.98	0.39	0.41	0.43	0.47	0.41	0.97	0.43
SD	0.24	0.22	0.25	0.25	0.23	0.13	0.13	0.14	0.16	0.15	0.21	0.13
Skew.	1.05	0.90	1.05	1.19	0.35	-0.61	-1.02	-1.25	-1.35	-0.96	1.16	-1.05
Kurtosis	3.58	2.79	4.00	4.66	3.37	2.90	3.46	4.23	3.84	3.10	3.79	3.45
ATHEX												
Mean	0.90	0.89	0.91	0.90	1.01	0.38	0.40	0.48	0.43	0.46	0.90	0.40
SD	0.50	0.53	0.56	0.57	0.74	0.16	0.16	0.16	0.16	0.16	0.53	0.15
Skew.	1.24	1.23	1.27	1.40	1.46	-0.42	-0.36	-0.50	-0.34	-0.65	1.29	-0.52
Kurtosis	3.46	3.36	3.49	3.92	3.87	2.13	2.01	2.41	2.47	3.21	3.52	2.16
CAC 40												
Mean	0.96	0.98	1.01	0.98	0.97	0.47	0.48	0.50	0.52	0.45	0.97	0.49
SD	0.20	0.20	0.25	0.24	0.24	0.12	0.10	0.10	0.11	0.13	0.19	0.11
Skew.	0.15	0.48	0.37	0.46	0.37	-0.03	-0.14	-0.10	-0.15	-0.29	0.36	-0.07
Kurtosis	2.37	2.33	2.36	3.53	2.80	2.13	2.33	2.13	3.29	2.68	2.45	2.22
DAX 30												
Mean	0.85	0.91	0.96	0.96	0.97	0.41	0.45	0.49	0.54	0.44	0.90	0.46
SD	0.16	0.16	0.24	0.22	0.22	0.12	0.14	0.15	0.15	0.15	0.16	0.13
Skew.	-0.39	-0.15	0.24	0.03	0.51	-0.23	0.02	0.08	-0.23	0.22	-0.13	-0.11
Kurtosis	3.13	2.20	2.01	2.09	3.00	2.41	2.10	2.08	2.51	2.43	2.64	2.23
FTSE 100												
Mean	0.94	0.99	1.00	0.92	0.86	0.28	0.29	0.32	0.29	0.25	0.96	0.31
SD	0.29	0.30	0.33	0.33	0.32	0.12	0.12	0.13	0.15	0.15	0.26	0.12
Skew.	0.97	0.38	0.74	1.37	0.26	0.11	-0.06	-0.14	0.19	0.31	0.85	-0.07
Kurtosis	6.09	3.96	4.71	6.28	3.88	2.58	2.82	2.62	2.24	2.01	5.39	2.64
IBEX 35												
Mean	0.88	0.90	0.93	0.93	0.91	0.42	0.44	0.47	0.46	0.39	0.90	0.44
SD	0.27	0.26	0.26	0.26	0.26	0.19	0.18	0.17	0.17	0.17	0.25	0.17
Skew.	0.48	0.33	0.15	0.22	0.16	0.55	0.46	0.18	0.03	0.39	0.36	0.41
Kurtosis	2.21	2.23	2.12	2.12	2.29	2.41	2.55	2.41	2.37	2.32	2.10	2.42
MIB												
Mean	0.78	0.82	0.85	0.86	0.87	0.38	0.35	0.37	0.36	0.36	0.81	0.38
SD	0.45	0.48	0.52	0.52	0.58	0.24	0.22	0.22	0.20	0.23	0.45	0.22
Skew.	-0.11	0.10	0.18	0.29	0.42	-0.18	-0.01	-0.11	-0.26	0.06	-0.01	-0.13
Kurtosis	2.36	2.32	2.32	2.49	2.50	1.98	1.95	2.06	2.03	1.87	2.36	2.00
PSI-20												
Mean	0.84	0.86	0.89	0.85	0.90	0.26	0.30	0.37	0.38	0.34	0.86	0.31
SD	0.42	0.39	0.41	0.40	0.41	0.14	0.15	0.18	0.21	0.16	0.38	0.15
Skew.	0.48	0.81	0.43	0.78	0.83	-0.65	-0.74	-0.81	-0.33	-0.07	0.54	-0.72

Kurtosis	4.07	4.55	3.52	3.67	2.47	2.10	2.13	2.47	1.83	1.82	3.94	2.19

Table 6. Value At Risk (VaR) at different time scales for an equally weighted portfolio.

	Pre-Crisis		In Crisis		Eurozone Crisis		Post Crisis	
AEX	VaR	Contribution to VaR	VaR	Contribution to VaR	VaR	Contribution to VaR	VaR	Contribution to VaR
Scale1	0.0089	50%	0.0228	51%	0.0131	47%	0.0113	48%
Scale2	0.0063	25%	0.0171	28%	0.0101	28%	0.0084	27%
Scale3	0.0048	15%	0.0114	13%	0.0077	16%	0.0063	15%
Scale4	0.0035	8%	0.0074	5%	0.0046	6%	0.0047	8%
Scale5	0.0022	3%	0.0053	3%	0.0033	3%	0.0028	3%
Recomposed data	0.0126		0.0320		0.0191		0.0163	
CAPM	0.0130		0.0328		0.0198		0.0172	
ATHEX								
Scale1	0.0107	46%	0.0204	48%	0.0249	49%	0.0226	45%
Scale2	0.0078	25%	0.0153	27%	0.0190	28%	0.0174	27%
Scale3	0.0066	18%	0.0103	12%	0.0129	13%	0.0145	19%
Scale4	0.0046	8%	0.0087	9%	0.0086	6%	0.0083	6%
Scale5	0.0030	3%	0.0055	4%	0.0068	4%	0.0065	4%
Recomposed data	0.0158		0.0294		0.0356		0.0337	
CAPM	0.0163		0.0304		0.0365		0.0343	
CAC 40								
Scale1	0.0098	52%	0.0242	52%	0.0159	48%	0.0123	49%
Scale2	0.0068	25%	0.0179	28%	0.0124	29%	0.0089	26%
Scale3	0.0050	14%	0.0112	11%	0.0090	15%	0.0067	15%
Scale4	0.0035	7%	0.0081	6%	0.0053	5%	0.0048	7%
Scale5	0.0022	3%	0.0048	2%	0.0036	2%	0.0028	3%
Recomposed data	0.0136		0.0335		0.0230		0.0175	
CAPM	0.0140		0.0341		0.0237		0.0183	
DAX 30								
Scale1	0.0095	49%	0.0204	50%	0.0132	44%	0.0117	48%
Scale2	0.0067	25%	0.0149	27%	0.0110	31%	0.0084	25%
Scale3	0.0054	16%	0.0107	14%	0.0082	17%	0.0064	15%
Scale4	0.0037	8%	0.0074	7%	0.0045	5%	0.0050	9%
Scale5	0.0022	3%	0.0048	3%	0.0032	3%	0.0029	3%
Recomposed data	0.0135		0.0288		0.0198		0.0168	
CAPM	0.0139		0.0296		0.0206		0.0176	
FTSE 100								
Scale1	0.0087	51%	0.0213	52%	0.0114	47%	0.0095	49%
Scale2	0.0059	24%	0.0157	28%	0.0090	29%	0.0071	27%
Scale3	0.0048	16%	0.0099	11%	0.0067	16%	0.0053	15%
Scale4	0.0032	7%	0.0070	6%	0.0040	6%	0.0035	7%
Scale5	0.0019	2%	0.0041	2%	0.0030	3%	0.0021	2%

Recomposed data	0.0121		0.0294		0.0168		0.0136	
CAPM	0.0125		0.0301		0.0175		0.0145	
IBEX 35								
Scale1	0.0099	53%	0.0218	55%	0.0151	44%	0.0127	49%
Scale2	0.0065	23%	0.0149	26%	0.0127	31%	0.0093	26%
Scale3	0.0049	13%	0.0103	12%	0.0093	17%	0.0070	15%
Scale4	0.0036	7%	0.0065	5%	0.0056	6%	0.0050	7%
Scale5	0.0025	4%	0.0037	2%	0.0040	3%	0.0029	3%
Recomposed data	0.0136		0.0294		0.0229		0.0182	
CAPM	0.0139		0.0301		0.0235		0.0188	
MIB								
Scale1	0.0088	56%	0.0187	50%	0.0169	50%	0.0141	53%
Scale2	0.0055	22%	0.0135	26%	0.0127	28%	0.0095	24%
Scale3	0.0041	12%	0.0099	14%	0.0094	15%	0.0070	13%
Scale4	0.0030	6%	0.0069	7%	0.0053	5%	0.0049	6%
Scale5	0.0023	4%	0.0048	3%	0.0036	2%	0.0034	3%
Recomposed data	0.0117		0.0265		0.0240		0.0194	
CAPM	0.0121		0.0274		0.0246		0.0200	
PSI 20								
Scale1	0.0062	47%	0.0172	49%	0.0124	47%	0.0117	43%
Scale2	0.0045	24%	0.0125	26%	0.0098	29%	0.0092	27%
Scale3	0.0035	15%	0.0097	16%	0.0069	15%	0.0074	17%
Scale4	0.0029	10%	0.0063	6%	0.0043	6%	0.0053	9%
Scale5	0.0018	4%	0.0044	3%	0.0031	3%	0.0034	4%
Recomposed data	0.0091		0.0246		0.0180		0.0178	
CAPM	0.0096		0.0256		0.0186		0.0185	

Table 7. Forecasted values of Beta and R^2 for the post-crisis period.

	Beta at each scale					R^2 at each scale					CAPM	
	1	2	3	4	5	1	2	3	4	5	Beta	R^2
AEX												
Mean	0.97	0.98	0.99	0.97	0.98	0.40	0.41	0.43	0.47	0.41	0.98	0.44
SD	0.25	0.23	0.25	0.26	0.23	0.13	0.13	0.14	0.16	0.15	0.20	0.13
Skew.	1.05	0.90	1.07	1.15	0.32	-0.63	-1.01	-1.27	-1.36	-0.94	1.21	-1.15
Kurtosis	3.78	2.84	4.11	4.52	3.13	2.87	3.43	4.23	3.88	3.07	4.06	3.59
ATHEX												
Mean	0.91	0.90	0.92	0.91	1.02	0.39	0.41	0.49	0.44	0.47	0.92	0.42
SD	0.49	0.54	0.58	0.58	0.75	0.15	0.15	0.16	0.16	0.16	0.54	0.14
Skew.	1.20	1.16	1.23	1.34	1.42	-0.43	-0.46	-0.63	-0.42	-0.67	1.26	-0.63
Kurtosis	3.35	3.20	3.34	3.70	3.70	2.24	2.17	2.56	2.50	3.17	3.41	2.40
CAC 40												
Mean	0.97	0.98	1.01	0.98	0.98	0.48	0.48	0.50	0.52	0.46	0.98	0.50
SD	0.20	0.20	0.25	0.24	0.23	0.12	0.10	0.10	0.11	0.13	0.18	0.10
Skew.	0.14	0.46	0.37	0.48	0.36	0.03	-0.09	-0.11	-0.17	-0.27	0.38	-0.04
Kurtosis	2.59	2.34	2.38	3.49	2.70	2.14	2.30	2.13	3.30	2.62	2.60	2.23
DAX 30												
Mean	0.92	0.93	0.97	0.98	0.98	0.44	0.45	0.50	0.55	0.45	0.94	0.49
SD	0.15	0.15	0.24	0.21	0.21	0.12	0.13	0.14	0.14	0.15	0.15	0.12
Skew.	-0.10	0.00	0.20	0.17	0.67	-0.04	0.08	0.03	-0.15	0.14	0.16	-0.04
Kurtosis	2.53	2.03	2.00	1.95	3.04	2.16	2.05	2.14	2.58	2.52	2.35	2.25
FTSE 100												
Mean	0.93	0.97	0.99	0.92	0.86	0.29	0.29	0.32	0.29	0.25	0.95	0.32
SD	0.30	0.30	0.32	0.34	0.32	0.13	0.12	0.13	0.15	0.15	0.25	0.12
Skew.	0.99	0.44	0.82	1.33	0.37	0.07	-0.05	-0.16	0.22	0.34	0.91	-0.09
Kurtosis	5.77	3.97	4.91	5.84	4.25	2.57	2.75	2.51	2.24	2.04	5.25	2.60
IBEX 35												
Mean	0.91	0.91	0.95	0.95	0.95	0.45	0.45	0.47	0.48	0.42	0.93	0.47
SD	0.27	0.26	0.26	0.26	0.24	0.19	0.18	0.18	0.18	0.16	0.24	0.17
Skew.	0.39	0.43	0.27	0.36	0.19	0.48	0.40	0.06	-0.10	0.48	0.30	0.26
Kurtosis	1.94	2.05	1.95	2.08	2.11	2.46	2.54	2.47	2.51	2.27	1.87	2.49
MIB												
Mean	0.78	0.78	0.82	0.82	0.82	0.38	0.34	0.35	0.35	0.34	0.81	0.38
SD	0.45	0.46	0.51	0.51	0.54	0.24	0.22	0.21	0.20	0.22	0.44	0.21
Skew.	-0.18	0.09	0.22	0.33	0.47	-0.18	0.02	-0.09	-0.23	0.11	-0.03	-0.10
Kurtosis	2.36	2.46	2.44	2.72	2.81	2.04	2.03	2.13	2.03	1.90	2.41	2.06
PSI 20												
Mean	0.86	0.85	0.88	0.85	0.92	0.27	0.29	0.37	0.38	0.34	0.87	0.32
SD	0.44	0.40	0.42	0.41	0.42	0.15	0.15	0.19	0.21	0.17	0.38	0.16

Skew.	0.52	0.85	0.43	0.80	0.80	-0.55	-0.63	-0.71	-0.23	-0.11	0.56	-0.63
Kurtosis	3.92	4.33	3.27	3.53	2.37	2.04	1.96	2.27	1.76	1.73	3.62	2.08

Table 8. Forecast of Value At Risk (VaR) at different time scales for an equally weighted portfolio. Post-crisis period.

	VaR	Contribution to VaR	VaR	Contribution to VaR	VaR	Contribution to VaR	VaR	Contribution to VaR
	AEX		ATHEX		CAC		DAX	
Scale1	0.0086	42%	0.0165	37%	0.0093	44%	0.0091	43%
Scale2	0.0068	26%	0.0140	27%	0.0071	26%	0.0068	24%
Scale3	0.0054	17%	0.0125	21%	0.0058	17%	0.0056	16%
Scale4	0.0045	11%	0.0080	9%	0.0045	10%	0.0048	12%
Scale5	0.0027	4%	0.0064	6%	0.0028	4%	0.0029	4%
Recomposed data	0.0133		0.0270		0.0141		0.0138	
CAPM	0.0144		0.0278		0.0150		0.0148	
	FTSE 100		IBEX 35		MIB		PSI 20	
Scale1	0.0073	44%	0.0098	43%	0.0102	47%	0.0090	38%
Scale2	0.0057	27%	0.0077	26%	0.0073	24%	0.0074	25%
Scale3	0.0045	17%	0.0061	17%	0.0058	15%	0.0064	19%
Scale4	0.0033	9%	0.0048	10%	0.0045	9%	0.0050	12%
Scale5	0.0021	4%	0.0030	4%	0.0031	4%	0.0035	6%
Recomposed data	0.0110		0.0150		0.0149		0.0146	
CAPM	0.0121		0.0157		0.0157		0.0155	

CAPM is the VaR computed using the betas that were estimated using the CAPM on the forecasted raw (undecomposed) returns.

Table 9. Number of times the Competitor model outperforms the Benchmark model in terms of R^2_{OOS} .

Competitor / Benchamrk	CAPM	CAPM Multiscale	WN
CAPM	-	140	265
CAPM Multiscale	150	-	264
WN	25	26	-

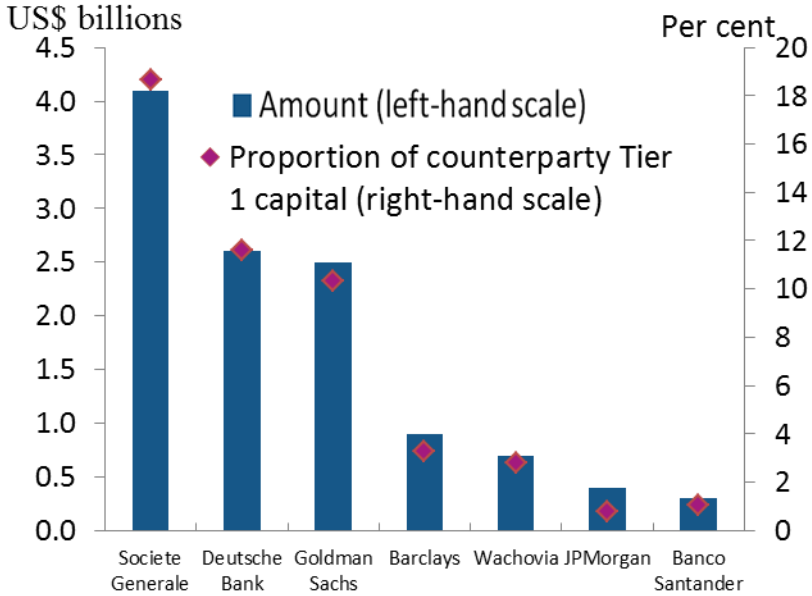


Figure 1. Selected counterparty exposures to AIG at the time of its failure.
Sources: American International Group (d) and Capital IQ.
(a) The chart shows collateral that AIG returned between 16 September and 31 December 2008 to retire CDS obligations which existed at the time of its failure.
(b) Selected counterparties shown. Does not represent total exposure to AIG.
(c) Tier 1 capital as of 30 June 2008 as reported in each bank's accounts. Goldman Sachs data are for 29 August 2008.

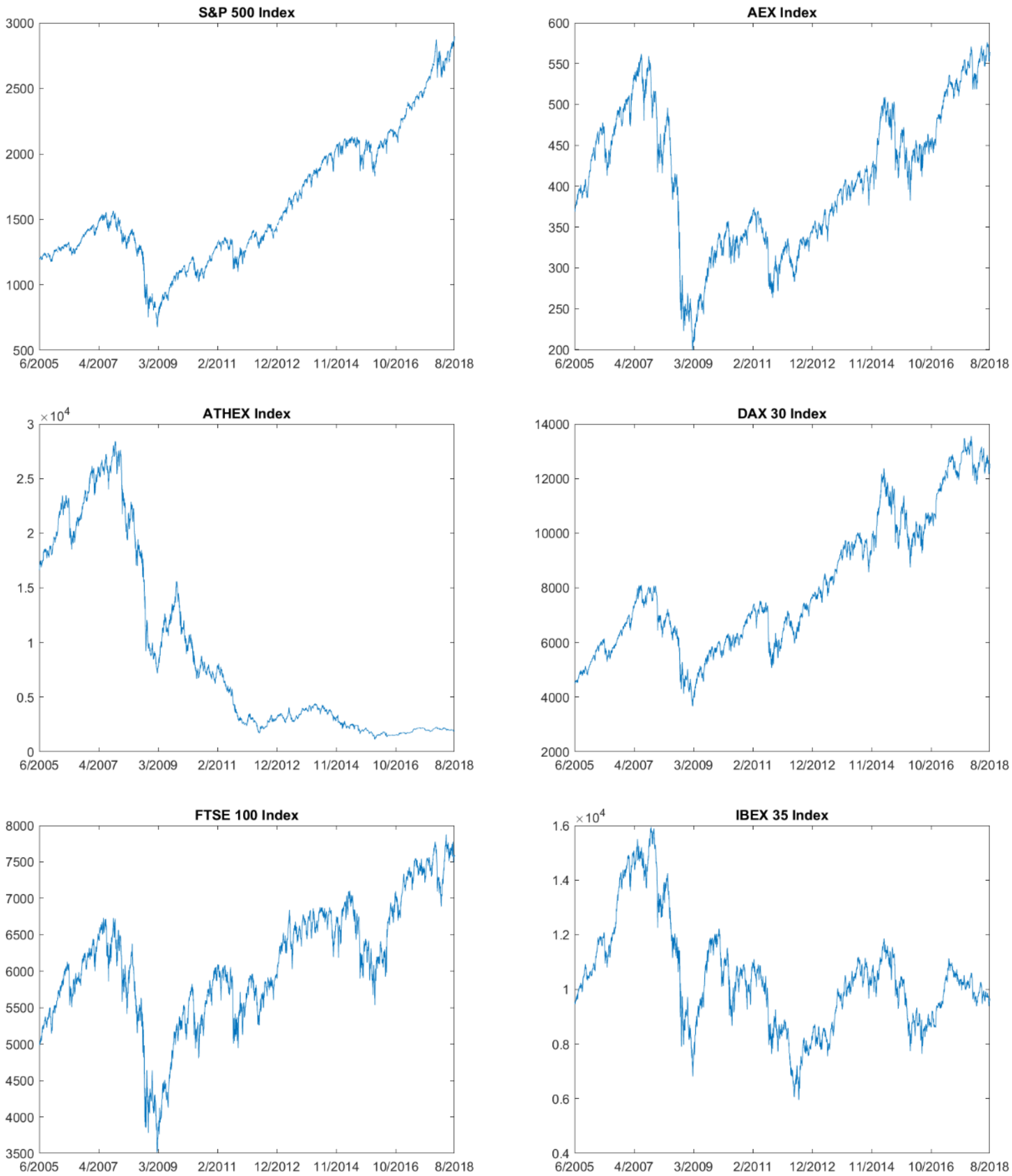
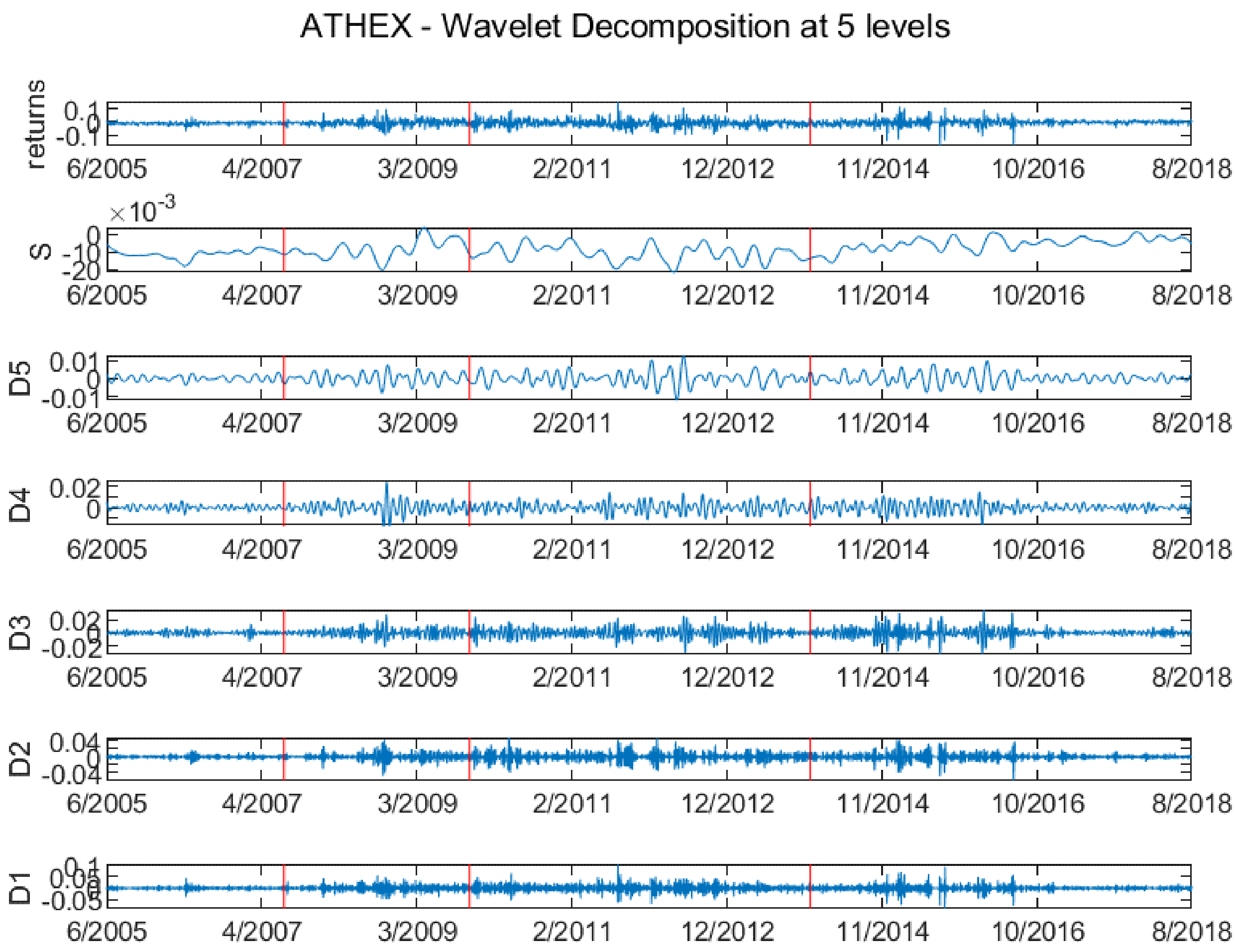
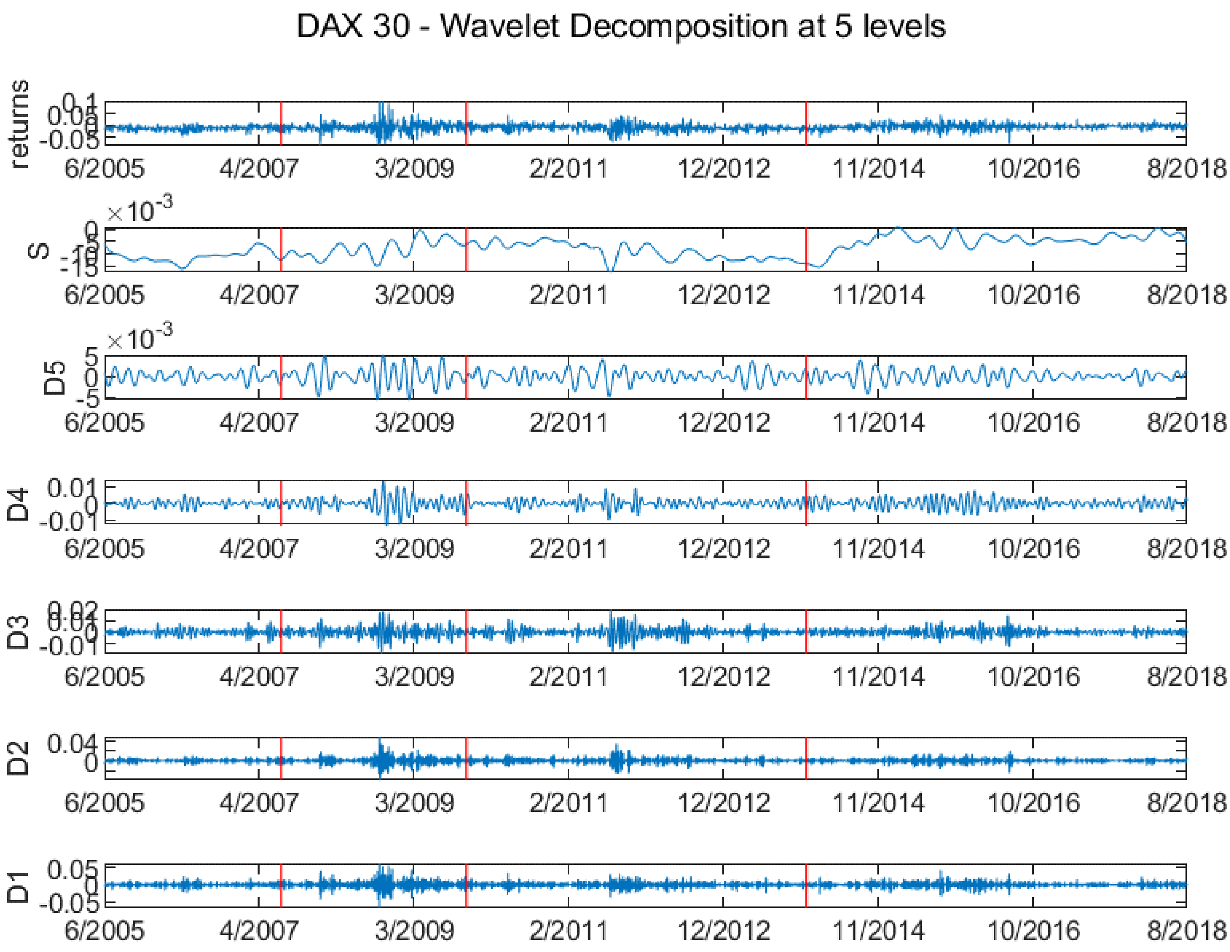


Figure 2. Temporal movements of stock indices for the markets of the U.S.A (S&P 500), Netherlands (AEX), Greece (ATHEX), Germany (DAX 30), UK (FTSE 100) and Spain (IBEX 35).


ATHEX - Wavelet Decomposition at 5 levels
returns
S
D5
D4
D3
D2
D1
6/2005
4/2007
3/2009
2/2011
12/2012
11/2014
10/2016
8/2018

Part (a)



Part (b)

Figure 3. Wavelet decomposition of the returns in Greece, part (a), and Germany, part (b). From top to bottom are the returns, the smooth and the details from level 5 to level 1. The vertical lines indicate the four different sub-periods.

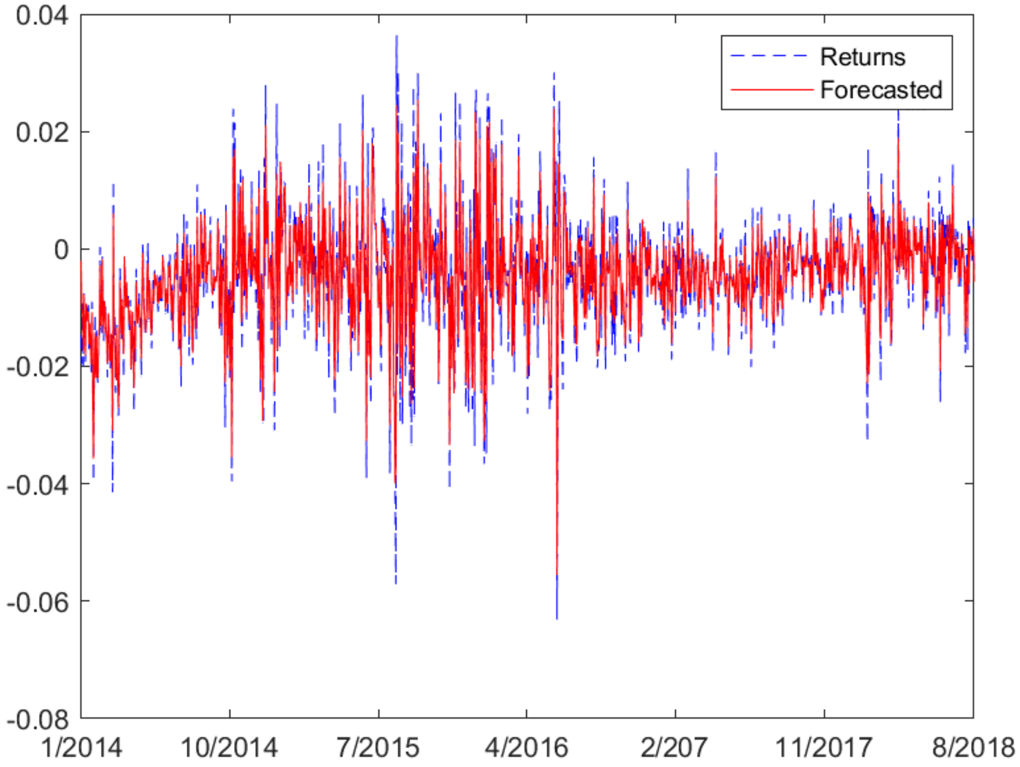


Figure 4. The real and forecast of excess returns of the AEX index

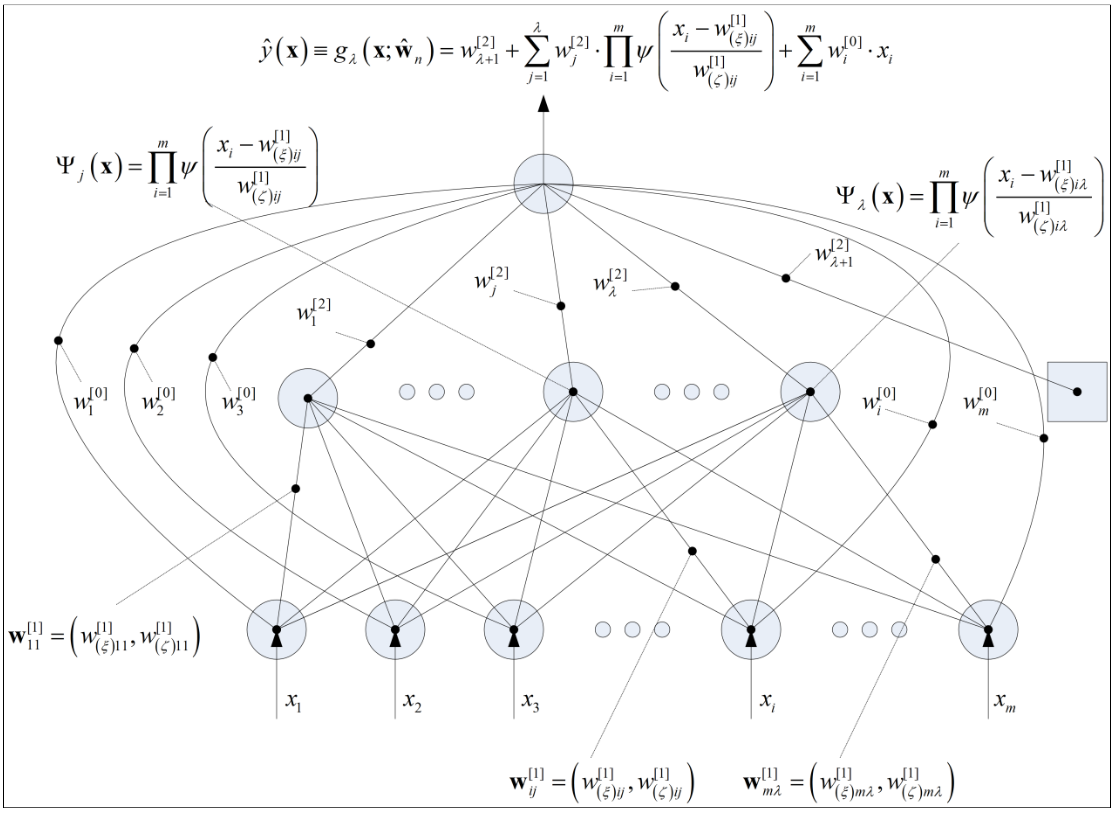


Figure 5. A Feedforward Wavelet Network.