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MACROECONOMIC CAUSES OF VOLATILITY IN THE EURO AREA'S AGGREGATE STOCK RETURN

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Abstract

The purpose of this paper is to determine whether macroeconomic and financial variables Granger cause time varying volatility in aggregate stock return of the Euro Area. Using the daily data from 2005-2013 realized volatility is calculated as the sum of squared daily returns over the month for Euro Stoxx, Euro Stoxx 50 and Euro Stoxx Optimized Banks index. These three index respectively proxy for the Euro Area stock return, blue chip companies and banking industry in the euro area.
The entire sample period is further divided into three sub-sample periods: pre-crash period from January 2005 to October, 2007, market crash period from November, 2007 to February, 2009 and post-crash period is from March, 2009 to December, 2013. This division is motivated to capture the effects of business cycle and the recent financial crisis of 2007-2009. Nine macroeconomic and financial variables used in this paper are: bank leverage, consumption growth, credit growth, commercial paper to treasury spread (CP), expected GDP growth, GDP growth, term spread, volatility of inflation and industrial production.
The In-sample analysis shows that the forecastability of macro variables varies through time and business cycle. Their predictability is higher during the crisis of 2007-2009 and when the bull or the bear market condition is considered in isolation. The blue chip index is found to be more sensitive to the changes in macro variables than the broad market index. However, the set of macro variables affecting the banking sector and their predictability pattern are different from the other two indices those represents the overall market. The most successful out-of-sample forecasting approaches involve simple combinations of macro variables, namely median and trimmed mean of individual forecasting variables.

Keywords: Volatility, Forecasting, Macroeconomic variables, Financial variables

1. INTRODUCTION

After more than three decades of research on volatility, the number of volatility forecasting models based on historical time series information is astronomical. In a survey on only ARCH/GARCH family models, Bollerslev (2008) documented more than a hundred different types of such published models in academic literature. Despite this enormous collection of studies, the dynamics between macroeconomic environment and volatility is little known and even less utilized in volatility forecasting literature (Engle & Rangel 2008).

Therefore, a natural question arises: What drives the time-varying stock return volatility? Schwert (1989) considers the possibility that volatility fluctuates with the level of economic activity. Although he finds only limited support for this notion, subsequent papers report more encouraging evidence using different forecasting variables and econometric approaches. The list of exogenous variables normally includes different measures of interest rate risk premiums, expected stock return, dividend growth, macroeconomic variables, recession, financial leverage, trading activities, etc (Christiansen, Schmeling & Schrimpf 2012, Paye 2012).

From the practical perspective, understanding the robustness and magnitude of the relation between macroeconomic variables and volatility remain as an important question. For instance, the expected change in stock market volatility due to the changes in macroeconomic condition is used in risk management to perform stress-test and to compute the value-at-risk over longer horizons. In addition, forecasted volatility is a state variable in the portfolio selection process of a mean-variance investor.

In general, characterizing the magnitude and pattern of variation in volatility series is important to ascertain its stylized facts against which asset pricing models are evaluated (Paye 2012). It is widely recognized that volatility is higher during recessions and following macroeconomic announcements. However, since the global financial crisis of 2007-2009 (Baur 2012) investigations on the economic source of volatility have gained renewed interest.

Paye (2012) and Christiansen et al. (2012) investigate a wide range of macroeconomic and financial variables for their impact on the realized volatility of the U.S. stock market. They find evidence that macroeconomic and financial variables Granger cause volatility, but do not provide consistent superior forecasts in out-of-sample analysis. However, Rapach, Strauss & Zhou (2010) show that the simple combination of macroeconomic variables can provide superior forecast in out-of-sample analysis.

Previous studies focusing on individual European countries find that the relation between macroeconomic variables and the respective country's stock market volatility is higher than that in the U.S. (Liljeblom & Stenius 1997, Errunza & Hogan 1998, Beltratti & Morana 2006). However, the association between the aggregate Euro area's macroeconomic and financial variables and the stock market volatility is not investigated yet. In addition, the dynamics of the stock market volatility of this region during the financial crisis of 2007-2009 is non-existent. The purpose of this paper is to fulfill these research gaps in volatility literature.

1.1. Purpose of the Study

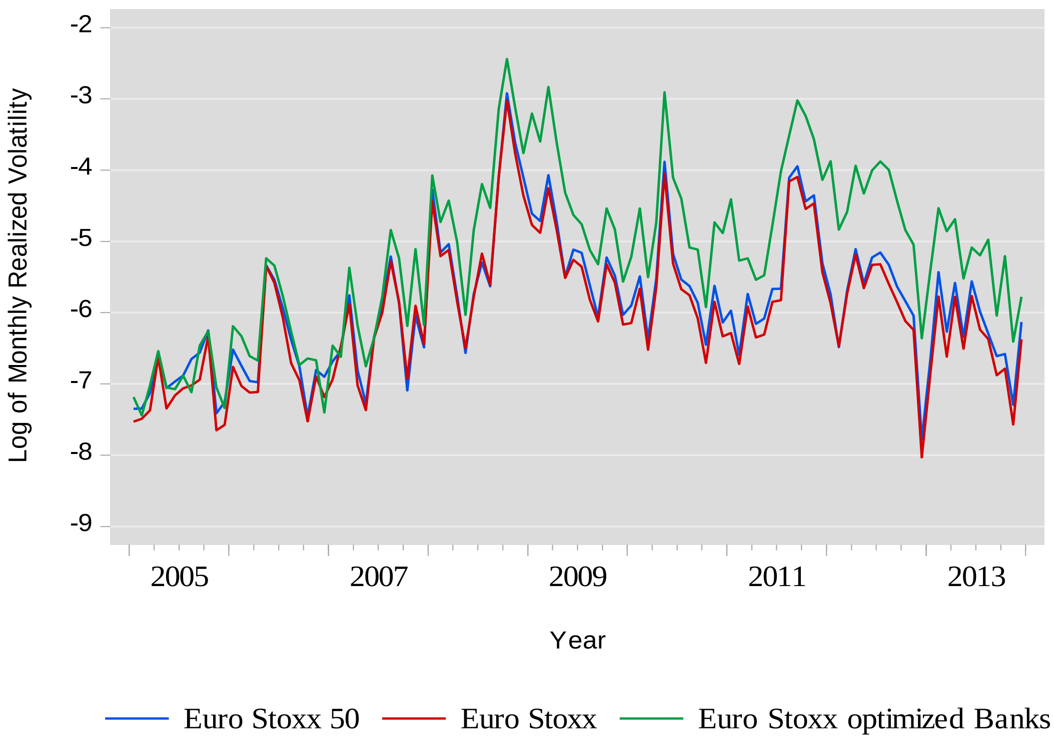
The purpose of this study is to assess whether the aggregate macroeconomic and financial variables of Euro area have any predictive power of the volatility of aggregate Euro Area stock indices. Recent literature identifies several channels that drive volatility. For instance, shocks to fundamentals (Bansal & Yaron 2004), time varying association between business cycle and expected returns (Mele 2007), investors learning about volatility (Veronesi 1999), and amplification of shocks to asset markets via financial intermediation (Brunnermeier & Pedersen 2009). (Paye 2012)

Motivated by the theoretical framework of those papers, several macroeconomic and financial variables have been considered for this paper. This includes two different measures of interest rate risk premiums, measure of changes in bank leverage, measures of current and expected GDP growth, credit growth, and three other major economic series: inflation, industrial production and consumption.

As a proxy of aggregate Euro area stock market, three Euro STOXX indices are used: Euro STOXX index, Euro STOXX 50 index and Euro STOXX optimized bank index. The first index is a proxy for the aggregate Euro area stock market while the second one represents 50 highly traded and the biggest stocks from the same area. The optimized bank index comprises stocks of the banking companies from the same region.

The simultaneous study of the broad and the blue chip index will allow assessing how increased liquidity and stock quality affect volatility. Graph 1 shows that the level of volatility of the blue chip index is close but slightly lower than that of the broad market index before the financial crisis of 2007-2009. Since the crisis, the blue chip index has become more volatile than the market in general. This asymmetric behavior of the blue chip index before and after the crisis is the main motivation for including it along with the broad market index.

Graph 1. Monthly realized volatility of aggregate Euro area stock indices.



The recent financial crisis of 2007-2009 and the Euro area sovereign debt crisis contributes to the higher level of volatility in the banking sector. The Euro STOXX optimized bank index reflects this fact in Graph 1. Even though, before the crisis this index was more volatile than the broad and the blue chip index, the dispersion further extends since the crisis began. It leads to the question whether the macroeconomic causes of volatility is the same for the banking sector and for the market in general. Therefore, comparing the set and the magnitude of the variables affecting the volatility of the banking sector and the overall market is the main purpose of studying the banking index in this paper.

1.2. Hypotheses

In this paper, both the in-sample and the out-of-sample analysis are performed to indentify the time varying effect of macroeconomic variables on the volatility. The in-sample analysis mainly addresses the question whether the macroeconomic and financial variables have actually caused volatility during the sample periods. Using the U.S. data Paye (2012), Christiansen et al. (2012) show the time varying impact of macroeconomic variables in stock volatility. Diebold & Yilmaz (2008) study approximately 40 stock markets and confirm the affinity between macroeconomic fundamentals and stock market volatility. Similar results are expected from the in-sample regression analysis of this paper and consequently, the directly testable null hypothesis would be:

> H_1: Aggregate Macroeconomic and financial variables do not Granger cause volatility in the Euro area's aggregate stock return.

In regression analysis, the rejection of this null hypothesis would match with the priori. The focus of out-of-sample analysis is whether the macroeconomic and financial variables could provide superior forecasts during the analysis periods. Prior empirical findings on superior predictability of exogenous variables in volatility forecasting are mixed. Using stock market data of 50 countries, Engle et al. (2008) find superior predictability of major macroeconomic series for forecasting volatility. Engle, Ghysels & Sohn (2008) also report similar results for the U.S stock return using inflation and industrial production series. However, Paye (2012) finds limited evidence to this notion. The directly testable null hypothesis for the out-of-sample analysis is:

> H_2: Macroeconomic and financial variables cannot produce superior volatility forecasts than parsimonious AR type models in the Euro area's aggregate stock return.

These two hypotheses form the main research purpose of this paper. However, the evaluation of these two hypotheses for individual macroeconomic and financial variable as well as their combination allows determining the set of factors cause volatility during different sample periods and across different indices.

1.3. Contribution

There is a comprehensive amount of literature on the macroeconomic causes of volatility which investigate different macroeconomic and financial variables and use varied econometric models. Therefore, there is a lack of generality in their results specifically about their efficiency in out-of-sample forecasting (Paye 2012). Moreover, these papers mainly study individual countries' data. Thus, the relation between the aggregate macro data of European economic and monetary union (Euro Area) and aggregate stock volatility remains unexplored.

This paper utilizes a unique dataset of aggregate macroeconomic and financial variables of the Euro Area to investigate the causes of volatility in aggregate stock return of this region. Furthermore, how these causes vary before, during and after the financial crisis of 2007-2009 is also investigated under both in-sample and out-of-sample settings. Therefore, the main contribution of this paper is to fulfill the research gap in volatility literature about the macroeconomic causes of volatility in aggregate Euro area stock return especially since the global financial crisis.

Understanding about these data is critical for policy making institutions like ECB and for investors with an internationally diversified portfolio. However, the selection of the stock indices in this paper allows further analyzing the dynamics of volatility on two features: company size and primary role in credit supplying activity. While the broad and the blue chip index captures the size effect, the banking index facilitates analyzing whether the macroeconomic causes of volatility differs from the overall market being in the different side of credit supplying activity.

1.4. Structure of the Thesis

The rest of the paper is organized in the following form: chapter two presents a brief introduction to properties, measures and general forecasting evaluation procedure of volatility, chapter three contains the theoretical background of realized volatility, chapter four includes the literature review on the impact of macroeconomic factors on volatility, chapter five describes the data and methodology, chapter six reports the empirical results and chapter seven concludes.

2. VOLATILITY

Volatility, a key concept in mathematical finance, is used extensively in portfolio construction, policy making and asset pricing literatures (Elyasiani & Mansur 2004). This chapter introduces the concept of volatility with its stylized facts which are essential in modeling and forecasting volatility. However, the main purpose of this paper is to assess whether the use of exogenous macroeconomic and financial variables can produce better volatility forecasts. Therefore, the general procedure of determining the superior forecasting model is also described in brief in this chapter.

2.1. Volatility

In finance, volatility is used as a measure of risk or uncertainty associated with an asset's return over time. More precisely, Alexander (2008: 90) defines volatility as, "Volatility of an asset is an annualized measure of dispersion in the stochastic process that is used to model the log returns." Volatility definitions and measures (implicitly) assume that the underlying asset return or price process is associated with a known standard distribution such as a standard normal or a t distribution. Analytically, this assumption allows to determine the probability density and the cumulative probability of the return or price process (Poon & Granger 2003) and to use it for forecasting, managing risks, constructing portfolio and so forth.

Volatility being the second moment of the return process is model dependent and unobservable. The unconditional volatility is estimated by standard deviation or variance of the asset return series (Alexander 2008: 101). The Estimation of conditional or instantaneous volatility requires a conditional mean generating model. Therefore, the accuracy of conditional volatility estimation depends on the accuracy of its conditional mean estimation. The use of different conditional mean models or estimation and forecasting period may lead to different estimates of volatility (Pagan & Ullah 1988, Poon et al. 2003). Thus volatility estimation requires a proper understanding of its characteristics and the underlying return process.

2.2. Stylized Facts of Volatility

This section introduces the properties of volatility already observed and documented in academic literature, such as volatility clustering, long memory, mean reversion, leverage effect, influence of exogenous variables and fat tail distribution. The performance of volatility forecasting models depends on how accurately these phenomena can be explained by the underlying models (Engle & Patton 2001). Therefore, understanding these characteristics is essential for explaining the relative performance of different volatility forecasting models. A brief description of these six properties is given below.

1) Volatility Clustering: A well documented stylized fact is that the expected future volatility is influenced by the volatility observed today. A high level of volatility is expected to be followed by another high level of volatility and a low volatility level is followed by a low level of volatility (Engle et al. 2001). Mandelbrot (1963) and Fama (1965) were the first to report the clustering phenomena in asset price returns. Subsequent studies like Schwert (1989), Baillie, Bollersler & Mikkelsen (1996) also confirm this phenomenon.

2) Long Memory: A discrete time series y_t with autocorrelation ρ_t at lag t demonstrate long memory if the value of $\lim_{n\to\infty} \sum_{t=n}^{n} |\rho_t|$ is nonfinite (Baillie 1996). This condition implies that today's value is serially correlated with its leg values. In other words, volatility does not drop or rise instantaneously rather it decays at a hyperbolic rate based on its dependence structure on its lag values and also on the information set available today (Ding, Granger & Engle 1993).

3) Mean Reversion: Mean reversion of volatility means there is a normal level of volatility to which long run forecast of volatility converges. This implies even though volatility clusters for a short period eventually it goes away. Thus the current information does not have any impact on the long run volatility forecast (Engle et al. 2001). When σ_t^2 is the long-run variance and $h_{t+k|t}$ is the conditional variance, in general the mean reversion process can be expressed as $\operatorname{plim}_{k\to\infty} h_{t+k|t} = \sigma_t^2 < \infty$.

4) Asymmetric Impact (Leverage Effect): The sign of shock has asymmetric impact on the equity stock return. Nelson (1991), Engle & Ng (1993) confirmed that volatility and equity returns are negatively correlated. A negative shock in return increases the debt-to-equity ratio which in turn increases the volatility of the stockholders return. This line of reasoning is known as the leverage effect of volatility. An alternative risk premium explanation holds that stockholders are risk averse. An increase in volatility reduces the demand of the stock and induces a further decline of its value. Thus increases the future volatility.

5) Fat Tail Distribution: In empirical finance it is established that the asset returns are non-normal and contain fatter tails (Mandelbrot 1963, Fama 1963, 1965). Volatility modeling normally assumes that its conditional density is normal and can be explained totally by its mean. Studies showed that the estimated standard error of conditional return variance, for instance GARCH term, cannot absorb the leptokurtosis in the most financial time series data (Bollerslev, Chou & Kroner 1992). Models take the asymmetric impact of the news into consideration can provide a fat tail distribution.

6) Influence by Exogenous Variables: Volatility clustering, asymmetric impact of volatility, mean reversion and long memory are contained in the volatility process endogenously. Other external variables like macroeconomic announcements, scheduled company announcements, time-of-day effect, stock market anomalies, bid-ask spread, trading volume, prices of other markets may have influence on the volatility process (Engle et al. 2001).

2.3. Volatility Estimation Procedure

The importance of volatility forecast in investment, security valuation, risk management, and monetary policy making has attracted a large number of researchers and practitioners to develop different volatility estimation and forecasting measures (Poon et al. 2003). The variation in these models arises from the assumption about return generating process, such as martingale, Geometric Brownian Motion; continuous vs. discrete time settings; conditional vs. unconditional modeling, etc. These wide ranges of models are summarized here under three broad categories:

1) Realized volatility: In general, realized volatility is an ex-post nonparametric estimation of variation in asset return. This type of models normally includes two estimation stages (Andersen & Benzoni 2008a). At first stage the error term of the return series is generated under a conditional mean and in the second step the average of the squared error term is obtained (Bollerslev et al. 1992).

   The varying assumption about the stock return leads to different measurement process of realized volatility. For instance, French, Schwert & Stambaugh (1987), Andersen, Bollerslev, Diebold & Labys (2003), and Paye (2012) assumed that asset return is a semi-martingale process with zero-mean. However, Schwert (1989) assumed stock return is a sub-martingale process and consequently, uses a demeaned squared return to construct volatility series.

2) Implied Volatility: Implied volatility is an ex-ante estimation of expected volatility by using option pricing formulas like Black-Scholes (1973). In Black-Scholes-Merton (BSM) option pricing formula, volatility is the only unobservable parameter. By applying BSM the latent volatility term can be obtained from the current market quote of option prices. Äiyö (2007) argues that volatility estimation achieved in this process contains information about the future volatilities and possess better predictability power for the ex-post estimation procedures.

   Technically, implied volatility is obtained under continuous time setting and for each quote the estimated volatility is constant for the remaining maturity of the respective option (Hull 1993). This implies that the estimated volatility is subjective to each instrument and to its maturity. Therefore, index methodology is applied to obtain an estimate for the volatility of overall market. CBOE volatility index (VIX), for instance, is a good indicator of implied volatility in the U.S. equity market (Traub, Ferreira, McArdle & Antognelli 2000).

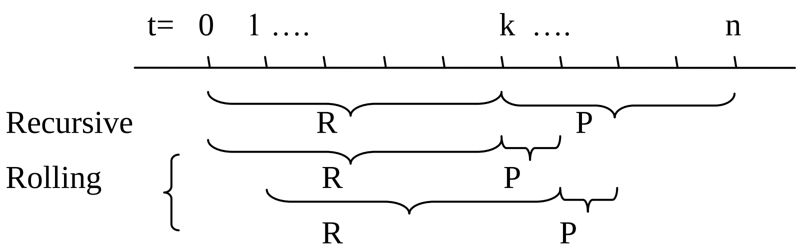
3) Econometric Modeling: Econometric modeling involves estimation and forecasting of conditional volatility assuming volatility itself is a stochastic process. Some popular models are: Exponentially Weighted Moving Average (EWMA), Autoregressive Conditional Heteroscedesticity (ARCH) (Engle 1982), Generalized ARCH (GARCH) (Bollerslev 1986), and Stochastic volatility.

   Mathematically, the serial correlation in the conditional second moment is the source of such type of modeling. Both practitioners and academics, among all these models, extensively use ARCH/GARCH family models. In fact, Lee & Hansen (1994) described GARCH(1, 1) as the workhorse of the industry for estimating time dependent volatility for discrete periods.

2.4. Evaluation of Forecasting Models

In this paper, Clark & West (2007) Mean Squared Prediction Error (MSPE) adjusted Equal Predictive Ability (EPA) test and Giacomini & White (2006) Superior Predictive Ability (SPA) tests are conducted under rolling window estimation procedure. The general set up of assessing the predictive ability of volatility forecasting models are described in this section and the details can be found in the referred articles.

Engle et al. (2001) indicate that the central role of volatility modeling is forecasting and the superiority of a volatility model depends on its forecasting accuracy. The test starts with estimating the parameters for the underlying model during a sample period and then uses it to forecast volatility in another (normally adjacent) period(s).



Under recursive forecasting procedure parameters are estimated once during the estimation period (R) and then the use the same parameters for the whole prediction horizon (P). Forecasts using a rolling window estimate the parameters of each prediction horizon by making the size of estimation period constant. If, the test statistics is non-normal critical values differ along the P/R. For instance, the critical value of the MSPE-adjusted equal EPA test of Clark & West (2007) under a rolling window initially falls as P/R increases from 0.1 but then rises as P/R approaches 20.

The next step in volatility forecasting evaluation requires for a loss function to determine the extent of variation in forecasted volatility. As volatility is unobservable, an obvious choice is to compare the model dependant volatility estimation with the daily squared return or the realized volatility. Different volatility forecasting literature uses different types of loss function. For instance, Patton (2011) reports nine different loss functions and Giacomini et al. (2006) reports six loss functions. These loss functions are different moderation or correction of Mean Squared Error (MSE) and Mean Absolute Error (MAE) expressed in the equation (1) and (2).

(1) $$MSE = \frac{1}{P}\sum_{t=1}^{P}(\hat{\sigma}_t^2 - \hat{\sigma}_{i,t}^2)^2$$

(2) $$MAE = \frac{1}{P}\sum_{t=1}^{P}\left|\hat{\sigma}_t^2 - \hat{\sigma}_{i,t}^2\right|$$

Here $\hat{\sigma}^2$ is a proxy for true volatility and $\hat{\sigma}_i^2$ is the forecasted (conditional) variance by a model. MSE and MAE in equation (1) and (2) are symmetric loss function as it does not penalize for any noise or asymmetry in the process. In contrast, Brailsford & Faff's (1996) Mean Mixed Error (MME) and Clark & West's (2007) MSPE-Adjusted involve additional terms to capture the asymmetric expectations. Clark & West (2007) test is described in details in the Methodology part of this paper.

The statistics obtained from the equation (1) and (2) can be ranked to determine the models with the best performance. The lower the MSE or MAE the better the predictive ability a model contains. This procedure only compares each model with a benchmark model. To facilitate the comparability between different models SPA or EPA tests form pair wise test statistics and analyze the critical value of it to determine the superiority of each model. The CW and GW tests are described in details in the methodology.

3. REALIZED VOLATILITY (RV)

Traditionally, volatility forecasting depends on complex econometric models, such as ARCH family models, Stochastic volatility and Implied volatility models, to accommodate its inherent latent properties. These models are systematically biased towards the past information set and mainly capture the persistence in volatility. But volatility is also a mean reverting process which implies that a unit root type model-depended estimation procedures are far from producing optimal forecasts. In contrast, the estimation of Realized volatility from high frequency data can bypass these problems and therefore, is a reliable measure of return variations. (Andersen & Benzoni 2008a)

Theoretically, over a fixed period, RV is related to the cumulative expected variability of the returns of a wide range of underlying arbitrage-free diffusive data generating processes. However, the short term expected return's association with realized return invokes very strong auxiliary assumptions. Thus, a finely sampled asset price mainly provides superior information about expected return volatility rather than expected return. This view has created an increased research interest into the measurement and application of realized volatility. (Andersen et al. 2008a)

3.1. Theoretical Background

The fundamental relation between daily squared return and return variance is described in this section. In this paper, the sum of daily squared return is used as the proxy for monthly volatility. Paye (2012) argues that this measure is related to that of RV and as the intra-period sampling frequency increases it leads in probability to a quadratic variation of arbitrage-free asset price process. Therefore, this section presents the conceptual background for this volatility measure. All the mathematical derivation in this chapter follows Andersen et al. (2008a).

To construct the basic rationale behind the realized volatility approach in a simplified setting, let's hold that the continuously compounded return follows a simple time-invariant Brownian motion like

(3) $$ds(t) = \alpha dt + \sigma dW(t),\ 0 \leq t \leq T$$

Where, $s(t)$ is the logarithmic asset price, $ds(t)$ is the continuously compounded return. α and σ $(\sigma > 0)$ are the constant drift and the diffusion coefficients respectively. For a given estimation period, say $[0; k]$, where $k > 0$ and for n intra-period observations, the return is $r(t, 1/n) = \mathrm{s(t)} - \mathrm{s}(\mathrm{t} - 1/n)$ for $t = 1/n, \dots, (n-1).k/n\,, k$. By assuming the returns are independent and identically distributed (i.i.d.) the intra-period mean and variance becomes α/n and σ^2/n. The expected return from the equation (3) for k periods is:

(4) $$\hat{\alpha}_n = \frac{1}{K}\sum_{j=1}^{n.k} r(j/n\,, 1/n) = \frac{r(k,k)}{K} = \frac{s(K)-s(0)}{K}$$

(5) $$var(\hat{\alpha}_n) = \frac{\sigma^2}{K}$$

Therefore, an increase in the number of intra-period observations does not influence the estimation of expected return rather it depends on the length of the data, *k*. Although the estimator is unbiased, the drift in mean $var(\hat{\alpha}_n)$ cannot be estimated consistently for a given *k*. Thus, for a precise inference requires for a large sample and when expected returns are allowed to vary conditionally, additional assumptions are required for sensible inference about α. Andersen et al. (2008a)

In case of squared returns this situation changes. The expected second and fourth moment of the return becomes dependent on the sampling frequency of the following form:

(6) $$E[r(j/n, 1/n)^2] = \frac{\alpha^2}{n^2} + \frac{\sigma^2}{n}$$

(7) $$E[r(j/n, 1/n)^4] = \frac{\alpha^4}{n^4} + 6\frac{\alpha^2\sigma^2}{n^3} + 3\frac{\sigma^2}{n^2}$$

In both equations, the terms with the drift coefficient are smaller than the terms with the diffusion coefficient. When *n* increases, these drift terms become insignificant and eventually left with the diffusion coefficient terms. Therefore, un-adjusted or un-centered squared return volatility can be estimated with a high degree of precision without specifying the drift component. Thus, equation (8) can be used to define the un-centered realized volatility.

(8) $$\hat{\sigma}_n^2 = \frac{1}{K}\sum_{j=1}^{n.k} r^2(j/n, 1/n)$$

The expectation and variance of RV would be in the form of the equation (9) and (10).

(9) $$E[\hat{\sigma}_n^2] = \frac{\alpha^2}{n^2} + \sigma^2$$

(10) $$Var[\hat{\sigma}_n^2] = 4\frac{\alpha^2\sigma^2}{n^2 k} + 2\frac{\sigma^4}{nK}$$

Andersen et al. (2008a) argues that as by following a standard L^2 argument $\hat{\sigma}_n^2 \rightarrow \sigma^2$ when $n \rightarrow \infty$. Therefore, for large n, realized volatility defined in the equation (8) is a biased but consistent estimator of the underlying volatility. Moreover, as $n \rightarrow \infty$ the distributional convergence,

(11) $$\sqrt{n.K}(\hat{\sigma}_n^2 - \sigma^2) \rightarrow N(0{,}2\sigma^4)$$

This explanation is valid when return of each intra-period follows time invariant Brownian motion. In the context of empirical financial it means market offers no arbitrage opportunity during each intra-period i.e. market in frictionless. Andersen and Bollerslev (1998a) is the first to show that the model is valid when asset return follows semi-martingale. These restrictions can further be relaxed for stochastic volatility, condition return, jumps in the process and so forth. In details discussion can be found in Andersen et al. (2008a), Andersen, Bollerslev, Diebold & Labys (2001, 2003), Andersen & Bollerslev (1997, 1998b), and Comte & Renault (1998).

3.2. Forecasting with Realized Volatility

Andersen & Bollerslev (1997) use Deutsche Mark-Dollar exchange rates data and report that the logarithmic RV series is stationary and decay at a hyperbolic rate. This implies RV has a long-memory and thus the dependence structure can be utilized in forecasting volatility (Andersen et al. 2008a). Subsequent studies also report the same properties of logarithmic RV series for equity markets e.g., Andersen, Bollerslev, Diebold & Ebens (2001), Areal & Taylor (2002), Martens (2002).

Andersen et al. (2001) use all the thirty stocks of Dow Jones Industrial Average (DJIA) over a five-year period and find that the unconditional distributions of the stock variances are leptokurtic and highly skewed to the right. However, the logarithmic standard deviation series is found to be approximately Gaussian with strong temporal dependence. In addition, the economic importance of the present day negative return on the subsequent period's variance is negligible and thus, ruling out the presence of asymmetric impact of negative return. The choice of empirical models in this paper is influenced by these properties of realized volatility. Due to its long-memory property autoregressive type models are used as the benchmark for evaluating the forecasts. In addition, log of the realized volatility series is used for regression analysis instead of the row series because of its log-normality.

3.3. Realized Volatility in Literature

Taylor (1986) is the first to model observable volatility through fitting ARMA type models in absolute and squared returns. Subsequent works include French et al. (1987) and Schwert (1989) who use daily returns to estimate a proxy for monthly realized volatility (Andersen et al. 2003). Recently Paye (2012) and Christiansen et al. (2012) used the similar procedure to forecast monthly realized volatility.

Hsieh (1991) is an early study of daily volatility using high-frequency intra-day data. He estimates the RV of S&P500 from 15-minute intra-day returns. Andersen & Bollerslev (1997, 1998b) and Zhou (1996) utilize realized volatility methodology to study the intra-day volatility of the currency market. Areal et al. (2002), Andersen et al. (2001), Andersen, Bollerslev & Meddahi (2005) and Fleming & Paye (2011) study the intra-day stock return volatility using RV methodology.

Comte et al. (1998) point to the potential association between instantaneous volatility and measures of RV. This paper along with Barndorff-Nielsen & Shephard (2001) and Andersen et al. (2003) helped to develop the theoretical background of realized volatility and Andersen et al. (2008a) summarizes the theoretical aspects under different environment and assumptions.

4. MACROECONOMIC CONDITION AND STOCK VOLATILITY

An early comprehensive work on macroeconomic factors' impact on the stock return volatility is Schwert (1989). Later works includes: Liljeblom et al. (1997), Errunza et al. (1998), Mele (2005, 2007), Beltratti et al. (2006), Abugri (2008), Engle et al. (2008), Diebold et al. (2008), Nguyen (2011), Christiansen et al. (2012), Paye (2012) and so forth. This chapter includes a brief review of these papers.

4.1. Theoretical Background

Volatility of stock return varies through time. Schwert (1989) argue that either a change in expected cashflow or the expected return can influence the volatility of the stock return. This phenomenon can easily be explained by the fundamental pricing formula of discounted cashflow of form:

(12) $$E_{t-1}[P_t] = E_{t-1}\left[\sum_{k=1}^{\infty}\frac{D_{t+k}}{(1+R_{t+k})^k}\right]$$

Where, $E_{t-1}[P_t]$ is the expected price P at time t based on the available information at (t-1). D_{t+k} and R_{t+k} are respectively the cashflow[1] and the discount rate at $t+k$. This equation shows that, in an efficient market, any expected change in the future cashflow (say, dividend) or in the discount rate would result into a change in tomorrow's expected price, ceteris paribus. While the stock price will be adjusting this expectation realized volatility will capture the magnitude of adjustment in stock return.

An increase in the expectation of future cashflow will have a positive impact in stock price while the same in expected discount rate would lead to a negative impact. At aggregate level, these changes are related to the change in the health of the economy

[1] When cashflow involves only dividends, equation (12) is essentially the dividend discount model.

(Schwert 1989). Therefore, it is rational to expect that macroeconomic factors which contain information about the economic condition should also provide information about the expected change in stock price. Therefore, they become potential candidates for forecasting the stock return volatility. This line of reasoning is turn relates to the efficient market hypothesis/theory.

4.2. Literature Review

The forecasting variables are used in this paper includes growth in GDP, expected GDP and consumption, volatility of industrial production and inflation, bank leverage, credit growth, commercial to treasury spread (CP) and term spread. In addition, the design of empirical analysis considers the effect of the business cycle. A brief review on these variables and business cycle based on previous literature is presented here.

4.2.1. Business Cycle

It is well established in literature that business cycle phases affects stock market volatility. In particular, stock market volatility is higher during recession (Officer 1973). Schwert (1989) reports volatility is counter cyclical. He uses the NBER recession dummy and regress it on volatility to study the association between the business cycle and stock return volatility. By using the S&P500 index data from 1965 to 1993, Hamilton & Lin (1996) document economic recessions as the single largest factor of stock return variance. In particular, they hold recession is accountable for about 60% of the total monthly variance of stock returns.

In a recent study, Paye (2012) analyzed the quarterly stock return (realized) volatility for S&P500 index over the period 1929-2010 and confirms that the volatility and GDP series track one another closely. He also notes that stock return volatility tends to be higher when the business conditions are poor, but the degree of affinity between volatility and business conditions varies through time.

Technically, the lagged volatility contains a rich set of information about current economic conditions because of stock return volatility's close relation with real economic conditions. Therefore, it becomes challenging to identify the macroeconomic and financial variables that contains additional relevant information for forecasting volatility in long-horizon. (Paye 2012)

4.2.2. Financial Variables

Financial variable such as bond returns is a better predictor of stock market volatility than other macroeconomic indicators (Schwert 1989). Bond returns are forward looking and capture the future expected rate of return by considering associated risks over the maturity period. Thus they provide a benchmark for adjusting the expected return of other financial assets, for instance, stocks. From the heuristic perspective, this forward looking information content proved to be vital in forecasting stock return volatility. In addition, the liquidity and credit crisis of 2007–2008 have brought the movement of interest rates under the scrutiny of investors as to predict the probable impact of financial intermediation to amplify shocks to asset markets.

Christiansen et al. (2012) argue that financial variables such as default spread and term spread (see 5.1 for definition) is a proxy for market credit risk and liquidity/maturity risk and thus contain information for the stock market expected risk premia. In their study, both the in-sample and out-of-sample analysis show that these variables have superior predictive ability over other macroeconomic indicators.

In general, expected returns for asset returns are lower during the boom and higher during the economic downturn (Fama & French 1989). Arnold & Vrugt (2006) document that changes in short-term interest rates are associated with business cycle. To exploit the information content of the short term risk premium Paye (2012) use commercial paper to treasury yield (CP) to forecast volatility and finds it as a consistent state variable for forecasting the U.S. stocks return volatility from 1927 to 1985.

Two other well documented financial indicators: leverage and bank credit growth, can explain the variability in stock return and thus expected to influence the stock market volatility (Paye 2012). During the financial downturn, leveraged investors' balance sheet effects can amplify relatively small initial shocks through a loss spiral by eroding net worth of the portfolio and eventually, they might need to sell assets from their portfolio to fulfill obligatory margin requirement. Thus, a loss spiral enters into a margin spiral: an increase of margin as the asset prices continue to drop; and cause further drop in the asset prices (Brunnermeier et al. 2009). Apart from balance sheet effects, Adrian & Shin (2010) provide additional evidence that lenders' capital limitations, network effects, and bank runs can also amplify shocks in financial markets.

4.2.3. Macroeconomic Variables

Theoretically, the conditional variance of stock returns depends on the conditional variances of future cash flows, the conditional variances of discount rates, and conditional covariance's between the two series (Paye 2012). Holding the discount rate constant, conditional variances of future aggregate cash flows is the only factor that drives the conditional variance of the aggregate return. In other words, shocks to fundamentals are the only channel for time-varying volatility. By analyzing approximately forty stock markets Diebold et al. (2008) report that volatile macroeconomic fundamentals cause higher volatility in the stock market. As macroeconomic fundamental he uses real GDP, world development indicator and real personal consumption expenditure.

Schwert (1989) uses industrial production and PPI inflation as fundamentals to explain the U.S. stock market volatility, but finds little evidence. Liljeblom et al. (1997) use Finnish data over the 1925-1991 and find that the associating between stock market volatility and fundamentals such as CPI inflation and IP volatility is higher than the U.S. counterpart. Errunza et al. (1998) investigate the explanatory power of macroeconomic variables for time varying European stock market volatility and reach to the same conclusion.

In their study Errunza et al. (1998) use inflation and industrial production growth rate as macroeconomic indicators. They reports that observed variability of real macroeconomic factors significantly affects the stock market volatility, but the level of association is country sensitive. David & Veronesi (2006) identify inflation and earnings uncertainty as sources of stock market volatility which can improve forecasting at horizons of one and two years ahead.

Engle & Rangel (2008) use Spline-GARCH model to assess the impact of CPI inflation volatility and GDP volatility on 48 countries and report that the volatility of GDP has a positive impact on the stock market volatility while the inflation volatility is country sensitive. Engle et al. (2008) use GARCH-MIDAS with volatility of inflation and industrial production growth for a quarter-ahead out-of-sample prediction which outperforms traditional volatility models at longer horizons. This result is consistent with the priori that macroeconomic variables can improve volatility forecast for a long horizon. However, they also find evidence that inflation and industrial production growth, account for between 10% and 35% of one-day ahead volatility. Thus, they provide evidence that macroeconomic factors can improve volatility forecasts at the short horizon as well.

Instead of taking the past time series information about macroeconomic factors, Arnold et al. (2006) rely on a one-quarter and a four-quarter ahead economic forecasts from the Survey of Professional Forecasters (SPF) over the period 1969–2004. He reports that stock market volatility is significantly related to the volatility of economic indicators up to 1996 and starts to disappear since then.

In a recent paper, Paye (2012) investigate the monthly and quarterly realized volatility of the U.S. stock market over the period 1927-2010. He finds that the individual macroeconomic variables provide poor incremental forecastability comparing to AR type models both in in-sample and out-of-sample analysis. But the ability to forecast volatility increases and during the time of financial turmoil. However, he also finds that a simple combination of these factors can provide superior forecasts.

A quick review of these papers show that the common macroeconomic indicators studied in literature are GDP, inflation, industrial production and consumption. The common consensus about the macroeconomic variables is that they can improve the volatility forecasts during recession. Besides, their forecastability increases as the forecasting horizon increases.

5. DATA AND METHODOLOGY

The empirical analysis concentrates on the Euro area aggregate macroeconomic variables' impact on stock market's volatility. Euro area is an Economic and Monetary Union (EMU) with Euro (€) as the common and sole legal tender and currently consists 18 European Union (EU) member states. In 1999, the EMU started with 11 members- Austria, Belgium, France, Finland, Germany, the Netherlands, Luxembourg, Italy, Ireland, Portugal, and Spain. Greece joined the EMU in 2001 and since 2007 six new members have joined the union.

The stock market data for this paper are based on those first 12 member-states of this union. This subset of countries represents on an average 98.79% of the nominal GDP of Euro area since 2007. Therefore, the results from this data set are expected to be an unbiased proxy for the whole Euro area. The test period (2005-2013) is limited by the data availability of aggregate macro variables. The first part of current chapter describes the data and the second part introduces the methodology.

5.1. Data

To measure the aggregate volatility of Eurozone stock markets five indices are used- Euro Stoxx (SXXE), Euro Stoxx ex Banks (SXXNBE), Euro Stoxx 50 (SX5E). All these indices are subsets of STOXX Europe 600 (SXXP) index with Eurozone filter. SXXP Europe 600 index includes 600 large, mid and small capitalized companies from 18 European countries[2]. SXXE includes constituents of SXXP from 12 Eurozone countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain.

[2] The 18 European countries are: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

SX5E includes 50 blue-chip stocks from the same 12 countries and is used by financial institutions to serve as underlying asset for different investment products such as Exchange Traded Funds (ETF), Futures and Options, and structured products worldwide. The constituents of this index are the stocks with the highest investment grade and liquidity in Euro Area. The SXO7E contains banking stocks of SXXP for 11 Eurozone countries (only Greece is left out from above 12 countries).

Data used in this paper are mostly collected from the Eurostat database and European Central Bank's (ECB) Statistical Data Warehouse (SDW). At SDW, aggregate government bond yield data are available only from September 6, 2004. Because of the lack of data empirical analysis of this paper starts from 2005. The variables and their construction procedure are described here:

- Change in bank leverage (Blev): Following Adrian & Shin (2010), Paye (2012) blev is derived as the ratio of total asset to equity of aggregate Monetary Financial Institutions (MFI) of Euro area. The aggregate MFI data excludes European System of Central Banks (ESCB) and available at monthly frequency at ECB's SDW under MFI balance sheet database.

  This variable conveys information about liquidity and credit condition. As bank leverage increases, banks become more vulnerable to the possibility of loss spirals and margin spirals (Paye 2012) and it can adversely affect the economy especially at the onset of a recession. This variable is used to assess how the quality of banks' asset affects the stock market especially since the financial crisis of 2007-2009.

- Credit growth (CRDT): The construction of this variable follows Hammami & Lindahl (2014). Bank credit growth is calculated as the log difference of outstanding credit balance of aggregated Euro area MFI (excluding ESCB). MFI credit is the total of loan and securities outstanding at the end of each month and the data is available at ECB's SDW under the MFI balance sheet database.

- Consumption growth (CONSUM): The continuous compounded growth rate of Euro area (changing composition) aggregate consumption at constant price of 2010 is used for constructing this variable. This is equivalent as the real growth rate of consumption during the test period.

- Commercial paper to treasury spread (CP): CP is calculated as the difference between three-month Euribor and AAA rated Euro area aggregated three-month government bond spot rate. Euribor rate is collected from ECB's SDW and is a proxy for the commercial paper interest rate. The three-month government bond is a proxy for the Treasury bill (T-bill). This variable captures the market liquidity risk for a short time.

- GDP growth (GDP): Real seasonally adjusted GDP is measure of current overall economic activity. Real GDP or GDP at constant prices is calculated by Laspeyres volume index using prices from a specific year, the base year. In general, constant price series need to be rebased between five to ten years because the prices of base year become increasingly irrelevant for contemporary use (Systems of national accounts (SNA) 1993: 493). In this paper, first difference in the logarithm of GDP volume index at constant price of 2010 is used as a proxy for real GDP growth.

- Expected GDP growth (EGDP): Expected GDP growth for the Euro area is collected from the European Economic Forecasts of spring and autumn publications produced by Directorate-General for Economic and Financial Affairs (DG ECFIN) for European Commission (EC). From each publication next two quarter's forecasted GDP is taken to construct the EGDP series.

- Volatility in industrial production (VOLIP): This variable is a proxy for the conditional volatility of the Aggregate Euro area industrial production. Following Engle, Ghysels & Sohn (2008) and Engle & Rangel (2008) this variable is derived by taking yearly average of the absolute values of the residuals from an AR(1) model for the continuous compounded growth of the industrial production.

(13) $$\Delta \log(y) = c + u_t$$

(14) $$\mathrm{u_t} = \rho u_{t-1} + e_t$$

(15) $$\sigma^2_{\mathrm{y,t}} = \frac{1}{4}\sum_{j=t-2}^{t+1} |e_t|$$

Here, y is the variable in concern i.e. industrial production. Data for the industrial production is obtained from the Eurostat database at monthly frequency. As the data for changing composition of Euro area is not available; the aggregate industrial production includes 17 euro area countries at constant price of 2010.

- Volatility of inflation growth (VOLPPI): *Volppi* is a producer's price index based proxy for the conditional volatility of inflation at monthly frequency. Construction of this variable follows the same procedure as *Volip*.

- Term spread (TERM): It is calculated as the difference between 10 year and three-month AAA rated Euro area aggregated government bond spot rate. This data is available in ECB's SDW under Financial market data-yield curve database.

5.2. Methodology

Conditional Volatility is unobservable because it depends on the ex ante expectation of the portfolio return. Following Taylor (1986), French et al. (1987), and Schwert (1989), Paye (2012), Christiansen et al. (2012) monthly volatility of stock indices are estimated by the sum squared daily return over the month[3].

[3] HAC consistent (see Merton 1980) regression of daily index return on a constant over monthly samples mostly reports a statistically insignificant average for daily return during the period 2005-2013.

(16) $$RV_t = \sum_{i=1}^{N_t} R_{i,t}^2$$

Where N_t denotes the number of trading days in month t and R denotes the continuously compounded daily return. Barndorff-Nielsen & Shephard (2002) and Andersen et al. (2003) show that, with the increase of intra-period sampling frequency, realized volatility measured by the equation (4) converges in probability to the quadratic variation of a frictionless, arbitrage-free asset price process.

5.2.1. In-sample analysis

To analyze the impact of macroeconomic and financial variables on the stock return volatility, equation (16) is estimated. Paye (2012) uses this equation to determine the Granger causality of the U.S. macroeconomic variables on S&P500 index.

(17) $$\mathrm{LVOL_t} = \alpha + \sum_{\mathrm{k=1}}^{\mathrm{k}} \rho_{\mathrm{k}} \, \mathrm{LVOL_{t-k}} + \beta' \mathrm{X_{t-1}} + \varepsilon_t$$

Here, $\mathrm{LVOL_t}$ is the log of monthly variance. $\mathrm{LVOL_{t-k}}$ is the lag values of LOVL. The lag of LVOL captures the long memory property of volatility and the lag length will be determined by using the SIC value of the estimated equitation. β' is a vector of coefficients for the macroeconomic and financial variables X_t . Under the null hypothesis of no granger causality, $\beta' = 0$. When X_t is scalar, this turns into a standard t-test and for vector of X_t can be tested via F-test.

5.2.2. Out of Sample Analysis

A common problem with stock return predictability is that many models perform poorly from an out-of-sample perspective (Goyal & Welch 2008). To check the robustness of the in-sample results an out of sample analysis will be conducted. The general setup of an out of sample forecasts analysis requires a loss function to evaluate the performance of each forecasting model and then comparing them with a benchmark model to select the model with Superior Predictive Ability (SPA) or test for Equal Predictive Accuracy (EPA).

As the benchmark model simple univariate AR model will be used of the form of equation (17) with $\beta' = 0$. A comparison between univariate AR model and the nested models with macroeconomic and financial variables would show the marginal predictive ability of additional variable(s) (see 2.2). In this paper, EPA and SPA of different models will be tested respectively by following the framework proposed by Clark et al. (2007) and Giacomini et al. (2006).

Clark and West (CW) is an adjusted MSPE framework for EPA test with the null hypothesis that parsimonious model perform equally well as nested model. In the context of this paper, the univariate AR model is the parsimonious one when the models with macro variables are nested. The performance of each model (parsimonious and nested) is measured by the MSPE of the following form.

$$\hat{\sigma}_i^2 \equiv P^{-1} \sum (LVOL_{t+1} - \widehat{LVOL}_{i,t+1})^2 \tag{18}$$

Where, $\hat{\sigma}_i^2$ is the MSPE series for model i, $LVOL_{t+1}$ is the realized volatility at time t+1 and $\widehat{LVOL}_{i,t+1}$ is the forecasted log variance by model *i*. P is the prediction horizon. For the recursive forecast P increases as the number of forecasts increases. But for rolling estimation P becomes a constant. In this paper one step ahead rolling estimation is conducted and thus P=1. MSPE adjusted CW test statistics take the form of equation (19) which makes an adjustment for the noise of larger model's forecast.

$$CW = \hat{\sigma}_1^2 - \hat{\sigma}_2^2 + P^{-1} \sum (LVOL_{1,t+1} - \widehat{LVOL}_{2,t+1})^2 \tag{19}$$

Where, $\hat{\sigma}_1^2$ and $\hat{\sigma}_2^2$ are the MSPE for the benchmark nested model respectively. The term $(LVOL_{1,t+1} - \widehat{LVOL}_{2,t+1})^2$ is the adjustment for bias-variance trade-off under mean square error loss. Computationally, CW it can be tested by running a regression on a constant and examining the associated t-value. Clark et al. (2007) reports the adjusted MSPE statistics is not asymptotically normal and critical value for associated t-stat is smaller than that of the normal one. The null $H_o: \hat{\sigma}_1^2 = \hat{\sigma}_2^2$ should be rejected if the t-stat for the constant is greater than +1.282 (for a one sided .10 test) or +1.645 (for a one sided .05 test)[4].

Given the perspective of this paper by following Paye (2012), unconditional predictive ability framework of Giacomini et al. (2006) is adopted. Upon the available information set $\mathcal{G}_t$ (σ-field) at time *t*, the null hypothesis of the GW test for two models is as equation (20).

$$H_0: E(\hat{\sigma}_1^2 - \hat{\sigma}_2^2 | \mathcal{G}_t) = 0 \tag{20}$$

Where, $\hat{\sigma}_1^2$ and $\hat{\sigma}_2^2$ are the MSPE estimated by equation (6) for model (1) and (2). The null hypothesis explicitly captures the effect of estimation uncertainty on relative forecast performance. By involving estimated MSPE instead of population MSPE, GW test concentrates on forecast methods. This framework can virtually be applied for any data-driven combinations of underlying forecasts. The GW test statistics takes the form of equation (21).

$$GW = \frac{E(\Delta\hat{\sigma}_i^2)}{\hat{\sigma}_p/\sqrt{P}} \tag{21}$$

[4] Under the alternative, $H_A: \hat{\sigma}_2^2 > \hat{\sigma}_1^2$. Thus CW requires a one tail (right tail) test and associated t-stat is positive.

(22) $$\Delta\hat{\sigma}_i^2 = \hat{\sigma}_1^2 - \hat{\sigma}_2^2$$

Where, $\hat{\sigma}_p$ is the heteroscedasticity and autocorrelation (HAC) consistent estimator of asymptotic variance, $\sigma_p^2 = var(E(\Delta\hat{\sigma}_i^2))$. Asymptotically GW statistics of equation (21) follows standard normal distribution (Giacomini et al. 2006). Computationally, the test can be executed by regressing $\Delta\hat{\sigma}_i^2$ in equation (21) on a constant with HAC framework and then testing the associated p-value for statistical significance. If the constant is statistically significant and greater than zero model (2) posses the superior predictive ability and vice versa. In comparison with the CW test, GW is a two tail test for SPA.

6. EMPIRICAL RESULT

This chapter contains the empirical results about Granger causality of ten macroeconomic and financial factors on three aggregate Euro area stock index's monthly realized volatility. The outlook of future volatility has impact on portfolio management, risk management, option trading and economic policy making. By using the stock return data of 2005-2013, the in-sample analysis shows the factors causes stock return volatility and out-of-sample analysis stresses on their predictive ability. In addition, the time varying properties of stock return volatility is studied in both cases.

6.1. Descriptive Statistics

Table 1 and Table 2 presents descriptive statistics for the stock indices and forecasting variables used in this paper respectively. These tables include mean, standard deviation, skewness, and kurtosis of each variable. To determine the level of persistence in the forecasting variables the first-and second-order sample autocorrelations (ρ_1 and ρ_2) is reported along with the *t* test statistic for the Phillips & Perron (PP) unit root test and the associated MacKinnon approximate p-value (Phillips & Perron 1998, MacKinnon 1996). As the variables reject the null hypothesis of unit root; it means that the persistence is not so severe so as to require alternative framework for inference (Paye 2012).

Panel A of Table 1 reports the monthly stock returns for the period 2005-2013. It shows aggregate market performed well than the top blue chip stocks. Euro stoxx index has an annualized percentage rate[5] (APR) of 1.8% while Euro stoxx 50 has 0.6%. The optimized banking index is the only loss making index with APR of -6.48%. The global financial crisis of 2007-2009 caused the banking companies stock price to drop heavily. From the price level of 1463 in May, 2007, the Euro stoxx optimized bank fell to 323 in

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[5] From the monthly return APR is calculated by multiplying the number of month with the mean return. For example: 0.0015 monthly return of the Euro Stoxx index results into an APR of (0.0005*12*100)% =1.8%. Return upto four decimal place s is taken to capture the basis point changes in return series.

Table 1. Descriptive statistics of STOXX indices.

Symbol	Name	Mean	Std Div.*	Skewness	kurtosis	ρ_1	ρ_2	Phillips and Perron Test	
								t-value	p-value
Panel A: Monthly Stock Return									
SXXE	Euro Stoxx	0.0015	0.05	-0.88	4.25	0.23	-0.07	-8.27	0.00
SX5E	Euro Stoxx 50	0.0005	0.05	-0.78	3.87	0.18	-0.12	-8.64	0.00
SXO7E	Euro Stoxx Optimized Banks	-0.0054	0.09	-0.38	4.02	0.23	-0.11	-8.12	0.00
Panel B: Natural Logarithm(log) of Monthly Stock Volatility									
SXXE	Euro Stoxx	-6.02	0.96	0.46	3.09	0.71	0.55	-4.27	0.00
SX5E	Euro Stoxx 50	-5.87	0.94	0.52	3.19	0.70	0.51	-4.42	0.00
SXO7E	Euro Stoxx Optimized Banks	-5.19	1.18	0.04	2.31	0.81	0.70	-3.45	0.01

* Std. Div. stands for standard deviation

Table 2. Descriptive statistics of forecasting variables.

Symbol	Name	Mean	Std. Div.*	Skewness	kurtosis	ρ_1	ρ_2	Phillips and Perron test	
								t-value	p-value
BLEV	Growth in bank leverage	-0.0031	0.01	-0.12	3.37	0.05	-0.13	-9.53	0.00
CONSUM	Consumption growth†	0.0016	0.00	0.05	2.67	0.82	0.63	-4.01	0.00
CP	Cp-to-treasury spread‡	0.4711	0.40	1.80	6.87	0.89	0.72	-2.59	0.10
CRDT	Credit growth	0.0028	0.01	0.01	3.00	0.43	0.35	-6.68	0.00
EGDP	Detrended Expected gdp†	-0.0106	0.19	-1.16	4.63	0.85	0.69	-2.80	0.06
GDP	GDP growth†	0.0017	0.01	-1.99	8.01	0.90	0.79	-2.63	0.10
DTERM	First diff. in term spread‡	0.0048	0.24	1.32	7.56	0.12	-0.02	-9.14	0.00
VOLINF	Volatility of PPI inflation	0.0032	0.00	1.26	5.17	0.82	0.61	-3.82	0.00
VOLIP	Industrial production volatility	0.0087	0.00	1.52	6.29	0.86	0.64	-2.97	0.04

*Std. Div. stands for standard deviation.
†Variables are in quarterly frequency. Rest of the variables is in monthly frequency.
‡Amounts are in annualized percentage rate (APR).

Feb., 2009 and reports a staggering drop of 77.92% over the 22-month period. This huge loss during this period is mainly responsible for the negative return for the optimized bank index for entire period. Thus according to the asymmetric impact of volatility i.e. bad news cause higher volatility than good news (see 2.2.); it is expected that the banking portfolio will be among the highest volatile stocks during the period.

Panel B of Table 1 represents the statistics of Natural Logarithm (log) of Monthly Stock Return Volatility calculated using equation (16). By construction, Realized Volatility (RV) is less than one (because returns are in basis points) and thus log of RV becomes negative. Consequently, a higher value of log of RV represents a higher the level of volatility. For example: -5.19 indicate high level of volatility than -6.02.

The table 1 shows that, the highest volatile index is that of optimized banks and the lowest volatile is the Euro stoxx. This phenomenon can be explained by the well-known portfolio diversification effect (Markowitz, 1952) i.e. a more diversified portfolio is less risky. A more specific conclusion would be a diversified portfolio with less weight on banking stocks performs the best during the period 2005-2013.

Table 2 presents the forecasting variables. Consumption, GDP and Expected GDP growth are quarterly data and the rest are at monthly frequency. Among variables with monthly frequency, commercial paper to treasury spread (cp) and term spread are in APR. The Philip and Perron unit root test shows that GDP growth is trend stationary and thus for the purpose of this paper we took the de-trended expected GDP and the term spread accepts the null hypothesis of unit root. Therefore, instead of using term spread in this paper, the first difference in term spread is used.

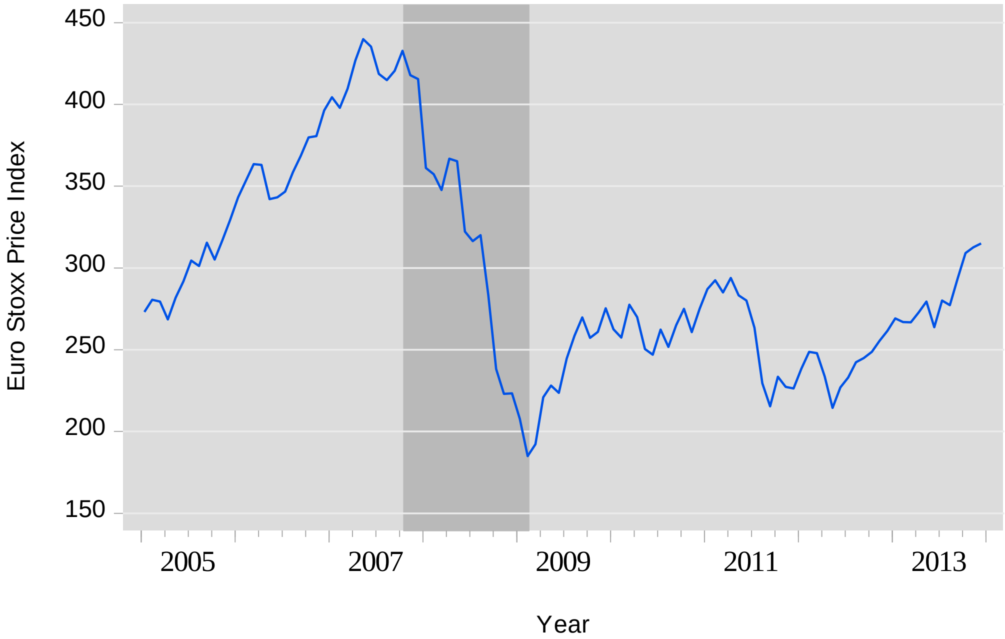
6.2. Benchmark Model

For the purpose of this paper, AR(1) model of the form of equation (17) with k=1 and $X_{t-1} = 0$ is used as the benchmark model. The choice of AR(1) model as the benchmark model is determined based on the Schwarz Information criterion (SIC).

During each sample period for all three indices, AR(1) model produces the lowest SIC amongst different alternative AR models with lag up to 12. Thus, AR(1) appears as the optimal model is used as the benchmark model for both the in-sample and the out-of-sample analysis.

The entire sample stresses from 2005-2013 which is further divided into three sub-sample: pre-crash period from January, 2005 to October, 2007; market crash period from November, 2007 to February, 2009; and post-crash period from March, 2009 to December, 2013. From November, 2007 the Euro Stoxx Index started to decline and continued until February, 2009. During this period, the index value dropped by 55.88% from 417 to 184 and thus significantly different from other rest of the sample period.

Graph 2. Euro STOXX Index.



The subsample periods allow comparing the time varying Granger causality effect of macroeconomic and financial variables in volatility. But the subsample of the crisis period is relatively small and therefore the results of this subsample period need to be analyzed with caution.

Table 3 contains the AR(1) regression result for the log of Realized Volatility of three stock indices (see table 1). $\hat{\beta}$ is the heteroskedasticity and serial correlation (HAC) consistent coefficient of lag volatility and ***, ** and * designate statistical significance at the 1%, 5%, and 10% level, respectively. R^2 is the of in-sample goodness-of-fit measured by the coefficient of determination and presented in percentage. All the variables are standardized prior to regression analysis and consequently the constant term is dropped.

Table 3. Benchmark models for in-sample analysis.

Index	2005.01-2013.12		2005.01-2007.10		2007.11-2009.02		2009.03-2013.12	
	$\hat{\beta}$	R^2	$\hat{\beta}$	R^2	$\hat{\beta}$	R^2	$\hat{\beta}$	R^2
Euro Stoxx	0.71***	52.23	0.77***	9.60	0.79***	19.14	0.62***	36.36
Euro Stoxx 50	0.70***	49.86	0.78***	3.38	0.75***	24.21	0.59***	31.85
Optimized Bank	0.81***	67.12	0.88***	18.05	0.77***	21.71	0.73***	39.56

Table 3 shows that the $\hat{\beta}$ is the highest for the optimized bank index for all testing periods except the crash period (2007.11-2009.02) and the lowest for the blue chip Euro Stoxx 50 index except the pre-crash period. Each benchmark models for entire period outperform all the subsample periods and shows worst performance during the before crisis period.

During the crisis period the goodness of fit measures improves and it further increases for the after crisis period. Statistically, the low value of R squared for the sub-sample periods can be improved by including additional explanatory variables. Thus, theoretically, it provides a strong motivation for the use of exogenous variables like macroeconomic and financial variables to explain and forecast the stock return volatility.

The value of R squared for all the indices are the highest for the entire sample period and followed by post-crash period. Both the periods include more than one primary trends i.e. rise and fall in index prices and have the largest and second largest sample size. Thus, it can be argued that the increased sample size with more than one primary trend may lead to better forecasts for these periods.

However, the pre-crash period is mainly associated with the increase of price and crash period is with decline. The value of R squared is the lowest during the pre-crash period and for all indices it increased by about 10% during the crash period. Even though the sample is smaller for the crash period the sudden increase may be associated with the increase of volatility of this period.

The unconditional volatility measured by the standard deviation[6] increased considerably about 48%-72% and these phenomena can be explained by the stylized fact "Asymmetric Impact of News" which asserts that volatility increases during the period of negative return (see 2.2). Fujiwara & Hirose (2014) argued that forecastability is higher during the period of volatile economic period. Thus, the increased volatility during the crash period may lead to a sudden improvement in value of the R squared comparing to the pre-crash period.

6.3. In sample Analysis

Table 4, 5, and 6 contains the in-sample regression result of equation (17) with k=1 for Euro Stoxx, Euro Stoxx 50, Euro Stoxx Optimized Bank, respectively. Each table contains only the slope coefficient of the forecasting variable in the respective regression and ΔR^2 which is the increase in the percentage of R^2 value relative a benchmark AR(1) model. To increase the readability, all the variables are standardized by following Paye (2012) and consequently the constant term is dropped.

[6] The sample standard deviation for the Euro stoxx, Euro Stoxx 50 and Euro Stoxx Optimized bank for the pre-crash period are 0.60, 0.65, and 0. 67 respectively and for the crash period are 1.03, 0.96, and 1.05 respectively.

The first column includes the symbol of forecasting variables (see table two for their description). ***, ** and * designate statistical significance at the 1%, 5%, and 10% level, respectively, based on heteroskedasticity and serial correlation (HAC) consistent standard errors. Each table reports for a kitchen sink regression that includes the fullest of forecasting variables. The F-statistic reported in the table tests the hypothesis that all of the slope coefficients of forecasting variables are simultaneously zero.

6.3.1. Forecasting Results

Table 4 reports the in-sample analysis result for Euro Stoxx index which represents a broad stock market index for Euro Area. For the entire sample period (2005.01-2013.12) four variables: commercial paper to treasury spread (CP), first difference in term spread (DTERM), growth in GDP (GDP), and volatility of inflation (VOLINF), Granger cause volatility at statistical significant level. Their individual predictive ability, captured by ΔR^2, ranges between 1% and 4% and in general suggests that financial variables specially CP is a better predictors than the macroeconomic variables such as GDP and VOLINF.

The predictability of the forecasting variables varies for the rest of the three sample periods. For the pre-crash period (2005.01-2007.10) credit growth (CRDT), expected GDP (EGDP) and GDP produce statistically significant forecasts. During the crash period (2007.11-2009.02) only three variables- CP, CRDT and VOLINF, show predictive ability. CP, GDP and VOLINF Granger cause volatility during the post crash period (2009.03-2013.12).

In general, GDP is negatively associated with volatility which indicates the counter cyclical relation between volatility and business cycle. The association is statistically significant for all the sample periods except the period of market crash. GDP shows the highest predictive power (5.51%) during the pre-crash period comparing to 1.35% and 0.92% for the entire sample and the post-crash period, respectively. A Stable economic growth, thus, contributes to a stable stock market by lowering volatility.

Table 4. In-sample analysis on Euro STOXX index.

Variables	2005.01-2013.12		2005.01-2007.10		2007.11 – 2009.02		2009.03 – 2013.12	
	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2
BLEV	- 0.01	0.01	0.01	0.02	- 0.05	0.27	0.01	0.01
CONSUM	- 0.09	0.65	- 0.02	0.06	0.12	0.42	- 0.15	2.84
CP	0.28^{***}	3.91	0.26	3.24	0.37^{**}	14.63	0.25^{*}	3.47
CRDT	0.05	0.23	-0.26^{*}	9.34	0.25^{**}	10.63	0.11	1.34
EGDP	- 0.03	0.09	-0.26^{**}	9.52	0.13	1.40	0.00	0.00
GDP	-0.13^{**}	1.35	-0.25^{*}	5.51	- 0.25	4.62	-0.08^{*}	0.92
DTERM	0.10^{*}	0.94	0.11	1.17	0.11	2.41	0.07	0.67
VOLINF	0.11^{*}	1.02	- 0.03	0.24	0.49^{**}	18.30	0.11^{*}	0.96
VOLIP	0.08	0.53	0.12	2.60	- 0.05	0.49	0.15	1.94
	F	ΔR^2	F	ΔR^2	F	ΔR^2	F	ΔR^2
SINK	34.76^{***}	4.69	28.15^{***}	39.33	30.70^{***}	50.72	12.00^{***}	12.95

Like GDP, Expected GDP (EGDP) also has a negative ass associating with the volatility for all the periods. However, for the pre-crash period the associating is statically significant at 5% level and has around 4% better predictive power than GDP. This finding is consistent with the results of GDP that the growth in the economy is generally considered as good news and consequently, reduces the risk form the stock market.

VOLINF has a statistically significant positive association with the volatility except the pre-crash period. The relation is at 10% significance level for the entire sample and the post-crash period. For the crash-period the significance increases to 5% level with 18.30% predictive power which is the highest for any variables. However, VOLINF's predictive power is around 1% for the rest of the two periods. VOLINF is, therefore, a far better predictor for the crash period or the bear market than other periods.

Two interest rate related variables used in this paper, measure the short term default risk premium and future expectation about interest rates. CP is the risk premium paid in interbank market over highly secured government bond rates for short term borrowing. Term spread assesses the risk associated with longer term bonds and contains expectation about future economic condition.

The framework of in-sample analysis evaluates how well the debt market risk measures forecast stock returns volatility. As measures of risk in the debt market all both the variables are expected to have a positive impact on the volatility. The in-sample analysis, in general, finds that positive association. In addition, based on the R squared value CP produces the best forecast for all four sample periods.

CP improves the R squared value by 3.91%, 14.63% and 3.47% for the entire sample period, the crash period and the post-crash period, respectively. DTERM has only a mere contribution around 1% for the entire sample period. These results indicate that the financial variables have a modest forecasting power for the long horizon and the predictability increases dramatically during shorter periods with one primary trend in stock price.

Among all the nine forecasting variables used in this paper, Credit growth (CRDT) is the only variable that shows an asymmetric impact on the volatility at a statistical significant level. The negative association during the bull market of the pre-crash period turns into a positive relation during the bear market of the crash period. This result is consistent with the results of Law & Singh (2014) who show that the relation between financial development and economic growth is non-linier and even starts to adversely affect the economy when reaches to a threshold point.

The predictive power of CRDT for these two periods is 10.63% and 9.34%, respectively. The asymmetric impact during the bull and bear market could eliminate each other's effect in long run and thus, results into an insignificant association with low predictive power for the entire sample and post-crash period. To policymakers, it indicates the necessity of maintaining a stable credit growth during the bull market in order to enhance the stability of stock market during the bear market.

The kitchen sink (sink) model includes all the nine predicting factors in a regression and improves the forecasts for pre-crash and crash period by 39.33% and 50.72%, respectively. The predicting power of AR(1) benchmark models for this two periods are respectively, 9.60% and 19.14% and are the lowest two among four analysis periods. These results indicate that for a specific phase in the business cycle, macroeconomic and forecasting variables can significantly improve the volatility forecasts.

The additional predictive power of macro variables in the kitchen sink regression for the post-crash and entire sample period is 12.95% and 4.69%, respectively. The additional explanatory power of the forecasting variables decreases as the sample horizon increases. In contrast, the predicting power of AR(1) benchmark model increases as the length of the sample period increases. The predicting power of the AR(1) benchmark model for the corresponding periods is 36.36% and 52.23%. The better performance of the benchmark models in longer horizon can be attributed to the long memory property of the volatility series. In long run, the volatility series itself contain information about the effects of past macroeconomic shocks and consequently, the explanatory power of exogenous macroeconomic and financial variables reduce.

Table 5, In-sample analysis on Euro STOXX 50 index.

Variables	2005.01-2013.12		2005.01-2007.10		2007.11 – 2009.02		2009.03 – 2013.12	
	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2
BLEV	- 0.02	0.02	- 0.03	0.10	- 0.04	0.13	0.02	0.04
CONSUM	- 0.10*	0.90	- 0.01	0.04	0.04	0.05	- 0.16*	3.52
CP	0.28***	4.02	0.15	1.21	0.38**	16.44	0.23*	3.20
CRDT	0.04	0.16	- 0.28*	11.40	0.25**	9.58	0.10	1.14
EGDP	- 0.04	0.12	- 0.27**	11.68	0.13	1.12	- 0.01	0.01
GDP	- 0.14**	1.65	- 0.26*	6.69	- 0.32*	6.15	- 0.08*	1.06
DTERM	0.12**	1.32	0.08	0.62	0.16	4.29	0.10	1.14
VOLINF	0.12*	1.33	- 0.01	0.05	0.55***	22.66	0.10	0.77
VOLIP	0.09*	0.75	0.14	3.95	- 0.01	0.02	0.16	2.12
	F	ΔR^2	F	ΔR^2	F	ΔR^2	F	ΔR^2
SINK	30.91***	5.16	34.09***	45.99	23.63***	45.61	10.19***	15.37

For large sample, the better performance of autoregressive models along with the poor forecasting power of exogenous variables challenges the benefit of using any nested model for volatility forecast. However, for crash period, the reported explanatory power of respective SINK models is 69.86% which are is the highest among all the sub-samples. Thus, forecastability increases at the onset of market crash.

Table 5 contains the results of in-sample analysis for the Euro STOXX 50 index which represents the 50 biggest companies in Euro area. With a few exceptions, the results are similar to those in table 4. Along with all the variables that Granger cause volatility in Euro Stoxx index, two more variables: consumption growth and volatility of industrial production, are found to have statistically significant impact on the volatility of Euro STOXX 50 index in longer horizons. In contrast, VOLINF ceases to have its significant impact on the volatility for the post-crash period.

Consumption growth (CONSUM) has a negative association with the volatility for the entire sample and the post-crash period at 10% significance level. CONSUM's forecastability is higher for the post-crash sub-sample period than that of entire sample. In fact, the forecasting power of CONSUM is the highest among three variables: GDP, CONSUM and CP which Granger causes volatility in this period. These results indicate the necessity of developing consumption growth targeting macroeconomic policy in order to increase the stability of stock market.

Like in table 4, table 5 also documents a counter cyclical association between GDP and volatility. In addition, for the blue chip Euro STOXX 50 index GDP shows statistically significant impact in all four periods with higher explanatory power than that of the broad market Euro STOXX index. For both the indices, GDP's forecasting power is the highest for the bull market of pre-crash period. However, when sample includes both bull and bear market phases, forecastibilty increases as sample size increases.

Expected GDP (EGDP; see 5.1) produces better forecasts than GDP for the bull market of pre-crash period at 5% significance level for both the broad and the blue chip index. Like GDP, EGDP's explanatory power is higher for the Euro STOXX 50 Index than that of the Euro STOXX index. For both the indices, VOLINF has the highest forecasting power for the crash period with explanatory power of 18.30% and 22.66% for the broad and the blue chip index, respectively. VOLIP shows forecatability for the entire sample period at 10% significance level with an explanatory power of 0.75%.

CP and DTERM show the similar pattern of forecastability for the both indices and have a positive impact on volatility for the entire sample period. Like the macroeconomic variables, forecastability of the financial variables is higher for the Euro STOXX 50 index than the Euro STOXX index. In addition, CP causes volatility for the crash and the post-crash period.

CRDT exhibits the similar asymmetric impact for the Euro STOXX 50 index as that of the Euro STOXX index. SINK models in table 5 ensure the finding of table 4. When bull or bear market condition is considered in isolation, forecastability of the benchmark models drops significantly, but it increases for the SINK models. The overall predictability becomes the highest for the bear market. In long-run, the predictability of the autoregressive benchmark models increases and the impact of the exogenous forecasting variables start to decay. In addition, the predictive power of benchmark model increases as the sample size increases for the long-run analysis.

In general, the pattern of Granger casualty for the broad and blue chip index is the same. However, the volatility of blue chip index follows the movement in macroeconomic and financial variables with higher precision than the broad market index. Normally, financial variables are better predictors of volatility than macroeconomic variables. During the bear or the bull market the influence of macroeconomic variables increases significantly which indicates that event study method may produce better results. In addition, the best results can be produced by using the combination of macroeconomic variables financial variables.

While table 4 and 5 report about the broad market and blue chip index, Table 6 shows how the same forecasting variables cause volatility in the banking index: one of the most volatile sector of the stock market during the analysis period. Results for the

Table 6. In-sample analysis on Euro STOXX optimized banks index.

Variables	2005.01-2013.12		2005.01-2007.10		2007.11 – 2009.02		2009.03 – 2013.12	
	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2	$\hat{\beta}$	ΔR^2
BLEV	- 0.05	0.27	- 0.10	1.28	- 0.17	4.10	0.01	0.01
CONSUM	- 0.11*	0.77	0.08	1.44	- 0.06	0.11	- 0.22***	7.19
CP	0.16***	1.42	0.11	0.56	0.24**	10.44	0.17**	2.56
CRDT	- 0.02	0.03	- 0.26**	11.89	0.14	4.24	0.02	0.06
EGDP	- 0.04	0.17	- 0.27***	14.05	0.01	0.00	0.01	0.02
GDP	- 0.10	0.69	- 0.19	3.42	- 0.46***	15.81	- 0.04	0.26
DTERM	0.05	0.20	0.03	0.16	0.09	1.94	0.04	0.24
VOLINF	0.07	0.49	- 0.03	0.32	0.54***	30.42	0.07	0.55
VOLIP	0.04	0.16	0.09	2.05	0.07	1.05	0.04	0.24
	F	ΔR^2	F	ΔR^2	F	ΔR^2	F	ΔR^2
SINK	36.74***	3.40	75.09***	39.49	56.54***	52.18	21.58***	19.50

banking index in table 6 are different than the previous two indices specifically for the entire sample and the post-crash period. However, similarity increases for the pre-crash and the crash period. CP and CONSUM cause volatility in the long-run whereas CRDT, VOLINF and EGDP affect only during shorter periods of bull or bear market.

The number of forecasting variables that causes volatility during the entire sample and post-crash period is the lowest for the banking index. Only consumption growth lessens the volatility for these periods whereas CP exacerbates its level. CONSUM adds up about 7.19% forecasting power for post-crash period while a mere 0.77% for the entire sample period. The similar pattern is found for the Euro STOXX 50 index but the forecasting capacity for the post-crash period is almost double for the banking index. Thus, consumption growth oriented macroeconomic strategies are supposed to provide stability in the stock price of big companies along with banks.

For all the three indices, CP predicts the volatility for the entire sample period at 1% significant level and at 5% level for the crash period. However, for the post-crash period the significance level is 5% for banking index but 10% for the other two indices. While the significance level improves for the banking index, predicting power drops for each period respective to those of other two indices. Nevertheless, for all three indices among four sample periods the highest prediction power is reported for the crash period.

While CP remains a consistent predictor of volatility for all three indices, credit growth (CRDT) ceases to have its asymmetric impact on the volatility of banking index. CRDT, in general, is negatively associated with the volatility of pre-crash period while positively associated with that of the crash period. For the banking index the association is statistically insignificant at 10% level. On contrary, CRDT’s 11.89% explanatory power for the pre-crash period is the highest among all three indices. These results can be summarized as such: excess credit during the market crash destabilizes the whole market by affecting the stock prices especially those of big companies.

During the bull market of pre-crash period, EGDP shows better forecasting power than the GDP for the previous two indices. For the banking index EGDP’s forecasting power reaches to the highest (14.05%) along with the improvement in statistical significance level. For the broad market and the blue chip index the significance level is 5% while for the banking index it is 1%. However, GDP does not show any Granger casualty for the banking index at 10% significance level. Thus, expected GDP is a better estimator of banking index's volatility then the market in general.

The overall explanatory power of the SINK models for four sample periods in same the order reported in the table 6 are 70.52%, 57.54%, 78.89%, and 59.06%. In which the contribution of combined forecasting variables are 3.40% 39.49% 52.18% and 19.50%. The overall explanatory power is the highest for the banking index among the three indices. The improved forecastability during the entire sample and the pre-crash period can primarily be attributed to the improved explanatory power of AR benchmark models. For the crash and the post-crash period, higher contribution of the combined forecasting variables results into an overall improvement in the forecastability.

Despite the difference in individual variables' forecastability for the market indices and the banking index, the results of SINK regressions show the similar pattern for all of them. In general, the explanatory power of AR models is higher for the entire sample and the post-crash period. On contrary, forecastability of macroeconomic and financial variables becomes higher for the pre-crash and the crash period: periods associated with only one primary trend in stock price.

6.3.2. Economic Significance

Because of standardizing all the variables, estimated coefficients measure the level of change in the standard deviation of the log of volatility due to a standard deviation shock in the respective forecasting variable[7]. Therefore, a coefficient with a value of 0.5

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[7] Under the partial differentiation of the estimation model (i.e. equation (12) with k=1 and c=0) with respect to the forecast variable(s) will produce a log-lin model of the form $\ln y/dx = \beta x/dx$. For standardized variables the slope ($dy/dx = \sigma_{lny}.\beta.y/\sigma_x$) or the elasticity ($(dy.x)/(dx.y) = \sigma_{lny}.\beta.x/\sigma_x$) of stock return volatility will vary depending on the initial level/magnitude of return volatility and forecasting variable respectively. But, for an absolute change in standardized forecast variable (dx), say one standard deviation of shock (i.e. $dx = \sigma_x$), the (continuous compounding) growth

implies that an one standard deviation shock in the forecasting variable would increase either the level of subsequent period's log of volatility by half of its standard deviation or the level of volatility by 48% (for the Euro STOXX index)[8].

CP, DTERM, VOLINF, and VOLIP are positively associated with the volatility whereas EGDP, GDP, CONSUM are negatively associated with it. Only CRDT has an asymmetric impact for the pre-crash and the crash period. Thus, it can be argued that an expansion in the overall economic condition stabilizes the stock market. On contrary, variables with positive association are fundamentally the source of risk in stock market.

In general, the broad market Euro STOXX index and the blue chip Euro STOXX 50 index show similar forecasting pattern. In addition, the coefficients of the common statistically significant forecasting factors for the two indices are almost the same. In contrast, the coefficients of the banking index vary from those of other two indices except for the pre-crash period. However, coefficient values for the pre-crash and the crash period are higher than those of the entire sample and the post-crash period.

6.4 Out of Sample Analysis

To check whether the variables considered in this paper can produce a superior out of sample forecasts than the parsimonious AR(1) benchmark model Clark & West (CW) and Giacomini & White (GW) tests are performed. CW is a right tail equal predictability test while GW is an unconditional two tail superior predictability test. Under the specification of this paper, GW test with a statistically significant positive

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in volatility ($dy/y = \sigma_{lny}.\beta.dx/\sigma_{\mathrm{x}} = \sigma_{lny}.\beta.\sigma_{\mathrm{x}}/\sigma_{\mathrm{x}} = \sigma_{lny}.\beta$) will be constant and equal to the product of the estimated coefficient and the standard deviation of the logarithm series of the index's volatility. (Damodar N Gujrati, 2003, 4th edition, pp 175-191).

[8] The standard deviation of the logarithm of Euro STOXX volatility is 0.96. Thus, for coefficient values of 0.1, 0.2, 0.3, 0.4 and 0.5 would respectively result into 9.60%, 19.20%, 28.80%, 38.40% and 48.00% continuous compounded growth in volatility. The corresponding numbers would lead to 10.08%, 21.17%, 33.38%, 46.81% and 61.61% simple growth in the volatility. The above interpretation would be close to those for the Euro STOXX 50 index as its standard deviation of its volatility's logarithm is 0.94. For optimized bank index the corresponding simple percentage growth in volatility would be 12.52%, 26.62%, 42.48%, 60.32%, 80.40%.

coefficient would suggest to use the nested model for forecasting over the benchmark model.

Two estimation windows: 24-month and 48-month rolling window, are used to calculate the one period ahead forecast. Cai & Liang (2010) use a 24-month rolling window to forecast monthly return and argue that the size is good enough for the OLS estimation procedure. The motivation of using a 24-month rolling estimation window is to include crash-period in the analysis because the empirical evidence suggests that forecastability is higher during the economic downturn (Officer 1973, Hamilton & Lin 1996). To access the impact of estimation horizon on forecasts, in addition, a 48-month rolling estimation window is used.

In addition to the CW and GW test, ΔR^2_{oos} value in percentage form is presented by following Campbell & Thompson (2008), Goyal & Welch (2008), Rapach et al.(2010) and Paye (2012). When, $\hat{\sigma}_i^2$ is the out-of-sample MSPE for the model of interest and $\hat{\sigma}_0^2$ is the out-of-sample mean squared prediction error (MSPE) based on the historical average, the out of sample R_i^2 for the model *i* would be

(23) $$R^2_{oos,i} = 1 - \frac{\hat{\sigma}_i^2}{\hat{\sigma}_0^2}$$

and ΔR^2_{oos} between benchmark model and the model of interest would be

(24) $$\Delta R^2_{oos,i} = \left(1 - \frac{\hat{\sigma}_i^2}{\hat{\sigma}_0^2}\right) - \left(1 - \frac{\hat{\sigma}_b^2}{\hat{\sigma}_0^2}\right) = \frac{\hat{\sigma}_b^2 - \hat{\sigma}_i^2}{\hat{\sigma}_0^2}$$

here $\hat{\sigma}_i^2$ and $\hat{\sigma}_\mathrm{b}^2$ are the out-of-sample MSPE for nested model and parsimonious AR(1) model respectively.

Rapach et al. (2010) show that simple combination of forecasting methods can improve out of sample forecasts. To check whether the simple combination of forecasting variables can improve the volatility forecasts in this paper four combination strategy is used. Construction of these strategies follows Paye (2012). The first two methods include the arithmetic mean and median of the forecasting variables. The third one is mentioned as MSPE and calculated by using the equation (25) and (26).

(25) $$\widehat{\omega}_{n,t}^{MSPE} = \frac{\phi_{n,t}^{-1}}{\sum_{j=1}^{N} \phi_{j,t}^{-1}}$$

(26) $$\phi_{n,t} = \sum_{p=R}^{t-1} (LVOL_{p+1} - \widehat{LVOL}_{n,p+1})^2$$

The fourth strategy is based on the trimmed mean where for each period's forecasts lowest two and highest two forecasts are dropped. Finally the combination of the variables takes the form of equation (27).

(27) $$\widehat{LVOL}_{t+1} = \sum_{n=1}^{N} \widehat{\omega}_{n,t} \widehat{LVOL}_{n,t+1}$$

The results of out-of-sample analysis differ significantly from those of in-sample analysis. In general, CW tests find more evidence of improved forecasts using individual forecasting variables than GW test. Like the results of in-sample analysis, the out-of-sample analysis results for the board market and blue chip index show the similar pattern. However, out-of sample results do not report individual variables' better forecasting power for the crash period: a common phenomenon for in-sample analysis. On contrary, better forecasts were found for the post-crash period with 48 month estimation window based on both CW and GW tests.

Table 7. Out-of-sample analysis on Euro Stoxx index.

Variables	2007.01- 2013.12 (R=2 year)			2007.11-2009.02 (R=2 year)			2009.03-2013.12 (R=2 year)			2009.03-2013.12 (R=4 year)		
	CW	GW	ΔR^2_{oos}	CW	GW	ΔR^2_{oos}	CW	GW	ΔR^2_{oos}	CW	GW	ΔR^2_{oos}
BLEV	-0.04	-0.05**	-6.36	-0.19	-0.21**	-23.73	0.00	-0.01	-2.30	0.00	-0.01	-1.04
CONSUM	-0.05	-0.01	-1.42	-0.11	-0.17**	-19.73	-0.01	0.01	2.06	0.01	-0.03	-5.08
CP	0.07**	-0.04	-5.70	0.06	0.01	0.76	0.08**	-0.01	-1.34	0.03*	0.01*	1.12
CRDT	0.03**	0.00	0.47	-0.04	-0.07	-7.95	0.05**	0.02	3.99	0.03**	0.02**	3.55
EGDP	0.00	-0.05	-6.64	0.05	0.02	2.12	-0.03	-0.08*	-12.69	-0.01	-0.02	-3.47
GDP	-0.01	-0.13	-16.21	0.05	-0.19	-22.18	-0.03	-0.10*	-17.02	0.02	-0.02	-3.75
DTERM	-0.02	-0.03	-4.36	-0.07	-0.12	-14.18	0.00	-0.01	-1.46	0.01	0.00	0.66
VOLINF	0.02	-0.04	-4.73	0.00	-0.15	-17.47	0.01	-0.02	-3.23	0.02	0.00	-0.36
VOLIP	0.00	-0.01	-0.90	0.01	0.01	1.33	0.00	-0.01	-1.77	0.01**	0.01	1.47
Combined Forecast												
Mean	0.02*	0.01	1.36	0.02	-0.01	-0.88	0.02*	0.01	2.31	0.01**	0.01**	2.07
Median	0.01**	0.01**	1.56	0.00	0.00	0.12	0.01**	0.01*	1.96	0.01**	0.01***	1.58
Mspe	0.02*	0.01	1.00	0.02	-0.02	-1.75	0.02	0.01	2.02	0.01**	0.01*	1.93
Trim-mean	0.01**	0.01*	1.41	0.00	-0.01	-0.69	0.01*	0.01	1.90	0.01**	0.01***	1.88

Table 8. Out-of-sample analysis on Euro Stoxx 50 Index.

Variables	2007.01- 2013.12 (R=2 year)			2007.11-2009.02 (R=2 year)			2009.03-2013.12 (R=2 year)			2009.03-2013.12 (R=4 year)		
	CW	GW	ΔR^2_{oos}	CW	GW	ΔR^2_{oos}	CW	GW	ΔR^2_{oos}	CW	GW	ΔR^2_{oos}
BLEV	-0.04	-0.05**	-6.78	-0.18	-0.22***	-21.52	0.00	-0.01	-2.40	0.00	-0.01	-1.35
CONSUM	-0.05	-0.01	-1.06	-0.13	-0.18**	-17.9	-0.01	0.02	3.06	0.01	-0.03	-5.17
CP	0.07*	-0.04	-5.62	0.06	0.01	0.55	0.09**	-0.01	-1.55	0.03*	0.00	0.10
CRDT	0.03*	0.00	0.45	-0.05	-0.07	-6.90	0.05**	0.02	3.93	0.03**	0.02**	3.33
EGDP	0.00	-0.06	-7.24	0.06	0.02	2.37	-0.03	-0.08*	-14.97	-0.01	-0.02	-4.01
GDP	-0.01	-0.11	-14.58	0.08	-0.13	-13.09	-0.03	-0.10*	-18.21	0.02	-0.03	-5.02
DTERM	-0.01	-0.03	-4.17	-0.09	-0.14	-14.46	0.01	0.00	-0.16	0.02*	0.01	1.05
VOLINF	0.04	-0.02	-3.16	0.09	-0.07	-7.18	0.02	-0.02	-3.10	0.02	-0.01	-0.98
VOLIP	0.01	0.00	-0.34	0.02*	0.01	1.31	0.00	-0.01	-1.07	0.02**	0.01	2.04
Combined Forecast												
Mean	0.02**	0.01	1.89	0.03	0.00	0.34	0.02*	0.02	3.19	0.02**	0.01**	2.40
Median	0.02**	0.01**	1.91	0.01	0.00	0.47	0.02**	0.02**	3.19	0.01**	0.01***	1.72
Mspe	0.03*	0.01	1.56	0.04	0.00	-0.11	0.02*	0.02	2.81	0.02**	0.01*	2.23
Trim-mean	0.02**	0.01*	1.54	0.00	-0.01	-0.77	0.02**	0.01*	2.65	0.01**	0.01***	2.20

For Euro STOXX index, based on CW test, CP and CRDT show superior forecasting power over the benchmark models for the period 2007-2013 and the post-crash period. However, GW test find better forecasting capacity only for the post-crash period with 48-month estimation window. The results are the same for the Euro STOXX 50 index except GW test does not find the evidence of superior predictability for the CP during the post-crash period. However, the improvements vary within the range of 1% to 4% which is close to the results of in-sample analysis for this period.

VOLIP also shows superior forecasts for the post-crash period with 48-month estimation window for the broad and the blue chip index. While CW test finds the evidence at 5% significance level, GW test rejects the possibility of any superior forecasts. However, the ΔR_{oos}^2 value shows that VOLIP improves the forecasts by 1.47 and 2.04% respectively for the broad market and blue chip index. For the same period and the blue chip index, DTERM also shows better forecasts according to CW test and the ΔR_{oos}^2 value. Thus, results for these two variables should be used with caution.

For the banking index, CW test confirms the superior predictability of CP for all the periods except for the crash period. While GW test rejects for any possible superior predictability, the ΔR_{oos}^2 value reports the best prediction for the post-crash period with 24-month estimation window. In addition, EGDP and CRDT show superior predictability based on CW test and ΔR_{oos}^2 value for the crash period and the post crash period with 24-month estimation window. EGDP add 8.58% out-of-sample prediction for the crash period which is the highest for any individual forecasting factors.

Despite individual macroeconomic factor's poor predictability, the simple combinations especially trimmed-mean and median, provide consistent superior forecasts. Again, the similarity is found in the results for broad market and the blue chip index. For this two indices trimmed mean and median produces better forecasts for the period 2007-2013, and for the two post-crash periods with different estimation horizon. But the additional forecasting power ranges within 1% - 3%. However, for the blue chip indices the forecasting power increases marginally than those of the broad market index.

Table 9. Out-of-sample analysis on Euro Stoxx optimized banks Index.

Variables	2007.01- 2013.12 (R=2 year)			2007.11-2009.02 (R=2 year)			2009.03-2013.12 (R=2 year)			2009.03-2013.12 (R=4 year)		
	CW	GW	ΔR^2_{oos}	CW	GW	ΔR^2_{oos}	CW	GW	ΔR^2_{oos}	CW	GW	ΔR^2_{oos}
BLEV	-0.02	-0.05*	-5.03	-0.07	-0.14	-13.79	-0.01	-0.03*	-4.08	-0.01	-0.02	-3.29
CONSUM	-0.05	0.01	1.46	-0.10	-0.16**	-15.18	-0.01	0.04	5.90	0.05	-0.01	-2.32
CP	0.09**	0.01	0.95	0.03	-0.04	-4.15	0.11**	0.03	5.13	0.05**	0.02	3.26
CRDT	0.01	-0.01	-1.56	-0.10	-0.12	-12.06	0.03*	0.01	1.47	0.01	0.00	0.31
EGDP	0.01	-0.08	-8.59	0.15 **	0.09	8.58	-0.05	-0.13	-21.04	-0.01	-0.04	-6.48
GDP	-0.02	-0.11	-12.72	0.07	-0.06	-6.27	0.00	-0.13	-20.63	0.00	-0.06	-8.94
DTERM	-0.02	-0.03	-3.34	-0.1	-0.13	-12.54	0.00	0.00	-0.32	0.00	0.00	-0.77
VOLINF	0.04	-0.04	-4.22	0.09	-0.08	-7.94	0.01	-0.05	-7.39	0.02	-0.01	-0.86
VOLIP	0.01	0.00	0.43	0.01	0.00	0.45	0.02	0.01	1.67	0.00	-0.01	-0.85
Combined Forecast												
Mean	0.04**	0.03*	3.27	0.09*	0.06	5.65	0.03*	0.02	3.05	0.01**	0.01	1.41
Median	0.02**	0.01*	1.49	0.00	-0.01	-0.78	0.02**	0.02*	2.65	0.00	0.00	0.51
Mspe	0.06**	0.03	3.14	0.17*	0.07	6.50	0.03	0.02	2.36	0.01**	0.01	1.25
Trim-mean	0.03**	0.02***	2.42	0.03**	0.02	2.38	0.02**	0.02*	2.69	0.00	0.00	0.36

For the banking index, median provide superior forecasts only for the period 2007-2013 based on both CW and GW tests. Along with this same period, trimmed mean also provide superior forecasts for the post-crash period with 24-month estimation window. For the 48-month estimation window mean also show superior forecasting power for all the three indices. However, 24-month rolling window produce the higher out-of-sample forecasting power based on ΔR_{oos}^2 values for the post-crash period for all the three indices.

In general, individual macroeconomic and financial variables have limited impact on the volatility forecasts. CP and CRDT are the two most successful predictors of volatility of the broad market and the blue chip index. However, the simple combination of forecasting variables specifically the median and the trimmed mean produce best forecasts for all the indices. As estimation horizon increase the mean value of the forecasting variables also become a consistent predictor. But better out-of-sample explanatory power is documented for the post-crash period with 24-month estimation window.

7. CONCLUSION

The purpose of this paper is to assess the relation between the macroeconomic and financial variables and the volatility of aggregate Euro area stock return. Volatility is unobservable and its estimation is model dependent. In this paper, by following the realized volatility approach monthly stock return volatility is calculated as the sum of squared daily return over a month. In the context of finance, it requires return to follow a semi-martingale process within the estimation period i.e. expected conditional daily return is zero within a month's interval. Mathematically, volatility estimation procedure allows for the interdependence among its lag values and facilitates forecasting based on time series data. Thus, parsimonious AR type models become the natural benchmark for evaluating other volatility forecasting models involving exogenous variables.

Fundamentally, price is forward looking and in finance, stock price is determined based on its discounted expected future cashflows. As the Efficient Market Hypothesis states that stock prices already involve all the available information, thus, it is expected that any change in the economic environment that affects the discount rate or cashflow can affect the stock price movement. Theoretically, by analyzing the stock return this fluctuation in stock price or the information content can be found and the use of volatility will allow for better forecasts in the stock price movement.

Because of the importance of volatility in financial decision making process, an astronomical number of forecasting models can be found in volatility literature. Most of them are mathematically driven and mainly based on ARCH type models while realized volatility is used as the benchmark for evaluating the superior forecastability of those models. However, in recent years the focus is shifted towards the measures of realized volatility using high-frequency intra-day data. The method used in this paper closely follows this realized volatility approach and this method can produce volatility estimation even when the GARCH model cannot estimate its parameters which satisfy required stationarity condition.

The entire sample period for the empirical analysis comprise 2005-2013 due to lack of Euro area's aggregate financial data availability prior to 2005. However, the entire sample period is further divided into three sub-sample periods: pre-crash period from January 2005 to October, 2007, market crash period from November, 2007 to February, 2009 and post-crash period from March, 2009 to December, 2013. This division is mainly motivated to capture the effects of the recent financial crisis of 2007-2009 in the volatility dynamics. However, the first and second sub-sample periods also represents the bull and the bear market respectively. Thus, these sub-sample periods also allow investigating the impact of business cycle on volatility.

The descriptive statistics show that Optimized bank index is the worst performing portfolio with the lowest return but with the highest risk. In general, overall market indices outperform the banking index and the broad market index performs better than the blue chip index. Thus, a general conclusion is that holding a diversified portfolio with less weight on banking stocks suppose to perform the best during the period 2005-2013. However, the stationary in stock indices suggests using autoregressive (AR) type models for evaluating the incremental benefit of macro variables in volatility forecast.

The in-sample analysis shows the time varying impact of macro variables on volatility. Normally, explanatory power of individual macro variables increase as the length of sample period increases when the sample periods consists both the bull and the bear market trends. On contrary, when the bull or the bear market condition is considered in isolation, the predictability of macro variables increases several folds. The blue chip index is found to be more sensitive to the change in macro variables than the broad market index. In general, the set of macro variables affecting the banking sector and their predictability pattern are different from the overall market.

In a nutshell, CP, DTERM, VOLINF, and VOLIP are positively associated with the volatility whereas EGDP, GDP, and CONSUM are negatively associated. Only CRDT show an asymmetric impact during the pre-crash and the crash period. Thus, an expansion in the overall economy stabilizes the stock market whereas the uncertainly about the inflation and industrial production increases the risk.

Between two risk premium measures in bond market the short-term default risk premium CP has the highest predictability power for the entire sample period. In general, expected GDP has higher explanatory power than the observed GDP series. During the post-crash period consumption growth appears to have a negative relation with the blue chip index and the banking index. Thus, based on the results of this paper, economic expansion with an increase in expenditure is a robust way to stabilize the stock market and the economy in general.

The asymmetric impact of credit growth indicates towards the necessity of controlling the credit expansion during the bull market in order to stabilize the bear market. However, the bank leverage does not affect the volatility of overall market or the banking sector. Thus, it is plausible that the asset quality but not the extent of owner's contribution is equity considered as risk in the stock market. This line of argument can also be used to explain the asymmetric impact of credit growth. Therefore, a further study can be conducted by forming explicit hypothesis on asset quality of banks.

Despite the inspiring results from the in-sample analysis, the out-of-sample analysis results reject the superior predictability of individual macro variables. Considering small estimation period (24-month rolling window) is responsible for this, two other estimation windows: 36 and 48 month, are used for the post-crash period (only the later one reported). The results are similar to that of the 24 month estimation window and thus, eliminate the possibility of biasness in the analysis for using a relatively small estimation window.

The out-of-sample results do not invalidate the results of in-sample analysis; rather stresses the point that the estimation period's economic environment does not match with that of the forecasting period. Technically, the scope of the in-sample analysis in this paper encompasses the ex-post realization of Granger causality of macro variables. On contrary, the out-of-sample analysis presents the ex-ante forecatability of macro variables within the sample periods. Despite individual macroeconomic factor's poor predictability, the simple combinations especially trimmed-mean and median, provide consistent superior forecasts.

Considering all the empirical results a general conclusion would be macroeconomic and financial variables Granger cause volatility in stock market but individual variables normally does not provide out-of-sample superior forecasts. However, the high frequency bond market risk indictors (i.e. risk premiums) are better forecasters of stock market volatility than the low frequency macroeconomic indicators. In addition, forecastability increases as the forecasting horizon increases and instead of individual macro variables their simple combination produces the best out-of-sample forecast.

This paper utilizes the realized volatility measure that relies on the total variation in observed stock price. This presents two possible ways to extend the current study. Firstly, a comparative study can be done on the relative merits of alternative volatility measures in forecasting with macro variables. In recent years, Spline-GARCH of Engle et al. (2008) and GARCH-MIDAS of Engle, Ghysels & Sohn (2008) use macroeconomic data at varied frequency to model conditional volatility. The macro variables of this paper appear to have significant impact on volatility can be included in these models to assess their respective efficiency.

Secondly, how macro variables transmit risk in individual stocks or factor mimicking (e.g., size, liquidity, industry, etc.) portfolio can be investigated. The cross section of asset prices is mainly influenced by the expectation about the market as well as individual companies. As the macro variables contain information about the economy in general, it is possible that only the systematic risk of the individual stocks or factor mimicking portfolio is influenced by the macro variables. Therefore, a thorough study on the systematic and idiosyncratic risk of the constituents stocks of these indices is required to confirm this hypothesis in general level.

LIST OF REFERENCES

Adrian, T. & H.S. Shin (2010). Liquidity and leverage. *Journal of Financial Intermediation* 19, 418–437.

Alexander, Carol (2008). *Market Risk Analysis Volume II - Practical Financial Econometrics*. West Sussex, England: John Wiley & Sons Ltd.

Allan, T. & C.W.J. Granger (2004). Efficient market hypothesis & forecasting. *International Journal of Forecasting* 20, 15-27.

Andersen, T.G. & L. Benzoni (2008a). Realized volatiity. *FRB of Chicago*, Working Paper No. 2008-14.

Andersen, T.G. & L. Benzoni (2008b). Stochastic volatiity. Working Paper Available at World Wide Web: <http://ssrn.com/abstract=1076672> or <http://dx.doi.org/10.2139/ssrn.1076672>

Andersen, T.G. & T. Bollerslev (1997). Heterogeneous information arrivals and return volatility dynamics: uncovering the long-run in high frequency returns. *Journal of Finance* 52, 975-100.

Andersen, T.G. & T. Bollerslev (1998a). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review* 39, 885-905.

Andersen, T.G. & T. Bollerslev (1998b) Deutsche Mark-Dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies. *Journal of Finance* 53, 219-265.

Andersen, T.G., T. Bollerslev & D. Dobrev (2007). No-arbitrage semi-martingale restrictions for continuous-time volatility models subject to leverage effects, jumps and i.i.d. noise: Theory and testable distributional implications. *Journal of Econometrics* 138, 125-180.

Andersen, T.G., T. Bollerslev, F.X. Diebold & H. Ebens (2001).The distribution of realized stock return volatility. *Journal of Financial Economics* 61, 43–76.

Andersen, T.G., T. Bollerslev, F.X. Diebold & P. Labys (2003). Modeling & Forecasting Realized Volatility. *Econometrica* 71, 529-626.

Andersen, T.G., T. Bollerslev & N. Meddahi (2005). Correcting the errors: volatility forecast evaluation using high-grequency data and realized volatilities. *Econometrica* 73: 1, 279–296.

Areal, N.M.P.C. & S.J. Taylor (2002). The realized volatility of FTSE-100 futures prices. *Journal of Futures Markets* 22, 627-648.

Arnold, Ivo J.M. & E.B. Vrugt (2006). Stock Market Volatility and Macroeconomic Uncertainty: Evidence from survey data. NRG working paper no. 06-08.

Baillie, R.T., T. Bollerslev & H.O. Mikkelsen (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* 74, 3-30.

Baillie, R.T. (1996). Long memory processes & fractional integration in econometrics. *Journal of Econometrics* 73, 5-59.

Bansal, R. & A. Yaron (2004). Risks for the long run a potential resolution of asset pricing puzzles. *Journal of Finance* 59, 1481–1509.

Barndorff-Nielsen, Ole E. & Neil Shephard (2001). Non-Gaussian Ornstein-Uhlenbeck-based models & some of their uses in financial economics. *Journal of the Royal Statistical Society* B63:2, 167-241.

Barndor-Nielsen, O.E. & N. Shephard (2002). Econometric analysis of realized volatility and its use in estimating stochastic volatility models. *Journal of the Royal Statistical Society* B64, 253–280.

Baur, D.G. (2012). Financial contagion and the real economy. *Journal of Banking and Finance* 36, 2680-2692.

Beckers, Stan (1980). The constant elasticity of variance model & its implications for option pricing. *The Journal of Finance* 35:3, 661-673.

Beltratti A. & C. Morana (2006). Breaks and persistency: macroeconomic causes of stock market volatility. *Journal of Econometrics* 131, 151–177

Black, F. & M. Scholes (1973). The pricing of options & corporate liabilities. *The Journal of Political Economy* 81: 3, 637-654.

Bollerslev, T., R. Chou & K.F. Krone (1992). ARCH modeling in finance: A review of the theory and empirical evidence. *Journal of Econometrics* 52, 5-59.

Bollerslev, T., R.F. Engle, & J.M. Wooldridge (1988). A capital asset pricing model with time-varying covariances. *The Journal of Political Economy* 96:1, 116-131.

Bollerslev, Tim. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* 31, 307-327.

Bollerslev, T. (2008). Glossary to ARCH (GARCH). *CREATES Research Paper 2008-49*. School of Economics and Management University of Aarhus.

Boudoukh, J., R. Michaely, M. Richardson & M. Roberts (2007).On the importance of measuring pay out yield: implications for empirical asset pricing. *Journal of Finance* 62, 877–915.

Brailsford, T.J. & R.W. Faff (1996). An evaluation of volatility forecasting techniques. *Journal of Banking & Finance* 20, 419-438.

Braun, Phillip A., Daniel B. Nelson & Alain M. Sunier (1995). Good news, bad news, volatility & betas. *The Journal of Finance* 50:5, 1575-1603.

Breen, W., L. Glosten & R. Jagannathan (1989). Economic significance of predictable variations in excess stock returns. *Journal of Finance* 44, 1177–1189.

Brennan, M.J. & Y. Xia (2001). Stock price volatility and equity premium. *Journal of Monetary Economics* 47, 249–283.

Brunnermeier, M.K. & L.H. Pedersen, (2009). Market liquidity and funding liquidity. *Review of Financial Studies* 22, 2201–2238.

Cai, Li & Bing Liang (2010). On the dynamics of hedge fund strategies. Available at SSRN: http://ssrn.com/abstract=2029273 or http://dx.doi.org/10.2139/ssrn.2029273

Campbell, J.Y. & M. Yogo (2006). Efficient tests of stock return predictability. *Journal of Financial Economics* 81, 27–60.

Campbell, J.Y. & S.B. Thompson (2008). Predicting excess stock returns out of sample: Can anything be at the historical average? *Review of Financial Studies* 21, 1509–1531.

Campbell, S.D. & F.X. Diebold (2009). Stock returns and expected business conditions: Half a century of evidence. *Journal of Business and Economic Statistics* 27, 266–278.

Christiansen, C., M. Schmeling & A. Schrimp (2012). A comprehensive look at financial volatility prediction by economic variables. *Journal of Applied Econometrics* 27, 956–977.

Clark, T.E. & K.D. West (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics* 138, 291–311.

Cochrane, J.H. (1991). Production-based asset pricing and the link between stock returns and economic fluctuations. *Journal of Finance* 46, 207–234.

Comte F. & E. Renault (1998). Long memory in continuous-time stochastic volatility models. *Mathematical Finance* 8, 291-323.

Cox, John C., Jonathan E. Ingersoll Jr. & Stephen A. Ross (1985). An intertemporal general equilibrium model of asset prices. *Econometrica* 53:2, 363-384.

David, A. & P. Veronesi (2006). Inflation and earnings uncertainty and volatility forecasts. Working Paper. University of Chicago.

David, A. & P. Veronesi (2009). What ties return volatilities to price valuations and fundamentals? *NBER Working Paper* no. 15563.

Deo, R., C. Hurvich & Y. Lu (2006). Forecasting realized volatility using a long-memory stochastic volatility model: Estimation, prediction and seasonal adjustment. *Journal of Econometrics* 131, 29-58.

Diebold, F.X. & K. Yilmaz (2008). Macroeconomic volatility and stock market volatility, worldwide. *NBER Working Paper no.* 14269.

Diebold, F.X. & M. Nerlove (1989). The dynamics of exchange rate volatility: A multivariate latent factor ARCH model. *Journal of Applied Econometrics* 4, 1-21.

Diebold, F.X. & R. Mariano (1995). Comparing predictive accuracy. *Journal of Business and Economic Statistics* 13, 253–265.

Ding, Z., C.W.J. Granger & R.F. Engle (1993). A long memory property of stock market returns and a new model. *Journal of Empirical Finance* 1, 83-106.

Elyasiani, Elyas, & Iqbal Mansur (2004). Bank stock return sensitivities to the long-term and short-term interest rates: a multivariate GARCH spproach. *Managerial Finance* 30:9, 32-55.

Engle, R.F. & J.G. Rangel (2008). The spline-GARCH model for low-frequency volatility and its global macroeconomic causes. *The Review of Financial Studies* 21:3, 1187-1222.

Engle, R.F. & A.J. Patton (2001). What good is a volatility model? NYU Working Paper.

Engle, R.F. & G. Gonzalez-Rivera (1991). Semiparametric ARCH models. *Journal of Business & Economics Statistics* 9:4, 345-359.

Engle, R.F. & T. Bollerslev (1986). Modeling the persistence of conditional variance. *Econometric reviews* 5:1, 1-50.

Engle, R.F. & V.K. Ng (1993). Measuring & testing the impact of news on volatility. *The Journal of Finance* 48:5, 1749-1778.

Engle, R.F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* 50:4, 987-1007.

Engle, R.F. (1990). Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market, *Econometrica* 58:3, 525-542.

Engle, R.F. (2001). GARCH 101: The use of ARCH/GARCH models in applied econometrics. *The Journal of Economic Perspectives* 15:4, 157-168.

Engle, R.F., E. Ghysels, & B. Sohn (2008). On the economic sources of stock market volatility. AFA 2008 New Orleans Meetings Paper. Available at SSRN: http://ssrn.com/abstract=971310 or http://dx.doi.org/ 10.2139/ssrn.971310

Errunza, V. & K. Hogan (1998). Macroeconomic determinants of European stock market volatility. *European Financial Management* 4:3, 361-377.

Estrella, A., & G. Hardouvelis (1991). The term structure as a predictor of real economic activity. *Journal of Finance* 46, 555–576.

Fama, E. F. & K.R. French (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics* 25, 23–49.

Fama, E.F. & K.R. French (1992). The cross section of expected stock returns. *Journal of Finance* 47:2, 427-465.

Fama, E.F. (1963). Mandelbrot and the Stable Paretian Hypothesis. *The journal of Business* 36:4, 420-429.

Fama, E.F. (1965). The behavior of stock-market prices. *The journal of Business* 38:1, 34-105.

Flannery, M.J. & C.M. James (1984). The effect of interest rate changes on the common stock returns of financial institutions. *The Journal of Finance* 39, 1141-1153.

Fleming, J. & B.S. Paye (2011). High-frequency returns, jumps and the mixture of normals hypothesis. *Journal of Econometrics* 160:1, 119-128.

French, K.R., G.W. Schwert & R.F. Stambaugh (1987). Expected stock returns and volatility. *Journal of Financial Economics* 19, 3–29.

Fujiwara, I. & Y. Hirose (2014). Interninacy and Forecastability. *Journal of Money, credit and banking* 46:1, 243-251.

Gallant, A. R., D.A. Hsieh & G. Tauchen (1989). On fitting a recalcitrant series: The Pound/Dollar exchange rate 1974-83, Unpublished. Department of Economics, Duke University, Durham, NC.

Gennotte, G. & T. Marsh. (1993). Variations in economic uncertainty and risk premiums on capital assets. *European Economic Review* 37, 1021-1041.

Ghysels, E., P. Santa-Clara & R. Valkanov (2005).There is a risk-return trade-off after all. *Journal of Financial Economics* 76, 509–548.

Giacomini, R. & H. White (2006). Tests of conditional predictive ability. *Econometrica* 74:6, 15-45.

Glosten, L.R., R. Jagannathan & D. Runkle (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance* 48, 1779–1801.

Goyal, A. & I. Welch (2008). A comprehensive look at the empirical performance of the equity premium prediction. *Review of Financial Studies* 21, 1455–1508.

Granger, C.W.J. & R. Joyeux (1980). An introduction to long-memory time series models and fractional differencing. *Journal of Time Series Analysis* 1:1, 15-29.

Granger, C.W.J. (1969). Investigating causal relations by econometric models & cross-spectral methods. *Econometrica* 37:3, 424-438.

Granger, C.W.J. (1980). Long memory relationships & the aggregation of dynamic models. *Journal of Econometrics* 14, 227-238.

Gujrati, Damodar N. (2003). *Basic Econometrics*. The McGraw−Hill Companies, 4th edition, 175-191.

Hamilton, J. & G. Lin (1996). Stock market volatility and the business cycle. *Journal of applied econometrics* 11, 573-593.

Hammami, Y. *&* A. Lindahl (2014). An intertemporal capital asset pricing model with bank credit growth as a state variable. *Journal of Banking & Finance* 39, 14–28.

Hansen, P.R. & A. Lunde (2003). Consistent preordering with an estimated criterion function, with an application to the evaluation & comparison of volatility models. Brown University Working Paper, 2003-01.

Hansen, P.R. (2001). A test for superior predictive ability. Brown University, Economics Working Paper. 2001-06.

Harvey, C.R. (2001). The specification of conditional expectations. *Journal of Empirical Finance* 8, 573–637.

Hsieh, D.A. (1991). Chaos and nonlinear dynamics: application to financial markets. *Journal of Finance* 46, 1839-1877.

Hull, J.C. & A.D. White (1993a). The use of control variates in option pricing. *Journal of Financial and Quantitative Analysis* 23, 237-251.

Hull, J.C. & A.D. White (1993b). Valuing derivatives securities using the explicit finite differences method. *Journal of Financial and Quantitative Analysis* 25, 87-100.

Hull, J.C. & A.D. White (2000). The essentials of LMM', *Risk Magazine*. Available from World Wide Web: http://m-nql.risk.net/data/Pay_per_view/risk/technical/2000/risk_1200_interestrates.pdf

Hull, J.C. (1993). *Options, Futures and Other Derivative Securities*. 2nd Edition, Prentice- Hall International Editions.

Janne, Äijö (2007). *Essays on macroeconomic news announcements and option-implied information.* Acta Wasaensia, 0355-2667, no. 175.

Koutmos, G. (1996). Modeling the dynamic interdependence of major European stock markets. *Journat of Busintss Finance & Accounting* 23:7, 975-988.

Law, S.H. & N. Singh (2014). Does too much finance hard economic growth? *Journal of Banking & Finance* 41, 36-44.

Lee, S.W. & B.E. Hansen (1994). Asymptotic theory for the GARCH(1,1) quasi-maximum likelihood estimator. *Econometric Theory* 10, 29-59.

Lettau, M. & J.A. Shanken (1990). Intertemporal asset pricing: An empirical investigation. *Journal of Econometrics* 45, 99–120.

Liljeblom, Eva & Marianne Stenius (1997). Macroeconomic volatility and stock market volatility: empirical evidence on Finnish data. *Applied Financial Economics* 7, 419-426.

Lloyd, William P. and Richard A. Shick (1977). A test of stone´s two-index model of returns. *Journal of Financial and Quantitative Analysis* 12, 363-376.

Ludvigson, S.C. & S. Ng (2007). The empirical risk-return trade-off: A factor analysis approach. *Journal of Financial Economics* 83, 171–222.

MacKinnon, J.G. (1994). Approximate asymptotic distribution functions for unit-root and cointegration tests. *Journal of Business and Economic Statistics* 12, 167–176.

Mandelbrot, B. (1963). The variation of certain speculative prices. *The Journal of Business* 36:4 394-419.

Markowitz, Harry M. (1952). Portfolio selection. *Journal of Finance* 7:1. 77–91.

Marquering, W. & M. Verbeek (2004). The economic value of predicting stock index returns and volatility. *Journal of Financial and Quantitative Analysis* 39, 407–429.

Martens, M. (2002). Measuring and forecasting S&P 500 index-futures volatility using high-frequency data. *Journal of Futures Market* 22, 497-518.

Mele, A. (2005). Understanding stock market volatility. *London School of Economics Financial Market Groups Review* 67, 10–15.

Mele, A. (2007). Asymmetric stock market volatility and the cyclical behavior of expected returns. *Journal of Financial Economics* 86, 446–478.

Merton, Robert C. (1973). An intertemporal capital asset pricing model. *Econometrica* 41:5, 867-887.

Merton, R.C. (1980). On estimating the expected return on The market: An exploratory investigation. *NBER Working Paper No.* 444.

Nelson, D.B. (1990). ARCH models as diffusion approximations. *Journal of Econometrics* 45, 7-38.

Nelson, D.B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica* 59:2, 347-370.

Nguyen, Tho (2011). US macroeconomic news spillover effects on Vietnamese stock market. *The Journal of Risk Finance* 12:5, 389-399.

Nielsen, L.T. (1999). Pricing and hedging of derivatives securities. Oxford University Press, Oxford.

Nieuwerburgh, S.V. (2008). Reconciling the return predictability evidence. *Review of Financial Studies* 21, 1607–1652.

Nikkinen, J., M.M. Omran, P. Sahlström, & J. Äijö (2008). Stock returns & volatility following the September 11 attacks: Evidence from 53 equity markets. *International Review of Financial Analysis* 17, 27–46.

Officer, R.R. (1973). The variability of the market market factor of New York Stock Exchange. *Journal of Business* 46, 434-453.

Pagan, A. R. & A. Ullah (1988). The econometric analysis of models with risk terms. *Journal of Applied Econometrics* 3, 87-105.

Patton, A.J. (2011). Volatility forecast comparison using imperfect volatility proxies. *Journal of Econometrics* 160:1, 246-256.

Paye, B.S. (2012). Deja vol: Predictive regressions for aggregate stock market volatility using macroeconomic variables. *Journal of Financial Economics* 106, 527–546.

Pelsser, A. (2000). *Efficient methods for valuing interest rate derivatives*. Springer Verlag, London, Berlin, Heidelberg.

Phillips, P.C., & Perron, P. (1998). Testing for a unit root in time series regression. *Biometrika* 75, 335–346.

Pierre, Collin-Dufresne, Robert S. Goldstein, & Christopher S. Jones (2008). Identification of maximal affine term structure models. *The Journal of Finance* 63: 2, 743-795.

Poon, Ser-huang & Clive W.J. Granger (2003). Forecasting volatility in financial markets: A review. *Journal of Economic Literature* 41, 478–539.

Rapach, D., J. Strauss & G. Zhou (2010). Out-of-sample equity premium prediction: combination forecasts and links to the real economy. *Review of Financial Studies* 23, 821–862.

Schwert, W.G. (1989). Why does stock market volatility change over time? *Journal of Financ*e 44:5, 1115-1153.

Shanken, J.A. (1990). Intertemporal asset pricing: an empirical investigation. *Journal of Econometrics* 45, 99–120.

Singleton, K.J. (1980). Expectations models of the term structure & implied variance bounds. *Journal of Political Economy* 88, 1159-1176.

Song, Frank M. (1994). A two factor ARCH model for deposit-institution stock returns. *Journal of Money Credit and Banking* 26, 323-340.

Spiegel, M. (2008). Forecasting the equity premium: where we stand today. *Review of Financial Studies* 21, 1453–1454.

Stambaugh, R.F. (1999). Predictive regressions. *Journal of Financial Economics* 54, 375–421.

Stock, J.H. & M.W. Watson (2004). Combination forecasts of optimal growth in a seven-country data set. *Journal of Forecasting* 23, 405–430.

Systems of national accounts (SNA), 1993. Available from World Wide Web: <https://unstats.un.org/unsd/ nationalaccount/docs/1993sna.pdf>

Systems of national accounts (SNA), 2008. Available from World Wide Web: <https://unstats.un.org/unsd/nationalaccount/docs/SNA2008.pdf>

Tai, Chu-Sheng (2000). Time-varying market, interest rate, and exchange rate risk premia in the US commercial bank stock returns. *Journal of Multinational Financial Management* 10, 397-420.

Taylor, S.J. (1986). *Modeling Financial Time Series.* John Wiley and Sons, Ltd.

Timmermann, A. (1993). How learning in financial markets generates excess volatility and predictability in stock prices. *Quarterly Journal of Economics 108*. 1135–1145.

Timmermann, A. (1996). Excess volatility and return predictability of stock returns in autoregressive dividend models with learning. *Review of Economic Studies* 63, 523–577.

Tokmakcioglu, K. & O. Tas (2014). Stock market and macroeconomic volatility comparison: an US approach. *Quality & Quality* 48:1, 217-224.

Tourus, W., R. Valkanov & S. Yan (2004). On predicting returns with nearly integrated explanatory variables. *Journal of Business* 77, 937–966.

Traub, H.D., L. Ferreira, M. McArdle & M. Antognelli (2000). Fear and Greed in Global Asset Allocation. *The Journal of Investing* 9:1, 27-31.

Veronesi, P. (1999). Stock market overreaction to bad news in good times: a rational expectations equilibrium model. *Review of Financial Studies* 12, 975–1007.

West, K.D. (1996). Asymptotic inference about predictive ability. *Econometrica* 64, 1067–1084.

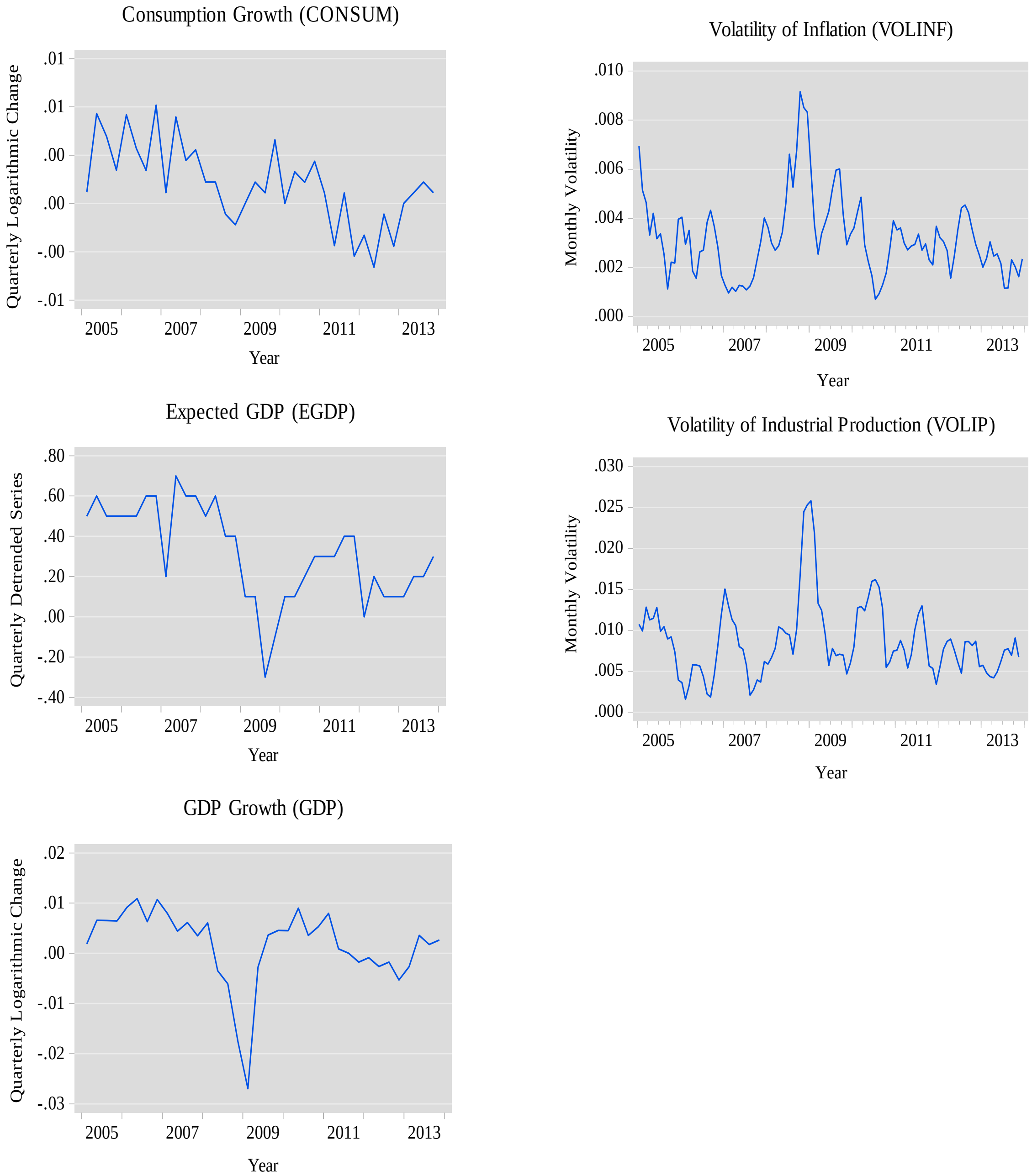
White, H. (2000). A reality check for data snooping. *Econometrica* 68, 1097–1126.

Whitelaw, R.F. (1994). Time variations and covariations in the expectation and volatility of stock market returns. *Journal of Finance* 49, 515–541.

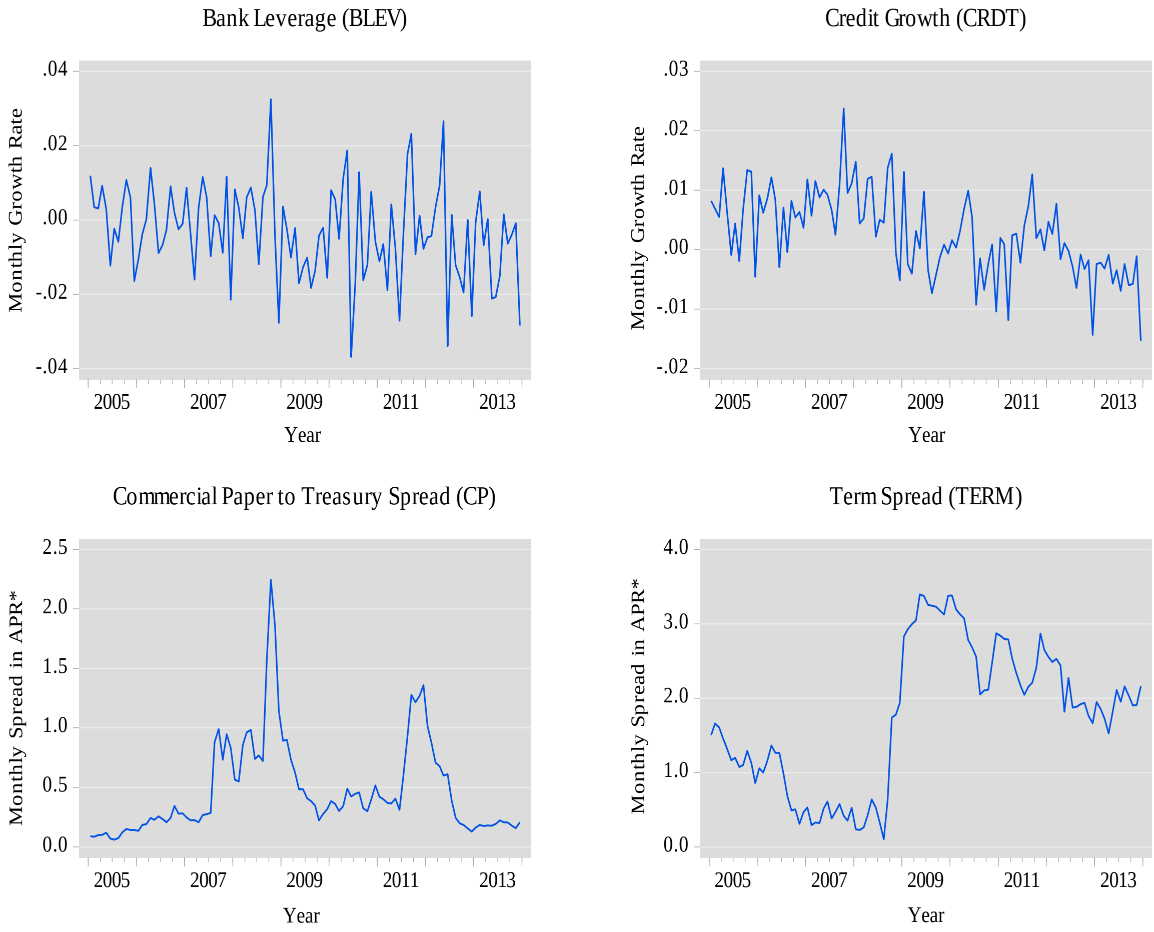
Zhou, B. (1996). High-frequency data and volatility in foreign exchange rates. *Journal of Business and Economic Statistics* 14, 45-52.

APPENDIX

Graph A1. Macroeconomic forecasting variables.



Graph A2. Financial forecasting variables.



*Annualized Percentage Return (APR)