The Effects of Economic Variables on Swedish Stock Market Volatility

A GARCH-MIDAS Approach

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Abstract:

This thesis applies the GARCH-MIDAS model to investigate the effects of macroeconomic variables, sentimental indicators, and financial variables on Swedish stock market volatility for the period January 2002 to December 2016. The GARCH-MIDAS framework allows the incorporation of data at different frequencies into the same model and decomposes volatility into two components. A short-term component and a long-term component of volatility. The findings show that some of the investigated variables affect stock market volatility. Among the investigated variables, the realized volatility is, in terms of variance ratios, considered the best determinant of volatility, followed by the level specification of the producer price index, unemployment and the term spread, and the volatility specification of the purchasing manager's index, exchange rate, and the industrial confidence.

Keywords: GARCH; MIDAS; stock market; volatility; macroeconomic; OMXSB; Sweden

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TABLE OF CONTENTS

List of Tables

List of Figures

1. Introduction

Volatility's importance in finance is not easily exaggerated. Volatility can be interpreted as a measure of risk and uncertainty. It also has a crucial role in many financial applications, such as asset allocation, risk management, and pricing derivatives. Institutions such as the European Central Bank, Finansinspektionen (the Swedish FSA), and the International Monetary Fund frequently report in heat maps estimates of low and high volatility across different markets.

Despite the importance of volatility, one question remains open. What are the economic sources of stock market volatility? In his seminal paper Schwert (1989) related the changes in U.S. stock market volatility to real and nominal macroeconomic volatility, the level of economic activity, and financial leverage. However, Schwert (1989) and much of the early literature found only weak evidence for the relationship between stock market volatility and macroeconomic variables. Liljeblom and Stenius (1997) found a significant impact of changes in the volatility of industrial production, money supply, and inflation on Finnish stock market volatility. Errunza and Hogan (1998) reported mixed results from investigating the volatility in the seven largest European stock markets and found that real activity measured as industrial production growth rate volatility Granger-cause stock market volatility for Italy and the Netherlands, but not the other markets. More recently, Engle, Ghysels and Sohn (2008) found that the increase in inflation increases U.S. stock market volatility, and that the increase of industrial production growth has a decreasing effect on volatility. Additional macroeconomic and financial variables that predict volatility have lately been found, for example in Paye (2012) and Christiansen, Schemling and Schrimpf (2012).

This thesis will address the question by investigating the relationship between Swedish stock market volatility and macroeconomic variables, sentimental indictors, and financial variables. The suitable framework of the GARCH-MIDAS methodology is applied to examine the effects of these variable on the long-run stock market volatility. Unlike the previous empirical literature, this thesis focus on the relationship between Nasdaq OMX Stockholm benchmark index and a range of macroeconomic variables, sentimental indictors, and financial variables using a GARCH-MIDAS approach. This choice is motivated by the belief that there is a need for further research on this in small open economies like Sweden as these markets often are overlooked by the literature in favor of American data. The new class of component GARCH models, called

GARCH-MIDAS, distinguish short-run from long-run movements, and was used by Engle, Ghysels and Sohn (2008) to revisit the economic sources of stock market volatility. The main advantage of the model is that it allows for the inclusion of data at different frequencies, such as daily stock returns and monthly macroeconomic variables, into the same model and permits us to better handle their relationship. The model was created with the motivating observation, which also can summarize the years of progress with volatility modeling, "*volatility is not just volatility*" (Engle, Ghysels and Sohn, 2008, p. 2), as there are for example dynamic, unconditional, conditional volatility, and different components of volatility that should be modeled separately.

The recent financial crisis and the Great Recession have clearly illustrated the need for a better understanding of the relationship between risks in financial markets and economic conditions. Thus, modelling and correctly assess future stock market volatility is of great importance. Prior to the crisis, risk management focused either on short-run risk (Value at Risk at one or 10-day horizon) or extrapolated the low volatility further into the future and failed to attend the "risk that risk will change" (Engle, 2009) and as a result long-term risks were underestimated (Engle, 2010). These long-term risks require volatility models which allow for effects of changes in relevant economic variables on the conditional variance of asset returns (Conrad and Schienle, 2015).

The research on volatility modeling has made considerable progress over time with financial data and its complications with non-normality, observed volatility clustering, and time-varying error term variance that violates the assumption of homoscedasticity. Robert Engle introduced in his 1982 paper the autoregressive conditional heteroscedasticity (ARCH) model on inflation in the United Kingdom, which was then later generalized (GARCH) by Bollerslev (1986). The ARCH and GARCH models do not view data "suffering" from heteroscedasticity as a problem to correct, GARCH models treat it as variance to be modelled and as a result, a prediction of the variance for each error term is computed that is of interest in finance applications (Engle, 2001). The two models found success in applications to equity, exchange market, and modelling returns where the data display signs of volatility clustering, meaning that periods of high volatility are typically followed by high volatility and vice versa, which was observed by Mandelbrot (1967).

Stock market volatility has been, by Black (1976) and Christie (1982), related to financial leverage, French, Schwert and Stambaugh (1987) related it to the volatility of expected returns. The time-varying volatility of stock market returns in industrial countries has been well-established in the literature with evidence from Bollerslev (1987), French, Schwert and Staumbaugh (1987), and Chou (1988). Officer (1973) addressed the variability of the market factor of the New York Stock Exchange. Schwert (1989) addressed the question of why stock return volatility is higher at certain times than others by relating American stock market volatility to the time-varying volatility of economic activity such as industrial production growth, bond returns, producer price inflation rate, short-term-interest rate, and money growth. Schwert (1989) found evidence for that stock market volatility is counter-cyclical with the business cycle. Risk premia have also been shown in asset pricing models to be countercyclical by Fama and French (1989) and Ferson and Harvey (1991), meaning that volatility typically is low during expansion and high during recession. Davis and Kutan (2003) researched the impact of macroeconomic volatility (output and inflation) on stock market volatility in 13 industrial and developing countries by using GARCH and EGARCH models to simultaneously estimate the relationship between output and stock returns. They found that the volatility of industrial production (real output) and inflation only have a weak predictive power for stock market returns and volatility; and no strong evidence for the Fisher effect in international equity returns. That is, if the Fisher effect holds for stock market returns, stock returns are supposed to function as a hedge against the inflation so that changes in inflation are equal to the changes in nominal stock return (Davis and Kutan, 2003). The Australian stock market volatility has been linked to the volatility of the business cycle and financial variables by utilizing the Generalized Least Squares (GLS) estimation by Kearney and Daly (1998).

The research on time-varying volatility has in the past been mostly limited to high frequency data, such as short-term interest rates and term premiums as a large set of data of lower frequency variables have been disregarded in the pursuit of alignment in terms of frequencies. Thus, it could be argued that the impact of variables such as inflation, unemployment rate, and sentimental indicators on volatility have not been sufficiently examined. It is after all still an open question whether and which financial and macroeconomic variables are significant drivers of volatility (Conrad and Schienle, 2015). Therefore, this thesis includes a large group of variables that are plausible to be linked to stock market volatility. These are referred to as the low-frequency variables, since they are observed at a lower frequency than the daily stock returns. The variables are the industrial production index, producer price index, new orders, industrial confidence indicator, manufacturing confidence indicator, consumer confidence indicator, purchasing manager's index, unemployment, exchange rate, and the term spread. In addition to the main objective of testing the level of these low-frequency variables, the volatility is also of interest as the literature (Diebold & Yilmaz, 2008) has found that the volatility of some macroeconomic variables leads to increased stock market volatility for a large cross section of countries.

The main findings can be summarized as follow. First, the realized volatility is the variable that, in terms of variance ratios, contributes the most to the total expected volatility, explaining 30% of it. The realized volatility has a positive impact on Swedish stock market volatility, so that a period of increased realized volatility is followed by a period of increased volatility. Second, the low-frequency variables do contain information that affect stock market volatility, although some of them did not have the expected effect. Third, in terms of the level specification of the variables, the three best variables are the producer price index, unemployment, and the term spread with contributions of 11.3%, 11.1% and 10.7% respective to total volatility. Fourth, the three best variables for the volatility specification are the purchasing manager's index, exchange rate, and the industrial confidence with contributions of 12.5%, 9.4%, and 9.3% respective to total volatility. The three variables have significant slope parameter but only the exchange rate has the expected sign on it. We might conclude that the variables do contain some information about the driving force of Swedish stock market volatility.

The remainder of this thesis is structured as follows. In section 2, the relevant literature is reviewed, Section 3 gives a description of the data. The employed methodology of the GARCH-MIDAS model is carefully described in section 4. In section 5, the empirical findings are analyzed. In section 6, the conclusion appears.

2. Literature review

This section will demonstrate the link between macroeconomic variables and asset returns, briefly describe the path to the GARCH-MIDAS model, and some of the empirical applications of the model.

2.1 The link Between Macroeconomic Variables and Asset Returns

The theoretical link between stock market returns and macroeconomic factors can be found in the Arbitrage Pricing Theory (APT), developed by Ross (1976). This more general alterative to the classic Capital Asset Pricing Theory (CAPM) of Sharpe (1964) and Lintner (1965) is not limited to only one exposure of systematic risk, the exposure to the market portfolio, often proxied by a broad stock market index. The APT allows asset returns to be influenced by risk premia associated with various factors. These factors could be macroeconomic variables, and the risk exposures determine the return volatility. Interpreted as risk factors, Chen, Roll and Ross (1986) presented economic variables, such as industrial production, spreads between low and high graded bonds, and inflation, that affect stock returns in time-series regressions and expected returns in cross-section regressions. In addition to represent priced factors in the ATP, macroeconomic variables probably influence firms´ expected cash flows and the discount rate for these flows and thus affect future consumption and investment opportunities, in view of that fact, they are state variables in intertemporal asset-pricing models (for example Campbell & Cochrane, 1999 and Merton, 1973). To no surprise, a long list of studies in the empirical literature have investigated the predictability of equity returns using macroeconomic variables such as interest rates (Ang & Bekaert, 2006; Campbell, 1987 & 1990), term and default spreads (Campbell, 1987; Fama & French, 1989), unemployment rate (Boyd, Hu & Jaganathan, 2005), inflation rate (Bodie, 1976; Fama & Schwert, 1977; Fama, 1981; Nelson, 1976; Kim & Ryoo, 2011), and industrial production (aggregated output) (Balvers, Cosimano & McDonald, 1990).

The changes in asset prices can be rationalized economically by relating them to changes in news that affect the expected future cash flows and thus the present value of the asset. This and the relationship between the macroeconomic variables and stock market volatility has been formalized in Varonesi’s (1991) rational equilibrium model where the stock market overreacts to bad news in good times and underreacts to good news in bad times. The sentimental indicators on the other hand can also be related to the stock market returns and volatility in a similar manner to the macroeconomic variables. If the confidence indicators capture information about the current or expected economic situation in line with the “information or “news” view of consumer confidence in Barksy and Sims (2012) that suggests a relationship between confidence and raised macroeconomic activity because confidence measures contain information about the current and future states of the economy. Thus, the indicators can reasonably be related to expectations of future dividends and returns and thus effect volatility. Campbell and Diebold (2009) found that survey data for the expected business conditions are a robust predictor of excess returns and suggested that expected business conditions may forecast future volatility.

2.2 The Path to GARCH-MIDAS and Its Empirical Applications

The popular ARCH and GARCH models of Engle (1982) and Bollerslev (1986) do capture the typical persistence in stock market volatility, however the dynamics of volatility might be better described by component models. They are based on the idea that volatility has a long-run component, which changes smoothly, and a short-run component that are changing more rapidly and fluctuates around the other component. Engle and Lee (1999) introduced a component model that decomposes stock market volatility into with two additive GARCH (1, 1) components, a short-run component and a long-run component. There are many related two-factor component models such as Ding and Granger (1996); Chernov, Gallant, Ghysels & Tauchen (2003); Adrian and Rosenberg (2008). More recently, Engle and Rangel (2008) proposed a multiplicative structure, the Spline-GARCH, which decomposes daily stock market volatility into a mean reverting unit GARCH and a slowly varying deterministic component, represented by an exponential spline. It allows for the low-frequency macroeconomic data to be linked to the high frequency of stock market returns. Engle and Rangel (2008) applied this model to a large panel of countries and they found that the long-term component behaves counter-cyclical and that the volatility in GDP, industrial production growth, short-term interest rates, and inflation are important determinants of stock market volatility. The drawback of the Spline-GARCH is that it cannot incorporate the macroeconomic directly into long-term component, since they are typically are observed at a lower frequency than the daily stock market returns. Engle and Rangel (2008) dealt with the frequency mismatch by estimating in steps and data aggregation.

Empirical studies often encounter the problem of data at different frequencies. This has commonly been addressed by either add high-frequency data to generate low-frequency data or decompose the low-frequency data into high-frequency data. Both methods suffer from information bias which has negative impact on parameter estimation and prediction.

The problem of mismatch in data frequency is addressed by the new regression scheme called Mixed Data Sampling (MIDAS). In the context of volatility, exemplified in Ghysels, Santa-Clara and Valkonov (2005) that studied the traditional risk-return trade-off and used monthly data to proxy expected returns, while the variance was estimated using daily squared returns. This new approach allows high-frequency data of stock returns to be combined with low-frequency macroeconomic data by a flexible weighting function that is parsimonious. MIDAS is explored further in (Ghysels, Santa-Clara & Valkonov, 2006; Andreou, Ghysels & Kourtellos, 2010; Wang & Ghysels, 2015).

The new component model GARCH-MIDAS, proposed by Engle, Ghysels and Sohn (2008), was inspired by the insight from the MIDAS approach to modify the volatility dynamics of the Spline-GARCH model. The GARCH-MIDAS model allows high-frequency data (stock market returns) and low-frequency macroeconomic variables (monthly, quarterly, or biannually) to be incorporated directly and extracting two components of stock market volatility, one short-term component and one long-term component. Engle, Ghysels and Sohn (2008) applied the new model to link the long-term stock market volatility to the level and volatility of macroeconomic variables using an extended version of Schwert's (1989) data set (spanning from 1890 to 2004).

Engle, Ghysels and Sohn (2008) found that producer price inflation and industrial production growth explain 10% to 35% of the daily U.S. stock market volatility. The model has been appraised and generated much interest and found many applications. Girardin and Joyeux (2013) employed the GARCH-MIDAS model to investigate the level and volatility of economic fundamentals on the long-run volatility of the Chinese stock market (the A-market and B-market) and found that the industrials production and inflation are valid explanatory variables. Asgharian, Hou and Javed (2013) used a principal component approach to combine the information from many economic variables such as the unemployment rate, exchange rate, and term spread, and augmented the long-term component to combine the realized volatility, the level, and the volatility of the economic variables in the MIDAS equation. Their findings show that the GARCH-MIDAS model performed better forecast than the traditional GARCH model. Conrad and Loch (2015) utilized the GARCH-MIDAS framework for both one- and two-sided MIDAS filters and found the term spread, housing start and the unemployment rate to be useful in explaining and forecasting U.S. stock market volatility. The agricultural commodity price volatility in the U.S. was linked to macroeconomic variables using the model by Magrini and Domnez (2013). The bond market was better explained by using the GARCH-MIDAS model with macroeconomic indicators than using the GARCH model by Nieto, Novales and Rubio (2015). Dorion (2016) proposed a different version of the GARCH-MIDAS model applied for long-term option pricing and by accounting for business conditions, reduced the option-pricing errors. The drivers of long-term volatility of cryptocurrencies have been investigated by using the model by Conrad, Custovic and Ghysels (2018).

The empirical relevance of the GARCH-MIDAS to model the volatility components of various assets and its low-frequency determinants as well as the theoretical link between macroeconomic variables and both the equity returns and the volatility of equity returns have been presented.

3. Data

The GARCH-MIDAS model is estimated with data of daily stock returns and monthly macroeconomic, sentimental indicators and financial variables. The data have been collected from Thomson Reuters DataStream, but they originate from different sources. The data are from January 2002 to December 2016 and have been selected to originate from after the start of the Great Moderation, which is characterized by the decline in macroeconomic volatility and muted business cycles in many developed countries, including Sweden (Stock & Watson, 2002; Ćorić, 2012; Cecchetti, Flores-Lagunes & Krause, 2006). The rationale for this is that even though the GARCH-MIDAS method is designed to accommodate fundamental changes in the economy, findings in Engle, Ghysels and Sohn (2008) suggest it does not fully capture this. This further motivates the chosen period to be after changes such as the Swedish central bank, the Riksbank, abandoning the fixed exchange rate in 1992 and gaining independence in 1999. There is also the desire to include current data. Ultimately, the period selection was driven by the data availability among the variables and this limits the estimation window to start with data from 2002. The industrial production index was replaced by a newly introduced index called production value index in 2017, which is why the data span until the end of 2016. The variables are in the next subsections characterized, further motivated, described by the descriptive statistics, and tested before entering the estimation for the GARCH-MIDAS methodology in section 4.

3.1 Stockholm Benchmark Index (OMXSB)

Created by Nasdaq OMX, the Stockholm benchmark index (OMXSB) is used to capture the market returns on the Swedish stock market. It is an indicator of the overall performance of NASDAQ OMX Stockholm The index is of daily frequency and have been manually corrected for non-trading days. The OMXSB is composed of the shares with top 10% turnover on OMX Stockholm, it has 93 constituents and their weights are based on a free float market capitalization, which is revised semi-annually (NASDAQ OMX, 2018). The OMXSB index has been chosen in favor over the OMX Stockholm All-Share index (OMXSPI), which is considered too broad and includes many illiquid stocks, as it includes all shares listed on OMX Stockholm; and the more regularly quoted stock index OMXS30. It consists of the 30 most traded stocks on OMX Stockholm and this low number of firms results in an index only including large firms. It is believed that the OMXSB reflects a larger part of the market movements than the OMXS30, although one drawback could be that some of the OXSB-stocks may be less liquid than the OMXS30-stocks. However, the OMXSB index is highly correlated with both OMXSPI (0.99755) and OMXS30 (0.99735), which is illustrated in figure A.1. The daily returns are calculated by the daily log first difference of the OMXSB index according to the following equation:

$$r_t = \log P_t - \log P_{t-1} \tag{3.1}$$

Where P_t is the OMXSB index at trading day t and P_{t-1} is the OMXSB index at the previous trading day.

3.2. Low-Frequency Variables

The monthly low-frequency variables are described in this subsection.

3.2.1 Industrial Production Index (IP)

Originating from Statistics Sweden (SCB), the monthly seasonally adjusted industrial production index is a timely measure of the output of the economy. GDP might be a better indicator; however, IP is closely correlated with GDP and GDP data is not available at monthly frequency. The IP serves as a proxy for the growth in the economy. The level of IP is measured as the monthly log first difference of the index.

3.2.2 Producer Price Index (PPI)

The monthly seasonally adjusted producer price index (PPI) originates from SCB. The level is measured as the monthly log first difference of the index. The PPI can, as described by Akcay (2011), be a useful indicator of future consumer inflation, as changes in costs for producers often precede changes in prices paid by consumers.

3.2.3 New Orders (NO)

The monthly seasonally adjusted new orders index originates from SCB and the level is measured as the monthly log first difference of the index. It is a survey-based index that measures the changes in the value of new orders and turnover in industry monthly (Statistiska Centralbyrån, 2017). It can be a proxy for short-term business conditions and unlike backward looking metric like GDP, it might be able to offer forward-looking insights into economic activity.

3.2.4 Business Confidence Indicators: Industry Confidence Indicator (IC) and Manufacturing Confidence Indicator (MCI)

The monthly seasonally adjusted total industry confidence indicator and manufacturing confidence indicator originates from NIER (National Institute of Economic Research, Sweden) and are part of the qualitative “Business Tendency Survey”. It is intended to provide an indication of actual outcomes, trends and expectations of the near future. The total industry indicator is based on the information in the confidence indicators for building and civil engineering, manufacturing, the retail trade and the private service sector (Konjuktur Institutet, 2018). The two indicators can be seen as a proxy for near-term and forward-looking business conditions such as future spending and capital investments. The levels for both indicators are measured as the monthly log first difference of each indicator.

3.2.5 Consumer Confidence Indicator (CC)

The level of CC is measured as the monthly log first difference of monthly seasonally adjusted consumer confidence indicator originating from NIER. The CC provides a qualitative indication of households' plans of consumption, view on the economy, inflation, personal finance, and saving. The survey is similar to CC surveys in other EU countries. The consumer confidence index has for many studies been used as a proxy for investor sentiment, such as in Lemmon and Portniaguina (2006). They found it to predict time-variation in U.S. stock returns and found evidence in line with the idea that investors overprice small-cap stocks relative to large-cap stocks when the consumer confidence is high and vice versa. Aydogan (2017) analyzed the effect of investor sentimental on stock markets using a TGARCH model and found it to be significant factor for explaining condition volatility for European markets.

3.2.6 Purchasing Manager's Index (PMI)

Created by Swedbank and Silf, the monthly seasonally adjusted PMI aims to be a Swedish equivalent to the ISM-index in the U.S. and a business cycle indicator signaling either a contraction or expansion. The level is measured as the monthly log first difference of the index. In the U.S., the changes in the PMI was found to have a positive relationship with stock returns by Johnson and Watson (2011) and by Christiansen, Eriksen and Møller (2014) to hold predictive power over recessions.

3.2.7 Unemployment Rate (Unemp)

The level of Unemp is measured as the monthly log first difference of the seasonally adjusted unemployment rate (persons aged 15-74 years), created by Statistics Sweden. The news in the unemployment rate have been, by Boyd, Hu and Jagannathan (2005), argued to contain information about the expected growth of corporate earnings and dividends, and the equity risk premium. This information should then be reflected in stock returns and volatility.

3.2.8 Exchange Rate (Krona)

The level of the exchange rate is measured as the monthly log first difference of the index the Swedish Krona TCW (total competitiveness weights) index. A higher value in the Swedish Krona TCW index means the SEK has depreciated and a lower value that it has appreciated.

3.2.9 Term Spread

The level of the term spread is defined as the spread between the bid yield for a 10-year and a three-month Swedish government bond. The term spread is often considered as a leading indicator for the business cycle and it captures cyclical variation in the expected returns (see, for example, Fama & French, 1989; Estrella & Mishkin, 1998). The term spread was found to be one of the leading variables in the US to best predict stock market volatility in Conrad and Loch (2015). It has also been used in the finance literature as a variable for other applications such as predicting output growth in Stock and Watson (1989), consumption growth in the US by Harvey (1988), and in Estrella and Hardouvelis (1991) to predict a binary recession indicator in probit regressions.

3.3 Volatility of the Low-Frequency Variables

This volatility is considered as the monthly variances in the low-frequency variable, that is, for example the industrial production volatility. The preferred measure for this is the realized volatility which cannot be used as daily data are not available. An alternative is to follow Engle, Ghysels and Sohn (2008) and use the approach of Schwert (1989) and take the squared residual from an autoregression with dummy variables as a proxy, but this would cost an additional one year of the dataset. The selected measure is to use the squared first difference of the level of the low-frequency variables a proxy, similarly to Asgharian, Hou and Javed (2013).

3.4 Descriptive Statistics and Data Characteristics

Table A.1 and table A.2 provides the summary statistics of the level and volatility of the low-frequency variables, and the daily stock return data. Figure A.2 gives a graphical illustration of the daily returns, monthly realized volatility, and the level and volatility of the low-frequency variables. The stock return data show the characteristics of non-normality with the rejection of the Jarque-Bera normality test and have a high kurtosis and negative skewness. In figure A.2, the amplitude of the daily returns varies over time and illustrates the familiar volatility clustering. The figures A.1 and A.2 also illustrate the evidence from Schwert (1989) that the stock return volatility is higher in recessions than in expansions. There are large spreads between the maximum and minimum values of the stock returns and the level variables. There are for example observations with negative term spread, indicating months with a higher yield on the 3-month government bond than the 10-year government bond. This is not surprising as the dataset include the period of the financial crisis of 2008 and the Great Recession and there might be a problem that this inclusion distorts the data. Another potential problem is that most of the variables are revised and may not be exactly the same information as in the first release data that was available to market participants. Table A.3 show the correlation between the level of the low-frequency variables and the realized volatility. The IC is as expected highly correlated (0.71) with the MCI. The realized volatility is most negatively correlated with IC (-0.36) and the term spread (-0.27). The confidence indicators have positively correlation with each other. The IP is negatively correlated with Unemp and as in Boyd, Hu and Jagannathan (2005) it seems that rising unemployment is followed by slower growth. The correlation between PPI and the Krona is positive suggesting that at times when the producer price index increases the krona is at the same time depreciating, which is intuitive.

The standard unit root test Augmented Dickey-Fuller test have been tested for all variables in order for ensuring stationarity and avoiding potential problems associated with non-stationarity such as spurious regressions. The results in table A.4 and A.5 rejects the null hypothesis of unit roots in the variables.

4. Methodology

The intention of this research is to investigate the direct effects of low-frequency macroeconomic, sentimental indicators, and financial variables on Swedish stock market volatility. For this purpose, the GARCH-MIDAS model is employed. The variant of the model in this thesis assumes that the long-term component changes at the same frequency as the low-frequency variables are observed, which is monthly. The econometric model and the estimation method for the research objective is described below.

Assume the log return on day i in month t (t is a choice variable and is selected as a part of the model specification and have N_t trading days) follows the process:

$$r_{i,t} = \mu + \sqrt{\tau_t \cdot g_{i,t}}\,\varepsilon_{i,t} \quad \forall_i = 1, \ldots, N_t$$
$$\varepsilon_{i,t} | \Phi_{i-1,t} \sim N(0,1) \tag{4.1}$$

$$\sigma_{i,t}^2 = \tau_t \cdot g_{i,t} \tag{4.2}$$

Where $\Phi_{i-1,t}$ is information set up to day (i-1) of period t. It is assumed that the expected return is constant ($E_{i-1,t}$ ($r_{i,t}$) =μ). The total conditional variance can be defined as in equation (4.2) and is decomposed into two components following the tradition of component GARCH models introduced by Engle and Lee (1999). The two components are the short-term component of volatility $g_{i,t}$ and the long-term (secular) component of volatility τ_t. The long-term component can be described by factors such as macroeconomic variables and are assumed to illustrate something about this source of stock market volatility. The volatility dynamics of the short-term component $g_{i,t}$ is assumed to be a daily GARCH (1, 1) process of Bollerslev (1986), where $\alpha > 0$, $\beta > 0$ and $\alpha + \beta < 1$.

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{\left(r_{i-1,t} - \mu\right)^2}{\tau_t} + \beta g_{i-1,t} \tag{4.3}$$

The specification of the low-frequency τ_t component departs from the tradition of Merton (1980), Schwert (1989), and others of measuring long-run volatility by realized volatility over a single period as the measure of interest. Instead, τ_t is defined by smoothing monthly realized volatility, denoted RV_t, in the spirit of MIDAS regression and MIDAS filtering:

$$\log \tau_t = m + \theta \sum_{k=1}^{K} \varphi_k (\omega_1, \omega_2) RV_{t-k} \tag{4.4}$$

$$RV_t = \sum_{i=1}^{N_t} {r_{i,t}}^2 \tag{4.5}$$

Where the long-term component τ_t and the realized volatility are fixed within the chosen time span of a month, $\varphi_k(\omega_{1,}, \omega_2)$ is the weighting scheme, and K is the number of periods over which we smooth the volatility. It is also referred to as the number of MIDAS lag years meaning that K equal to 12 is one MIDAS lag year. The number of K could for example be chosen by minimize the Bayesian information criterion (BIC). Equation (4.4) is the specification for the long-term component used in the logarithmic version of GARCH-MIDAS specification with realized volatility. A non-logarithmic version could also be employed but the logarithmic version is chosen as it matches the model specifications with the other variables described below.

The GARCH-MIDAS models with one-sided filter that incorporate the macroeconomic, financial and sentiment information directly in terms of their level or volatility have the following two specifications for the long-term component in the fixed span specification of monthly frequency:

$$\log \tau_t = m_l + \theta_l \sum_{k_l=1}^{K_l} \varphi_k \left(\omega_{1,l}, \omega_{2,l}\right) X_{l,t-k} \tag{4.6}$$

$$\log \tau_t = m_v + \theta_v \sum_{k_v=1}^{K_v} \varphi_k \left(\omega_{1,v}, \omega_{2,v}\right) X_{v,t-k} \tag{4.7}$$

Where, the subscripts l and v stand for the level and volatility of the low-frequency variable X so that the different weighting schemes $\varphi_k(\omega_{1,l}, \omega_{2,l})$ and $\varphi_k(\omega_{1,v}, \omega_{2,v})$ are for the level and volatility. The logarithmic speciation is chosen to ensure non-negative issues of the long-term component τ_t even when the low-frequency variable X take negative values. To complete the model, a weighting scheme needs to be specified for equations (4.4), (4.6), and (4.7). Engle, Ghysels and Sohn (2008) propose either the common exponential weighting function or the beta lag polynomial as below (the beta lag structure is discussed further in Ghysels, Sinko and Valkanov (2007).

$$\varphi_k(\omega) = \frac{\left(\frac{k}{K}\right)^{\omega_1 - 1}\left(1 - \frac{k}{K}\right)^{\omega_2 - 1}}{\sum_{j=1}^{K}\left(\frac{j}{K}\right)^{\omega_1 - 1}\left(1 - \frac{j}{K}\right)^{\omega_2 - 1}} \tag{4.8}$$

Girardin and Joyeux (2013) and Engle, Ghysels and Sohn (2008 and 2013) yielded in their studies similar results for both weighting schemes. This thesis uses the beta lag polynomial as it is flexible to accommodate various lag structures. The weighting shape depends on the weight parameters (ω_1 and ω_2) in equation (4.8) and can either be fixed or freely estimated. Asgharian, Hou and Javed (2013) described three alternatives. The first alternative is to estimate both ω_1 and ω_2 without restrictions within the model. The second alternative is to fix ω_1 and estimate ω_2 within the model. The last alternative is to fix both ω_1 and ω_2. To avoid counterintuitive weighting patterns such as a lower weight for more recent observations (ω_1 larger than 1); and because there are no prior preferences for the choice of ω_2, the second alternative is the most sensible. Following Engle, Ghysels and Sohn (2013), Asgharian, Hou and Javed (2013) and Girardin and Joyeux (2013), the weight ω_1 will be equal to one, which makes the weighs monotonically decreasing over the lags.

Three different GARH-MIDAS model specifications are used in this thesis. The difference between the models is the specification of the long-term component, τ_t,. The first model is the GARCH-MIDAS model for time-varying conditional variance with realized volatility and it is formed by Equations (4.1)-(4.5). The second and third model incorporate the information from the macroeconomic, sentiment indicators, and financial variables in terms of their level or volatility. The second model is formed by equation (4.1)-(4.3), and (4.6) and thus have the level of the low-frequency variable in the MIDAS equation, τ_t. The third model is formed by equation (4.1)-(4.3), and (4.7) and thus have the volatility of the low-frequency variable in the MIDAS equation, τ_t. As previously mentioned, all three model specifications have monthly frequency in the MIDAS equation to capture the long-term component, as it is assumed that it changes at the same frequency as the low-frequency variables are observed.

The number of lags (K in equations (4.4), (4.6), and (4.7) in the MIDAS equation is 36, also known as 3 “MIDAS lag years”, for the three model specifications. The estimation thus “costs” three years of data for initialization. Conrad and Loch (2015) found robust estimation results as long as the chosen number of lags is large enough (they used 3 MIDAS lag years). Engle, Sohn and Ghysels (2008) showed that the optimal weights decay around 30 lags regardless of the choice of t and the number of MIDAS lag years for their long time-series, and similarly, Asgharian, Hou and Javed (2013) found the optimal weights around 36 lags. Only whole lag years have been considered and due to the short dataset, the number of lags will be 36, which should ensure the capture reasonable dynamics of the long-term component τ_t.

The three model specifications have the objective to estimate the parameter space $\Theta = \{\mu, \alpha, \beta, m, \theta, \omega_1, \omega_2\}$. This parameter space is more parsimonious compared to other component volatility models and the number of parameters is fixed, meaning that GARCH-MIDAS models with different time spans can be compared to each other. The maximum likelihood method is used to estimate the parameters for the GARCH-MIDAS model and the following log-likelihood function is maximized:

$$LLF = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N_t}\left[\log(2\pi) + \log g_{i,t}\tau_t + \frac{\left(r_{i,t} - \mu\right)^2}{g_{i,t}\tau_t}\right] \tag{4.9}$$

The consistency and asymptotic normality of the estimator for a rolling window version of the GARCH-MIDAS model with realized volatility has been established in Wang and Ghysels (2015). However, no asymptotic results are yet available for the general GARCH-MIDAS model with fixed time span realized volatility or low-frequency macroeconomic variable (Conrad & Loch, 2015; Conrad & Schienle, 2015). I follow the convention of the GARCH-MIDAS literature (Engle, Ghysels & Sohn, 2013; Conrad & Loch, 2015) and use the standard t-statistic for the estimated parameters. The model specifications are estimated in MATLAB 2017A using the MIDAS MATLAB ®Toolbox[1] (Ghysels, 2013) and the Global Optimization Toolbox and multiple starting approaches to find optimum.

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[1] The toolbox is developed and published by Hang Qian and is a repack of the MIDAS program written by Eric Ghysels and is available on the Matlab File Exchange

To assess how much each one of the macroeconomic, sentimental indicators and financial variables contributes to the total expected volatility, variance rations (VR) are computed as suggested by Engle, Ghysels and Sohn (2008). The interpretation of variance ratios is that they can be viewed as a measure of fit, a high variance ratio implies that a large share of the total expected volatility can be explained by the long-term component. However, a low variance ratio does not necessarily indicate a poor fit as it could also be due to smooth movements in the underlying low-frequency variable (Conrad and Loch, 2015). The variance ratio is calculated as in equation (4.10) for each model specification with low-frequency variable X.

$$VR(X) = \frac{Var(\log(\tau_t{}^X))}{Var\left(\log\left(\tau_t{}^x \cdot g_{i,t}{}^X\right)\right)} \tag{4.10}$$

5. Empirical Findings and Analysis

The three different specifications of the GARCH-MIDAS model described in section 4 have been employed to find the determinants of the long-term Swedish stock market volatility and decompose the volatility into two components. Table 5.1-5.3 show the estimated parameters for each model specification and low-frequency variable. In each case with 3 MIDAS lags, that is 36 months of lags. The parameters μ, α, and β are highly significant at the 1% level for all three model specifications. An interesting feature of the GARCH-MIDAS model, and reported in Engle, Ghysels and Sohn (2008), is that both α and β are larger than 0 and their sum is noticeable less than 1, while in standard GARCH models the sum is usually near 1. Thus, the estimates for the short-term component $g_{i,t}$ are significant. Next are the estimates for the long-term component, τ_t. There is no doubt that the long-term component based on the different macroeconomic, sentimental indicators, and financial variables captures the long-run volatility in different ways. The estimated parameter of most interest is the slope parameter, θ, in the specification of the MIDAS filter. The significance and sign of the slope parameter determines how the realized volatility and the low-frequency variables affect the long-run stock market volatility.

On contrary to the estimate for the short-term component, the slope parameter is not always significant and does not always take the expected sign for the different model specifications and different variables. The estimated weighting schemes of selected models are plotted in figure A.3

and they are all monotonically decreasing, and the maximum weight is at the first lag. The estimate of ω_2 determines the rate of decay, a low value of ω_2 generates a slowly decaying pattern and a high value generates a rapidly decaying one. The rate of decay differs across the variables and model specifications.

Table 5.1: Parameter Estimates for GARCH-MIDAS with Realized Volatility

$\mu * 10^3$	α	β	θ	ω_2	m	LLF/BIC
0.70^{***}	0.11^{***}	0.86^{***}	110.38^{***}	9.14^{**}	-9.20^{***}	9002
(3.78)	(10.39)	(55.58)	(5.21)	(2.36)	(-70.35)	-17955

Note: This GARCH-MIDAS model is estimated with monthly fixed RV and 3 MIDAS lag years in the MIDAS filter. The estimation period covers the period from January 2002 to December 2016. The numbers in the parenthesis is t-statistics and *,**,***, denotes the significance level at 10%, 5%, and 1%. LLF is the optimal log-likelihood function value, and BIC is the Bayesian information criterion.

Table 5.2: Parameter Estimates of GARCH-MIDAS with Level Variables

Variable	$\mu * 10^3$	α	β	θ_l	ω_2	m	LLF/BIC
IP	0.72^{***}	0.10^{***}	0.89^{***}	-36.97^{*}	5.53^{*}	-8.61^{***}	8997
	(3.92)	(12.05)	(93.83)	(-1.72)	(1.67)	(-47.29)	-17945
PPI	0.70^{***}	0.10^{***}	0.88^{***}	163.58^{***}	1.01^{***}	-8.88^{***}	9001
	(3.76)	(11.61)	(84.46)	(3.59)	(11.74)	(-55.92)	-17952
NO	0.69***	0.098^{***}	0.89^{***}	-2.16	26.43	-8.68^{***}	8998
	(3.75)	(12.13)	(94.31)	(-0.33)	(0.30)	(-51.97)	-17947
IC	0.70^{***}	0.10^{***}	0.89^{***}	41.32^{**}	1.06^{***}	-8.74^{***}	9000
	(3.78)	(11.91)	(92.35)	(2.21)	(6.30)	(-53.79)	-17949
MCI	0.70^{***}	0.10^{***}	0.88^{***}	47.73^{**}	1.08^{***}	-8.73^{***}	8999
	(3.80)	(11.98)	(91.89)	(2.35)	(6.15)	(-56.01)	-17987
CC	0.70^{***}	0.10^{***}	0.88^{***}	-30.90^{*}	2.74^{**}	-8.69^{***}	8999
	(3.74)	(11.59)	(81.49)	(-1.91)	(1.96)	(-63.10)	-17948
PMI	0.70^{***}	0.10^{***}	0.89^{***}	44.33^{***}	1.00^{***}	-8.71^{***}	9000
	(3.80)	(12.08)	(93.54)	(3.10)	(37.38)	(-55.09)	-17950
Unemp	0.71^{***}	0.10^{***}	0.88^{***}	-44.30^{***}	1.75^{**}	-8.67^{***}	9001
	(3.84)	(11.86)	(89.70)	(-3.01)	(2.56)	(-52.89)	-17989
Krona	0.69^{***}	0.10^{***}	0.89^{***}	72.25^{**}	1.28^{**}	-8.66^{***}	8996
	(3.74)	(11.99)	(95.67)	(2.05)	(2.21)	(-51.26)	-17942
Term Spread	0.70^{***}	0.10^{***}	0.88^{***}	-30.74^{***}	28.32	-8.27^{***}	9000
	(3.83)	(11.98)	(90.86)	(-2.70)	(0.60)	(-35.71)	-17945

Note: This GARCH-MIDAS model is estimated with monthly levels of the low-frequency variables and 3 MIDAS lag years in the MIDAS filter. The estimation period covers the period from January 2002 to December 2016. The numbers in the parenthesis are t-statistics and *, **, denotes the significance level at 10%, 5%, and 1%. LLF is the optimal log-likelihood function value, and BIC is the Bayesian information criterion.

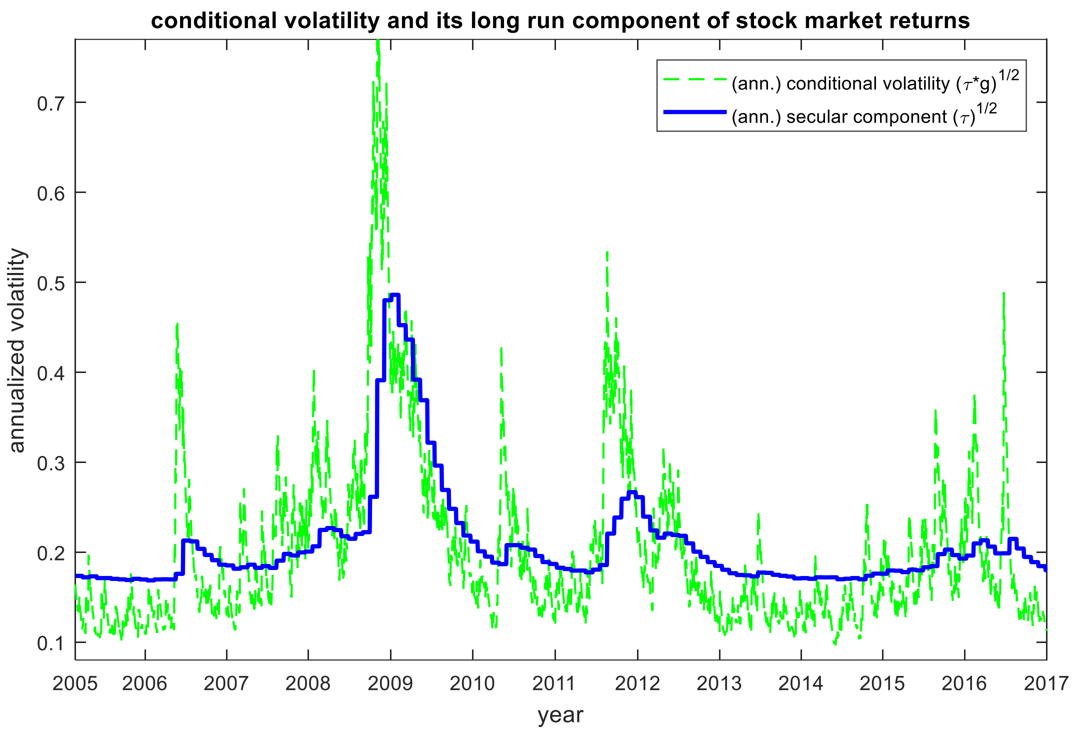
Table 5.3: Parameter Estimates of GARCH-MIDAS with Volatility Variables

Variable	$\mu * 10^3$	α	β	θ_v	ω_2	m	LLF/BIC
IP	0.69^{***}	0.10^{***}	0.88^{***}	25.50^{**}	49.85	-8.85^{***}	9001
	(3.78)	(11.79)	(89.98)	(2.35)	(1.18)	(-53.67)	-17953
PPI	0.70^{***}	0.10^{***}	0.88^{***}	4020.20^{**}	2.21	-8.94^{***}	8999
	(3.78)	(11.88)	(92.30)	(2.24)	(1.50)	(-45.61)	-17976
NO	0.70^{***}	0.10	0.89^{***}	-15.94	4.14	-8.59^{***}	8998
	(3.77)	$(11.71)^{***}$	(92.65)	(-0.64)	(0.57)	(-37.91)	-17947
IC	0.70^{***}	0.10^{***}	0.89^{***}	-415.65^{***}	1.40^{***}	-8.10^{***}	8999
	(3.76)	(11.77)	(90.73)	(-3.13)	(2.60)	(-34.10)	-17949
MCI	0.70^{***}	0.10^{***}	0.89^{***}	-31.42	15.36	-8.54^{***}	8998
	(3.75)	(12.18)	(94.84)	(-1.07)	(0.96)	(-42.32)	-17948
CC	0.70^{***}	0.10^{***}	0.88^{***}	91.14*	6.49	-8.95^{***}	8999
	(3.74)	(11.78)	(83.50)	(1.70)	(1.49)	(-44.14)	-17948
PMI	0.70^{***}	0.10^{***}	0.88^{***}	-235.91^{**}	2.48^{**}	-7.74^{***}	9002
	(3.79)	(11.07)	(82.28)	(-2.77)	(2.49)	(-20.63)	-17955
Unemp	0.70^{***}	0.10^{***}	0.89^{***}	47.13^{*}	1.00^{***}	-8.96^{***}	8999
	(3.75)	(11.97)	(91.45)	(1.86)	(6.35)	(-40.74)	17948
Krona	0.70^{***}	0.10^{***}	0.88^{***}	555.55^{***}	1.00^{***}	-9.07^{***}	9001
	(3.76)	(11.91)	(88.72)	(3.37)	(14.04)	(-50.98)	-17953
Term Spread	0.70^{***}	0.10^{***}	0.89^{***}	443.49	47.59	-8.68^{***}	8998
	(3.75)	(12.20)	(93.88)	(0.04)	(0.02)	(-50.11)	-17946

Note: This GARCH-MIDAS model is estimated with monthly volatility of the low-frequency variables and 3 MIDAS lag years in the MIDAS filter. The estimation period covers the period from January 2002 to December 2016. The numbers in the parenthesis is t-statistics and *,**,***, denotes the significance level at 10%, 5%, and 1%. LLF is the optimal log-likelihood function value, and BIC is the Bayesian information criterion.

Turning to the model specification with realized volatility. Its estimated parameters are all significant. The slope parameter is significant at the 1% level and has as expected a positive sign meaning that an increase of realized volatility leads to an increase in long-term volatility. The estimated weight pattern gives larger weight to recent observations. It is intuitive that recent realized volatility is more important than older realized volatility. The decomposition of volatility into two components can be illustrated in figure 5.1, with the long-term component of volatility and the total volatility (conditional volatility) for the GARCH-MIDAS model with realized volatility. The long-term component based on the realized volatility seems to follow the conditional volatility to a large extent and have captured reasonable dynamics.

Figure 5.1: GARCH-MIDAS with Realized Volatility
The figure illustrates the conditional volaitlity and its long-run component estimated by the GARCH-MIDAS model with monthly fixed RV and 3 MIDAS lag years in the MIDAS filter. The estimation period covers the period from January 2002 to December 2016. Annualized scale.



The model specifications with variables other than realized volatility have their volatility components illustrated in figure A.3. It is clear from table 5.2 and 5.3 that the GARCH-MIDAS model specification with volatility estimated a fewer number of significant θ_v and ω_2 parameters for the long-term component than the GARCH-MIDAS model specification with the level of the low-frequency variables. The log-likelihood values do not differ much between the level and volatility specification for each variable, but there are more cases with higher value in the level specification compared to the volatility specification. This indicates that the level specification in general offer the best fit in terms of log-likelihood value. The great exception is the volatility of PMI that scored the highest together with the realized volatility.

The IP level has a negative parameter estimate for $\theta_{l,}$ but only at the 10% significance level. Hence, an increase in industrial production decreases stock market volatility. The parameter of IP volatility θ_v has a positive impact with significance at the 10% level, meaning that increased uncertainty of IP increases the stock market volatility. Both signs of θ_l and θ_v are similar to the finding in Engle, Ghysels and Sohn (2008) and follows the countercyclical pattern reported by the past literature.

The level of PPI has at the 1% level a positive slope parameter θ_l equal to 163.58. Hence, an increase in PPI level increases stock market volatility. The parameter ω_2 is also highly significant and equal to 1.012 and this puts 0.0289 on the first lag of PPI level. The marginal effect of a 1% increase in the low-frequency variable (at time t-k) on the stock market volatility (at time t) can be calculated as in Engle, Ghysels and Sohn (2008):

$$e^{\theta * \varphi_k(\omega)} - 1 \approx \tag{5.1}$$

Where the parameter estimates for θ_l in table 5.2 are first rescaled by multiplication of 10^{-2} before entering the computation to make the variable represented in percentage unit. In the case with PPI, the parameter estimate θ_l is equal to -1.6358 after being rescaled. The computation in equation (5.1) finds that an increase of 1% of PPI level during the current month would increase the next month long-term Swedish stock market volatility by 4.84%. The parameter θ_v shows that the volatility of PPI impacts stock market volatility positively at the 1% significance level. The relationship between PPI and stock market volatility are consistent with the findings in Engle, Ghysels and Sohn (2008).

Neither the level nor the volatility of new orders appear to have any impact on stock market volatility and this is illustrated in figure A.4.c.

The two confidence indictors IC and MCI have both similar results for the level specification with significant positive slope parameter estimates for θ_l and ω_2**.** The optimal weighting function for IC is characterized by a significant ω_2 =1.06, which results in a slowly decaying weighting pattern illustrated in figure A.3.e. The increase of 1% of IC level during the current month would increase the next month long-term Swedish stock market volatility by 1.25%. For the MCI the increase of 1% of MCI level during the current month would increase the next month long-term Swedish stock market volatility by 1.47%. The positive relationship for MCI and IC on volatility is not expected. If the indicators are proxies for near-term and forward-looking business conditions such as future spending and capital investments, an increase in the positive outlook should not increase volatility.

The IC volatility θ_v has a significant negative impact on stock market volatility and the parameter estimate ω_2 = 1.397 gives a more rapidly decaying weighing pattern than the level specification and thus the older observations of IC volatility is of less importance relative to older level observations of IC. The IC uncertainty matters most near-term in terms of the economic impact on stock market volatility. The MCI has on the other hand, insignificant results for the slope parameter $\theta_{v.}$ The third confidence indicator, CC, has in contrast to the IC and MCI, a negative θ_l at the 10% significance level indicating that a rise in CC level decrease stock market volatility. Conrad and Loch (2015) found the same negative relationship but for consumer sentiment in the U.S. The CC volatility parameter θ_v has at the 10% significance level a positively impact on stock market volatility.

PMI has a positive significant estimate for θ_l and an increase of PMI level by 1% during the current month increases next month stock market volatility by 1.28%. This result appears to be counterintuitive. If the increase of PMI is supposed to be signaling either an expansion or movement toward an expansion of the business cycle, then the PMI should have a negative impact on volatility. The volatility of PMI has a significant negative impact on stock market volatility. This is also counterintuitive as it implies that the uncertainty of the business cycle decreases stock market volatility instead of increasing it.

Unemployment level has a significant and negative $\theta_{l.}$ This is the opposite of the findings in Conrad and Loch (2015). The increase of Unemployment is associated with a lower stock market volatility. The volatility of unemployment increases stock market volatility at the 10% significance level. The unexpected sign of the slope parameter for the level, θ_l, may be explained by McQueen and Roley (1993) and their finding that “good news” about economic activity when the economy is strong will be negative for the stock market as this will increase discount rates relative to expected cash flows. In this spirit, Boyd, Hu and Jagannathan and Hu (2005) found that surprisingly high unemployment raises stock prices during an economic expansion and lowers them during a contraction.

The positive sign on the slope parameter for the level of Krona implies that the deprecation of the currency increases stock market volatility. The volatility in the currency increases stock market volatility and is similar to the findings in Kennedy and Nouzrad (2016) for the USD volatility and the U.S. stock return volatility.

The level of the term spread has a negative slope parameter indicating that when the yield on the 3-month government bond and 10-year government bond moves further away, the stock market decreases. This relationship is consistent to the findings in Conrad and Loch (2015) and illustrates the term spread's role as a leading indicator for the business cycle. The volatility of the term spread has an insignificant impact on the stock market volatility.

The assessment of how much each one of variables contributes to the total expected volatility can be found in table 5.4. The variance ratios suggest that the long-term component based on realized volatility contributes with 30% of the total volatility and thus is the best model in terms of variance ratios. Among the low-frequency variables on the level specification, the three best variables are the PPI, unemployment, and the term spread with contributions of 11.3%, 11.1% and 10.7% respective to the total volatility. These three variables have in common a highly significant slope parameter taking the expected sign, except for unemployment taking the opposite sign for the slope parameter. The three best variables for the volatility specification are PMI, Krona, and IC with contributions of 12.5%, 9.4%, and 9.3% respective to total volatility. The three variables have a significant slope parameter, but only the Krona has the expected sign on the slope parameter. The results show that there is room for improvement of explaining Swedish stock market volatility with variables other than realized volatility.

Table 5.4: Variance Ratios

Level-Variable	Variance Ratio % (Level)	Variance Ratio % (Volatility)
RV	30.03	
IP	8.46	4.0
PPI	11.34	4.17
New Orders	0.26	1.18
Industrial Confidence	6.44	9.29
Consumer Confidence	9.88	8.01
PMI	7.77	12.53
MCI	6.49	1.71
Unemployment	11.14	2.46
Krona	4.31	9.41
Term Spread	10.67	0.00

Note: The table show the variance ratios measured in percent.

6. Conclusion

The research objective of this thesis was to investigate the sources of Swedish Stock market volatility. I have used the GARCH-MIDAS approach to estimate the long-term component of Swedish stock market volatility using information from macroeconomic variables, sentimental indicators and financial variables. This includes both the level and volatility of the industrial production index, producer price index, new orders, industrial confidence, manufacturing confidence, consumer confidence, purchasing manager's index, unemployment, exchange rate, and the term spread. The model has the main advantage that it can link the information from high-frequency data of daily returns from the OMXSB index with the information from the low-frequency economic variables directly into one single model without information loss resulting from data aggregation or estimation in steps. Hence, I have contributed by investigating possible determinants of Swedish stock market volatility for the period January 2002 to December 2016.

The main findings can be summarized as follow. First, the realized volatility is the variable that, in terms of variance ratios, contributes the most to the total expected volatility, explaining 30% of it. The realized volatility has a positive impact on Swedish stock market volatility, so that a period of increased realized volatility is followed by a period of increased volatility. Second, the low-frequency variables do contain information that affect volatility, although some of them did not have the expected effect. Third, in terms of the level specification of the variables, the three best variables are the PPI, unemployment, and the term spread with contributions of 11.3%, 11.1% and 10.7% respective to the total volatility. Fourth, the three best variables for the volatility specification are the PMI, Krona, and IC with contributions of 12.5%, 9.4%, and 9.3% respective to the total volatility. The three variables have significant slope parameters, but only the Krona has the expected sign on it. We might conclude that the variables do contain some information about the driving force of Swedish stock market volatility.

The recent financial crisis has highlighted the need for a better understanding of the relationship between macroeconomic conditions and stock market volatility. Knowledge of how volatility responds to changes in macroeconomic conditions proxied by various variables can then prove to be useful. Suggestions for further research could be to include the absolute returns, testing the forecasting ability of each model specification, and examining subsamples with perhaps fewer MIDAS lag years in the estimation and study the post-crisis period better. It could also be of interest to investigate if the economic variables tested in this thesis are determinants of the Swedish stock-bond correlation using the DCC-MIDAS specification.

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Appendix

Table A.1: Summary Statistics for Daily Stock Return, Monthly Realized Volatility, and Monthly Factor-Level Variables

Variable	Obs	Mean	Median	Max	Min	STD	Skewness	Kurtosis	JB p-val
Daily Stock Returns	3767	0.00018	0.00059	0.09166	-0.08447	0.01417	-0.027	7.239	0.000
Realized volatility	180	0.00420	0.00238	0.04278	0.00036	0.00528	3.617	21.257	0.000
IP	180	0.00042	-0.00206	0.11962	-0.10203	0.04147	0.107	2.769	0.689
PPI	180	0.00123	0.00129	0.01785	-0.02123	0.00610	-0.053	3.898	0.047
NO	180	0.00028	0.00088	0.16084	-0.20992	0.04298	-0.051	7.508	0.000
IC	180	0.00128	0.00285	0.08766	-0.14155	0.03067	-0.436	5.624	0.000
CC	180	0.00009	0.00278	0.10697	-0.15015	0.00369	-0.479	4.510	0.000
PMI	180	0.00118	0.00196	0.14463	-0.16403	0.04569	-0.139	3.592	0.201
MCI	180	0.00165	0.00212	0.14805	-0.11965	0.04432	0.112	3.159	0.754
Unemp	180	0.00087	0.00000	0.13193	-0.10677	0.04506	0.303	3.201	0.217
Krona	180	-0.00020	0.00058	0.07658	-0.07365	0.01750	0.029	6.160	0.000
Term Spread	180	0.01340	0.01294	0.0331	-0.00621	0.00818	0.354	2.861	0.142

Note: The daily log OMXSB return data is from 2002.01.02-2016.12.30 and the low-frequency variables are from 2002.01-2016.12. The JB p-val is the p-value for Jarque–Bera test for normality.

Table A.2: Summary Statistics for Monthly Factor-Volatility Variables

Variable	Obs	Mean	Median	Max	Min	STD	Skewness	Kurtosis	JB p-val
IP	180	0.005297	0.002945	0.048958	0.000000029	0.00702	2.612	12.478	0.00
PPI	180	0.000061	0.000023	0.001527	0.0000000017	0.00013	7.892	84.097	0.00
NO	180	0.005253	0.001297	0.12619	0.000000447	0.01433	5.869	42.461	0.00
IC	180	0.001476	0.000646	0.01429	0.00000000001	0.00217	2.852	13.40	0.00
CC	180	0.002812	0.00094	0.03269	0.00000251	0.00531	4.020	21.29	0.00
PMI	180	0.004075	0.00195	0.023907	0.000000301	0.00526	1.9917	6.93	0.00
MCI	180	0.004463	0.002143	0.03808	0.000000477	0.00605	2.4321	10.669	0.00
Unemp	180	0.005800	0.00206	0.03676	0.0	0.007845	1.8705	6.36	0.00
Krona	180	0.00636	0.000205	0.02257	0.00000000148	0.001835	9.787	115.14	0.00
Term Spread	180	0.0000061	0.0000021	0.000105	0.0	0.0000121	5.139	35.97	0.00

For 2002.01.02 – 2016.12.30. The null hypothesis of the Jarque-Bera test is that a series is normally distributed. The JB p-val is the p-value for Jarque–Bera test for normality.

Table A.3: Correlation Between the Variables

	RV	IP	PPI	NO	IC	CC	PMI	MCI	Unemp	Krona	Term Spread
RV	1										
IP	-0.06	1									
PPI	-0.01	-0.02	1								
NO	-0.14	0.09	0.08	1							
IC	-0.36	-0.03	0.06	0.11	1						
CC	-0.22	-0.00	-0.07	-0.09	0.24	1					
PMI	-0.24	-0.04	-0.07	0.18	0.26	0.13	1				
MCI	-0.19	-0.12	0.01	0.05	0.71	0.18	0.11	1			
Unemp	0.09	-0.12	0.01	0.013	-0.06	-0.03	-0.05	0.00	1		
Krona	0.19	-0.08	0.39	0.028	-0.26	-0.04	-0.06	-0.21	0.08	1	
Term Spread	-0.27	0.08	-0.02	0.103	0.40	0.22	0.29	0.25	0.01	-0.20	1

Note: The table show the correlation between the monthly realized volatility of the stock returns (RV) and the level of the monthly low-frequency variables. Data cover the period from January 2002 to December 2016

Table A.4: Unit Root Test – Augmented Dickey-Fuller Test (ADF)

	ADF Test Statistic (Constant)	ADF Test Statistic (Constant and Trend)
Daily Stock Returns	-62.02***	62.018***
Realized Volatility	-5.72***	-5.75***
IP	-8.11***	-8.10***
PPI	-11.11***	-11.12***
NO	-20.94***	-20.88***
IC	-10.73***	-10.70***
CC	-13.71***	-13.67***
PMI	-13.21***	-13.18***
MCI	-15.37***	-15.33***
Unemp	-4.28***	-4.40***
Krona	-13.98***	-14.03***
Term spread	-3.13**	-3.18**

Note: The table show the test-statistics for the level of the low-frequency variables.
*,**,***, denotes rejection of the null hypothesis at the 10%, 5%, and 1% significance level.
The null hypothesis of the Augmented Dickey-Fuller test is that a series have a unit root (non-stationary process).

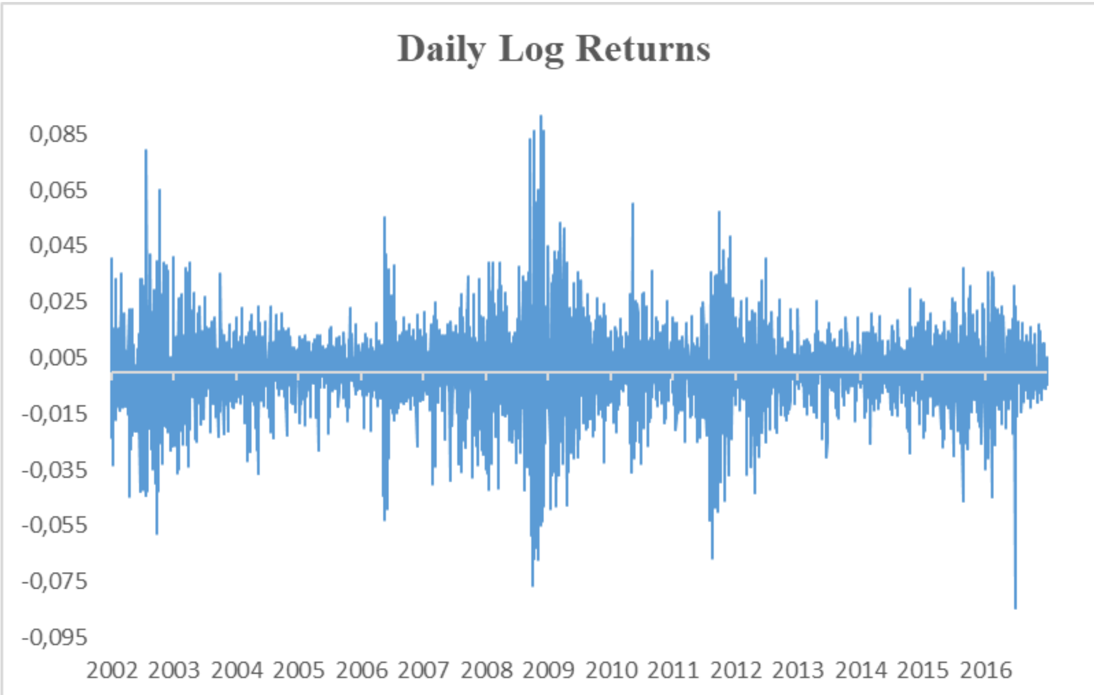
Table A.5: Unit Root Test – Augmented Dickey-Fuller Test (ADF) – Volatility

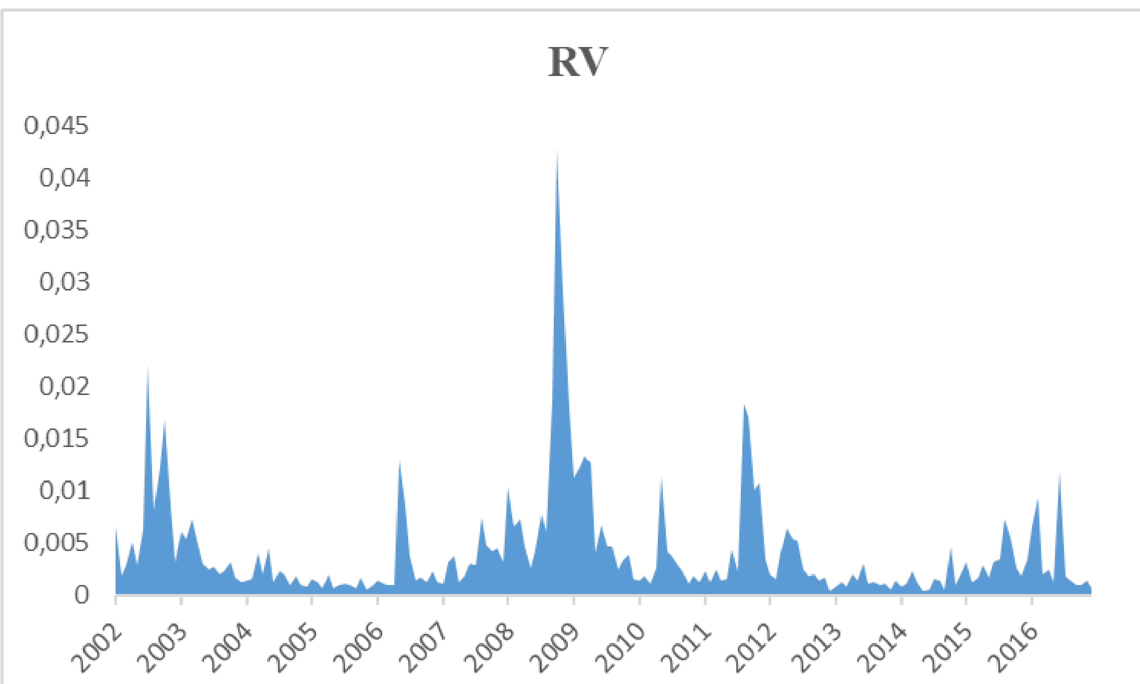
	ADF Test Statistic (Constant)	ADF Test Statistic (Constant and Trend)
IP	-6.20-***	-6.20***
PPI	-9.21***	-9.33***
NO	-8.40***	-8.65***
IC	-8.63***	-9.08***
CC	-10.23***	-10.24***
PMI	-9.08***	-9.09***
MCI	-10.39***	-10.36***
Unemp	-9.12***	-9.25***
Krona	-9.93***	-9.91***
Term spread	-5.13***	-5.14***

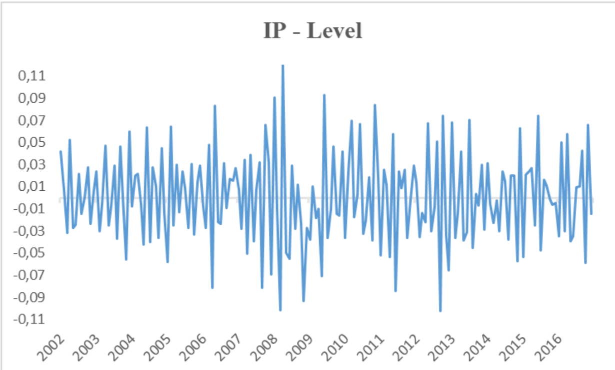
Note: The table show the test-statistics for the volatility of the low-frequency variables.
*,**,***, denotes rejection of the null hypothesis at the 10%, 5%, and 1% significance level.
The null hypothesis of the Augmented Dickey-Fuller test is that a series have a unit root (non-stationary process).

Figure A.1: Graphical illustration of OMXSPI, OMXS30 and OMXSB Price Index.

Figure A.2: Plot of Daily Log Returns, Monthly RV, and the Economic Variables
These figures show the daily stock returns of the OMXSB index, monthly realized volatility, and the monthly level and volatility of the economic variables described in section 3. The data range from January 2002 to December 2016.






IP - Level
0,11
0,09
0,07
0,05
0,03
0,01
-0,01
-0,03
-0,05
-0,07
-0,09
-0,11
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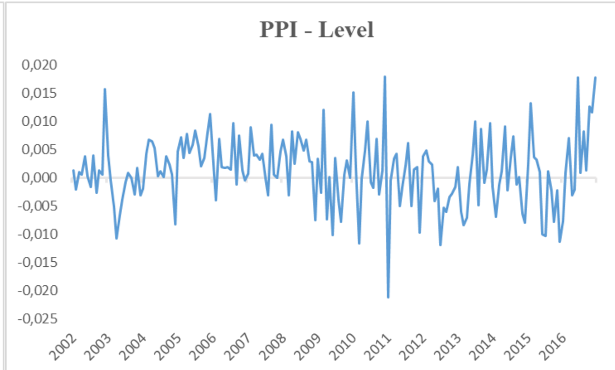
2014
2015
2016


PPI - Level
0,020
0,015
0,010
0,005
0,000
-0,005
-0,010
-0,015
-0,020
-0,025
2002
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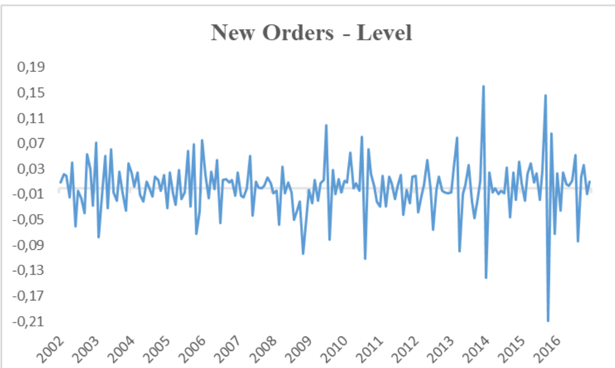
New Orders - Level
0,19
0,15
0,11
0,07
0,03
-0,01
-0,05
-0,09
-0,13
-0,17
-0,21
2002
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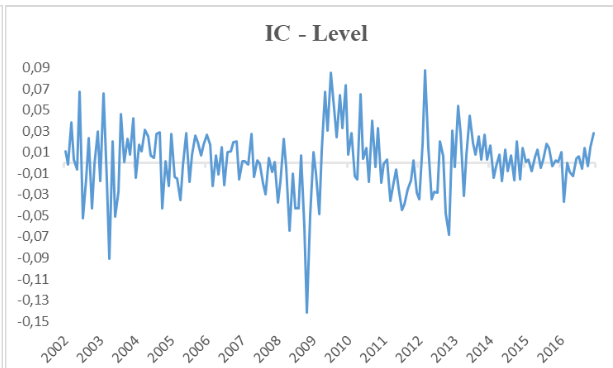
IC - Level
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0,07
0,05
0,03
0,01
-0,01
-0,03
-0,05
-0,07
-0,09
-0,11
-0,13
-0,15
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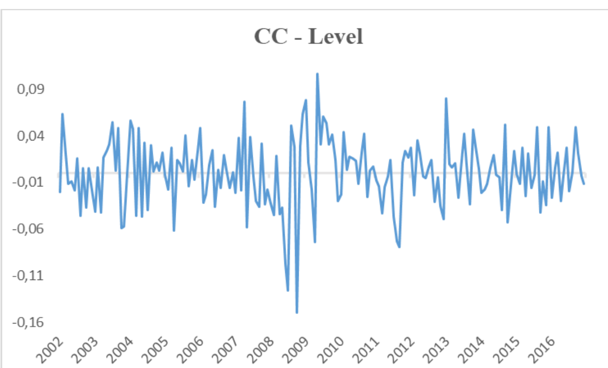
2016


CC - Level
0,09
0,04
-0,01
-0,06
-0,11
-0,16
2002
2003
2004
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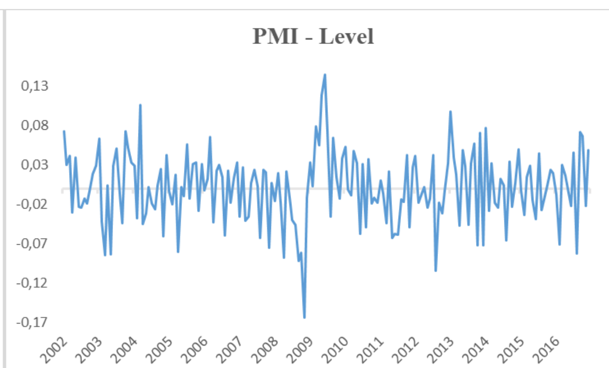
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016


PMI - Level
0,13
0,08
0,03
-0,02
-0,07
-0,12
-0,17
2002
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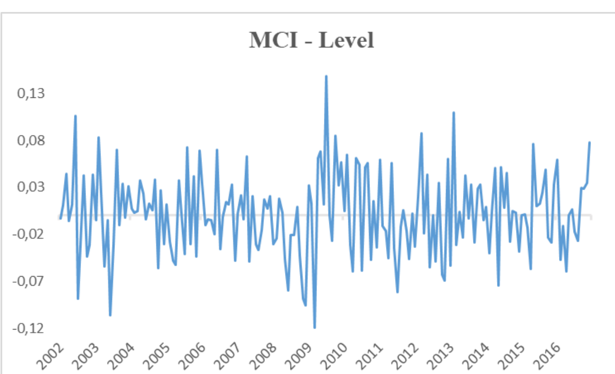
2016


MCI - Level
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0,08
0,03
-0,02
-0,07
-0,12
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2009
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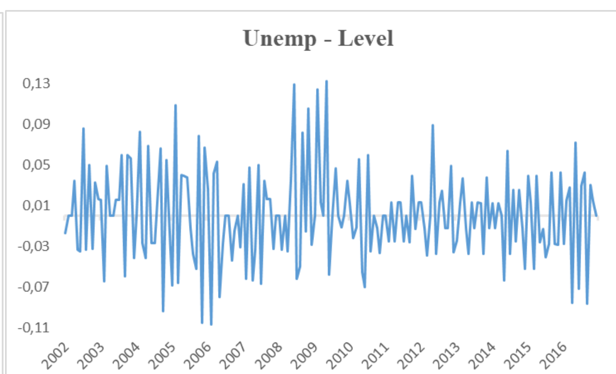
Unemp - Level
0,13
0,09
0,05
0,01
-0,03
-0,07
-0,11
2002
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2007
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2009
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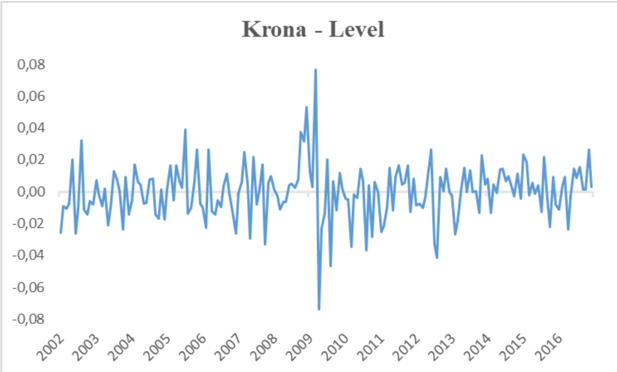
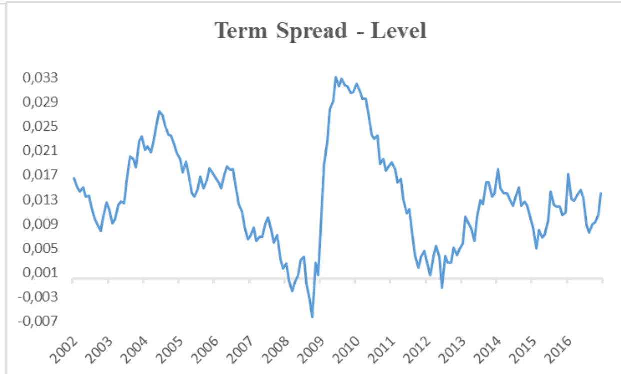
2014
2015
2016


Krona - Level
0,08
0,06
0,04
0,02
0,00
-0,02
-0,04
-0,06
-0,08
2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016


Term Spread - Level
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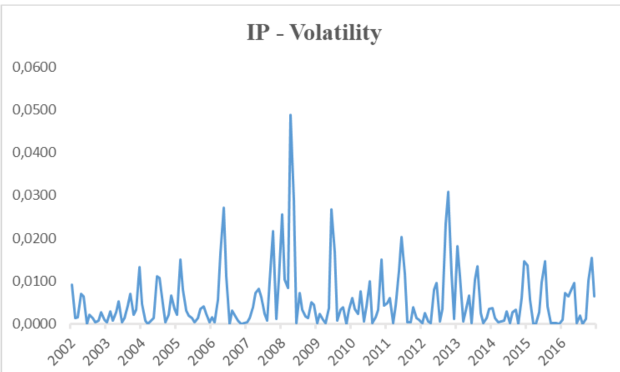
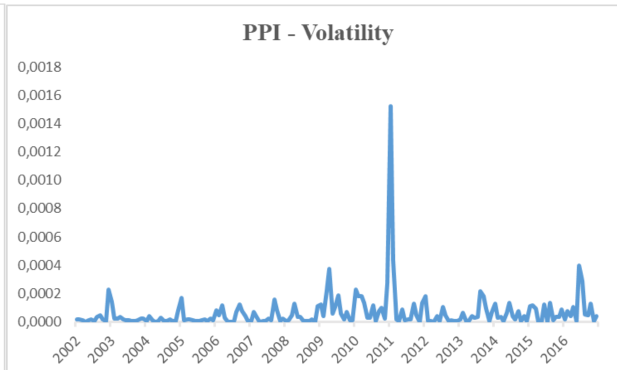
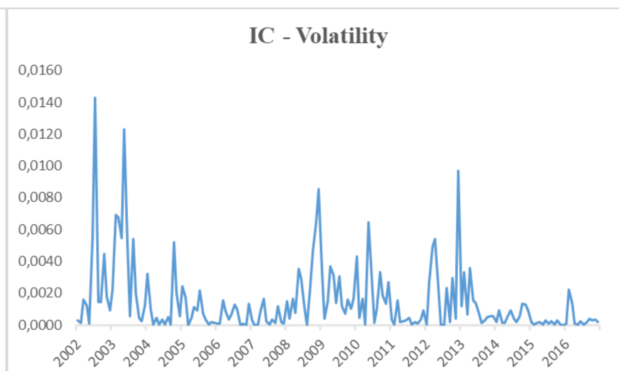
0,029
0,025
0,021
0,017
0,013
0,009
0,005
0,001
-0,003
-0,007
2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016


IP - Volatility
0,0600
0,0500
0,0400
0,0300
0,0200
0,0100
0,0000
2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016


PPI - Volatility
0,0018
0,0016
0,0014
0,0012
0,0010
0,0008
0,0006
0,0004
0,0002
0,0000
2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016


New Orders - Volatility
0,14
0,13
0,12
0,11
0,10
0,09
0,08
0,07
0,06
0,05
0,04
0,03
0,02
0,01
0,00
2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016


IC - Volatility
0,0160
0,0140
0,0120
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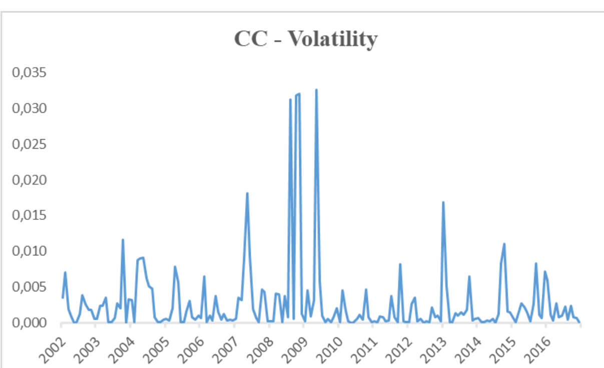
0,0080
0,0060
0,0040
0,0020
0,0000
2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016


CC - Volatility
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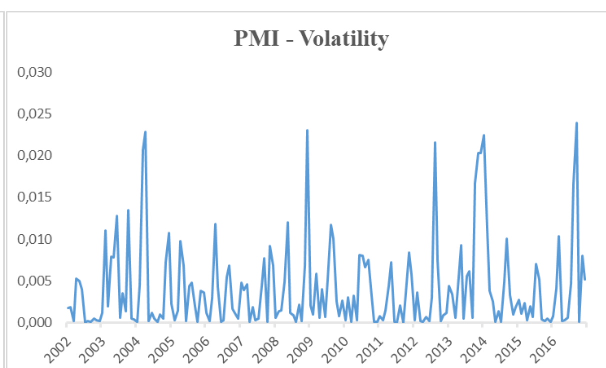
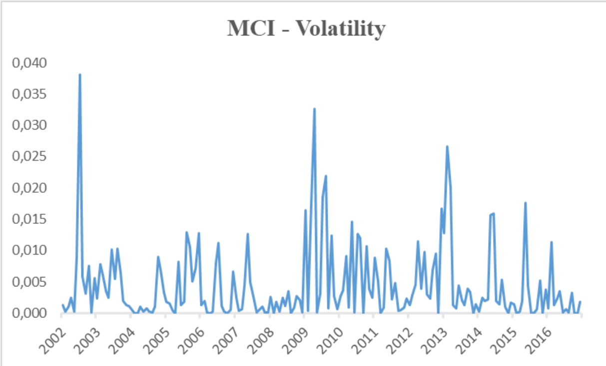
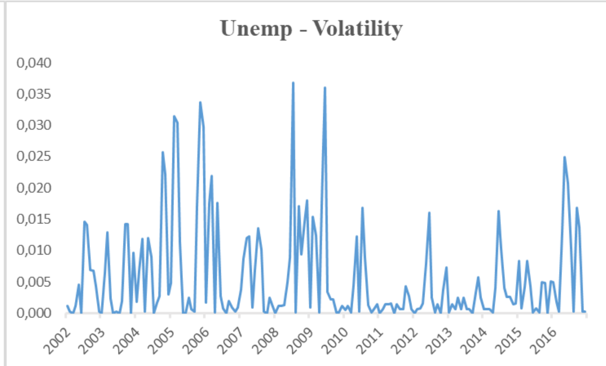
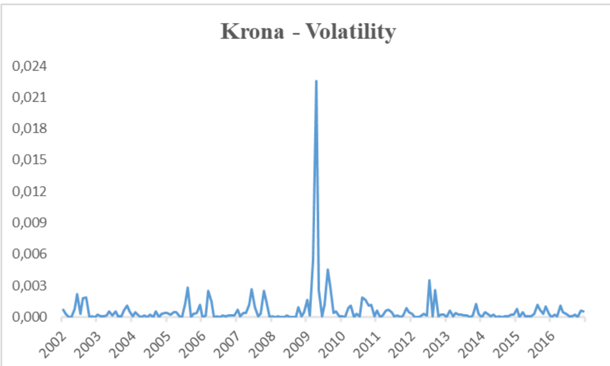
0,025
0,020
0,015
0,010
0,005
0,000
2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016


PMI - Volatility
0,030
0,025
0,020
0,015
0,010
0,005
0,000
2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016


MCI - Volatility
0,040
0,035
0,030
0,025
0,020
0,015
0,010
0,005
0,000
2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016


Unemp - Volatility
0,040
0,035
0,030
0,025
0,020
0,015
0,010
0,005
0,000
2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016


Krona - Volatility
0,024
0,021
0,018
0,015
0,012
0,009
0,006
0,003
0,000
2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016

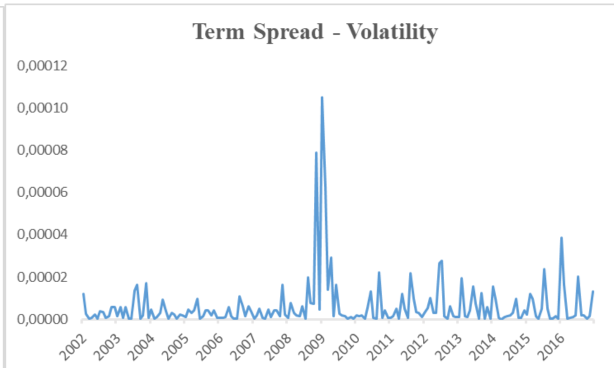

Term Spread - Volatility
0,00012
0,00010
0,00008
0,00006
0,00004
0,00002
0,00000
2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016

Figure A.3: Optimal Weighting Functions of Selected Models

These figures illustrate the estimated optimal lag weights of GARCH-MIDAS models with monthly data of selected low-frequency variables and 36 lags in the MIDAS filter. The horizontal axis shows lag period in months and the vertical axis depicts the weights.

Figure A.3.a: RV

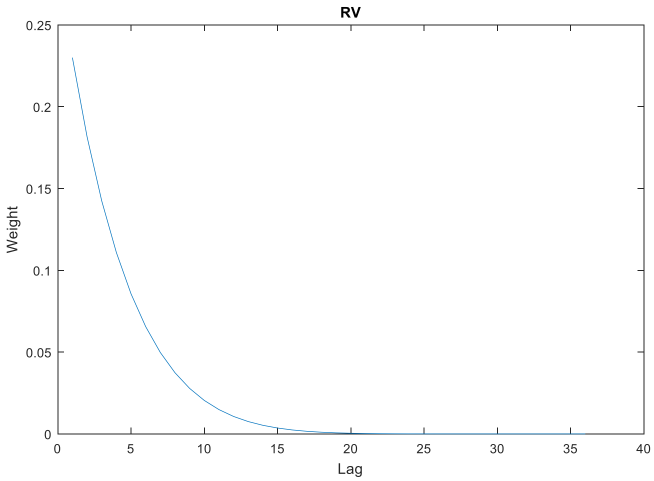


Figure A.3.b: IP level

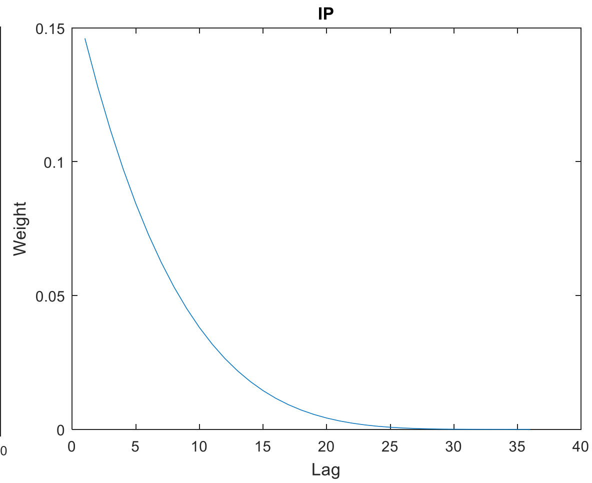


Figure A.3.c: PPI level

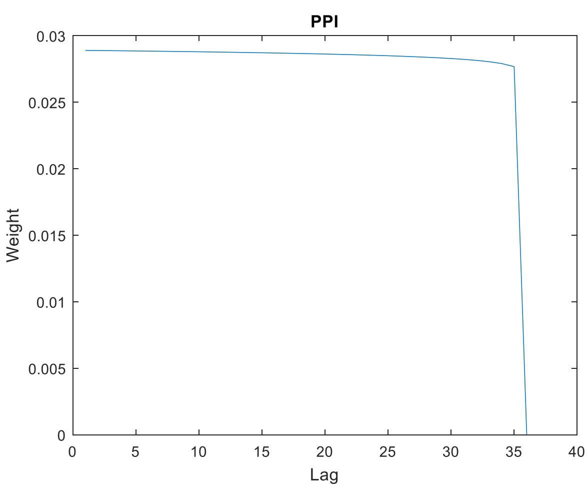


Figure A.3.d: NO level

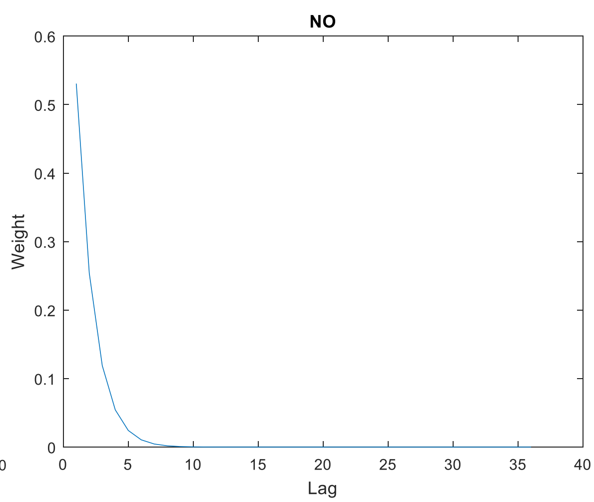


Figure A.3.e: IC level

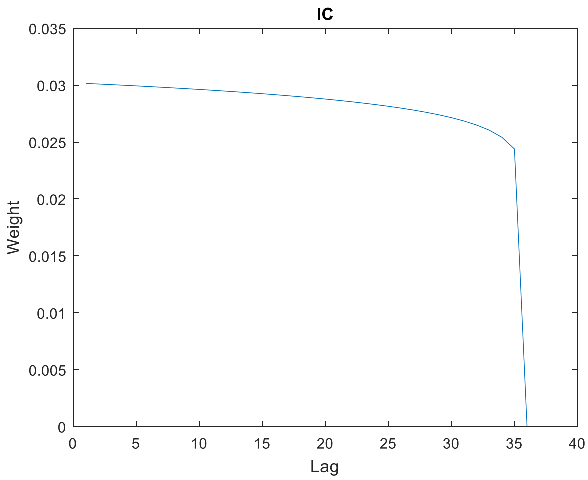


Figure A.3.f: MCI level

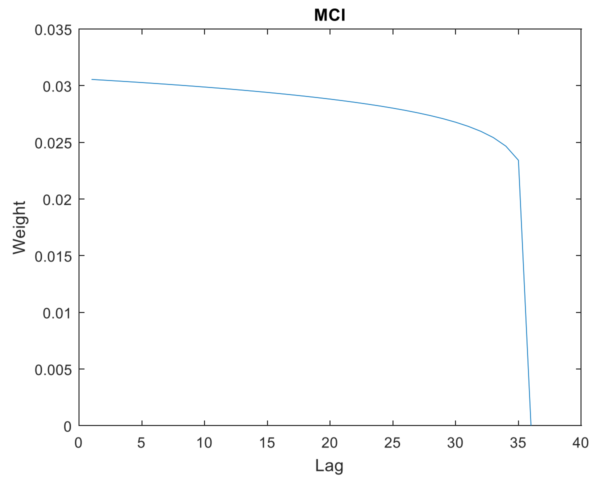


Figure A.3.g CC level

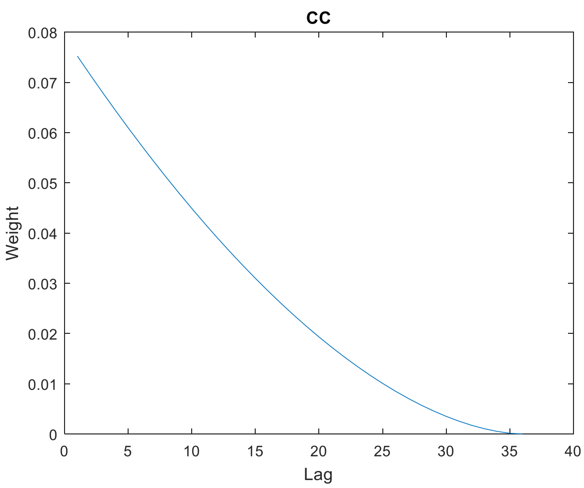


Figure A.3.h: PMI level

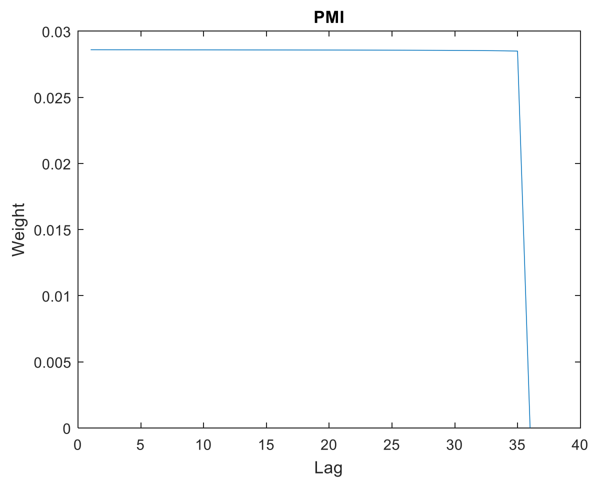


Figure A.3.i: Unemp level

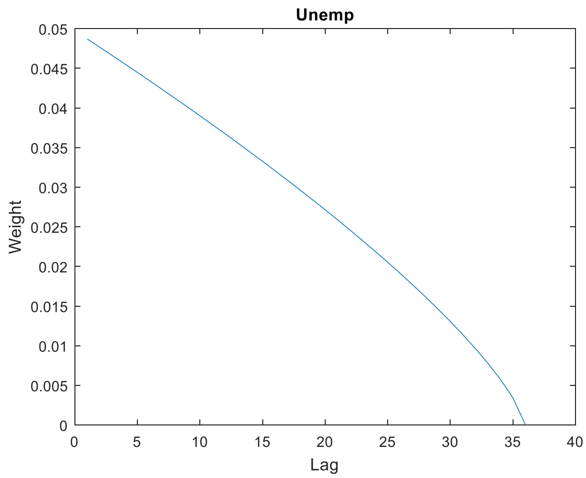


Figure A.3.j: Krona level

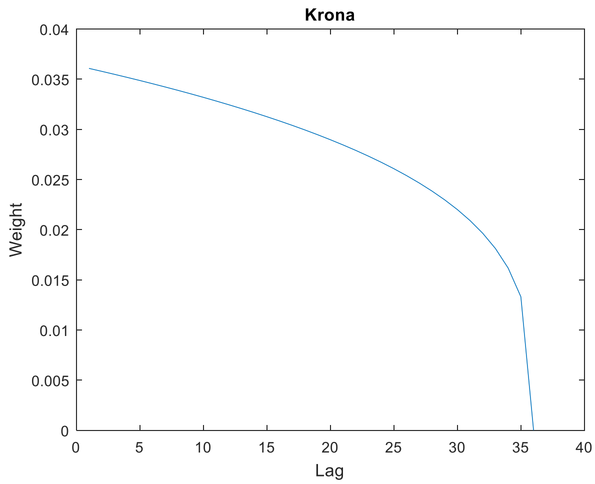


Figure A.3.k: Term Spread level

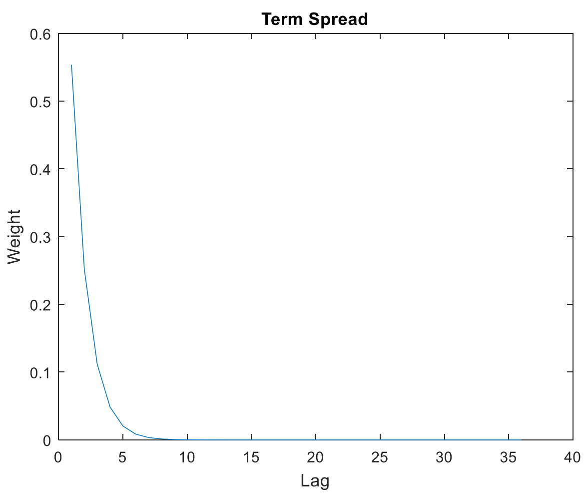


Figure A.3.L: IP Volatility

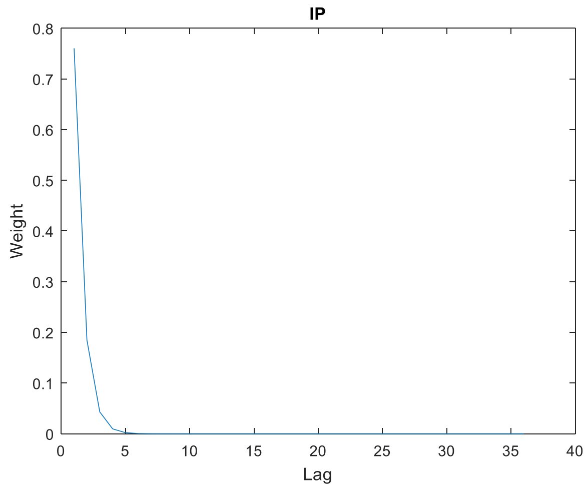


Figure A.3.m: PPI Volatility

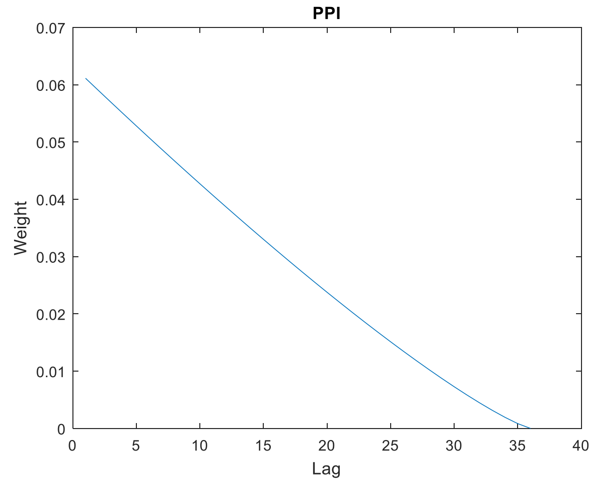


Figure A.3.n: NO Volatility

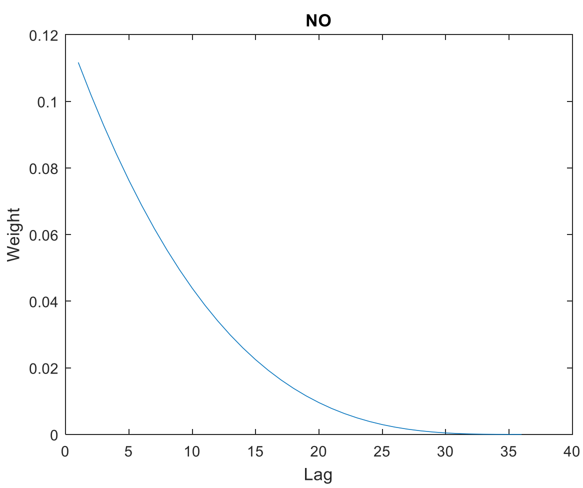


Figure A.3.o: IC Volatility

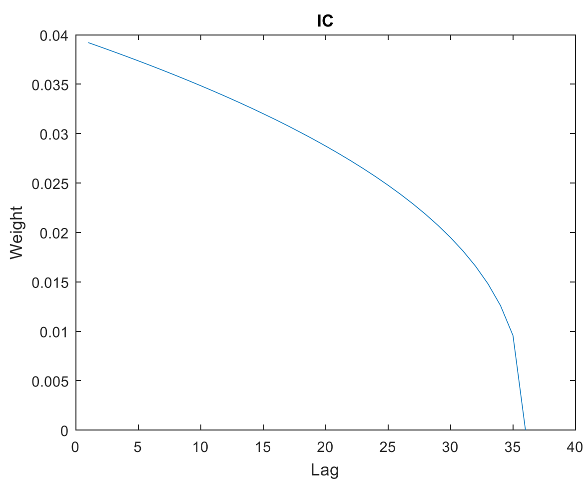


Figure A.3.p: CC Volatility

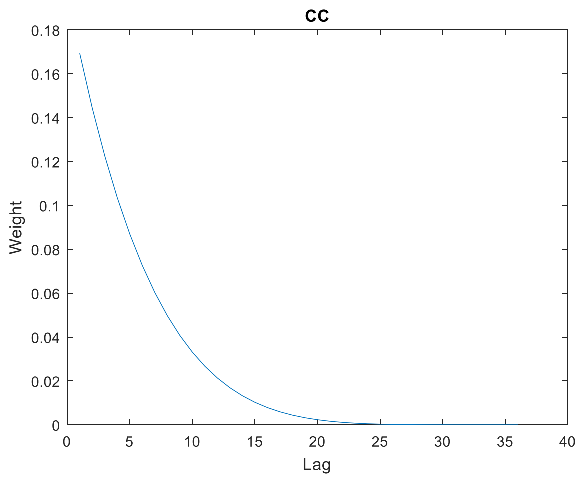


Figure A.3.q: PMI Volatility

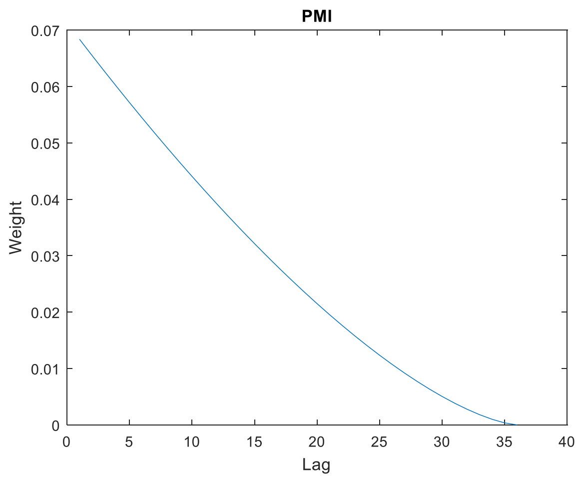


Figure A.3.r: Unemp Volatility

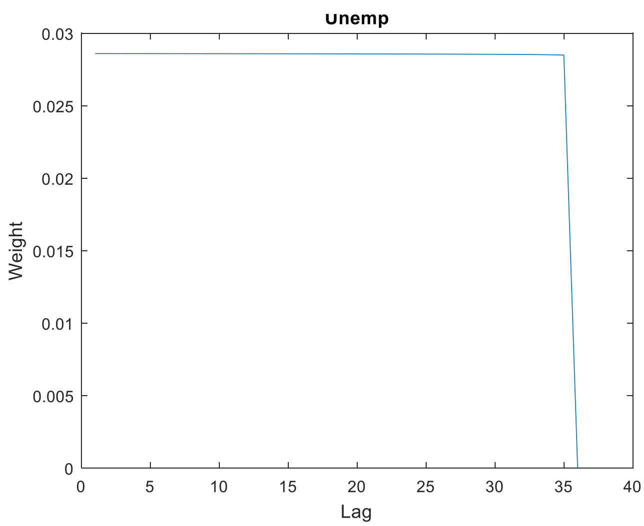


Figure A.3.s: Krona Volatility

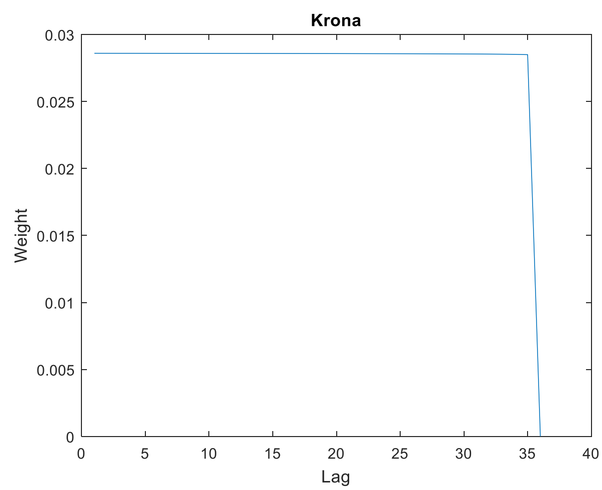


Figure A.4: GARCH-MIDAS with Low-Frequency Variables

The figures illustrate the conditional volaitlity and its long-run component estimated by the GARCH-MIDAS model with the level or volatility of the low-frequency varibales and 3 MIDAS lag years in the MIDAS filter. The estimation period covers the period from January 2002 to December 2016. Annualized scale.

Figure A.4.a: GARCH-MIDAS with IP (level)

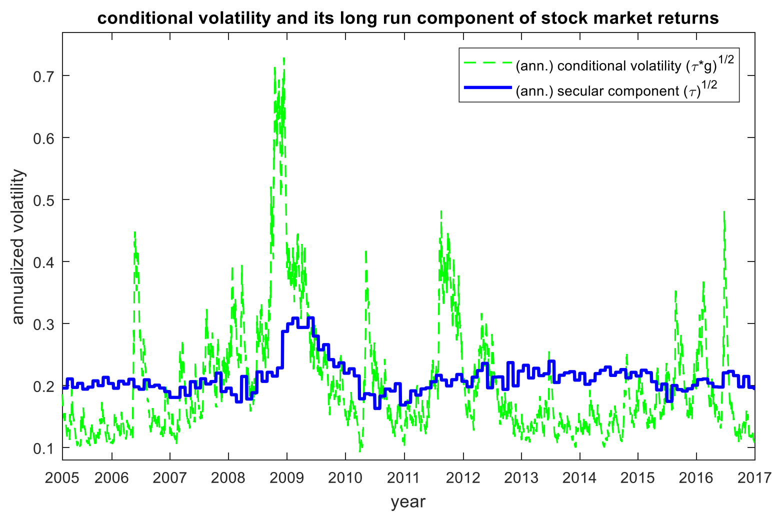


Figure A.4.b: GARCH-MIDAS with PPI (level)

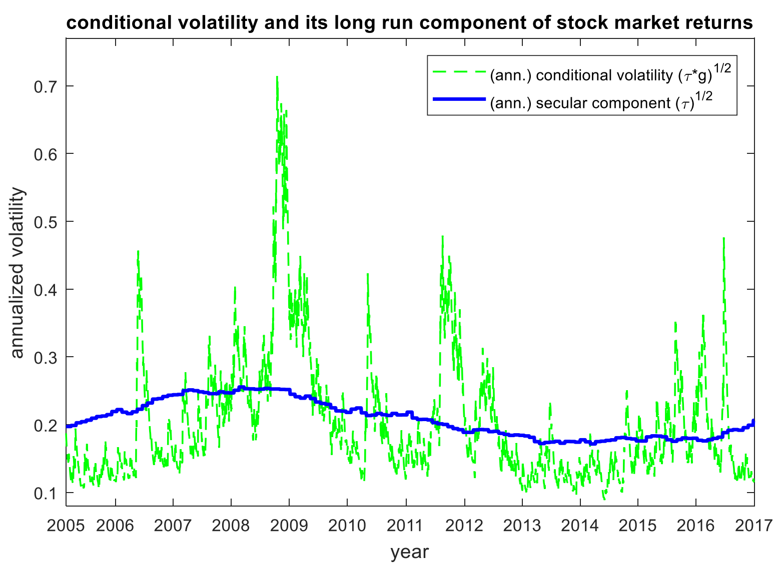


Figure A.4.c: GARCH-MIDAS with NO (level)

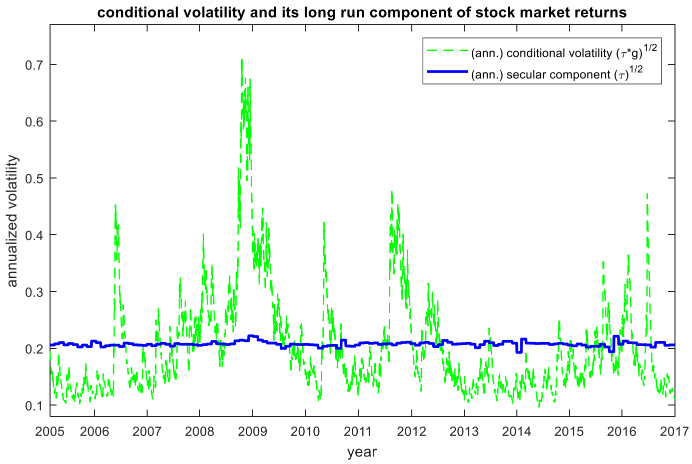


Figure A.4.d: GARCH-MIDAS with IC (level)

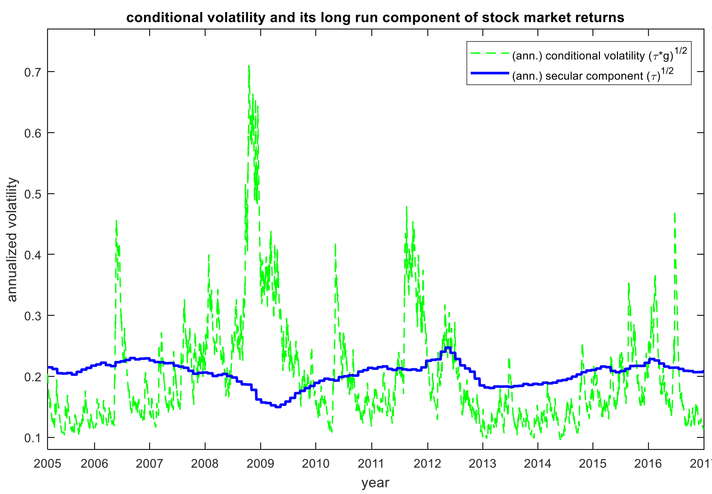


Figure A.4.e: GARCH-MIDAS with MCI (level)

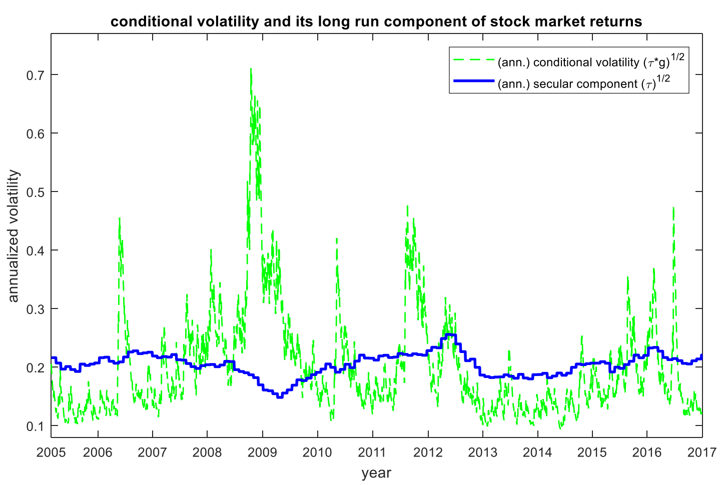


Figure A.4.f: GARCH-MIDAS with CC (level)

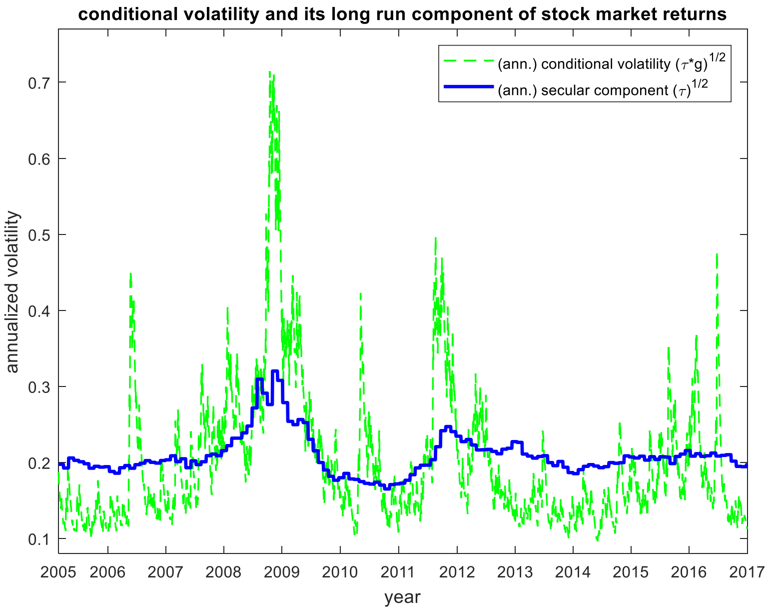


Figure A.4.g: GARCH-MIDAS with PMI (level)

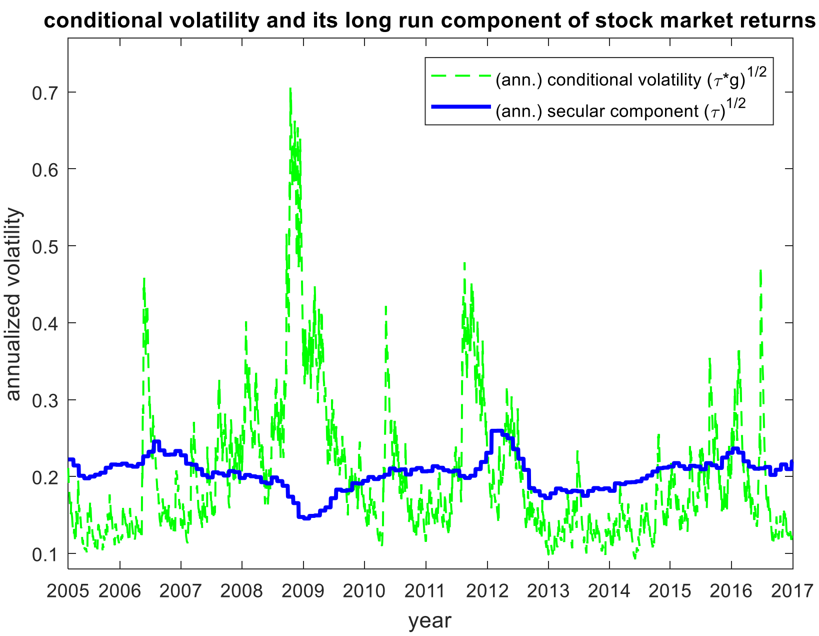


Figure A.4.h: GARCH-MIDAS with Unemp (level)

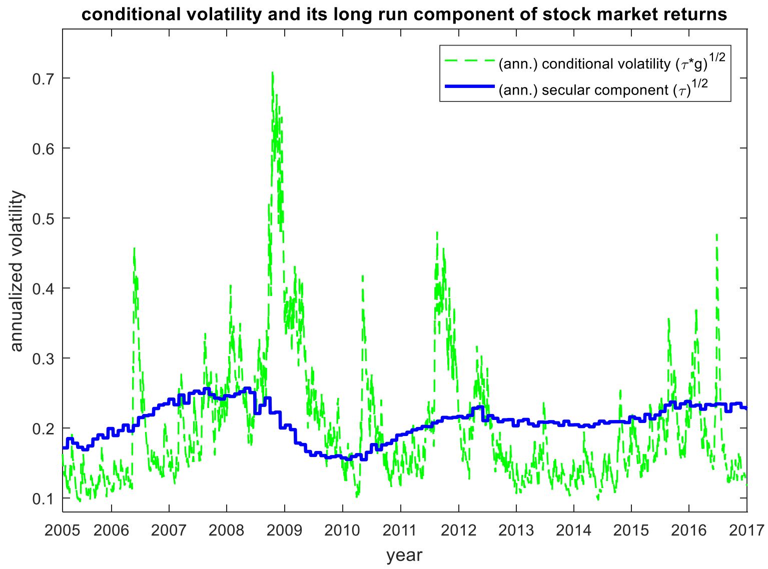


Figure A.4.i: GARCH-MIDAS with Krona (level)

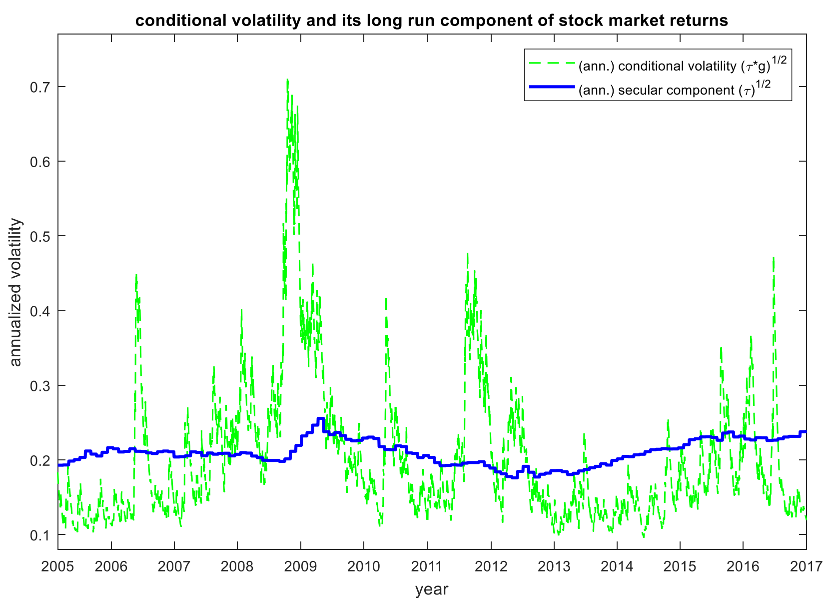


Figure A.4.j: GARCH-MIDAS with Term Spread (level)

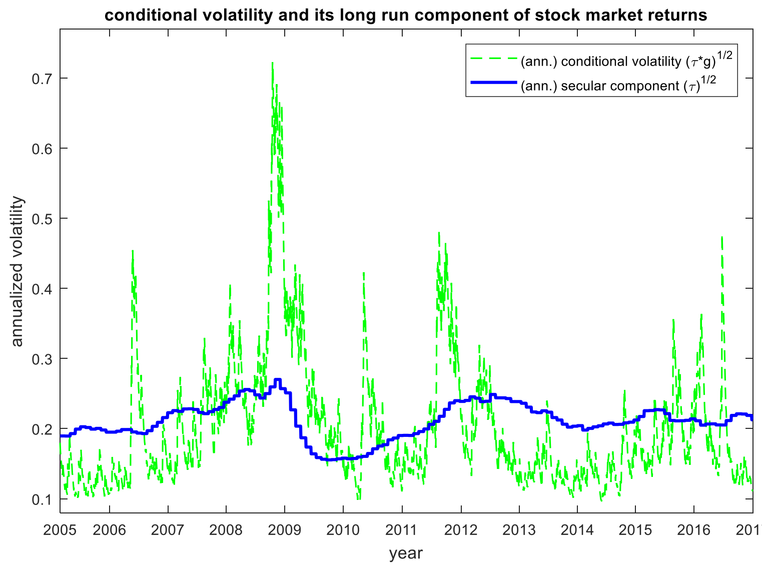


Figure A.4.k: GARCH-MIDAS with IP (Volatility)

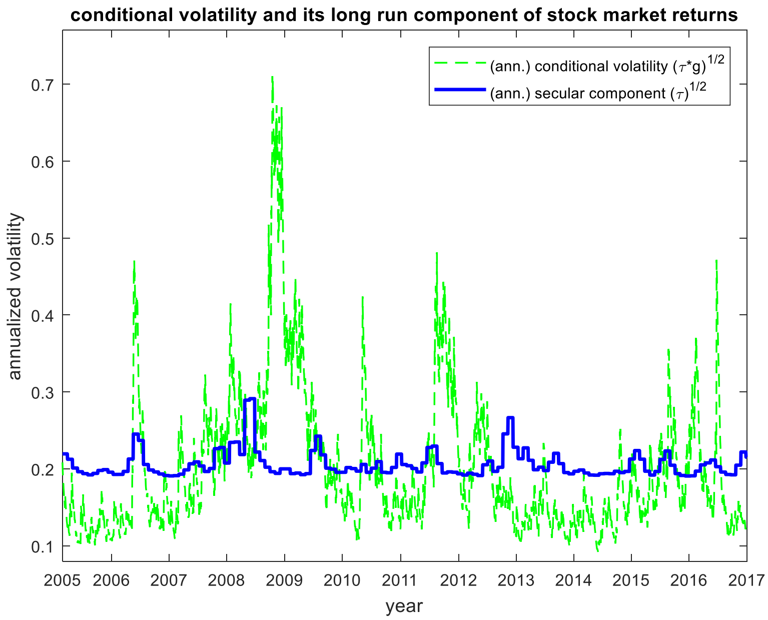


Figure A.4.l: GARCH-MIDAS with PPI (Volatility)

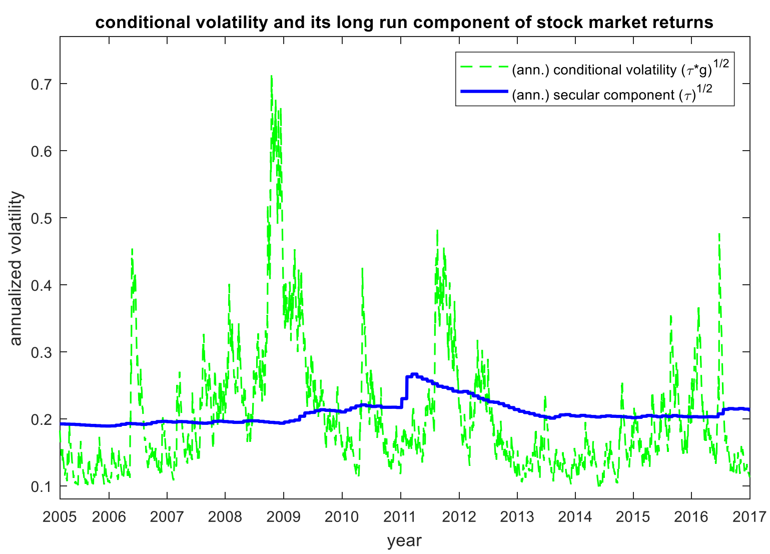


Figure A.4.m: GARCH-MIDAS with NO (Volatility)

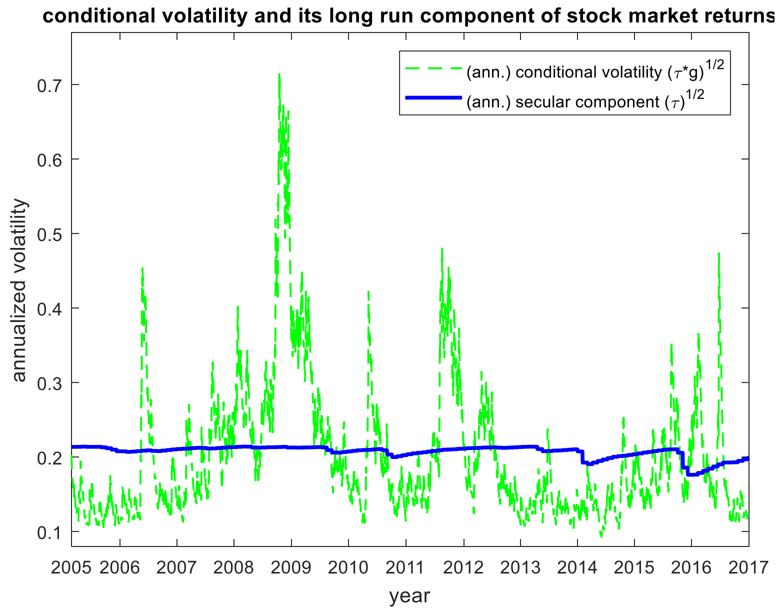


Figure A.4.n: GARCH-MIDAS with IC (Volatility)

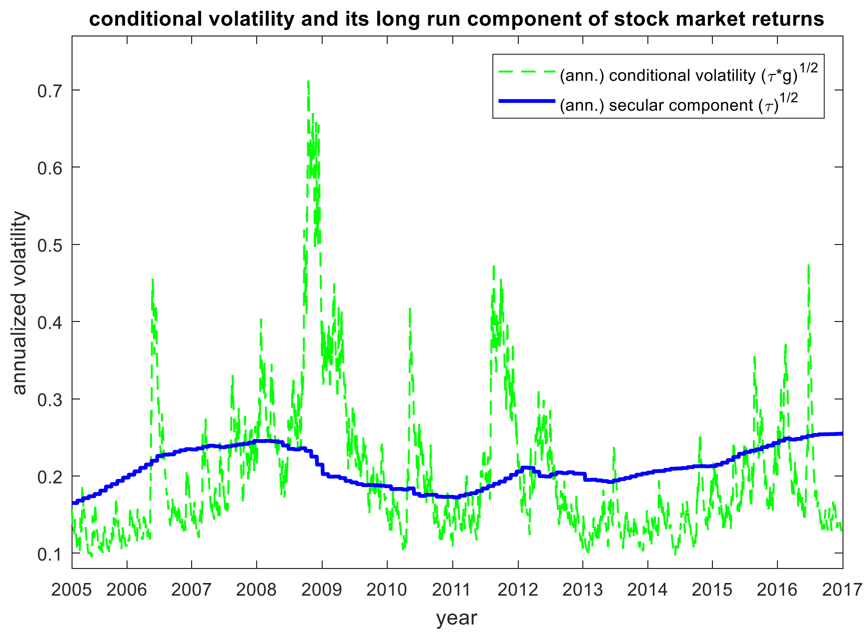


Figure A.4.o: GARCH-MIDAS with MCI (Volatility)

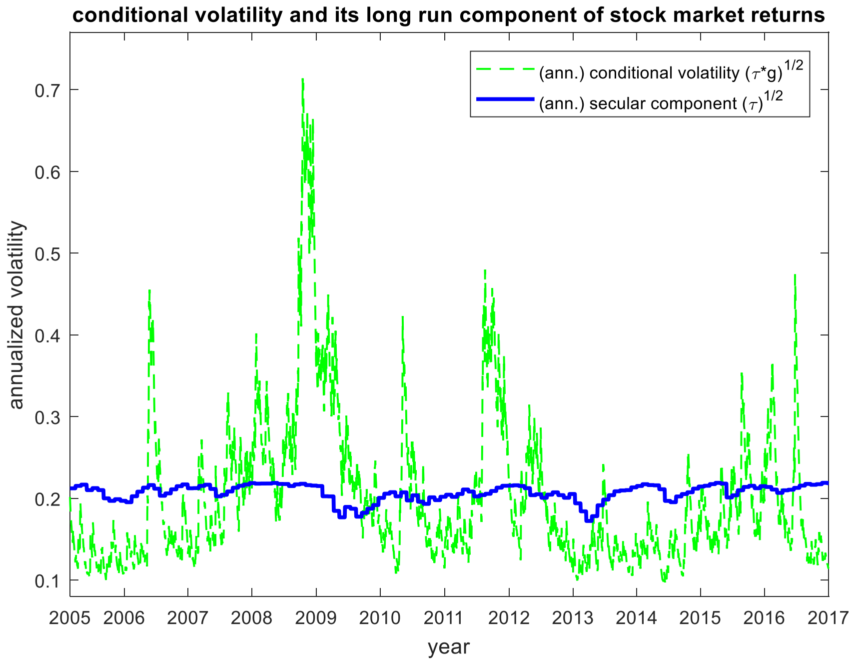


Figure A.4.p: GARCH-MIDAS with CC (Volatility)

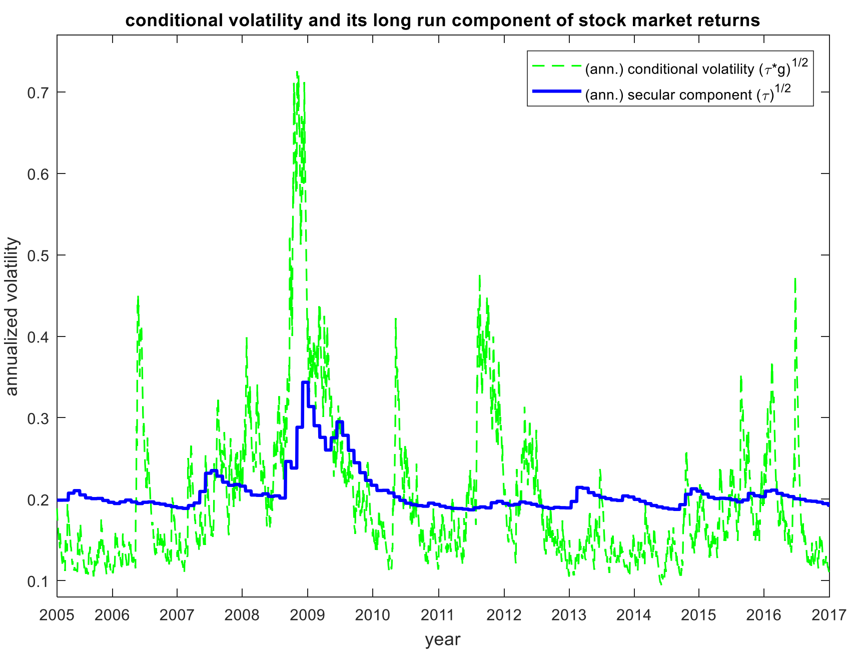


Figure A.4.q: GARCH-MIDAS with PMI (Volatility)

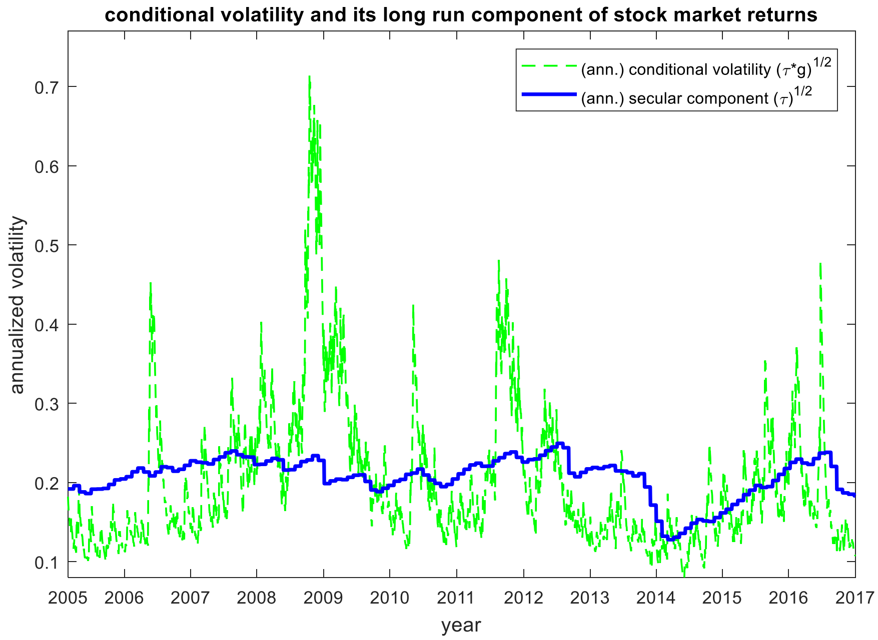


Figure A.4.r: GARCH-MIDAS with Unemp (Volatility)

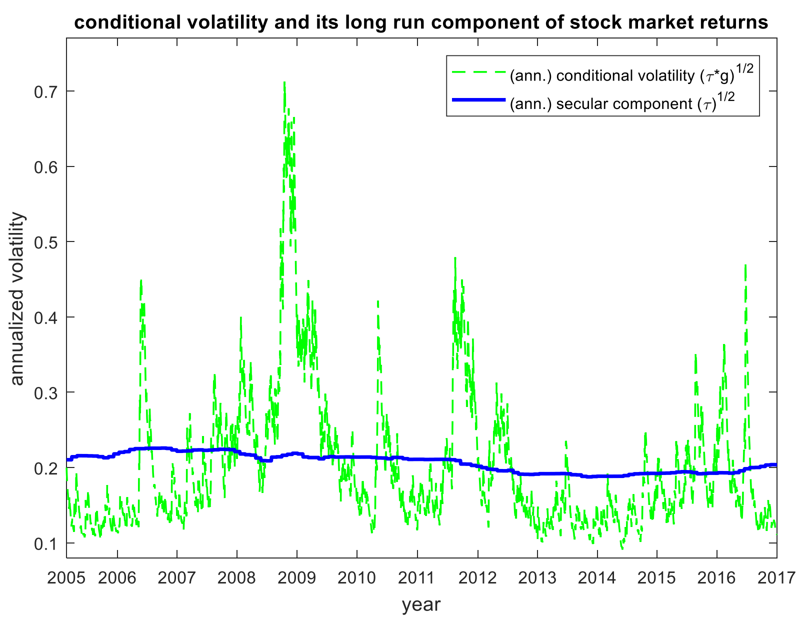


Figure A.4.s: GARCH-MIDAS with Krona (Volatility)