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İKTİSAT (İNG.) ANA BİLİM DALI
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NOWCASTING CONSUMER SENTIMENT DURING THE RECENT FLOAT: THE TURKISH CASE

M.A. Thesis

HAVVANUR YEŞİL YARADANAKUL

İstanbul, 2018

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Advisor: PROF. SADULLAH ÇELİK

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İKTİSAT (İNGİLİZCE) Anabilim Dalı İKTİSAT (İNGİLİZCE) Bilim Dalı TEZLİ YÜKSEK LİSANS öğrencisi Havvanur Yeşil Yaradanakul'nın NOWCASTING CONSUMER SENTIMENT DURING THE RECENT FLOAT: THE TURKISH CASE adlı tez çalışması, Enstitümüz Yönetim Kurulunun 22.03.2018 tarih ve 2018-8/32 sayılı kararıyla oluşturulan jüri tarafından oy birliği / ~~oy çokluğu~~ ile Yüksek Lisans Tezi olarak kabul edilmiştir.

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ABSTRACT

"NOWCASTING CONSUMER SENTIMENT DURING THE RECENT FLOAT: THE TURKISH CASE"

Sentiment indices play a crucial role in reflecting the current stance of the economy. In this regards, this paper proposes ADL-MIDAS regressions constructed with mixed frequency data for predicting consumer confidence indices (CCI) in an emerging economy, Turkey. The evidence shows that models constructed with exchange rate variable outperform others. It is also demonstrated that, for shorter horizons, BHT CCI estimations are better in terms of RMSEs; whereas for longer horizons, there is an improvement over regressions with CBRT CCI. Moreover, the effect of both consumer confidence indices on volatility of four daily variables is investigated by applying GARCH-MIDAS model. Empirical findings suggest that sentiment index significantly influences volatility dynamics of daily returns of exchange rate, oil price, gold price and stock exchange. The results also indicate that the relation between consumer confidence index and long run component of volatility of daily returns is counter cyclical.

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ÖZET

"ESNEK KUR DÖNEMİNDE TÜKETİCİ DUYARLILIĞININ MIDAS YÖNTEMİ İLE TAHMİNİ: TÜRKİYE ÖRNEĞİ"

Duyarlılık endeksleri, ekonominin mevcut durumunu yansıtmada önemli bir rol oynamaktadır. Bu bağlamda, bu çalışmada, Türkiye'deki tüketici güven endekslerinin (TGE) öngörülmesi için karışık frekans verileriyle oluşturulmuş ADL-MIDAS regresyonları kullanılmaktadır. Sonuçlar, döviz kuru değişkenli inşa edilen modellerin diğerlerinden daha iyi performans sergilediğini göstermektedir. Daha kısa horizon değeri için BHT TGE tahminlerinin ortalama karesel hatalar açısından daha iyi olduğu gösterilmiştir; daha uzun vadelerde, TCMB TGE için oluşturulan regresyonlarda iyileşme elde edilmiştir. Ayrıca, her iki tüketici güven endeksinin, dört değişkenin günlük getiri oynaklığına etkisi, GARCH-MIDAS modeli kullanılarak araştırılmıştır. Ampirik bulgular, duyarlılık endekslerinin, hisse senedi, döviz kuru, petrol fiyatı ve altın fiyatındaki getirilerin oynaklık dinamiklerini önemli ölçüde etkilediğini göstermektedir. Sonuçlar ayrıca, tüketici güven endeksi ile günlük getirilerin oynaklığının uzun vadeli bileşeni arasındaki ilişkinin ters yönlü olduğunu ortaya koymaktadır.

To My Family

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LIST OF ABBREVIATIONS

ADL-MIDAS	Augmented Distributed Lag Mixed Data Sampling
BASKET	Exchange Rate of Equally Weighted Basket Including US Dollar
BHT	Bloomberg HT
BHT CCI	Bloomberg HT Consumer Confidence Index
BIST100	Borsa Istanbul 100 Index
CBRT	Central Bank of Republic Of Turkey
CBRT CCI	Central Bank of Republic Of Turkey Consumer Confidence Index
CUR	Capacity Utilization Rate
DMSFE	Discounted Mean Square Forecast Error
DOLLAR	Exchange Rate of Dollar
ECM	Error Correction Model
EURO	Exchange Rate of Euro
FADL-MIDAS	Factor-Augmented Distributed Lag Mixed Data Sampling
GARCH-MIDAS	Generalized Autoregressive Conditional Heteroskedasticity Mixed Data Sampling
GDP	Gross Domestic Product
HLFS	Household Labor Force Survey
ISE100	Istanbul Stock Exchange 100 Index
MIDAS	Mixed Data Sampling
MVAR	Multivariate Autoregressive Modeling
OLS	Ordinary Least Squares
RMSE	Root Mean Square Error
RV	Realized Variance
TURKSTAT	Turkish Statistical Institute

1. INTRODUCTION

Forecasting method is the process of trying to predict the future condition of the economy. It is an important decision-making tool for businesses and governments, since policy decisions in real time are taken according to the state of the economy. In other words, to take control of macroeconomic strategies, precise and well-timed forecasts of significant indicators is important to authorities concerned with policy making and development strategies. However, in recent time, nowcasting methodology, which is a new forecasting tool, has gained a lot of attention by the academic literature. Traditionally, market participants monitor economic data to have an idea about the particular aspects of current state of the economy. They 'nowcast' the fundamental issues by judgmental processes. Yet, the reason behind this growing interest of nowcasting method is that it is difficult to infer the current state of the economy by these kinds of judgments. Hence, it is necessary to use an econometric methodology which is a formal way of analyzing economic fundamentals. In other words, as in the quote below;

"A nowcasting model should formalize key features of how market participants and policy makers read data in real time, which involves: monitoring many data releases, forming expectations about them and revising the assessment on the state of the economy" (Bańbura et al., 2013, p.5).

With these in mind, 'nowcasting is defined as the prediction of the present, the very near future and the very recent past'. (Banbura, Giannone and Reichlin, 2011, p.2)

"The basic principle of nowcasting is the exploitation of the information which is published early and possibly at higher frequencies than the target variable of interest in order to obtain an 'early estimate' before the official figure becomes available". (Bańbura, et al., 2013, p.2)

In other words, by using timely high frequency variables, like financial variables; low frequency variables followed closely by markets can be predicted. This method contributes the use of large data set and enables us to exploit the data with their original announced frequencies. As a result, using data with their original frequencies provides more accurate forecasting results, since any significant information may influence the nowcasting exercises and their precision. From the point of view of short term forecaster, there is no reason to throw away any information, but it is of course relevant to understand how reliable each release is as a signal of current economic conditions (Giannone, Reichlin and Small, 2008, p.666). Hence, nowcasting is a very beneficial tool in economics, because obtaining early estimates of key economic indicators is very helpful for policy decisions and investment strategies in real time.

Accordingly, policy makers and economic forecasters are paying particular attention to some economic indicators. Especially, from the point of consumption side, household spending is providing a significant information as it reflects the latest state of the demand side of economy. Yet, it is not giving adequate information about the economic agents' well-being. According to Katona (1968, p.22), consumers' discretionary expenditures are a function both of ability to buy and willingness to buy. In accordance with, the index of consumer sentiment reflects consumer perceptions of the likelihood of financial distress, which have a potent effect on the decision to purchase (Mishkin, 1978, p.229). Thus, it can be inferred that consumer sentiment can be more helpful than aggregate expenditure levels in predicting the state of a country. Consumer sentiment is thought to be a leading economic indicator which possesses information on the current and future path of an economy (Celik, 2010, p.121). To put it differently, there is a close relationship between economic variables and consumers' attitudes. Individuals' expectations and assessments about economic outlook affect the consumer sentiment and consumer sentiment has a significant influence on the economic outlook at the end. This dynamic interaction between economic agents and economy itself demonstrates the importance of the use of consumer sentiment in monitoring economy as a whole. Therefore, to measure the individuals' expectations regarding present and near future, consumer confidence indices have formed by public

and private institutions in developed countries. Lately, emerging economies have started to construct their own confidence indices, as well.

As a result, it can be claimed that, by means of the confidence indices, market participants can anticipate the future changes in aggregate consumer expenditures. Different from other economic indicators, this index contains important information as it is formed by individuals' predictions based on present and future conditions. Hence, in developed countries having more stable economic conditions, it can be beneficial to use this index for future assessments. Yet, over the short run, developing countries have very unstable economy due to their dynamic nature. It results in sensitive perception of consumers about their economic environments. To put it differently, in emerging markets where the economy is usually subject to several external or domestic shocks over a short period of time, consumer confidence should be viewed more of an indicator including current and past information as the future is viewed as uncertain rather than risky (Celik, 2010 p. 122). According to Mishkin et al. (1978, p.218), as the degree of uncertainty increases, the perceptions of the probability of financial distress would increase. In this case, obtaining the early estimates of confidence index is important to understand the movements in the developing economies in the very near past or present.

At this point, nowcasting methodology shows its importance. In these economies, it is possible to make predictions about consumer sentiment in the short run before its announcement date by using this approach. Especially, in emerging economies like Turkey, due to their dynamic nature of households' attitudes, consumers' behavior tends to change according to the more frequent variables, like exchange rate. Specifically, there are many studies trying to show the relationship between consumer sentiment and exchange rate or stock exchange. However, in these developing countries, it is believed that gold price and oil price are also significant variables to understand the consumer attitudes. In this manner, nowcasting consumer confidence index in Turkey with high frequency variables which are exchange rate, stock exchange, gold price and oil price is the main focus of this thesis. Moreover, by dividing the data set into different subgroups, which are before crisis period and full-time period, it is examined whether there is an effect of crisis on sentiment indices.

Existing papers has tried to employ many methods to understand consumer sentiment. The econometric approaches like OLS, MVAR, Cointegration, ECM, etc. are most used ones. However, traditional models fail to consider the information hidden in the high frequency data. To nowcast consumer confidence by taking highly frequent variables into account, the variant of Mixed Data Sampling (henceforth, MIDAS) regressions, namely Augmented Distributed Lag–Mixed Data Sampling (henceforth, ADL-MIDAS), discussed by Andreou, Ghysels and Kourtellos (2013) is applied in this study. This method allows using time series data sampled at different frequencies. Therefore, it provides an advantage of using data with their original announcement frequencies. Consequently, any information that may have influence on nowcasting can be evaluated by using data with different announcement dates. Additionally, GARCH-MIDAS, proposed by Engle, Ghysels and Sohn (2013) is implemented to test whether sentiment indices can explain the volatility dynamics of interested variables in Turkey. At the end of the day, the dynamic relationship between consumer sentiment and high frequency variables is understood in both directions.

Under these circumstances mentioned above, this research has three contributions. Basically, it provides recent information about the characteristics of consumer sentiment. In addition to the commonly used variables like exchange rate and stock exchange; timely series of oil price and gold price are considered as important to an emerging economy, Turkey, and included to the analysis. Secondly, this research introduces a recent forecasting methodology, namely MIDAS regressions, which allow incorporating the high frequency data without any modification. Finally, the question of how much volatility of our interested high frequency variables is related to an important leading economic indicator, i.e. CCI will be tried to be answered with this research.

Regarding these three, this thesis is quite different compared to other researches in the literature by introducing a new perspective to examine the role of high frequency variables on the nowcasting of consumer sentiment, and the influence of CCI on the volatility of those variables in Turkey during the recent float. It should also be noted that Turkey, as being a small open economy, shows similar macroeconomics dynamics to other developing countries. At this point, understanding the functional

property of consumer sentiment in Turkey can be beneficial to have an overview about other emerging economies.

The rest of the paper is organized as follows: Chapter 2 briefly reviews the literature on the nowcasting methodology, specifically MIDAS and researches about consumer confidence index, by focusing on theoretical studies first and then by summarizing some empirical studies. In the following Chapter 3, the measures of consumer sentiment indices; specifically, two types of consumer confidence indices in Turkey are described. Chapter 4 describes the data used with their characteristics and Chapter 5 briefly explains the basic MIDAS methodology and its variations, ADL-MIDAS and GARCH-MIDAS, used in this study, and Chapter 6 contains the design of exercises and empirical results. Chapter 7 draws conclusions followed by references and appendix.

2. LITERATURE REVIEW

This chapter briefly discusses previous literature including both theoretical and empirical studies covering nowcasting methodology, specifically the MIDAS, and researches about consumer sentiment. As mentioned previously, understanding the functional identity of consumer sentiment and its relationship with some macroeconomic variables is appealing to both practitioners and academics, as it provides early understanding of movements in aggregate demand or business cycles. Although displaying studies related to nowcasting of consumer confidence index is the main focus of this section; considering the previous literature, it is hard to find any research applying nowcasting approach, namely MIDAS model, for sentiment indices. Similarly, for volatility dynamics of interested high frequency variables in this study, there is very few research including sentiment measures as a macroeconomic variable. Nevertheless, to have an opinion about how this method works, it is beneficial to refer some researches explaining theoretical background of MIDAS regression model. Furthermore, there is a significant body of literature on the use of MIDAS regressions for forecasting and nowcasting different indicators. For better understanding of nowcasting exercise of consumer sentiment in Turkey, briefly stating some of them is important to build empirical relationship. In addition to the literature covering MIDAS models, researches including consumer sentiment are discussed, afterwards.

Pioneering work done regarding MIDAS framework include Ghysels, Santa-Clara and Valkanov (2004), Ghysels, Santa-Clara and Valkanov (2006), Clements and Galvao (2009), Andreou, Ghysels and Kourtellos (2010), Andreou, Ghysels and Kourtellos (2013) and Foroni and Marcellino (2013). Recent work has used simple MIDAS regressions or its combination with other econometric models to improve forecasting performance, Ghysels, Santa-Clara and Valkanov (2005), Kuzin, Marcellino and Schumacher (2011), Baumeister, Guérin and Kilian (2015), among others.

Ghysels, Santa-Clara and Valkanov (2004), introducing the Mixed Data Sampling regression models, is a fundamental source to understand theoretical background of MIDAS. The important feature of these regressions is that they can include time series data at different frequencies. It is concluded that, in general, the

variable of interest includes low frequency data; whereas the relevant data used to nowcast interested variable contains high frequency data. Therefore, this approach facilitates the use of mixed data sample regressions without any necessity of reducing all data to the same frequency. Also, in this study, asymptotic properties and comparison of this approach with traditional distributed lag models is covered.

Accordingly, Ghysels, Santa-Clara and Valkanov (2006) explain the MIDAS model. The main focus is volatility and related processes, they argued, especially in macroeconomics and finance. In this study, it is possible to find various lag structures of the MIDAS approach as well as its new extensions. Additionally, there are examples of application of this framework.

In similar fashion, Andreou, Ghysels and Kourtellos (2010) and Foroni and Marcellino (2013 are example of studies regarding the regression models using mixed frequency data. In these researches, MIDAS model is studied in detail. Yet, the more detailed information about this framework is introduced in the 5th chapter.

The studies stated above are basically showing the theoretical part of the MIDAS framework with empirical examples. For better understanding the application of this approach, Ghysels, Santa-Clara and Valkanov (2005) and Andreou, Ghysels and Kourtellos (2013) could be referred as an example of researches exploiting the high frequency data that is financial data. The former investigates that compared to other models, like rolling window or GARCH estimators; forecasting power of MIDAS on stock market variance is better. By using this approach, they find positive relationship between risk and return in the stock market. The latter one is related with nowcasting of GDP growth by incorporating the information in daily financial data. The effect of financial crisis is also covered. Empirical results show that in providing improvement for forecast exercises; MIDAS approach, specifically FADL-MIDAS, outperforms the benchmark models. Baumeister, Guérin and Kilian (2015) also use high frequency financial data to forecast monthly oil prices with MIDAS model. Besides, it concludes that, in general, the impact of including high frequency financial data on forecasting of monthly oil price is regarded as noteworthy.

Speaking of current-quarter forecast of GDP, Clements and Galvão (2009) and Lahiri and Monokroussos (2013) are researches trying to find the impact of leading indicators on nowcast of GDP. Both of them show that predictive ability of MIDAS using monthly variable on quarterly GDP data is significant and MIDAS improves the nowcasting exercise.

Now, to perceive methods which are close to that in our research; Armesto, Engemann and Owyang (2010), Li et al. (2015), Ghysels and Ozkan (2015) and Duarte, Rodrigues and Rua (2017) can be stated here as an example for an application of ADL-MIDAS approach. Firstly, Armesto, Engemann and Owyang (2010) forecasts monthly and quarterly macroeconomic variables by using both monthly and daily indicators for different horizons. The second one incorporates the high frequency Google search data into an ADL-MIDAS model to forecast Chinese consumer price index. Similarly, via ADL-MIDAS model, predicting the annual federal budget with mixed frequency data consisting of fiscal series and macroeconomic indicators is the aim of third article referred. Finally, Duarte, Rodrigues and Rua (2017) uses a mixed frequency approach to the forecasting of private consumption with high frequency data retrieved from ATM/POS. Basically, these studies take advantage of exploiting the high frequency data by following ADL-MIDAS model. They concluded that ADL-MIDAS performs better by reducing RMSEs in forecasting low frequency variables of interest.

In addition to the above articles, recent work has frequently used GARCH-MIDAS models, as well. The GARCH-MIDAS regressions providing volatility predictions appear Engle, Ghysels and Sohn (2013), Asgharian, Hou and Javed (2013), and Girardin and Joyeux (2013).

Engle, Ghysels and Sohn (2013) visit the relation between stock market volatility and macroeconomic activity. They proposed a new framework, GARCH-MIDAS, to show the difference between short term and secular movements. They find that macroeconomic variables have crucial role at short and long horizons.

Asgharian, Hou and Javed (2013) suggest the role of macroeconomic variables in predicting volatility of stock returns in US. This paper examined whether information

contained in macro variables can allow understanding short and long term components of variance. Similarly, Girardin and Joyeux (2013) examine the effect of volume and economic variables on the long run volatility of stock market by using GARCH-MIDAS model.

Last but not least, in emerging market, Turkey, there are some works using ADL-MIDAS method for several subjects of interest (Sensoy, Ozturk and Hacihasanoglu, 2014; Turhan, Şensoy and Hacihasanoglu, 2015; Sen Dogan and Midilic, 2016). To summarize, the first study constructs 2 types of financial fragility indices for Turkey and compares their performances for economic activity. In particular, Capacity Utilization Rate (CUR) which is monthly variable is tried to be forecasted by high frequency variables of two indices. Results of the ADL-MIDAS suggest that the index obtained by dynamic principal component with 2 months lag delivers the minimum RMSE in forecasting CUR. In Şen Doğan and Midiliç (2016), GDP growth is nowcasted by using credit data and financial data respectively. Credit data is found statistically significant for predicting GDP growth. Similarly, the information content of the financial data contributes forecasting of GDP of Turkey. Also, Turhan, Şensoy and Hacihasanoglu (2015) is an example for nowcasting of capacity utilization rate by using daily exchange and interest rate concluding that exchange rate is better forecaster for manufacturing industry. The main conclusion of them is that using high frequency data by ADL-MIDAS enhances the forecasting power. Alper, Fendoglu and Saltoglu (2012) is also an example of volatility forecast conducted for emerging economies' stock markets including ISE100 resulting that MIDAS model offers better forecasting precision during financially turbulent time, but for tranquil period, cannot give statistically significant volatility forecast.

These studies above demonstrate the theory and applications of MIDAS framework. It is obvious that, by allowing use of different frequency data, this approach makes easier the prediction of interested variable with low frequency data. At this point, research object of this thesis, consumer sentiment, can be predicted by MIDAS regressions by using variables more frequent than the consumer confidence index. On the other hand, CCI can be incorporated to the daily GARCH processes regardless of its

monthly announcement frequency. Hence, understanding the movement of consumer confidence before its announcement day can help to take actions when it is necessary.

Of course, it is beneficial referring some previous studies about consumer sentiment, as well. As it is mentioned before, consumption expenditure is a very essential economic indicator associated with economic growth as it constitutes the important share of total output. That is why, there are huge amount of studies trying to analyze what affects the household expenditure level. In general, economic variables like consumer price index, unemployment, personal income, etc. are considered important determinants for consumers' spending. These kinds of indicators can be considered as part of consumers' capability of buying. However, ability to buy and willingness to buy are different. 'When people feel that they are making progress and they are optimistic regarding their own and economy's prospects, new wants arise' (Katona, 1968, p.21), resulting a statistically significant and positive influence on consumer spending. In this regard, consumer confidence index can capture the information about present and future economic situation which cannot be obtained by other economic variables. Therefore, at least some part of information gap could be fulfilled by a variable like consumer confidence index as it tries to measure both the ability to buy and willingness to buy of economic agents (Güneş and Çelik, 2009, p.2).

There are huge amount of studies analyzing this relationship between consumer confidence and consumption expenditures. Among others, Acemoğlu and Scott (1994), Carroll et al. (1994) and Gelper et al. (2007) are studies questioning the forecasting power of consumer confidence on household spending. Basically, they concluded that index of sentiment is a better measure for future household expenditures.

On the other hand, Fuhrer (1993) and Howrey (2001) end up with different results showing that forecasting power of sentiment indices lose its significance when some other variables are included and also Abeele (1983), Garner (1991), Ludvigson (1996), Desroches and Gosselin (2002) demonstrate that the relation between consumer sentiment and future sale or economic activity is weak. Similarly, Kamakura and Gessner (1986) and Fan and Wong (1998) opposed the usefulness of consumer sentiment in predicting consumption growth; whereas, Mueller (1963), Eppright et al

(1998), Bram and Ludvigson (1998), and Souleles (2004) are examples of researches stating the usefulness of confidence index on forecasting consumer spending.

Furthermore, it is possible to speak briefly about some skeptical articles and some using unconventional methods. To illustrate, Flavin (1991), Alessi and Lusardi (1997), Batchelor and Dua (1998), Souleles (2001), Dominitz and Manski (2004) and Van Oest and Frances (2008), can be referred, here.

In addition to the studies conducted for the relationship between consumer sentiment and household expenditures; the influence of some high frequency variables on consumer confidence is part of researches in the literature, as well. Mishkin (1978) is the first study investigating that there is a link between consumer confidence and financial variables. He argues that since sentiment index is determined by consumers' perceptions of the probability of financial distress which changes according to the households' balance sheets, it is obvious to relate consumer confidence with financial variables.

Of course, there are several studies pointing out the similar relationship between consumer confidence and high frequency variables (Otoo, 1999; Jansen and Nahuis, 2003; Güneş and Çelik, 2009).

To be more precise, Praet and Vuchelen (1989) analyzed consumer confidence index by oil prices, interest rates, exchange rates and the U.S. stock market index for four European countries. As a result, consumer confidence index is negatively related with oil prices and interest rates, and positively related with exchange rates.

Likewise, among others, Golinelli and Parigi (2003), Vuchelen (2004), Celik, Aslanoglu and Uzun (2010b) are examples of studies basically demonstrating the relationship between consumer confidence index and financial variables such as interest rate, exchange rate, and stock prices. By using some economic and financial variables, Golinelli and Parigi (2003) analyze the consumer sentiment indices for some developed countries. It concludes that consumer confidence 'depends on the history of the country, on the characteristics of its economic system, on the period of time' (Golinelli and Parigi, 2003, p.22).

In the study of Vuchelen (2004), whether the information content of consumer sentiment can be captured by economic and financial variables such as interest rates, unemployment, stock market indices, exchange rate etc. is the main question. He finds negative signs for the coefficients of interest rate, exchange rate and oil price; whereas the coefficient of stock price is insignificant.

Different from above articles, Celik, Aslanoglu and Uzun (2010a) uses panel data analysis for six emerging economies; Brazil, China, Mexico, Poland, South Africa and Turkey between 2002M1 – 2009M8. The main objective is to have an idea about the existence of a long run relationship between consumer confidence and economic variables. This study concludes that there is a dynamic and structural relationship and according to the FM-OLS results, for the panel group of emerging countries, both industrial production and stock exchange have statistically significant coefficients with positive signs.

Speaking of stock exchange, Otoo (1999) argues whether changes in equity prices have an impact on consumer sentiment in the period 1981-99. In this study, it is investigated that stock market returns Granger-cause changes in consumer sentiment, but not vice versa which means that increase in equity values boosts sentiment.

Similar to the results of Jansen and Nahuis (2003); Bremmer and Crist (2003) finds that there is no long-run relationship between U.S. measures of consumer confidence and stock indices. Yet, when short-run relationship is considered between these variables, Granger-causality test indicate that measures of the Dow Jones, S&P 500, and the NASDAQ influence the index of consumer confidence, but the opposite direction does not hold. This paper is the extension of the Otoo (1999)'s findings to the more commonly used stock exchange indices.

According to the Celik, Aslanoglu and Uzun (2010b), exchange rate is regarded as significant variable affecting individuals' understanding of future state of a country. They end up with negative relationship between consumer confidence and exchange/ interest rates. In contrast to general expectation, they get negative sign for the stock exchange.

In addition to the studies trying to show the impact of exchange rate and stock prices, studies exploiting the data of important commodity prices, like oil and gold prices should be reviewed in more detail, as well. In emerging countries like Turkey, there is a dynamic relationship between consumers' overall economic perceptions and oil/gold prices. Hence, the effect of prices of these commodities cannot be ignored in the sense that they are closely monitored by individuals.

In particular, Celik (2010) shows that changes in consumer confidence index is explained by industrial production, stock exchange, exchange rate, business tendency surveys and oil price. Generally, all sign and magnitude of coefficients are as they expected.

Ebrahim, Inderwildi and King (2014) addresses the interactions between global macroeconomic performance and oil price volatility. It argues the responses of consumption, investment, industrial production, inflation and unemployment to oil price volatility. When they are analyzing the impact of oil price on consumption, they conclude that change in oil price increases uncertainties resulting lower consumer confidence.

By using correlation analysis and least square methods, Liu (2015) figures out the links between the oil price changes and the index of sentiment in Canada, at both national and regional levels. Decrease in oil prices influence consumer confidence negatively. Moreover, when regional impact is considered, reaction of oil-producing regions and the oil-consuming regions is different.

The interaction between gold price and consumer confidence is mentioned in Fei and Adibe (2010) studying commonly provided explanations about gold and its price movements. They include real gold price, various "fear" indicators, U.S. inflation rate, real long-term interest rate, indicators of real economic activity and the exchange rate. By substituting the University of Michigan Index of Consumer Expectations for the fear indicator, it is concluded that decrease in consumer confidence is an indication of rising gold prices in the longer term which means that the sign is consistent with the theory.

From the other side, it is possible to find studies showing the effect of consumer surveys on oil price, and precious metals, as well (Roache and Rossi, 2010; Batten et al, 2010; Anderson et al, 2011; Sethi and Gupta, 2014).

All in all, the relationship between consumer sentiment and different variables of interest has shown in the literature. In general, the forecasting power of these variables and the nexus between consumer confidence and chosen variables in short and long run are subjects of these studies. Yet, neither of these papers managed to show the nowcasting of consumer confidence index with exchange rate, stock exchange, oil price and gold price by using mixed frequency data. Moreover, few of them try to analyze the effect of sentiment indices on some daily returns. Therefore, this study is the first attempt demonstrating the nowcasting of consumer sentiment and analyzing its effect of volatility dynamics of daily returns in emerging country, namely Turkey. Additionally, by conducting MIDAS models, it allows to use mixed frequency data preventing the loss of any significant information.

3. MEASURES OF CONSUMER CONFIDENCE INDICES

Interviewing several individuals in each month is a popular method for understanding how individuals feel about the economy. In this respect, surveys of consumer attitudes, namely consumer sentiment indices, are constructed by many public and private institutions based on questions about households' perceptions of the current economic situations and their expectations for near future. By gathering answers of couple of questions indicating whether respondents are positive, negative or neutral about the economy; these monthly reports demonstrate aggregate expectations about prevailing business conditions and developments in the country. In other words, sentiment measures "…reflect the overall outlook for the economy: when consumers are optimistic about the outlook for the economy, they give upbeat responses to interviewers" (Carroll, Fuhrer and Wilcox, 1994, p.1398). Therefore, these aggregate consumer expectation measures are considered as beneficial indicators to monitor early signals of economic conditions in turbulent times. As consumer confidence indices contain a priori information, analysts have paid increased attention to observe fluctuations in these measures which might be useful in anticipating changes in the current and future economic activities.

After the first survey of consumer attitudes is created by Professor George Katona at the University of Michigan's Institute for Social Research in the 1940s, researches on the measurement of sentiment indices have commenced. Accordingly, since 1960s the consumer sentiment indices of developed countries like Canada, US has been available; while the emerging economies like Brazil, China, Turkey has been conducting consumer tendency surveys starting from the late 1990s.

Specifically, in United States, there are two major nationwide indices of consumer sentiment which are The Conference Board's index, namely the Consumer Confidence Index and the University of Michigan's index, namely Index of Consumer Sentiment. They are evaluated within the range of 0-200 such that the index value above 100 indicates optimistic outlook and the index value below 100 is pessimistic one. Measuring the temporal variations in the consumer sentiment is the main usage of these indices. Although both indices are similarly designed, it is possible to find differences in

detail. To be more precise, measuring household's expectations by 5 main questions about current and expected economic conditions is primary objective of both indices. However, the wording and the time period of these questions are different from each other.

3.1. Measures of Consumer Confidence Indices in Turkey

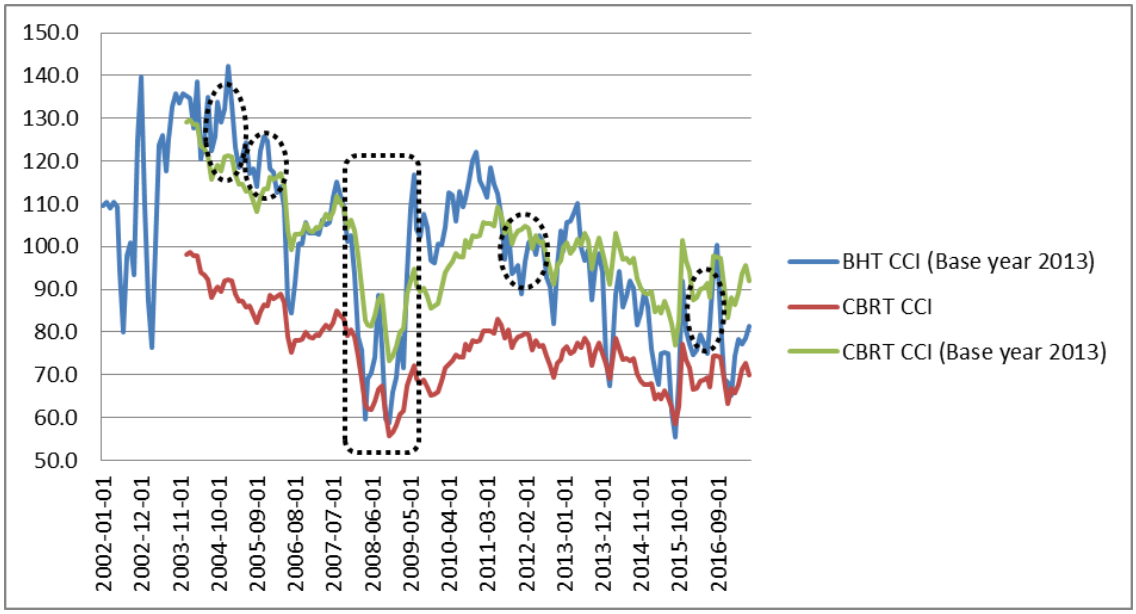
Leading economic indicators, like sentiment indicators, 'anticipate a business cycle by tending to turn down before the down cycle begins and to turn up before the expansionary cycle begins' (Schröder and Hüfner, 2002, p.1). According to the common sense that the direction of economy is affected by consumers' opinions and expectations, these measures are widely tracked by professionals, financial analysts, policymakers and journalists. Moreover, due to the widespread availability, they provide firms with successful business performance by letting them to reach prior signals of consumer attitudes.

To measure and publicize the most recent consumer attitudes in Turkey, there are two kinds of consumer confidence indices announced regularly by Bloomberg HT and the Central Bank of Republic of Turkey – Turkish Statistical Institute (CBRT-TURKSTAT). These are Bloomberg HT Consumer Confidence Index (henceforth, BHT CCI) and the Central Bank of Republic Turkey – Turkish Statistical Institute Consumer Confidence Index (henceforth, CBRT CCI), respectively.

In Figure 1, BHT CCI and CBRT CCI over the period in which both are available are exhibited for general understanding of these indices. Naturally, ups and downs in the patterns of these two series are similar, as these two indices reflect the measure of public confidence in the same economy. General trend demonstrates the decrease of confidence level i.e. pessimism in the economy over the years. If some periods are considered in detail, both indices are closely related to each other. For instance, the rectangular area displays the period of global financial crisis, so that it is possible to observe the effect of crisis on declining pattern of both indices. Again, in the last years, it seems that they follow similar patterns. Yet, sometimes they demonstrate different movements. To exemplify it, it can be clearly observed that the BHT CCI has

fluctuated over a wider range than CBRT CCI. Moreover, when closer investigation of the circled periods in the figure reveal that, different results can be obtained due to conflicting patterns; that is, in these periods, BHT CCI has increasing (decreasing) pattern while the trend is decreasing (increasing) for CBRT CCI. Now, these two indices are explained in detail.

Figure 1. BHT CCI and CBRT CCI



3.1.1. BHT CCI

The CNBC-e CCI (BHT CCI, in recent years) is published in a monthly frequency with an index value 100 fixed for base period January 2002 sharing similar methodology with the Michigan University Index of Consumer Sentiment. It is based on a sample of approximately 15,000,000 individuals selected from the database of survey provider. The following Table 1 displays the questions that are posed to the survey respondents in each month.

The answers to the first two questions above reflect the respondent's personal condition and expectations, whereas the following two measure the expectations

concerning the Turkish economy. Finally, consumers' current consumption tendency is evaluated according to the last one.

Table 1. Bloomberg HT Index Questions

Q1	1) We would like to learn your current economic situation. Can you compare your (and your family's) current financial situation with last year?
	Better *Worse* *Same* *No Idea*
Q2	2) What do you think your (and your family's) future financial situation will be in a year?
	Better *Worse* *Same* *No Idea*
Q3	3) Can you compare your current expectations about Turkish economy with the previous month?
	Better *Worse* *Same* *No Idea*
Q4	4) What do you think Turkish economy's situation will be in a year?
	Better *Worse* *Same* *No Idea*
Q5	5) Do you think that the current period is a good time to buy durable consumer goods such as TV, refrigerator and furniture or vehicles or residence?
	Good Time Bad Time Same

The BHT CCI is produced by assembling 704 completed surveys obtained from the respondents between the 27th day of the previous month and the 26th day of the current month. To conduct these surveys, the distribution of them should require 7 criteria below:

1) 70 percent is selected from Istanbul, Ankara and Izmir, 30 percent selected from other cities and big districts in Turkey.

2) 60 percent is selected from 36-55 age group; 40 percent is selected from 18-35 age group.

3) 50 percent is male, and the other half is female.

4) 50 percent of the total surveys are composed of new records.

5) A minimum of 30 percent of new records belongs to individuals who had been successfully surveyed in the previous month.

6) A maximum 20 percent of 704 completed surveys may be composed of additional respondents and these respondents are not called again in the next month.

7) Last and perhaps the most importantly, respondents are not surveyed more than twice. This helps to minimize the biases in the answers of respondents.

Finally, the consumer confidence index is calculated according to following formula:

Index Value = (Current period value / Base period value) *100

Current period's value for each question is being calculated as =

((Number of optimistic answers for the question – Number of pessimistic answers for the question) / 704) *100) + 100

The current period values of each question are summed up to obtain current period's value for the overall index. All in all, the index value satisfying the above criteria is announced at 09:00 on the first day of every month or the next business day.

3.1.2. CBRT CCI

The second type of consumer confidence index in Turkey is a joint work of Turkish Statistical Institute and the Central Bank of Republic of Turkey starting from January 2004. Its model is in consistence with the balance method of European Union. This index is obtained regarding the surveys composed of the 5 questions (Q1, Q2, Q4, Q5 and Q7 in the HLFS) shown in the Table 2.

Table 2. CBRT-TURKSTAT Index Questions

Q1	Compared to the past 6 months, how do you assess your present purchasing power situation?		
	Much more better	*A little bit better*	*Remain the same*
	A little bit worse	*Much more worse*	*No idea*
Q2	How do you expect your purchasing power situation to change over the next 6 months?		
	Much more better	*A little bit better*	*Remain the same*
	A little bit worse	*Much more worse*	*No idea*
Q4	How do you expect the general economic situation in Turkey to develop over the next 3 months?		
	Much more better	*A little bit better*	*Remain the same*
	A little bit worse	*Much more worse*	*No idea*
Q5	How do you expect the job opportunities in Turkey to change over the next 6 months?		
	Increase sharply	*Increase slightly*	*Remain the same*
	Fall slightly	*Fall sharply*	*No idea*
Q7	Do you think now it is the right moment for people to buy durable consumption goods such as refrigerator, TV, furniture, etc.?		
	Yes, it is the right time now	*It is neither the right time nor the wrong time*	
	No, it is not the right time now	*No idea*	

To conclude, although these indices above are very recent; in terms of collection, calculation and announcement, they are considered very functional and robust indices (Celik, 2010, p.127).

4. RESEARCH DATA (FULL SAMPLE AND SUBSAMPLE)

The dataset in this study includes monthly consumer confidence index in Turkey namely, BHT CCI and CBRT CCI and 4 daily indicators. The BHT CCI is available from 2002 onwards, whereas the CBRT CCI measure has been published since 2004. The daily indicators cover exchange rate, stock exchange, oil price and gold price. Table 3 shows the list of all indicators, briefly.

To achieve our main objective of nowcasting the low frequency variable, all high frequency data series used in econometric analysis are taken in the log difference form and sentiment indices are in natural logarithms. The first in-sample estimation runs from January 2004 to June 2016 for CBRT CCI and from January 2002 to June 2016 for BHT CCI. On the other hand, out-of-sample forecasts start from the July 2016 until June 2017, for both indices.

Additionally, the subsample until global financial crisis is also used to understand the influence of turbulent times on consumer sentiment which corresponds to in sample estimation period between January 2004- December 2007 for CBRT CCI and January 2002- December 2007 for BHT CCI. The remaining 24 months between January 2008 and December 2009 are left as an out of sample forecast period, for both indices.

The same time intervals are considered again to analyze the time varying volatility between interested variables. In this case, the direction of the research topic is reversed. In other words, instead of understanding the effect of high frequency variables on consumer sentiment by applying ADL-MIDAS approach; GARCH-MIDAS is used to observe the volatility of high frequency (daily) variables by given monthly consumer confidence index. By this way, the relationship between these significant variables in both directions and with different approaches is understood.

Table 3. Variables Included

	Frequency & Form	Time Period	
		Full Sample Period	Subsample Period
Consumer Confidence Index			
BHT CCI [1]	Monthly variable, in log	January 2002-June 2017	January 2002-December 2009
CBRT CCI[2]		January 2004-June 2017	January 2004-December 2009
Exchange Rate			
USD/TRY[3] **EUR/TRY**[4] **BASKET**	Daily variable, in log returns	January 2002- June 2017	January 2002- December 2009
Gold Price [5] **(TRY per Ounce)**	Daily variable, in log returns	January 2002- June 2017	January 2002- December 2009
Oil Price[6] **(TRY per Barrel)**	Daily variable, in log returns	January 2002- June 2017	January 2002-December 2009
Stock Exchange[7] **(BIST100-Mean)**	Daily variable, in log returns	January 2002- June 2017	January 2002- December 2009

Source:

[1] http://www.bloomberght.com/ekonomik-veriler-ve-gundem/bloomberght-guven-endeksi

[2] http://www.tuik.gov.tr/PreIstatistikTablo.do?istab_id=1600

[3] http://evds.tcmb.gov.tr/cgi-bin/famecgi?cgi=$ozetweb&DIL=TR&ARAVERIGRUP=bie_dkdovizgn.db

[4] http://evds.tcmb.gov.tr/cgi-bin/famecgi?cgi=$ozetweb&DIL=TR&ARAVERIGRUP=bie_dkdovizgn.db

[5] http://www.gold.org/research/download-the-gold-price-since-1978

[6] http://tonto.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RBRTE&f=D

[7]https://www.google.com/finance/historical?cid=456528970194751&startdate=Jun%2021%2C%202000&enddate=Jun%2020%2C%202017&num=30&ei=7ftIWbC8OsHksAH2naSYCA&start=3480

It should be noted that monthly-daily combination is used throughout this research. Since there are situations of holidays and it increases the inequality in the number of days in a month, average of the data which is one day before and after the missing values is used for those days.

Before proceeding, some figures are illustrated to demonstrate how variables with different frequencies look like. Although they are in different frequencies, these illustrations can help us to capture general behavior of high frequency variables when they considered together with the consumer confidence indices. By understanding these trends, expected signs for coefficients of each variable in ADL-MIDAS can be inferred.

Basically, in figures 2,4,6,8 the movements of daily variables between monthly CBRT CCI observations are demonstrated. Similarly, Figure 3,5,7,9 show how these daily observations fluctuate between monthly BHT CCI values in related period of time.

First of all, Figure 2 and 3 portrays the relationship between exchange rate and two consumer confidence indices. In the long run, when it is directly focused of the general trend, it seems that there is an inverse relationship between these variables; however, it is wrong way of seeing this negative association. The correct way is following the arrows (black and red colored) for different time intervals. The blacks represent the trend of high frequency variables, while the reds are for sentiment indices. In the end, the opposite directions of these arrows show the negative relation between exchange rate and consumer confidence index, which lead us to expect negative coefficient from the regression results for exchange rate's slope coefficient in ADL-MIDAS.

Equivalently, the interaction of consumer confidence index with oil/gold price has similar dynamics resulting in negative coefficients to be expected. On the other hand, stock price has different characteristics; that is, when the arrows are closely tracked, the positive relationship is clearly observed for several periods.

All in all, these inferences facilitate to understand the general relationship between high and low frequency variables. However, before analyzing low frequency variable, CCI, via econometric procedures, the problem of frequency mismatch in our sample should be resolved at first. In this regards, Chapter 5 presents MIDAS methodology to handle this issue.

Figure 2. BHT CCI and Exchange Rate

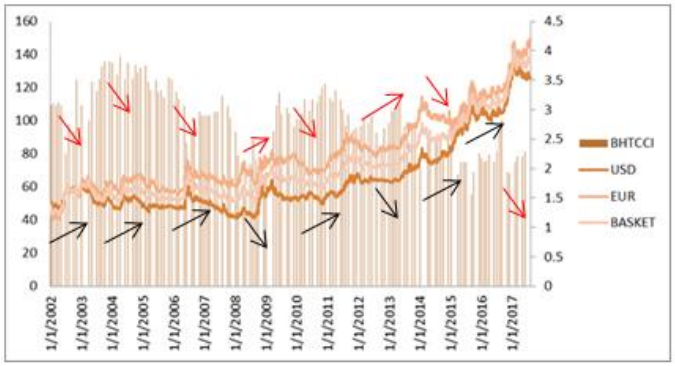


Figure 3. CBRT CCI and Exchange Rate

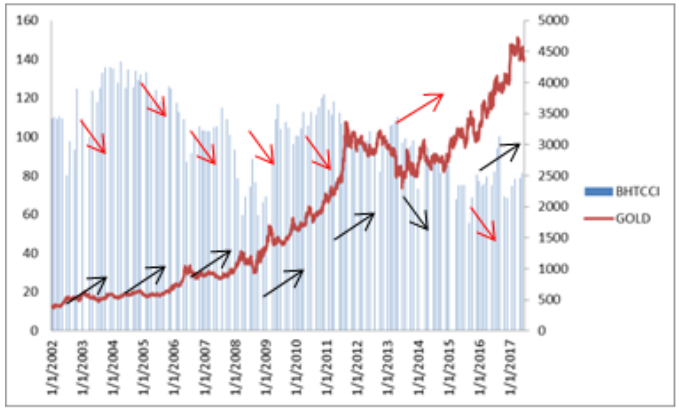


Figure 4. BHT CCI and Gold Price

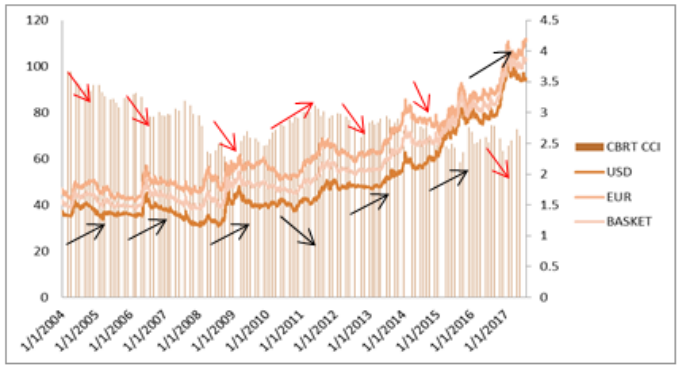
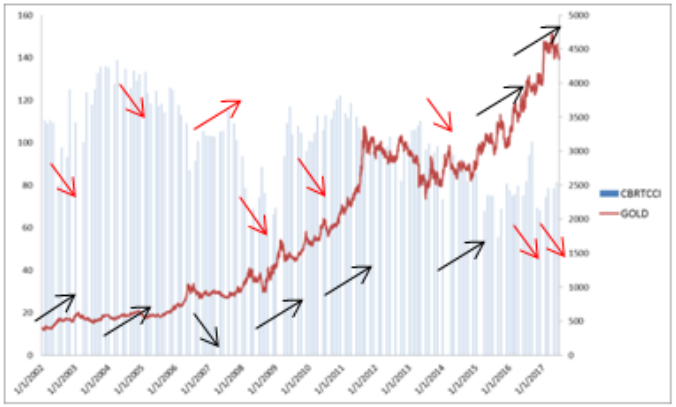


Figure 5. CBRT CCI and Gold Price



5. THE MIDAS METHODOLOGY

Most time series model includes data with different frequencies. Precisely, many high frequency variables are incorporated to most of macroeconomic analysis, because of their dynamic structure and in time availability. However, these advantages present a dilemma for economic analysis because using high frequency information directly in sample with some low frequency data is not an easy task. Normally, the aggregating processes like taking average of high frequency data is the simplest method to overcome the problem of frequency mismatch. For example, this thesis tries to understand the relation between monthly consumer confidence index and daily exchange rate. Averaging daily exchange rate of 22 observations (business days) and then, regressing consumer confidence index on the average of exchange rate is the simplest way of dealing with unbalanced frequency. Nevertheless, it should be noticed that aggregation methods are resulting a loss of information influencing the precision of the economic forecast, since it modifies the dynamics of original data due to restrictive equally weighting process. Andreou, Ghysels and Kourtellos (2013) demonstrated these kinds of econometric issues. Moreover, regressing dependent variable separately on each of explanatory variables is an alternative method to deal with the problem of being in different frequencies; however, it causes parameter proliferation. Yet, recent developments in mixed frequency sampling methods have facilitated the anticipation of low frequency variables by incorporating information content of high frequency data since each day in a related month can have different influence on forecast results. Therefore, contrary to other models requiring a lot of parameters and/or having complexities in computation processes, models easy to implement in many researches is needed.

Figure 6. BHT CCI and Oil Price

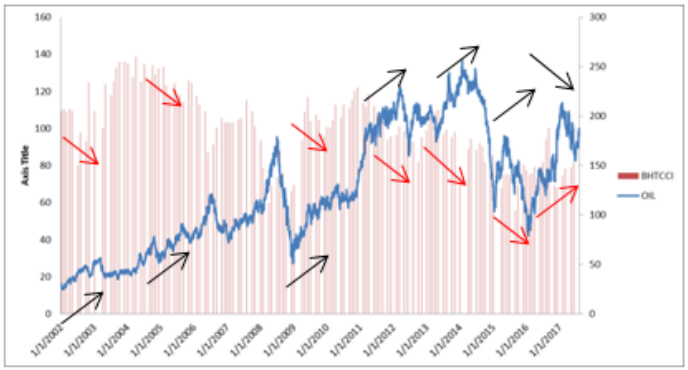


Figure 7. CBRT CCI and Oil Price

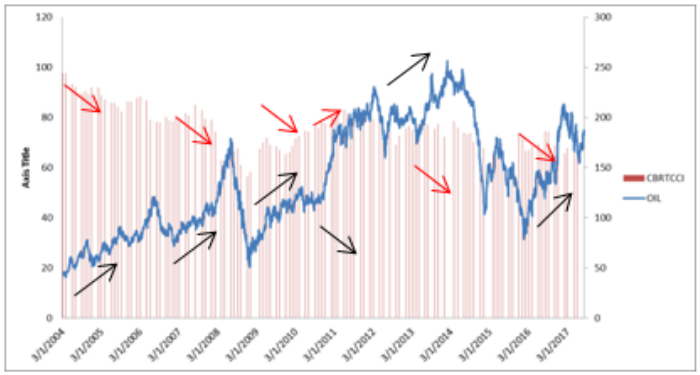


Figure 8. BHT CCI and Stock Exchange

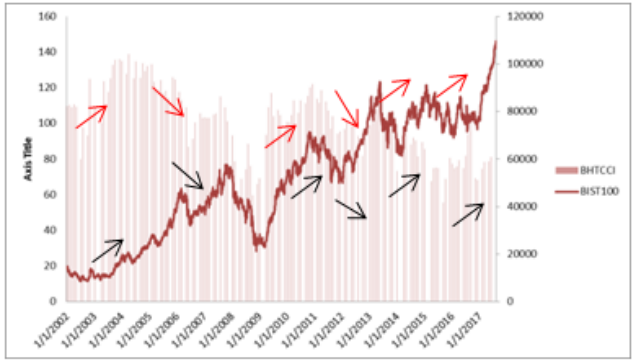
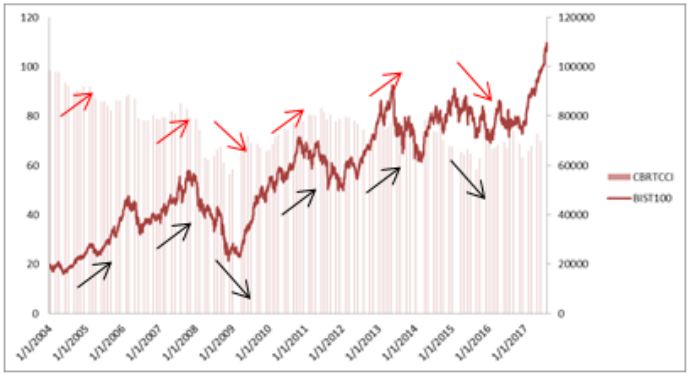


Figure 9. CBRT CCI and Stock Exchange



In this regards, MIDAS regressions developed by Ghysels, Santa-Clara and Valkanov (2004) are one of the simple, parsimonious and flexible method solving the aforementioned issues by allowing variables with different frequencies in the same sample. In other words, this proposed rigorous framework 'controls for parameter proliferation, and also preserves the timing of information' (Armesto, Engemann and Owyang, 2010, p.526). Hence, instead of reducing all data to same frequency, i.e. aggregating the daily (or monthly) series to a monthly (quarterly) sampling frequency, it is possible to apply MIDAS framework without any modification. Particularly, actual information hidden in the high frequency data cannot be reflected by taking average or maximum.

As a result, this section describes the general MIDAS model and its variations used in this thesis. In order to provide basic idea behind nowcasting and volatility exercises, the details of MIDAS methods and the way how they are implemented in macroeconomic forecasting is main focus of this part. Many important features of MIDAS model mentioned to demonstrate the flexibility of this approach lead us to prefer it as our forecasting method. Now, basic MIDAS model with some important concepts is introduced with its novelty. Then, different MIDAS frameworks applied in this study; namely ADL-MIDAS and GARCH-MIDAS are explained in two subsequent sections.

5.1. Basic Midas Methodology and Some important Concepts

To begin with, a brief overview can be useful to understand the general MIDAS model. For illustrative purpose, assume that one is interested in forecasting a quarterly variable, Y_{t+1}^{Q} and $X_{j,t}^{D}$ is another variable observed N_D times in a quarter; that is, $X_{j,t}^{D}$ is a daily variable with N_D=66 (22*3) business days, for simplicity. Simply aggregating daily data to quarterly frequency is one of the most used traditional methods like in the following equations 5.1 and 5.2:

$$X_t^Q = (X_{N_D,t}^D + X_{N_{D-1},t}^D + \ldots + X_{1,t}^D) / N_D \quad (5.1)$$

$$Y_{t+1}^Q = \mu + \beta X_t^Q + \varepsilon_{t+1} \quad (5.2)$$

where μ, β are unknown parameters and ε_{t+1} is error term and it can be clearly seen that the above equations uses equal weighting scheme by averaging daily data. Alternatively, constructing a following model 5.1.3 estimates different βs for each daily variable and it causes a parameter proliferation since 68 slope coefficients should be estimated.

$$Y_{t+1}^{Q} = \mu + \sum_{j=0}^{N_D-1} \beta_{N_{D-j}} X_{N_{D-j,t}}^{D} + \varepsilon_{t+1} \tag{5.3}$$

In a different manner, the basic single MIDAS model for h step ahead forecast proposed by Ghysels (2015) is:

$$y_{t+h} = \beta_0 + \beta_1 C(L^{1/m};\theta_h) x_t^{(m)} + \varepsilon_{t+h}^{(m)} \tag{5.4}$$

where t is low frequency time unit and m is the number of times the higher sampling frequency data appears in the same basic time unit. Also, $C(L^{1/m};\theta) = \sum_{i=0}^{N} c(i;\theta)L^{i/m}$, $L^{1/m}$ is a lag operator such that $L^{1/m}x_t^{(m)}=x_{t-1/m}^{(m)}$ and the lag coefficient in $c(i;\theta)$of corresponding $L^{i/m}$ is parametrized as function of a low dimensional vector of hyperparameters θ (Duarte, Rodrigues and Rua, 2017, p.63) . It is assumed that sum of the weights of the polynomial $C(1;\theta) = \sum_{j=0}^{N} c(i;\theta) = 1$ providing identification of the parameter β and $\varepsilon_{t+h}^{(m)}$ is standard i.i.d. error term. At this point, it should be noted that the determination of the number of high frequency lag variables is crucial, as well. Thus, if our monthly data is influenced by 3 months of lagged high frequency x_t^H then N = 66 lags are needed to be incorporated. The parameterization of the lagged coefficients of $c(k;\theta)$ in a parsimonious way is one of the key features of MIDAS (Ghysels, 2015, p.4). Therefore, various specifications for $C(L^{1/m};\theta)$ should be explained, as well.

There are five polynomial specifications that should be considered. In detail, these functional forms are U-MIDAS approach, normalized Beta probability density function with restricted and unrestricted cases, normalized exponential Almon lag polynomial, Almon lag polynomial specification of order P and polynomial specification with step functions. However, detailed information about two most

commonly used ones in the literature[1] is given, here. Firstly, the unrestricted case of β lag specification with the assumption of nonzero last lag is introduced in the following equation:

$$c_i^{u,nz} = c(i;\ \theta = [\ \theta_1,\ \theta_2,\ \theta_3]) = \frac{x_i^{\ \theta_1 - 1}(1-x_i)^{\ \theta_2 - 1}}{\sum_{i=1}^{N} x_i^{\ \theta_1 - 1}(1-x_i)^{\ \theta_2 - 1}} +\ \theta_3 \tag{5.5}$$

Additionally, equation 5.6 displays the restricted case with the nonzero last lag assumption. The following equations 5.7 and 5.8 are of the cases for unrestricted and restricted zero last lag.

$$c_i^{r,nz} = c(i;\ \theta = [1,\ \theta_2,\ \theta_3]) \tag{5.6}$$

$$c_i^{u,z} = c(i;\ \theta = [\ \theta_1,\ \theta_2, 0]) \tag{5.7}$$

$$c_i^{r,z} = c(i;\ \theta = [1,\ \theta_2, 0]) \tag{5.8}$$

where $x_i = i\ /$ (N+1).

The Exponential Almon Lag is the second type of parameterizations of $c(i;\ \theta)$ given by the following equation 5.1.9:

$$c(i;\ \theta) = \frac{e^{\theta_1 i + \cdots + \theta_Q i^Q}}{\sum_{i=1}^{N} e^{\theta_1 i + \cdots + \theta_Q i^Q}} \tag{5.9}$$

Another point that is worth mentioning is timing issue of high frequency data. Firstly, the horizon value (henceforth, h) selection is very critical for MIDAS applications. This value determines time point from where your data should start and which data should be included into the regression time frame. Therefore, changes in the value of h directly influences forecast results and its precision since it influences the starting date of high frequency variable. Also, it shows whether your high frequency data affects your low frequency data in a shorter or longer term. In other words, researchers can easily determine the impact of including or excluding some recent high frequency data by making adjustments in h value.

[1] See Ghysels (2015) for further details.

Lag selection is also related to the timing of both high and low frequency variables and it is advised to select optimal lags according to AIC or BIC. These values are denoted by Xlag and Ylag[2] and provide information about the number of lagged high frequency independent variables and autoregressive low frequency variables, respectively. The selections of horizon and lag values with examples are considered later, in the related model.

Having said that lag selection and horizon values are important, start date (EstStart) and terminal date of estimation window (EstEnd)[3] should be carefully specified, as well. The former one is adjusted according to the lagged values, while the latter is adjusted by h value. Moreover, if there is an extra information of low frequency data left after EstEnd, then it will be provided out of sample forecast results for these unused observation time. In other words, the realized data will be compared to estimated values and RMSEs for each model will be obtained which is very beneficial to assess models' performances.

The last important property that should be mentioned here is that MIDAS regressions provide the use of three different estimation schemes: Fixed Window, Rolling Window, and Recursive Window[4]. These three options for estimation methods provide us flexibility to obtain better forecast results.

5.2. ADL-MIDAS

This subsection provides a brief overview of the ADL-MIDAS model considered in the nowcasting exercise. Andreou, Ghysels and Kourtellos (2013) introduce this type of regression model by extending ARDL models. Thus, ADL-MIDAS regressions forecast low frequency variables at horizon h by regressing y_{t+h}^{L} on y_t^L and x_t^H . Specifically, if h is altered by 1/m, then nowcast of the low frequency variable can be achieved. This model can be written by the following equation:

$$y_{t_L+h}^{L} = a_h + \lambda_h \, y_{t_L+h}^{L} + b_h C\,(L^{1/m}; \theta_h)\, x_t^H + \varepsilon_{t_L+h} \qquad (5.10)$$

[2] Ylag values are used in case of including autoregressive term, like in ADL-MIDAS approach.
[3] See Ghysels (2015) for further details.
[4] See Gysels (2015) for details of these three schemes.

In more detail ADL-MIDAS (p_Y^M, p_X^D) can be written as:

$$Y_{t+1}^M = \mu + \sum_{j=0}^{p_Y^M-1} \mu_{j+1} Y_{t-j}^M + \beta \sum_{j=0}^{p_X^D-1} \sum_{i=0}^{N_D-1} w_{N_D-i+j*N_D}(\theta^D) X_{N_{D-i,t-j}}^D + \varepsilon_{t+1} \quad (5.11)$$

where N_D is the number days in a month; p_Y^M and p_X^D mean the lags of Y_{t+1}^M and $X_{N_{D-i,t-j}}^D$, respectively. $\sum_{j=0}^{p_Y^M-1} \mu_{j+1} Y_{t-j}^M$ appear for AR terms of the regressand. β is slope coefficient and weights sum to one; that is, $\sum_{j=0}^{p_X^D-1} \sum_{i=0}^{N_D-1} w_{N_D-i+j*N_D}(\theta^D) = 1$ allowing identification of β. Furthermore, ADL-MIDAS (p_Y^M, p_X^D, J_X^D) model to use information between t and t+1 by adding J_X^D leads can be written by the following equation (Li et al., 2013):

$$Y_{t+1}^M = \mu + \sum_{j=0}^{p_Y^M-1} \mu_{j+1} Y_{t-j}^M + \beta \sum_{j=0}^{p_X^D-1} \sum_{i=0}^{N_D-1} w_{J_X^D+N_D-i+j*N_D}(\theta^D) X_{N_{D-i,t-j}}^D + \beta \sum_{i=0}^{J_X^D-1} w_{J_X^D-i}(\theta^D) X_{J_X^D-i,t+1}^D \quad (5.12)$$

where J_X^D is the lead of regressors. This model allows us to realize nowcasting of low frequency variables by using information between t and t+1.

For this study, for instance, consumer confidence index which is a monthly time series y_t that is available only once between months *t-1* and *t* is tried to be forecasted by using a variable x_t^H that is observed at a higher sampling frequency (m times) over the same period (e.g., m=22 working days in our case). In other words, our regressors are sampled m times more frequently than our regressand. These $x_t^{(m)}$s are exchange rate, gold price, oil price and stock exchange series sampled at daily frequency and results are obtained via changing high frequency data by 1/m increments.

As a small remark, it would be beneficial to illustrate lag and horizon value selection by simple examples, as well. If the Xlag (Ylag) value is equal to nine (one), this means that explanatory variables (low frequency variable) include nine (one) lagged high (low) frequency variables. If horizon value is set equal to one in forecasting, say, quarterly variable with monthly variable, then it means that monthly variables are

incorporated up to one month before the low frequency quarterly data. In summary, changes in h value will change included recent high frequency regressors. In order to avoid confusion, following two time-frame of the estimation processes are provided as examples. If you determine lag and horizon values as Xlag=9, Ylag=1 and h=1; then mixed frequency regression time frame is displayed as follows (for example, Start date is 01 Jan 1985, Terminal Date is 01 Jan 2009 and Y is quarterly data, X is monthly data):

Reg Y(01/01/85) on Y(10/01/84), X(12/01/84), X(11/01/84), … , X(04/01/84)

Reg Y(04/01/85) on Y(01/01/85), X(03/01/85), X(02/01/85), … , X(07/01/84)

…

Reg Y(01/01/09) on Y(10/01/08), X(12/01/08), X(11/01/08), … , X(04/01/08).

The first row of the time frame in above figure clearly shows that for the regression of quarterly variable at 01/01/1985, one quarter lag of Y and 9 months lag of X included to the regression. Also, horizon value set to one implies that dependent variable in period t is accompanied by high frequency regressors in period t-1, t-2, etc., i.e. X lags are included until one month before to the low frequency variables. It enables researcher the use of all available data to forecast quarterly variable. On the other hand, if horizon value is reset to 3, the dependent variable is regressed on high frequency data in t-3, t-4, etc. The time frame below includes X lags until one quarter ago because of horizon value; h=3.

Reg Y(01/01/85) on Y(10/01/84), X(10/01/84), X(09/01/84), … , X(02/01/84)

Reg Y(04/01/85) on Y(01/01/85), X(01/01/85), X(12/01/84), … , X(05/01/84)

…

Reg Y(01/01/09) on Y(10/01/08), X(10/01/08), X(09/01/08), … , X(02/01/08).

In the first row, for instance, researcher does not exploit recent information compared to h=1 case which is including all information coming from X(12/01/1984) and X(11/01/1984).

As a result, researchers should be careful when they are setting the values for horizon and lag values, due to their significant effect on the regression results. Proper horizon and lag settings will improve forecast results and its precision. More importantly, by tweaking h values, it is possible to get nowcasting results. In case of above example, i.e. combination of quarterly-monthly estimation, by changing h value from 3 to 1, MIDAS (ADL-MIDAS in this research) with 2 months of leads is estimated which means the program is forecasting with one month horizon value, instead of 3 months (one quarter).

5.3. GARCH- MIDAS

This section will give a brief overview of new class of component GARCH model based on MIDAS model. This new framework referred as GARCH-MIDAS is proposed by Engle, Ghysels and Sohn (2013) allowing us to include macroeconomic variables directly into the specification to obtain long term component. GARCH-MIDAS model is described as below. Assume that the return, $r_{i,t}$ on day *i* in month *t* is written by the following equation:

$$r_{i,t} = \mu + \sqrt{\tau_t . g_{i,t}}\varepsilon_{i,t}, \quad \forall i = 1, \dots, N_t \tag{5.13}$$

where N_t is the number of business days in month and $\varepsilon_{i,t} \mid \Phi_{i,t-1} \sim N(0,1)$ with $\Phi_{i,t-1}$is the information set up to $(i\text{-}1)^{th}$ day of period *t*. It should be noted that volatility is decomposed into short run and long run components of volatility; $g_{i,t}$ and τ_t. The former refers daily fluctuations related to short lived effects of volatility. On the other hand, the long run component, which is also called secular component, presents the unconditional volatility and is intended to capture the slowly changing deterministic conditions in the economy. The short run component following (daily) GARCH (1, 1) process can be written as:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta\, g_{i-1,t} \tag{5.14}$$

where, $\alpha > 0$, $\beta \geq 0$, $\alpha + \beta < 1$.

The long run component, τ_t which is defined as smoothed realized volatility can be specified as:

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) RV_{t-k} \tag{5.15}$$

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 \tag{5.16}$$

where RV_tdenotes fixed time span monthly realized volatility at time t. In order to complete GARCH-MIDAS model, the weighting scheme for the MIDAS filter in equation 5.15 can be specified as follows:

$$\varphi_k(\omega) = \begin{cases} \dfrac{(k/K)^{\omega_1 - 1}(1 - k/K)^{\omega_2 - 1}}{\sum_{j=1}^{K}(j/K)^{\omega_1 - 1}(1 - j/K)^{\omega_2 - 1}} & Beta \\ \omega^k / \sum_{j=1}^{K} \omega^j & Exp.Weighted \end{cases} \tag{5.17}$$

It should be noted that, Beta lag is very flexible since it can show monotonically increasing, decreasing or hump-shaped weighting scheme[5]. Here, the equations 5.13-5.17 form our model for time varying conditional variance with fixed time span RVs and our parameter space is $\Theta = \{\mu, \alpha, \beta, m, \theta, \omega_1, \omega_2\}$. In fixed time span RV, there is restriction in which τ_t is fixed for month *t*. By removing this restriction, both *g* and τ can change at the daily frequency. For this purpose, the rolling window RV is introduced by the following equation:

$$RV_i^{(rw)} = \sum_{j=1}^{N'} r_{i-j}^2 \tag{5.18}$$

where r_{i-j} is used to show the process of rolling back the days. Specifically, if the value N' is set to 22, then it is called monthly rolling window RV, while the cases for $N' = 65$ and $N' = 125$ indicate quarterly or biannual rolling window RVs,

[5] See Ghysels Sinko Valkanov (2007) for further details about different paterns of Beta lag.

respectively. Therefore, the long run component τ_t is redefined by considering equation 5.18[6]:

$$\tau_i^{(rw)} = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) RV_{i-k}^{(rw)} \quad (5.19)$$

Now, in addition to the models with two different specification, fixed span and rolling window RV; the GARCH-MIDAS models directly involving macroeconomic data can be specified as:

$$\log \tau_t = m_l + \theta_l \sum_{k=1}^{K_l} \varphi_k(\omega_{1,l}, \omega_{2,l}) X_{t-k}^{l} \quad (5.20)$$

where X_{t-k}^{l} represent macroeconomic variable that we want to relate to the low frequency component volatility which is consumer confidence index in this thesis. The subscript *l* refers to the level of macroeconomic variable under examination.

All in all, GARCH-MIDAS has very nice features. First of all, it enables us to incorporate data with different frequencies, so that high frequency daily data can be combined with monthly series. Also, because of fixed number of parameters to be estimated irrespective of number of lags, it is very parsimonious model compared to other component models. It enables comparison of GARCH-MIDAS models associated with different time spans.

[6] The '*t' is* dropped in this equation because everything is of daily frequency.

6. EMPIRICAL FINDINGS AND DISCUSSION

6.1. Design of the exercise

In this chapter, brief information about the construction of the variants of MIDAS models, namely ADL-MIDAS and GARCH-MIDAS is given. For the nowcasting and forecasting monthly consumer sentiment, high frequency data by pursuing ADL-MIDAS model conducted with both single and multivariable models. On the other hand, predictive ability of changes in consumer sentiment on the volatility of returns of high frequency variables is focused in the second part of the empirical research. It is GARCH-MIDAS model that lead us to examine the direct link between volatility of interested variables and sentiment index without two step procedure stemming from data series sampling at different frequencies. As a result, ADL-MIDAS and GARCH-MIDAS models are conducted with one sentiment index series each time. In all cases, frequency mismatch is not an obstacle which reinforces the usefulness of these methods among researchers.

In case of ADL-MIDAS applications, six models with single predictors (daily variables) for full sample and subsample periods are formed to evaluate the determinants of consumer confidence to obtain in sample and out of sample estimation results. Moreover, three models with combination of four high frequency variables are used to get additional out of sample estimation results. For these estimation periods, by using the Beta weighting function, three estimation techniques, mentioned in Chapter 5, are implemented; namely Fixed Window Scheme, Rolling Window Scheme and Recursive Scheme. Although they demonstrate similar results in terms of RMSEs values, there are some significant differences in the regression outcomes.

In the first place, it should be noted that performances of each high frequency variables and their combinations are determined by evaluating root mean square errors (RMSEs, henceforth) for each model, separately. These RMSEs are very important in a sense that small values of them indicate better forecast results in understanding functional identity of consumer sentiment. In other words, given the types of predictors at hand, model with one or more variable with smaller value of RMSE outperforms

others. Hence, to get these RMSEs, in sample estimation methods for given periods are applied to both BHT CCI and CBRT CCI. Moreover, these estimations provide with slope coefficients, t statistics, AIC, BIC and R square values which yields further information about models used.

To conduct this research, horizon and lag value selection is very important. As it is mentioned in Chapter 5, MIDAS regressions take horizon and lag values into account to determine which data will be included to the related regression time frame. In most of the cases, horizons are specified based on the purpose of nowcasting. Specifically, the values of 5, 11, 16 and 22 days of horizons are chosen to refer approximately 1, 2, 3 and 4 weeks of business days, respectively. Furthermore, the model specification is selected according to the value of horizons which give better RMSEs. Normally, for some cases in the literature, AIC and BIC is used for this purpose; however, in this case, they do not change in significant amounts when the values of horizons are revised.

Determination of the appropriate lag values for each high and low frequency variables is another important point. In the estimation processes, the lag value for low frequency (Y) variable is decided to be equal to one month (Ylag=1 month) based on the fact that increased number of lag value for Y variable does not alter the results in a significant amount. Similarly, after 2 months, in general, there is not so much improvement in the models in terms of RMSEs, when the lag values for high frequency variables (Xlags) are modified. Therefore, Xlag values are set to one and two months for each different model which are approximately equal to the 22 days and 44 days (i.e. business days), respectively. For better understanding of what is mentioned about the lag selection, Figure 10-15 portray the relationship between consumer confidence indices and Xlag values until 132 days (approximately 6 months). According to the illustrations in Figure 10-15, it can be easily recognized that after some point, the results for the full sample period do not improve considerably by increasing the lag length of high frequency variables[7].

[7] Similar conclusion canbe drawn for Ylag values. It is available upon request.

Definitely, since the main concern of ADL-MIDAS application in this paper is to follow the behavior of consumer sentiment by some important macroeconomic factors, it would be very crucial to demonstrate how estimated values are far from the actual ones. To serve this purpose, after finding out the appropriate horizon and lag lengths which are displayed in the preceding two paragraphs, out of sample estimation is carried out for the period of 12 months starting from July 2016 to June 2017. Furthermore, similar results are obtained according to appropriate lag lengths and horizons for subsample period, which is attributed to the period of global financial crisis. Therefore, two years of out of sample results are given for interval 2008M1-2009M12.

All in all, for ADL-MIDAS case, by using 9 models with 3 estimation schemes and 2 different lag lengths, there are computations of 54 cases for each confidence indices for in sample estimation with full sample period. When the subsample is considered, 6 models with 3 estimation schemes and 1 month value of Xlag, that is equal to 18 cases, will be visited for each index. On the other hand, out of sample forecasts constitute 12 months of estimated values for each index by using 3 estimation techniques for full sample period; while the crisis period will be examined in detail by showing the 24 months of outcome.

In second part of the empirical estimation, GARCH-MIDAS approach with same time period and same variables is introduced. The only difference is that this part of research is conducted from the other direction; i.e. to understand the volatility of daily variables with two consumer confidence index. Before introducing GARCH-MIDAS outcomes, there is some preliminary information that should be given. First of all, the value of 'period' for all high frequency variables is set equal to 22. This number basically corresponds to the number of times in which the daily variables repeat throughout the month, in this case. The other important issue is choice of the 'numLag' value. In order to capture reasonable dynamics of τ_t, one MIDAS lag year[8] for the value

[8] Optimal lag number, k, equals one year for fixed span specification refers 12 months spanned by 12 lagged monthly RV's in the MIDAS filter, since τ_t is fixed for each month. For rolling window RV, τ component changes in daily basis, therefore 12 months lag value refers 264 business days spanned by 264 lagged monthly rolling window RV's in the MIDAS filter; that is, K=264 (22 business days in a month).

of 'numLags'[9] is considered in MIDAS codes. It should also be mentioned for the weighting function (or smoothing function) that Beta lag structure is used, since it is very flexible. The model is estimated via maximum likelihood method; specifically the following Log Likelihood Function shown in equation 6.1 is maximized:

$$\text{LLF} = -\frac{1}{2}\sum_{t=1}^{T} \left[\log g_t(\Phi)\tau_t(\Phi) - \frac{(r_t-\mu)^2}{g_t(\Phi)\tau_t(\Phi)} \right] \quad (6.1)$$

Additionally, some related literature for the selection of ω_1 and ω_2 in which $\omega_1 = 1$ and $\omega_2 = \omega$ is followed and reported in regression outcomes. It is stated that regardless of value of ω_2 ; if ω_1 is equal to 1, Beta function behaves in a monotonically decreasing pattern. Thus, for ω_1 =1, more recent observation contributes more to the secular volatility.

Also, it is found that w_2 values are always greater than one meaning that larger values of it produce rapidly decreasing pattern10.

In the end of the GARCH-MIDAS estimation, we obtain parameter estimates of μ, α, β, θ, ω and m values for six daily variables with corresponding t values, standard errors, LLF/BIC values and RMSEs for both sentiment indices. Furthermore, for all 6 daily returns, we estimate total and secular volatilities with 2 specifications; i.e. fixed span and rolling window. As a result, we will be able to understand impact of changes in the level of BHT CCI and CBRT CCI on the volatility of each high frequency returns by simply looking at the obtained parameter estimates.

[9] 'NumLags' value specifies the number of lags in filtering the long run component by MIDAS weights.
[10] See Hoang (2015) for further details.

Figure 10. RMSEs for different Xlags (BHT CCI, Fixed Window Estimation)

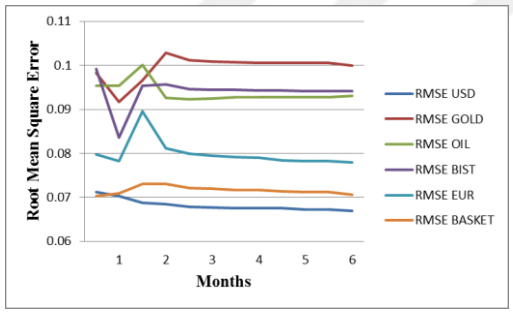


Figure 11. RMSEs for different Xlags (CBRT CCI, Fixed Window Estimation)

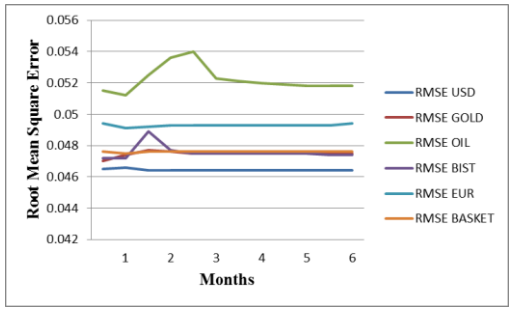


Figure 12. RMSEs for different Xlags (BHT CCI, Rolling Window Estimation)

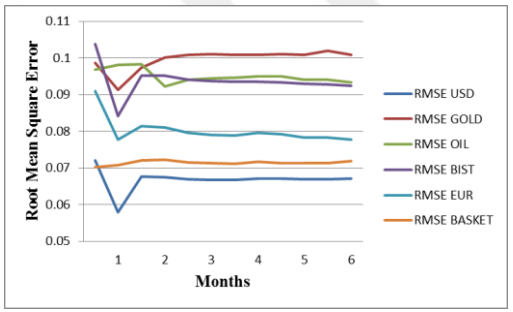


Figure 13. RMSEs for different Xlags (CBRTCCI, RollingWindow Estimation)

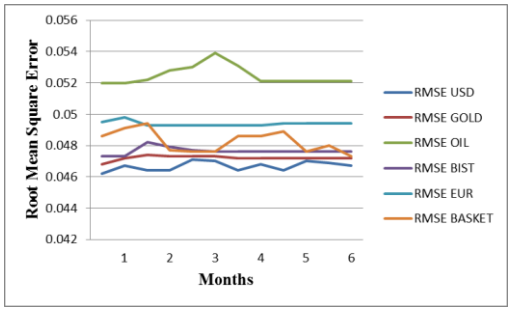


Figure 14. RMSEs for different Xlags (BHT CCI, Recursive Estimation)

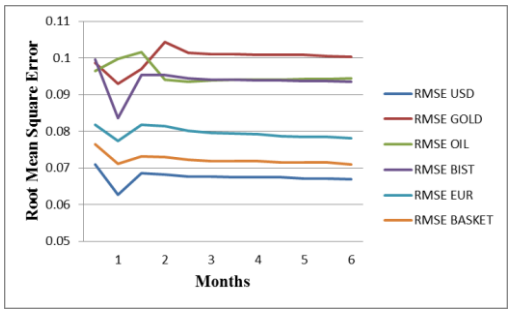
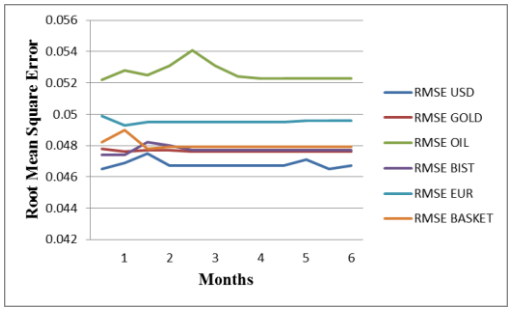


Figure 15. RMSEs for different Xlags (CBRTCCI, Recursive Estimation)



Now, we have all information to comprehend overall estimation outcomes of two subsequent subchapters. The models are solved in MATLAB R2017A with intuition coming from MIDAS Matlab Toolbox Version 2.2. For two models, ADL-MIDAS and GARCH-MIDAS, some part of the codes can find their intuition from Armesto, Engemann and Owyang (2014)'s and Engle, Ghysels and Sohn (2013)'s methods, respectively.

6.2. ADL-MIDAS

6.2.1. In Sample Estimation Results

This chapter includes in sample estimation results obtained by 3 estimation schemes for full sample period. It covers the RMSEs and regression results for each model. Specifically, Table 4, 5 and 6 show the in sample estimation results at different horizons by implementing 3 estimation schemes, respectively. There are several findings emerging from these outcomes. Most importantly, examining these three tables in detail yields to form an opinion about the forecasting performances of each variable based on their related RMSEs. Then, the regression results, shown in Table 7-12, strengthen our findings.

First and foremost, it should be noticed from the Table 4-6 that the RMSEs for BHT CCI increase with forecast horizons (h); however for the case of CBRT CCI, the RMSE for the latest horizon is the smallest. Regarding all high frequency variables with 1 or 2 months lag values; horizon value equal to 22 days works out better for CBRT CCI; whereas 5 days produces finer results for BHT CCI, except few cases in total. In case of BHT CCI, it is reasonable to get smaller RMSEs for shorter horizon, because it enables the use of almost all available information during the time period that surveys are conducted which corresponds to the period starting 5 days before the 27th[11] of related month[12]. As expected, and in line with the literature the forecasting performance increases (i.e. smaller RMSEs) as horizon value decreases. On the other hand, CBRT CCI performs better for the longer horizon values. Although one would expect that the

[11] Represents the end of BHT CCI surveys conducted until 27th day of related month.
[12] See Chapter 5 for the explanation of horizon value.

use of more recent data is more informative for forecast precision, it does not seem to be the case of CBRT CCI. In detail, it seems that it is not using the recent available data in that month, but the last month. Yet, CBRT CCI surveys are conducted in first 15 days of the related month. In general, especially in the first week, respondents use the information from the previous month during the survey. Therefore, the short time period which CBRT CCI surveys are implemented can be a reason for why the longer horizon value (h=22) performs well in the determination of smallest RMSEs. One thing that should be expressed here is that, oil price[13] is an exception for most of the cases with CBRT CCI. Possible reasons related to this will be considered later.

Now, Table 4 demonstrates RMSE values for fixed window estimation approach. Besides, in almost all cases for two indices with fixed window estimation scheme, the superior RMSEs are attained in the models constructed with exchange rate of US dollar and exchange rate of equally weighted basket including US dollar and euro. By considering the general consumer expectations in Turkey, it can be deduced that it is in line with the literature; since people are highly sensitive to the exchange rate movements. On the other hand, the models with gold price and stock price deliver similar RMSEs with slight differences. Again, it is not a surprise conclusion assuming the fact that gold and stock prices are variables which are frequently accepted as an important indicator of current economic situation among people. In the determined horizons, forecast accuracy of model constructed with oil price is lower than other variables. To have a clear vision of Table 4, Figure 16-19 thoroughly reveal these arguments mentioned for both indices with two different lag values. Figure 16 and 17 is drawn to illustrate the RMSEs obtained by the models with BHT CCI, while Figure 18 and 19 is for CBRT CCI. As a result, when the horizon increases, forecast accuracy deteriorates for the former one, whereas it reaches its highest value for the latter.

[13] See Figure 18, 19, 22, 23, 26, 27.

Table 4. RMSEs From In Sample Estimations, Fixed Window

		Forecasted Variable							
		CBRT CCI, h days ahead				BHT CCI, h days ahead			
Forecasting Experiment		h=5	h=11	h=16	h=22	h=5	h=11	h=16	h=22
1 monthly lag of CCI	USD/TL	0.0507	0.0479	0.0497	**0.0466**	**0.0703**	0.0745	0.095	0.1008
22 daily lags of Exchange Rate	EUR/TL	0.052	0.0528	0.0509	**0.0491**	**0.0783**	0.082	0.0986	0.1078
	BASKET	0.0516	0.0503	0.05	**0.0475**	**0.0709**	0.0774	0.0976	0.105
1 monthly lag of CCI	USD/TL	0.0491	0.0481	0.0505	**0.0464**	**0.0684**	0.0727	0.0915	0.1017
44 daily lags of Exchange Rate	EUR/TL	0.0503	0.0527	0.052	**0.0493**	0.0812	**0.0789**	0.0934	0.1063
	BASKET	0.0501	0.0505	0.0511	**0.0476**	**0.073**	0.0749	0.0927	0.1046
1 monthly lag of CCI 22 daily lags of Gold Price		0.0534	0.0507	0.0514	**0.0474**	**0.0917**	0.1002	0.0987	0.1089
1 monthly lag of CCI 44 daily lags of Gold Price		0.0516	0.0508	0.0522	**0.0476**	0.1029	**0.1005**	0.1018	0.106
1 monthly lag of CCI 22 daily lags of Oil Price		0.0544	0.0532	**0.0492**	0.0512	**0.0953**	0.0997	0.1031	0.1051
1 monthly lag of CCI 44 daily lags of Oil Price		0.0506	0.0485	**0.0494**	0.0536	**0.0926**	0.1012	0.1009	0.1039
1 monthly lag of CCI 22 daily lags of BIST 100		0.0514	0.0534	0.0534	**0.0472**	**0.0836**	0.0973	0.0846	0.1031
1 monthly lag of CCI 44 daily lags of BIST 100		0.0506	0.0529	0.0537	**0.0477**	0.0956	0.0927	**0.0813**	0.1071

Source: Author's Estimations
Note: The smallest RMSEs are shown in bold.

Results for Rolling Window and Recursive Schemes at various horizons are reported in Table 5 and Table 6, separately. Roughly, similar inferences can be drawn. Again, in both Table 5 and 6 with different estimation schemes, the dollar exchange rate outperforms other high frequency variables at horizon value 5 and 22 for BHT CCI and CBRT CCI, respectively. Then, gold price and stock price come after in terms of forecast performances, except for the model constructed by BHT CCI and 44 days lags of gold price. To illustrate, Figure 20-27 can be considered for both indices. As it is mentioned before, in generally, the more horizon value that BHT CCI has, the less forecast accuracy that the models have. Conversely, the more horizon value that CBRT CCI has, the more forecast performance the models have (except some cases). As a result, these arguments can be supported simply by using Figure 16-27, as well.

Table 5. RMSEs From In Sample Estimations, Rolling Window

		Forecasted Variable							
		CBRT-CCI, h days ahead				BHT-CCI, h days ahead			
Forecasting Experiment		h=5	h=11	h=16	h=22	h=5	h=11	h=16	h=22
1 monthly lag of CCI	USD/TL	0.0515	0.048	0.0499	**0.0467**	**0.0579**	0.0752	0.0949	0.1015
22 daily lags of Exchange Rate	EUR/TL	0.0527	0.0531	0.0509	**0.0498**	**0.0778**	0.0815	0.1019	0.1096
	BASKET	0.0524	0.0506	0.0501	**0.0491**	**0.0707**	0.0779	0.0945	0.1067
1 monthly lag of CCI	USD/TL	0.0496	0.0483	0.0509	**0.0464**	**0.0674**	0.0729	0.0922	0.1022
44 daily lags of Exchange Rate	EUR/TL	0.0507	0.0529	0.0521	**0.0493**	0.081	**0.0793**	0.0942	0.1073
	BASKET	0.0506	0.0508	0.0514	**0.0477**	**0.0723**	0.0776	0.0937	0.1057
1 monthly lag of CCI 22 daily lags of Gold Price		0.054	0.0509	0.0514	**0.0472**	**0.0913**	0.1009	0.0986	0.1086
1 monthly lag of CCI 44 daily lags of Gold Price		0.0524	0.0509	0.0523	**0.0473**	**0.1002**	0.101	0.1008	0.1055
1 monthly lag of CCI 22 daily lags of Oil Price		0.0538	0.0546	**0.0496**	0.052	**0.0981**	0.0995	0.1014	0.1043
1 monthly lag of CCI 44 daily lags of Oil Price		0.0538	**0.049**	0.0494	0.0528	**0.0923**	0.1019	0.1019	0.1031
1 monthly lag of CCI 22 daily lags of BIST 100		0.0527	0.0528	0.0529	**0.0473**	0.0842	0.0975	**0.0833**	0.1037
1 monthly lag of CCI 44 daily lags of BIST 100		0.0509	0.0526	0.0533	**0.0479**	0.0951	0.0921	**0.0805**	0.1058

Source: Author's Estimations

Note: The smallest RMSEs are shown in bold.

Figure 16. RMSEs for Fixed Window Estimation of BHTCCI, in case of Xlag=22

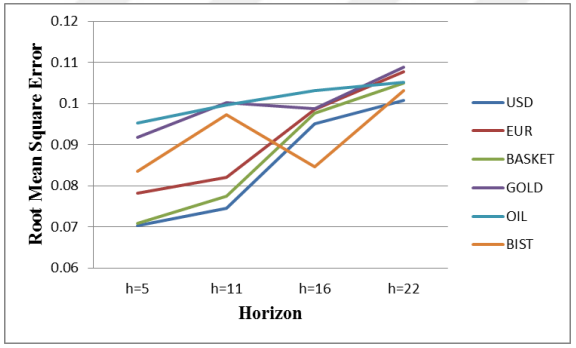


Figure 17. RMSEs for Fixed Window Estimation of BHTCCI, in case of Xlag=44

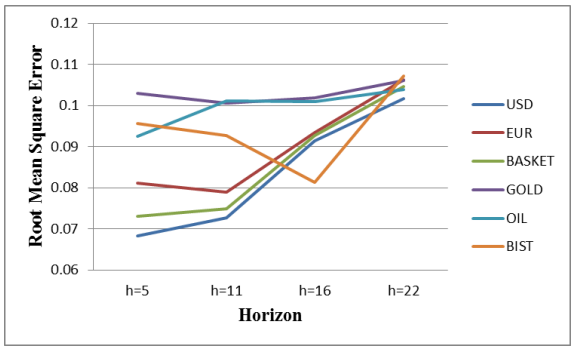


Figure 18. RMSEs for Fixed Window Estimation of CBRTCCI, in case of Xlag=22

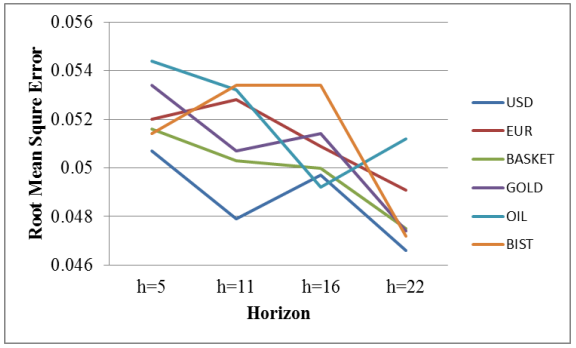


Figure 19. RMSEs for Fixed Window Estimation of CBRTCCI, in case of Xlag=44

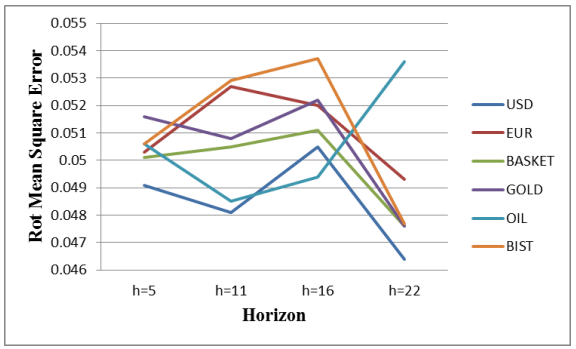


Figure 20. RMSEs for Rolling Window Estimation of BHTCCI, in case of Xlag=22

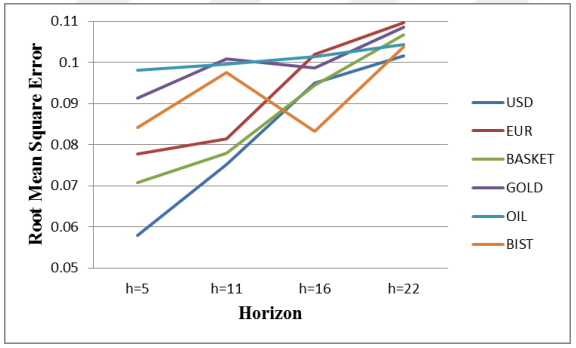


Figure 21. RMSEs for Rolling Window Estimation of BHTCCI, in case of Xlag=44

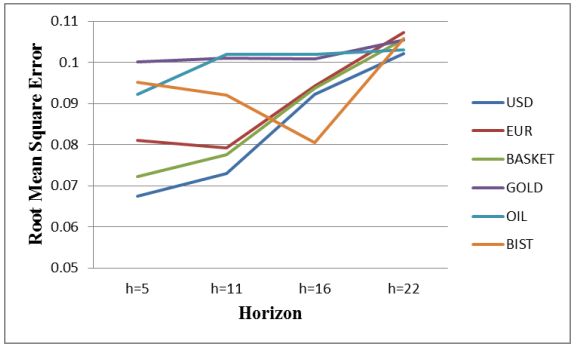


Figure 22. RMSEs for Rolling Window Estimation of CBRTCCI, in case of Xlag=22

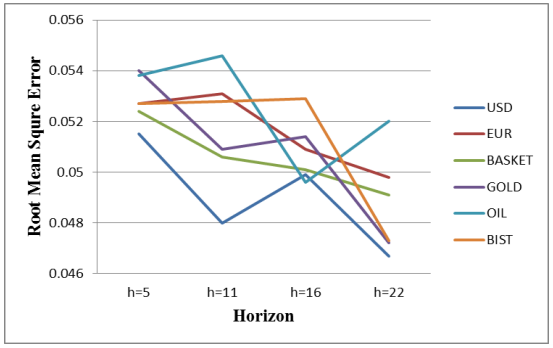


Figure 23. RMSEs for Rolling Window Estimation of CBRTCCI, in case of Xlag=44

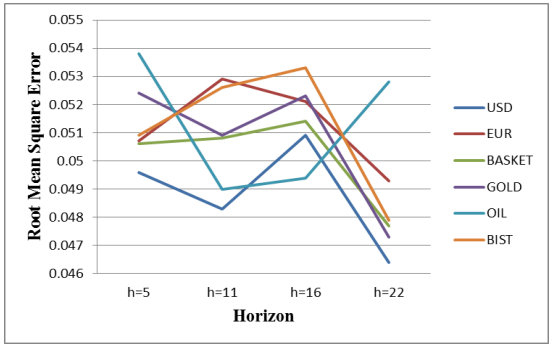


Table 6. RMSEs From In Sample Estimations, Recursive

		Forecasted Variable							
		CBRT-CCI, h days ahead				BHT-CCI, h days ahead			
Forecasting Experiment		h=5	h=11	h=16	h=22	h=5	h=11	h=16	h=22
1 monthly lag of CCI	USD/TL	0.0515	0.0484	0.0492	**0.0469**	**0.0628**	0.0752	0.0954	0.1015
22 daily lags of Exchange Rate	EUR/TL	0.0526	0.0532	0.0511	**0.0493**	**0.0773**	0.0822	0.0984	0.1083
	BASKET	0.0523	0.0508	0.0504	**0.049**	**0.0711**	0.078	0.0976	0.1056
1 monthly lag of CCI	USD/TL	0.0479	0.0485	0.0512	**0.0467**	**0.0683**	0.0728	0.0924	0.1025
44 daily lags of Exchange Rate	EUR/TL	0.0508	0.0531	0.0522	**0.0495**	0.0814	**0.0793**	0.0941	0.1066
	BASKET	0.0504	0.051	0.0516	**0.0479**	**0.073**	0.076	0.0935	0.1052
1 monthly lag of CCI 22 daily lags of Gold Price		0.054	0.051	0.0515	**0.0476**	**0.093**	0.1007	0.0991	0.1091
1 monthly lag of CCI 44 daily lags of Gold Price		0.0527	0.0511	0.0524	**0.0477**	0.1043	**0.101**	0.1022	0.1062
1 monthly lag of CCI 22 daily lags of Oil Price		0.0537	0.0545	**0.0497**	0.0528	**0.0997**	0.0992	0.1069	0.1054
1 monthly lag of CCI 44 daily lags of Oil Price		0.0538	0.0492	**0.0499**	0.0531	**0.094**	0.1021	0.1018	0.1042
1 monthly lag of CCI 22 daily lags of BIST 100		0.0532	0.0532	0.053	**0.0474**	**0.0836**	0.0994	0.0834	0.1042
1 monthly lag of CCI 44 daily lags of BIST 100		0.051	0.0527	0.0534	**0.048**	0.0954	0.0926	**0.0811**	0.1069

Source: Author's Estimations

Note: The smallest RMSEs are shown in bold.

To sum up, all three tables (Table 4-6) investigated separately show the predictive content of each high frequency indicators on consumer confidence index and help nowcasting of consumer sentiment. As these analyses indicate, model constructed with exchange rate is the most relevant among other models, which is generally followed by stock price and gold price. On the other hand, changing the estimation scheme from fixed window approach to rolling window approach and from fixed window approach to recursive approach cause some slight differences. There is an increase in RMSEs in the total eight models out of twelve, which basically lead us to prefer fixed window approach as an estimation scheme. Yet, all of these three models are not giving desired information about oil price, which is normally regarded as an

Figure 24. RMSEs for Recursive Estimation of BHTCCI, in case of Xlag=22

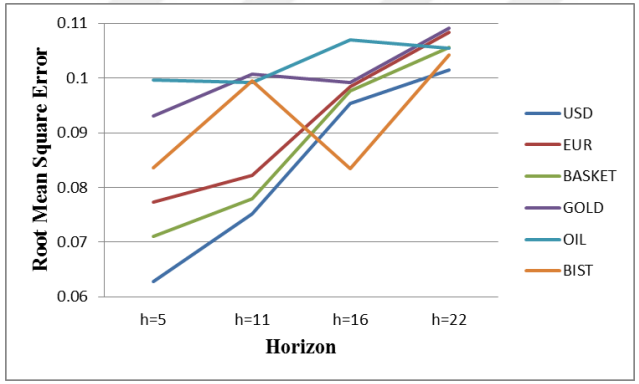


Figure 25. RMSEs for Recursive Estimation of BHTCCI, in case of Xlag=44

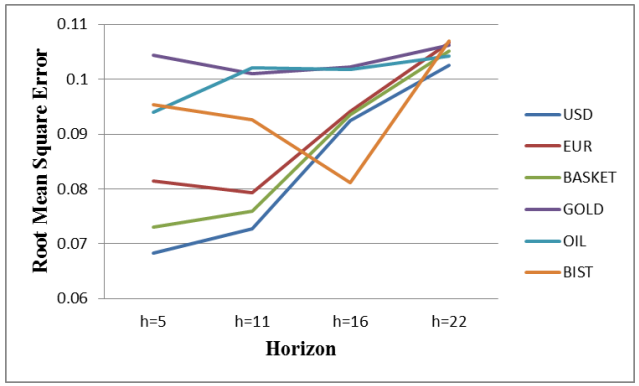


Figure 26. RMSEs for Recursive Estimation of CBRTCCI, in case of Xlag=22

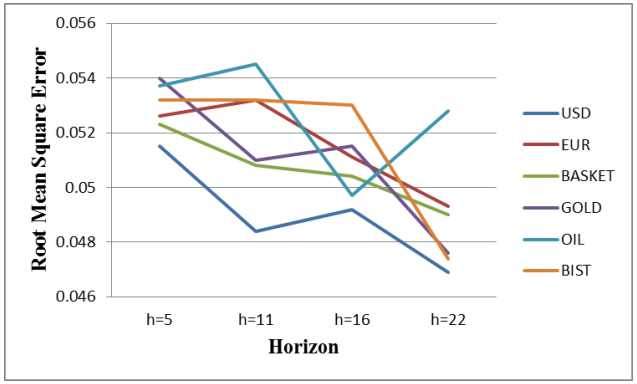
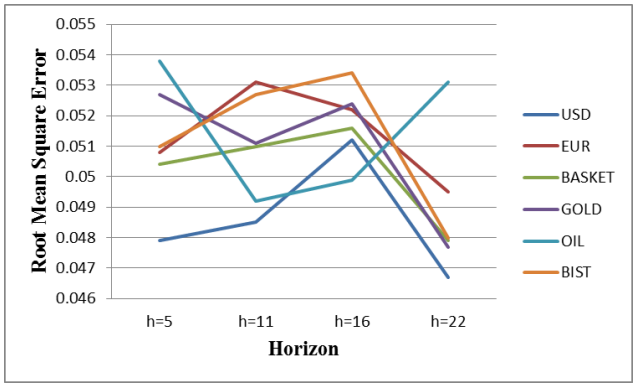


Figure 27. RMSEs for Recursive Estimation of CBRTCCI, in case of Xlag=44



important indicator for consumer confidence, in emerging countries like Turkey. Indeed, these approaches provide with different regression result that should be investigated in detail, as well.

Now, given the fact that the best results in terms of RMSEs are generally obtained at horizon 5 and 22 for BHT CCI and CBRT CCI, respectively; the slope coefficients, t statistics and R square values for each indices are displayed at that horizons in consideration. Specifically, by using three estimation schemes, Table 7, 8 and 9 shows the ADL-MIDAS regressions results of models constructed for BHT CCI; while Table 10, 11 and 12 stands for CBRT CCI. In these tables, how different lag values influence the regression results can be seen, as well. Although the values of BHT CCI are available after 01.01.2002, the analysis period runs from 04.27.2002 to 07.27.2016 due to the necessary adjustments made for the appropriate lag selection. On the other hand, despite the data availability of CBRT CCI after 01.01.2004, the estimation period starts with 03.16.2004 until 07.16.2016 for the same reason mentioned.

To begin with, Table 7 includes regression results obtained by BHT CCI according to the fixed window approach. The results for 22 business days (1 month) of Xlag value are in the third and fourth column; while fifth and sixth columns consists of the outcomes for Xlag = 44 business days (2 month). We observe that eleven out of twelve cases are statistically significant. Moreover, signs of all coefficients are as expected.

Specifically, exchange rate, gold price and oil price (although it is not statistically significant for one of the lags) have negative coefficients and stock price has positive coefficient for both lag lengths. Regarding all coefficients in case of 22 and 44 lag lengths, the largest effect on BHT CCI comes from the exchange rate variable, specifically exchange rate of equally weighted basket including US dollar and euro (BASKET). One unit increase in the BASKET variable cause BHT CCI to decrease

Table 7. ADL-MIDAS Regression Results for BHT CCI by Fixed Window Estimation

		BHT CCI with 1 month Xlag		BHT CCI with 2 month Xlag	
HF Variables		**ADL-MIDAS R Square**	**ADL-MIDAS Slope**	**ADL-MIDAS R Square**	**ADL-MIDAS Slope**
Exchange Rate	**USD/TL**	0.85718	**-0.2883*** **	0.86718	**-0.3482*** **
			(-8.7528)		(-9.4179)
	EUR/TL	0.84354	**-0.2457*** **	0.85178	**-0.3126*** **
			(-7.5537)		(-7.8983)
	BASKET	0.85808	**-0.3052*** **	0.86791	**-0.3752*** **
			(-8.9886)		(-9.4077)
Gold Price		0.82033	**-0.1363*** **	0.82689	**-0.2018*** **
			(-5.3059)		(-5.8525)
Oil Price		0.79262	-0.0043	0.79597	**-0.0360***
			(-1.3392)		(-1.8107)
Stock Exchange		0.83453	**0.0965*** **	0.87122	**0.1789*** **
			-5.9426		-9.6744

Source: Author's Estimations.

Note : t-statistics are in parenthesis and significant values are shown in bold.

***, ** and * denotes significance at 1, 5 and 10% level.

0.3052 basis point in case of Xlag=22 and 0.3752 basis point in case of Xlag=44. In a similar manner, one unit increase in gold price and oil price is followed by 0.1363 (0.2018) and 0.0043 (0.0360) basis point of decrease in consumer sentiment for Xlag=22 (Xlag=44). On the other hand, the movements of stock price and sentiment index are in the same direction providing that one unit rise in BIST value boost BHT CCI in an amount of 0.0965 and 0.1789 basis units for each lag length, respectively. Finally, by looking all the coefficients, one would expect that more lag length value for each variable will result in more influence of that variable on sentiment index. In other words, when lag value rises from 22 to 44, there is an increase in the absolute value of all coefficients.

Furthermore, by looking at the R square values shown in the third and fifth columns, it can be concluded that all models fit our data quite well; that is, they reveal higher value of R squares taking values between 79% and 87%. The exchange rate, precisely BASKET, has more R square value than the other variables which supports the idea that BHT CCI is nowcasted better by using exchange rate variable.

Similarly, the regression results obtained by rolling window approach for BHT CCI are demonstrated in the Table 8. At first glance, it seems that there is not so much change in the signs of coefficients. Indeed, BASKET variable is still performing better when the R squares values are considered and has more influence on BHT CCI when the magnitudes of all coefficients are taken into consideration. However, it is important to notice that, by switching estimation technique to Rolling Window approach, magnitudes of all slope variables and significance of oil price with 22 days lag is changed.

It is presented in the table 8 that eleven out of twelve cases are statistically significant. One unit increase in the BASKET variable cause BHT CCI to decrease 0.295 basis point in case of Xlag=22 and 0.3806 basis point in case of Xlag=44. Additionally, compared to the Fixed Window approach, any change in the value of BIST has more influence than Gold price on BHT CCI for both 22 days and 44 days of lag values. Hence, one unit increase in the BIST variable cause BHT CCI to increase 0.1087 basis point in case of Xlag=22 and 0.1689 basis point in case of Xlag=44. In a similar manner, one unit increase in gold price is followed by 0.0856 and 0.1007 basis point of decrease in consumer sentiment for Xlag=22 and Xlag=44, respectively.

Even though oil price is not statistically significant in the case of fixed window estimation with 22 days of lag value, it is statistically significant and has negative impact on BHT CCI in rolling window estimation with 22 days lag length value for oil price. Indeed one unit increase in oil price with 22 days of Xlag causes 0.0093 basis points decrease in BHT CCI. Furthermore, by switching fixed window estimation to the rolling one, there is an improvement in the goodness of fit values which are revolving between 82% and 89%.

Table 8. ADL-MIDAS Regression Results for BHT CCI by Rolling Window Estimation

		BHT CCI with 1 month Xlag		BHT CCI with 2 month Xlag	
HF Variables		**ADL-MIDAS R Square**	**ADL-MIDAS Slope**	**ADL-MIDAS R Square**	**ADL-MIDAS Slope**
Exchange Rate	**USD/TL**	0.88111	**-0.2682*** **	0.89225	**-0.342*** **
			(-8.7268)		(-9.6014)
	EUR/TL	0.87308	**-0.2587*** **	0.87571	**-0.3181*** **
			(-8.1134)		(-7.3981)
	BASKET	0.88339	**-0.295*** **	0.89227	**-0.3806*** **
			(-9.1725)		(-9.3562)
Gold Price		0.84974	**-0.0856*** **	0.85117	**-0.1007*** **
			(-3.8504)		(-4.2604)
Oil Price		0.82955	**-0.0093** **	0.83025	-0.0287
			(-2.2457)		(-1.5316)
Stock Exchange		0.86101	**0.1087*** **	0.88084	**0.1689*** **
			-6.3542		-8.5558

Source: Author's Estimations.

Note: t-statistics are in parenthesis and significant values are shown in bold.

*** , ** and * denotes significance at 1, 5 and 10% level.

Table 9 displays the last scheme for BHT CCI for the full sample period. All of the cases out of twelve are statistically significant in recursive scheme. Similar to the other estimation schemes, BASKET has more influence on BHT CCI than other variables. One unit increase in BASKET with 22 days of Xlag (44 days of X lag) causes 0.3127 (0.3777) basis points decrease in BHT CCI. Gold price is a variable having the second highest negative effect on BHT CCI; that is, one unit increase in price of gold causes 0.1377 and 0.1883 basis points fall for each lag lengths. The following variable stock price, on the other hand, has positive relation; one point rise is reflected as 0.1003 and 0.1776 basis points increase in consumer sentiment. Interestingly, in the recursive scheme, oil price is statistically significant for both lag lengths yielding a negative trend with consumer sentiment.

Table 9. ADL-MIDAS Regression Results for BHT CCI by Recursive Estimation

		BHT CCI with 1 month Xlag		BHT CCI with 2 month Xlag	
HF Variables		**ADL-MIDAS R Square**	**ADL-MIDAS Slope**	**ADL-MIDAS R Square**	**ADL-MIDAS Slope**
Exchange Rate	**USD/TL**	0.8589	**-0.2725*** **	0.87258	**-0.3525*** **
			(-8.655)		(-9.8134)
	EUR/TL	0.84921	**-0.25*** **	0.85555	**-0.3144*** **
			(-8.0004)		(-7.9975)
	BASKET	0.86378	**-0.3127*** **	0.87218	**-0.3777*** **
			(-9.5563)		(-9.6452)
Gold Price		0.82415	**-0.1377*** **	0.82632	**-0.1883*** **
			(-5.4665)		(-5.4731)
Oil Price		0.80481	**-0.0332** **	0.80177	**-0.0393** **
			(-2.105)		(-2.0277)
Stock Exchange		0.83929	**0.1003*** **	0.86937	**0.1776*** **
			-6.3672		-9.4678

Source: Author's Estimations.

Note: t-statistics are in parenthesis and significant values are shown in bold.

***, ** and * denotes significance at 1, 5 and 10% level.

However, its effect is very small compared to the other high frequency variables. One unit increase in price of oil causes 0.0332 and 0.0393 basis points decrease in BHT CCI for each lag lengths. Finally, by switching fixed window estimation to the recursive one, improvement in R square values can be obtained, generally.

Now, it is time to consider CBRT CCI by same techniques used. By applying three estimation schemes; namely fixed window, rolling window and recursive, respectively; Table 10, 11 and 12 demonstrate the results obtained for the models constructed with CBRT CCI.

According to Table 10, ten out of twelve coefficients are statistically significant. Considering all coefficients, exchange rate, specifically BASKET and USD, has more influence on CBRT CCI. To illustrate, one unit increase in BASKET causes 0.0589 and 0.0580 basis points decrease in CBRT CCI for each lag lengths and one unit

increase in USD will result in 0.0548 and 0.0599 basis points decrease in sentiment index. One of the interesting things about these results is that, gold price is not statistically significant for lag length value of 44. However, it has negative relationship; that is, reducing one unit of gold price lead CBRT CCI to fall 0.0184 basis points. The second interesting thing is that oil price displays different trend with BHT CCI. Contrary to the results in the Table 6-8, it shows positive relation with sentiment index. Likewise, stock exchange has also a positive coefficient and changing it one unit will

Table 10. ADL-MIDAS Regression Results for CBRT CCI by Fixed Window Estimation

		CBRT CCI with 1 month Xlag		CBRT CCI with 2 month Xlag	
HF Variables		**ADL-MIDAS R Square**	**ADL-MIDAS Slope**	**ADL-MIDAS R Square**	**ADL-MIDAS Slope**
Exchange Rate	**USD/TL**	0.91427	**-0.0548***** (-4.2527)	0.91361	**-0.0599***** (-3.8858)
	EUR/TL	0.90725	**-0.0397***** (-2.7117)	0.90688	**-0.0387**** (-2.4542)
	BASKET	0.91182	**-0.0589***** (-3.776)	0.91117	**-0.0580***** (-3.4421)
Gold Price		0.90802	**-0.0184*** (-1.7623)	0.90779	-0.0184 (-1.4104)
Oil Price		0.90163	0.001 -0.2845	0.90455	**0.0179**** -2.0429
Stock Exchange		0.91165	**0.0229***** -3.2125	0.91219	**0.0317***** -3.0281

Source : Author's Estimations.

Note : t-statistics are in parenthesis and significant values are shown in bold.

***, ** and * denotes significance at 1, 5 and 10% level.

increase CBRT CCI by 0.0229 and 0.0317 points for 22 and 44 days of lag length, respectively. Finally, all R square terms are between 90% and 92% with the highest R squares belonging to exchange rate and stock price.

In Table 11, all of twelve coefficients are statistically significant and have expected signs except oil price. Again, BASKET and USD have negative relationship with CBRT CCI and reducing one unit of them lead CBRT CCI to fall 0.0610 (0.0712) and 0.0653 (0.0729) for Xlag=22 (Xlag=44), respectively. Similar to the previous

results, one unit increase in stock price causes 0.0285 and 0.0373 basis points rise in CBRT CCI for each lag lengths. Gold price is again statistically significant for both lag values, surprisingly in the rolling window scheme. It has also a negative coefficient and changing it one unit will influence CBRT CCI by 0.0214 and 0.0197 points for 22 and 44 days of lag length.

Table 11. ADL-MIDAS Regression Results for CBRT CCI by Rolling Window Estimation

		CBRT CCI with 1 month Xlag		CBRT CCI with 2 month Xlag	
HF Variables		**ADL-MIDAS R Square**	**ADL-MIDAS Slope**	**ADL-MIDAS R Square**	**ADL-MIDAS Slope**
Exchange Rate	**USD/TL**	0.88227	**-0.0653***** (-4.6621)	0.88137	**-0.0729***** (-4.2621)
	EUR/TL	0.87005	**-0.0486***** (-3.0923)	0.86942	**-0.0497***** (-2.6665)
	BASKET	0.87714	**-0.0610***** (-3.961)	0.87686	**-0.0712***** (-3.7491)
Gold Price		0.87162	**-0.0214**** (-1.9816)	0.87125	**-0.0197*** (-1.6533)
Oil Price		0.86603	**0.0084**** -2.3212	0.86605	**0.0085**** -2.2794
Stock Exchange		0.877	**0.0285***** -3.7216	0.87741	**0.0373***** -3.0427

Source : Author's Estimations.

Note : t-statistics are in parenthesis and significant values are shown in bold.

***, ** and * denotes significance at 1, 5 and 10% level.

On the other hand, different from regression results belonging to BHT CCI, oil price has statistically significant positive relationship with CBRT CCI. Finally, by switching fixed window to rolling window approach, the general level of R square terms declines and are revolving between 86% and 89%.

Finally, in Table 12, the regression results for the recursive estimation schemes are obtained for the full sample period. Eight out of twelve cases are statistically significant which is the least number of significant coefficients among all other schemes with two indices. Analogous results are attained for exchange rate and stock price. To be more specific, BASKET and USD are variables having more influence on CBRT

CCI; that is one unit increase in USD causes 0.0566 and 0.0640 basis points decrease in CBRT CCI for each lag lengths and one unit increase in BASKET causes 0.0626 and 0.0712 basis points decrease in CBRT CCI for each lag lengths. Yet, contrary to the BHT CCI, gold price does not generally yield a significant relationship with CBRT CCI. Again, oil price does not provide reliable information to understand the changes in CBRT CCI. Lastly, the goodness of fit values ranging from 86% and 88% are generally smaller than that are obtained in the fixed window and rolling window estimation schemes.

All in all, to assess the forecasting performances of each model constructed with 6 daily variables and two monthly sentiment indices, the RMSEs are estimated, for four different horizons in full sample estimation period. Then, the regression results are considered for horizons providing smallest RMSEs. All tables generally display consistent results except some cases. With exception of these cases, results with different estimation schemes and different CCI show that, there is an inverse relation between CCI and exchange rate, gold price and oil price; while positive trend is realized for stock price. Also, the goodness of fit values demonstrates that models are generally fit well with high value of R square ranging from 79% to 92%. However, without looking RMSEs values, in sample and out of sample forecast results; R square values do not ensure forecast performance. Hence, comparison of all results retrieved by in sample and out of sample forecasts help to understand the contribution of each variable to both indices.

Table 12. ADL-MIDAS Regression Results for CBRT CCI by Recursive Estimation

		CBRT CCI with 1 month Xlag		CBRT CCI with 2 month Xlag	
HF Variables		**ADL-MIDAS R Square**	**ADL-MIDAS Slope**	**ADL-MIDAS R Square**	**ADL-MIDAS Slope**
Exchange Rate	**USD/TL**	0.9068	**-0.0566***** (-4.5110)	0.90658	**-0.0640***** (-4.1933)
	EUR/TL	0.8986	**-0.0435***** (-2.9488)	0.8997	-0.019 (-1.5844)
	BASKET	0.90401	**-0.0626***** (-4.0603)	0.87686	**-0.0712***** (-3.7491)
Gold Price		0.90002	**-0.0207***** (-1.9547)	0.8997	-0.019 (-1.5844)
Oil Price		0.89208	0.0004 -0.1232	0.89333	0.0097 -1.4021
Stock Exchange		0.90401	**0.0260***** -3.5943	0.90433	**0.0340***** -2.9553

Source: Author's Estimations.

Note : t-statistics are in parenthesis and significant values are shown in bold.

***, ** and * denotes significance at 1, 5 and 10% level.

Regarding all outcomes above, we can derive some inferences for CCI and CBRT CCI. For three estimation schemes with four variables; explanatory power of regression equations are revolving between 79% and 92% shows that a large portion of both sentiment indices can be explained by using four daily variables. Although there is remaining unexplained part of the information content of consumer sentiment, they can be considered as a proxy for consumer confidence index in a large extent. When the sign and magnitudes of all coefficients are considered, they are almost all in line with the findings in the literature. To be more specific, negative coefficients of exchange rate variable (in terms of dollar, euro and basket) show that household in Turkey becomes more optimistic when their purchasing power rises. On the other hand, increase in exchange rate accompanied by inflation lead to pessimistic households losing their confidence. Moreover, the magnitude of coefficients of exchange rate of equally weighted basket (including US dollar and euro) is greater compared to exchange rate of dollar and euro in all but few cases with different lag structures and estimation schemes. This is not surprise for Turkey due to its export/import balance; that is, its imports are in

dollar terms, whereas exports are in euro terms. In the end, exchange rate of equally weighted basket carries more reliable information about the stance of overall economy which is closely related to the expectations. Then, exchange rate of dollar follows basket. Again, it is not unexpected result when Turkeys' dependency to dollar currency is considered. Especially in case of TRY currency appreciation, intermediate goods are started to be imported in Turkey. There is an input substitution problem due to lack of production in these goods. Hence, currency depreciation severely affects Turkey as it imports intermediate goods. Although export is main aim for economic growth, since there is a need for capital inflow to Turkey; dependency to imported intermediate goods can indirectly affect consumer confidence by leading capital outflow. Moreover, the more lag values of exchange rate included, the more influence realized on both indices meaning that they are closely related to exchange rate variable.

Secondly, positive coefficients of stock price can be attributed many reasons. The close link between stock market and the real economy can be considered as the main reason behind this positive relationship. In other words, the connection between stock market and sentiment indices can be explained by expectations about economy wide conditions. As stock prices rise and profits of the companies increase, people can consider these movements as an indicator of improved economic activity resulting possibility of increase in wages and employment opportunities in the future. These optimistic expectations are directly reflected to the consumer confidence index level leading stock prices and confidence levels go hand in hand. Considering all schemes with two indices, incorporation of one month extra information about this asset prices leads to obtain higher coefficients of stock prices.

Understanding the effect of oil and gold prices are very important for Turkey due to its economic structure. First of all, exchange rate effect should not be ignored, here; oil and gold prices are in TRY forms. Yet, it is clear that they have their own contributions, because they are closely monitored by households in Turkey. Gold is considered as a safe haven against short term fluctuations. In turbulent times, there is a tendency to hold gold and decrease in willingness to consume confirming the negative coefficients obtained in the outcomes for both indices. Furthermore, as being a small

economy without its own oil resources; i.e. oil importing country, consumers monitor oil prices due to its effect on wealth via commuting and heating channel and consider oil price returns as an indicator for future price levels since the aggregate price levels of the goods in household consumption are also affected by the oil prices. So, households' financial positions can be influenced by changes in oil price in a direct or indirect way.

Closer look to the details of BHT CCI survey questions lead us to see that consumers are expected to answer Question 5 asking "Do you think that the current period is a good time to buy durable consumer goods such as TV, refrigerator and furniture or vehicles or residence?" To see the direct influence, we can consider the fuel costs and other energy related costs are heavily dependent on oil price level. It is very likely, for example, to have a negative relationship between oil price and BHT CCI as automobile sales rely on fuel costs. It can be asserted that consumer confidence about purchasing durable goods (for example, vehicles) is high when oil price is in low levels. On the contrary, there are indirect effects that should be mentioned. According to Elder and Serletis (2009, p.1), the high uncertainty of the oil prices can defer industrial investments. Accordingly, increased level of oil price creates similar effect; that is, decrease in investments may lead pessimism against employment expectations which directly influence sentiment measures. On the contrary, oil price declines can be beneficial to firms and household by decreasing their energy costs, increasing job opportunities and improving financial conditions resulting in a positive effect on sentiment index. To conclude, since oil is one of the very frequently purchased good, people are responsive to the price changes of oil. At this point, the small amount of its coefficient confirms that the effect of oil price is not remarkable compared to other variables. Naturally, oil price influences consumers' behaviors in the long term. Hence, higher coefficients obtained in case of 2 months lag of oil prices can be a reason for it.

On the other hand, CBRT CCI gives conflicting result compared to BHT CCI. In fact, among three estimation schemes of CBRT CCI, the results are not consistent either. Closer look to the survey questions reveal that CBRT CCI survey respondents' reactions are not directly oil related. The question about employment opportunities (Q5 in CBRT CCI surveys), however, is very indirect for respondents to see the relation

between oil prices and job opportunities. It can be a reason for having conflicting results in case of CBRT CCI.

Finally, overall RMSE and R squares values should be considered in detail. Results reveal that RMSEs of all models are low indicating high forecast performances in forecasts of CBRT CCI compared to BHT CCI. Moreover, overall explanatory power of models constructed with CBRT CCI is higher. High number of CBRT CCI surveys conducted; that is high sample size, can explain these differences in both RMSE and R square values. Yet, there is some interesting part of our outcomes. In terms of horizon values, both indices give complementary results. In detail, approximately one week of horizon value for BHT CCI and 4 weeks of horizon value for CBRT CCI perform better according to related RMSEs. In both surveys, respondents are expected to consider retrospective information about their own and country's economic wellbeing. Also, they asses their prospective financial situations based on their expectations. Specifically, closer investigation of the similar survey questions in both indices (Q1, Q2, and Q4) shows that BHT CCI survey respondents should consider the related economic information for long term period (1 year) when they are reacting. However, individuals answering CBRT CCI questions should assess comparatively low period of time (3 and 6 months) during the survey. Hence, it can be concluded that, by their nature, the former requires long term thinking compared to the latter.

On the other hand, our estimations give interesting results from different perspective. We know that horizon value influence the starting date of high frequency variables for determined lag values. Hence, the number of recent high frequency data included to the regression time frame can be increased by decreasing horizon values. Accordingly, forecasts for BHT CCI with one week horizon include more recent information than CBRT CCI with four week horizon; that is, models for BHT CCI utilize/consider more recent daily information than models for CBRT CCI. Hence, these related horizon values tell that when more recent retrospective information included to the ADL-MIDAS regressions, the forecast performance for nowcasting BHT CCI is better. On the other hand, CBRT CCI estimations perform better if more horizon value is determined during the estimation process. As a result, if an individual want to make

short term forecasts about consumer sentiment, they should consider nowcasting BHT CCI, whereas, if he has long term thinking, CBRT CCI index should be considered as an indicator of confidence. In this sense, consumers evaluating economic conditions and individuals trying to nowcast sentiment indices should have complimentary view of thinking that is one of the interesting parts of our results.

6.2.2. Out of Sample Estimation Results

In this section, out of sample estimation results from 2016M7 to 2017M6 are estimated by using 6 models constructed with exchange rate (dollar, euro, and basket), gold price, oil price and stock exchange, independently. In addition to the models constructed with one independent variable, we also applied forecast combination method to get out of sample forecast results with four indicators. Specifically, we combined each of gold price, oil price and stock price with dollar/euro/basket, separately. The figures below are drawn according to the RMSEs for one variable case and 4 variables cases. For the one variable cases, RMSEs are used to forecast 12 months sentiment index; while for combined cases the Discounted Mean Squared Forecast Error (DMSFE) values are used, since there are many applications in the literature showing that DMSFE gives better results compared to the other methods. Figure 28-30 show out of sample periods throughout 12 months with 3 estimation schemes with one-month Xlag value[14]. Specifically, Figure 28-30 stand for the estimation results for BHT CCI in July 2016-June 2017; whereas Figure 31-33 are drawn to show the forecast results of CBRT CCI for same time interval.

[14] See Appendix B for plots of out of sample estimation results with two months of Xlag value.

Figure 28. Out of Sample Estimation Results for BHT CCI between July 2016 and June 2017 (Fixed Window, 5 days horizon, 22 days Xlag)

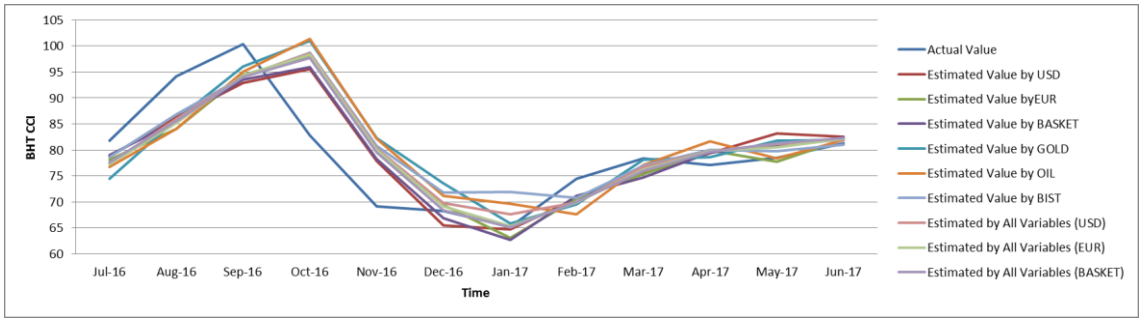


Figure 29. Out of Sample Estimation Results for BHT CCI between July 2016 and June 2017 (Rolling Window, 5 days horizon, 22 days Xlag)

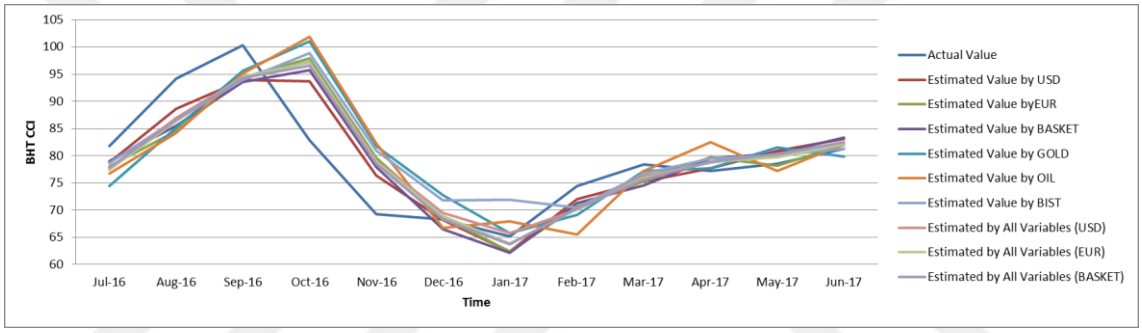
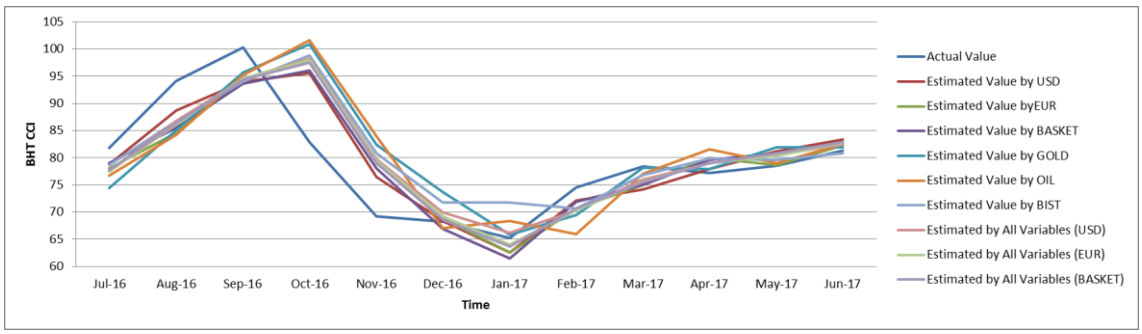


Figure 30. Out of Sample Estimation Results for BHT CCI between July 2016 and June 2017 (Recursive, 5 days horizon, 22 days Xlag)



In the first place, the overall picture indicates that BHT CCI estimations results are very promising. When it is closely examined, there is some gap between actual and estimated values with different variables. In first two months approximately, our estimation underestimates the values of BHT CCI; whereas in the next three months, it overvalues estimation of BHT CCI. However, after 5 months the gap between actual and estimated value narrows; that is, our estimation results catches approximately actual

values. In Appendix A, Table A1-A6 illustrates actual and estimated values of BHT CCI for ADL-MIDAS models with full sample period. These tables help us to make a comparison between actual and forecasted variables with different Xlag values and three estimation schemes. For some months, the difference between them becomes smaller and almost zero. Finally, we cannot conclude which estimation scheme is better by considering these figures, since they are demonstrating close trends.

Alternatively, Figure 31-33 represent the results for CBRT CCI. Compared to BHT CCI, these figures display more differences between actual and estimated values. Although there are some overlaps in some months, overall out of sample forecast results do not satisfy our expectations. In case of fixed and rolling window, the general trend seems close. However, in recursive window estimation scheme, our forecasts are diverged from actual values for some variables. In Appendix A, Table A7-A12 illustrates actual and estimated values of CBRT CCI in the ADL-MIDAS models with full sample period. Again, these tables provide an overview about actual and forecasted variables with different Xlag values and three estimation schemes.

Figure 31. Out of Sample Estimation Results for CBRT CCI between July 2016 and June 2017 (Fixed Window, 22 days horizon, 22 days Xlag)

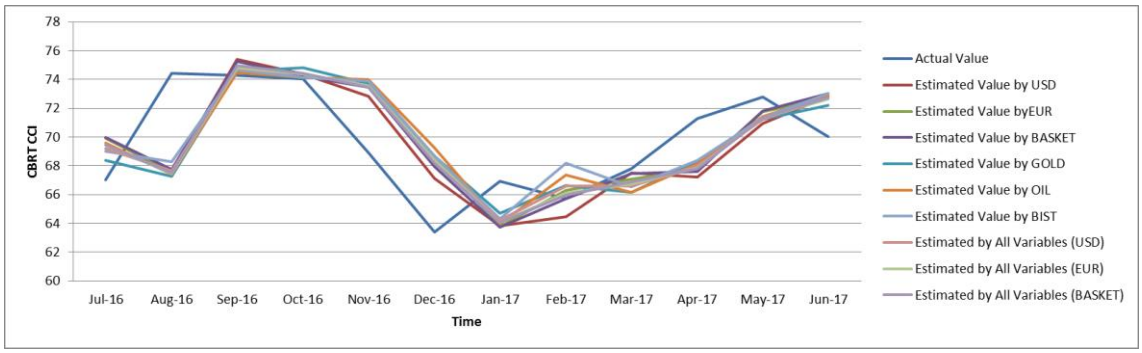


Figure 32. Out of Sample Estimation Results for CBRT CCI between July 2016 and June 2017 (Rolling Window, 22 days horizon, 22 days Xlag)

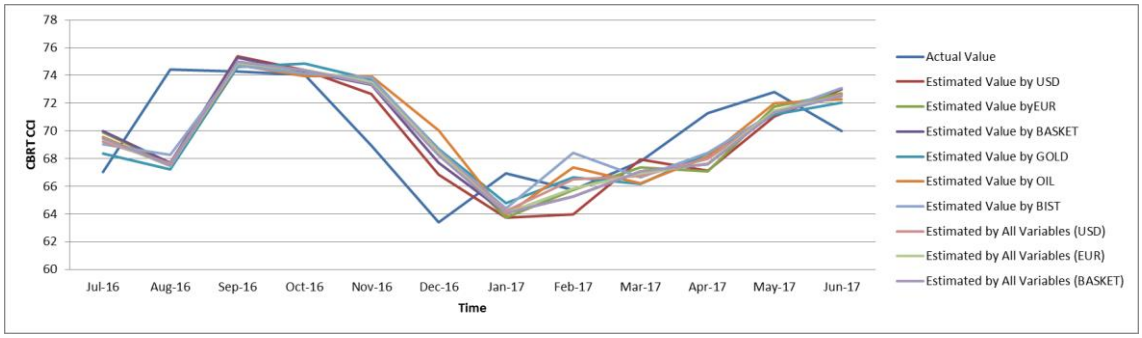
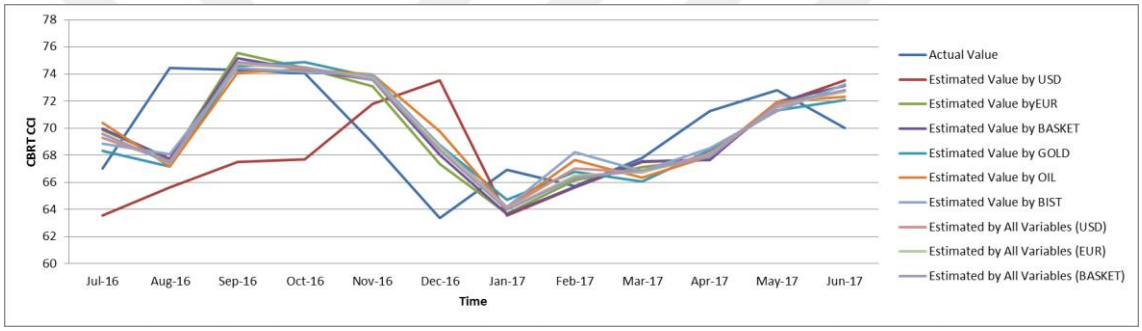


Figure 33. Out of Sample Estimation Results for CBRT CCI between July 2016 and June 2017 (Recursive, 22 days horizon, 22 days Xlag)



In conclusion, our four variables allow us to construct models which perform well in forecasting consumer sentiment. Considering the final remarks in previous section, these figures also confirm that BHT CCI forecast are better in the long term as they catch actual data after 5 months approximately. On the other hand, there are some overlaps between actual and estimated values of CBRT CCI in early period compared to the later months of out of sample estimation period showing that CBRT CCI can be better forecasted by short term way of thinking. Overall results show that we can forecast BHT CCI index better compared to CBRT CCI by using four main variables. It is encouraging to have these results by using very recent data and without any information loss stemming from frequency mismatch.

6.2.3. ADL-MIDAS for Subsample

This chapter includes in sample and out of sample estimation results obtained by 3 estimation schemes for the subsample period which corresponds to the time

interval 2002M1-2009M12 and 2004M1-2009M12 for BHT CCI and CBRT CCI, respectively. The last 2 years; that is 24 months stand for global financial crisis period, are left as an out of sample forecast estimation. Specifically, this subsection covers RMSEs and regression results for each index in related in sample estimation periods. Furthermore, our out of sample estimation outcomes during crisis period allow us to observe in what extent we can forecast consumer sentiment of Turkey by using recent available and past information. More importantly, does consumer confidence index carry similar information with our daily variables which are very sensitive to crisis period is very important question that we try to understand at the end of this part. In crisis period, by showing that we can closely measure sentiment indices with highly volatile daily variables and lag of consumer sentiment, it can be concluded that consumers' expectations are adapting the current stance of the economy like other daily variables.

Specifically, Table 13 and 14 shows in sample estimation results at different horizons by implementing three estimation schemes for BHT CCI and CBRT CCI, respectively. These three tables yield us to form an opinion about the forecasting performances of each variable based on the related RMSEs before the global financial crisis.

In both tables with three schemes, h equals 11 and 16 values perform better for BHT CCI and CBRT CCI, respectively. These horizon values, again, do not contradict with our previous results; i.e. for smaller horizons BHT CCI, for longer horizons CBRT CCI can be nowcasted better; however, compared to full sample estimation results, the sharp distinction between these two values is reduced probably due to small number of years in estimation period. Again, Figure 34-39 summarizes the results obtained in Tables 13-14.

Table 13. RMSEs for BHT CCI between 2002 and 2007

	Fixed Window				Rolling Window				Recursive			
Variables	**h=5**	**h=11**	**h=16**	**h=22**	**h=5**	**h=11**	**h=16**	**h=22**	**h=5**	**h=11**	**h=16**	**h=22**
USD	**0.103**	0.105	0.125	0.138	**0.107**	0.109	0.118	0.139	0.102	**0.101**	0.116	0.134
GOLD	0.143	**0.136**	0.140	0.143	**0.150**	0.122	0.140	0.121	0.142	**0.120**	0.137	0.133
OIL	0.159	**0.148**	0.154	0.158	**0.136**	**0.136**	0.144	0.144	**0.133**	0.145	0.143	0.150
BIST	0.149	**0.101**	0.107	0.123	0.120	**0.095**	0.105	0.118	0.134	**0.097**	0.105	0.117
EUR	0.129	**0.122**	0.132	0.138	0.119	**0.110**	0.125	0.136	**0.106**	0.108	0.122	0.134
BASKET	**0.110**	0.110	0.125	0.137	0.112	**0.110**	0.119	0.134	**0.105**	0.108	0.114	0.132

Note: The samallest RMSEs in each estimation scheme are shown in bold.

Table 14. RMSEs for CBRT CCI between 2002 and 2007

	Fixed Window				Rolling Window				Recursive			
Variables	**h=5**	**h=11**	**h=16**	**h=22**	**h=5**	**h=11**	**h=16**	**h=22**	**h=5**	**h=11**	**h=16**	**h=22**
USD	0.048	0.047	**0.044**	0.060	**0.046**	0.063	0.046	0.049	0.045	0.047	**0.045**	0.048
GOLD	0.058	0.051	0.050	**0.049**	**0.047**	0.050	0.053	0.049	**0.047**	0.050	0.050	0.049
OIL	0.057	0.057	**0.057**	0.056	0.056	**0.053**	0.055	0.055	0.056	0.051	**0.055**	0.056
BIST	0.049	0.056	**0.047**	0.057	0.050	0.050	**0.046**	0.051	0.048	0.051	**0.045**	0.050
EUR	0.046	0.047	**0.044**	0.058	0.046	0.050	**0.043**	0.053	0.042	0.047	**0.042**	0.054
BASKET	0.046	0.046	**0.043**	0.059	**0.043**	0.047	0.046	0.048	**0.043**	0.046	0.046	0.050

Note: The samallest RMSEs in each estimation scheme are shown in bold.

In Appendix C-Tables C1-C3, it is given the regression results of subsample; i.e. before crisis period. To summarize, similar to results gathered for the full sample period, most of the variables are statistically significant and all significant coefficients has expected signs; that is, there is negative relationship between exchange rate / gold price / oil price and consumer confidence indices and there is positive relationship between stock price and consumer sentiment. Oil price, again, gives different results in different cases.

Figure 34. RMSEs for BHT CCI between 2002-2007 (Fixed Window)

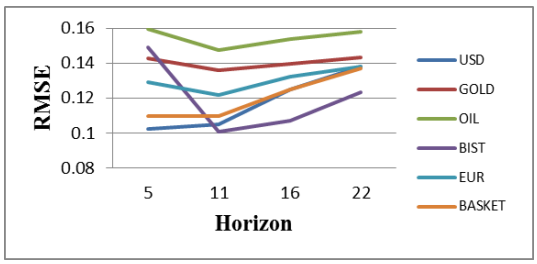


Figure 35. RMSEs for BHT CCI between 2002-2007 (Rolling Window)

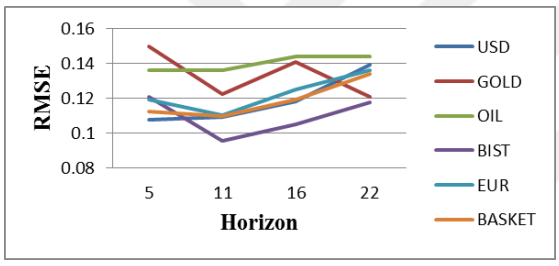


Figure 36. RMSEs for BHT CCI between 2002-2007 (Recursive Window)

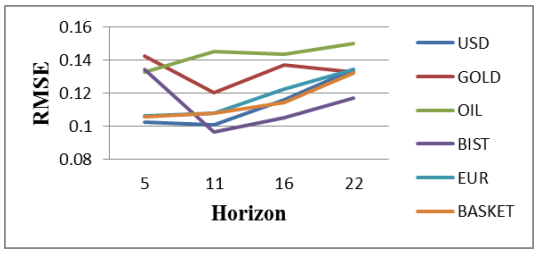


Figure 37. RMSEs for CBRT CCI between 2002-2007 (Fixed Window)

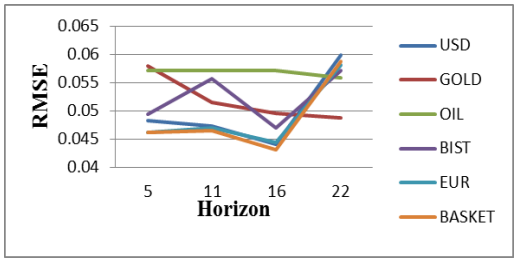


Figure 38. RMSEs for CBRT CCI between 2002-2007 (Rolling Window)

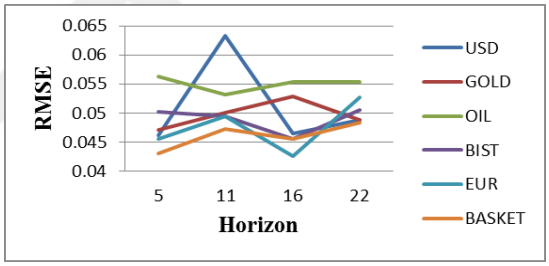
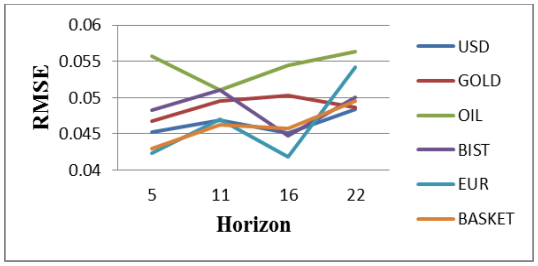
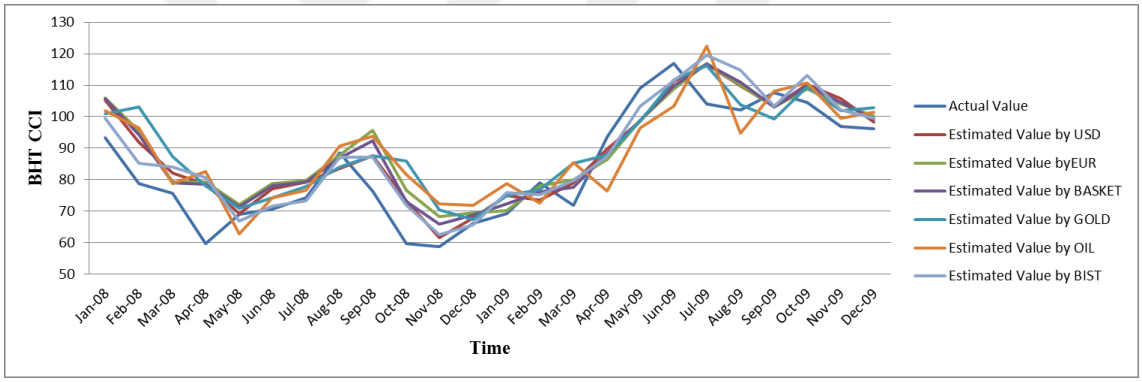


Figure 39. RMSEs for CBRT CCI between 2002-2007 (Recursive Window)



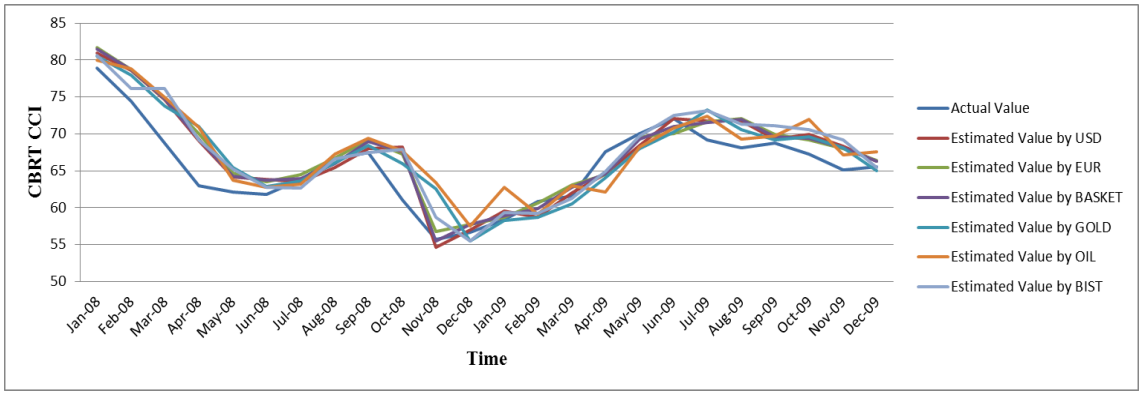
Given the past information at hand, ADL-MIDAS regressions constructed with our four variables give nice out of sample estimates for both consumer confidence indices. For crisis period, Figure 40-41 display out of sample results with fixed window scheme for BHT CCI and CBRT CCI, respectively. In Appendix D, Figure D1-D4 demonstrates results obtained by other estimation schemes for both indices. Even though there are slight differences between estimated values and actual values, we can conclude that all have similar pattern throughout 24 months. Appendix E can facilitate to make comparison between actual and estimated values, in detail. As we can see, overall value of actual BHT CCI and CBRT CCI are very close to the values estimated by our variables, especially for some months.

Figure 40. Out of Sample Estimation Results for BHT CCI, Crisis Period (Fixed Window Scheme, 11 days horizon, 22 days Xlag)



To conclude, in the next chapter, we will see that volatilities of our daily variables are very high during global financial crisis period. However, when we consider out of sample results for that period, they are still giving promising outcomes together with information coming from past consumer confidence indices for forecasting consumer sentiment in crisis period which lead us to accept the fact that consumer confidence index adapt quickly to this turbulent period.

Figure 41. Out of Sample Estimation Results for CBRT CCI, Crisis Period (Fixed Window Scheme, 16 days horizon, 22 days Xlag)



Accordingly, it carries similar signals with these high frequency variables and helps us to understand the current stance of the economy even in turbulent times. As a result, by using data, monthly and daily, coming from before crisis period, we are able to understand economic conditions and household's behavior during 24 months of crisis years which proves the forecasting power of sentiment indices for future, even for volatile time interval.

6.3. GARCH-MIDAS

In this section, GARCH-MIDAS model discussed in the Chapter 5 is used to understand the effect of consumer sentiment indices on the volatility dynamics of four high frequency variables, individually. The estimation of GARCH-MIDAS models constructed with 4 daily returns and 2 monthly confidence indices are included to serve this aim. That is why; each daily variable is modeled one by one. For congruency between the variables, log returns, i.e. daily returns of exchange rate, stock exchange, gold price and oil price with is used with monthly series of consumer confidence indices in the form of natural logarithm. These returns are computed according to the following formula:

$$r_t = \ln \frac{A_t}{A_{t-1}} \times 100 \qquad (6.2)$$

where A_t and A_{t-1} are daily values at time t and t-1, respectively. As it is mentioned before, there are two specifications for GARCH-MIDAS RV, namely fixed span and rolling window. First of all, in the following two subsections, those including BHT CCI and CBRT CCI, models with fixed span and rolling window realized volatilities (RVs) are examined for interested daily returns. Realized volatilities are used to understand the best fit of the model. Thereafter, models in which both consumer confidence indices are directly enter the specification of long term volatility component are investigated to understand how changes in sentiment level influences conditional and secular volatility of high frequency variables. As a result, one can distinguish between two confidence indices and answer whether they affect all variables or specific ones by describing the deterministic component of volatilities, separately.

6.3.1. BHT CCI

First of all, Table 15, 16, 17 and 18 show the parameter estimates for GARCH-MIDAS with Realized Variance for monthly fixed span and rolling window specifications. In these tables, estimated parameters are reported in the 3rd-8th columns together with their standard errors in parenthesis. Also, 9th column demonstrates the LLF function and BIC values underneath and RMSEs are in the last column.

Herein, two specifications of GARCH-MIDAS with RV, i.e. fixed span and rolling window, are considered for all daily variables. Table 15-18 reveals that for both specifications, roughly similar values for LLF and BIC values are obtained for BHT CCI. Therefore, this situation shows that holding τ fixed for monthly time periods or allowing it to change daily does not have an important effect on likelihood behavior.

Table 15 shows results for parameter estimates of model constructed with daily exchange rate returns (basket, dollar and euro). Outcomes in this table demonstrate that almost all parameters with the exception of μ are statistically significant. Especially, it should be noted that coefficient, θ, of the sum of the weighted realized volatilities is highly significant. This indicates that the information included in the one MIDAS lag

year of RV help explaining the low frequency component of volatility. Hence, these θ estimates shows that higher levels of past realized volatilities cause higher level of τ.

Table 15. Parameter Estimates for GARCH-MIDAS with Realized Variance of Exchange Rate Returns (same period with BHT CCI)

MIDAS Regressor		μ	α	β	θ	ω	m	*LLF/BIC*	RMSE
Fixed RV	Basket	0.000005	0.18645***	0.75638***	0.21005***	2.9746***	0.0031849***	13887.00	0.000194
		(0.000081)	(0.009906)	(0.010497)	(0.011254)	(0.502880)	(0.000437)	-27724.20	
	Dollar	-0.000004	0.13278***	0.82009***	0.18476***	3.1931***	0.0044021***	13432.80	0.000269
		(0.000099)	(0.007613)	(0.009052)	(0.012301)	(0.742110)	(0.000497)	-26815.80	
	Euro	0.000101	0.068253***	0.93175***	0.091609**	4.9973***	0.0012588*	13299.80	0.000185
		(0.000072)	(0.002575)	(0.002392)	(0.041186)	(0.508910)	(0.000694)	-26549.70	
Rolling RV	Basket	0.000009	0.18893***	0.74214***	0.20705***	4.4529***	0.0031192***	13892.20	0.000192
		(0.000081)	(0.010050)	(0.012338)	(0.009758)	(0.832280)	(0.000373)	-27734.50	
	Dollar	-0.000007	0.13191***	0.81955***	0.19104***	3.7584***	0.0041083***	13432.20	0.000277
		(0.000098)	(0.007463)	(0.008381)	(0.011923)	(0.933370)	(0.000507)	-26814.60	
	Euro	0.000103	0.068322***	0.93168***	0.091184**	4.9929***	0.0012645*	13311.20	0.000181
		(0.000071)	(0.002625)	(0.002469)	(0.041486)	(0.751070)	(0.000681)	-26572.50	

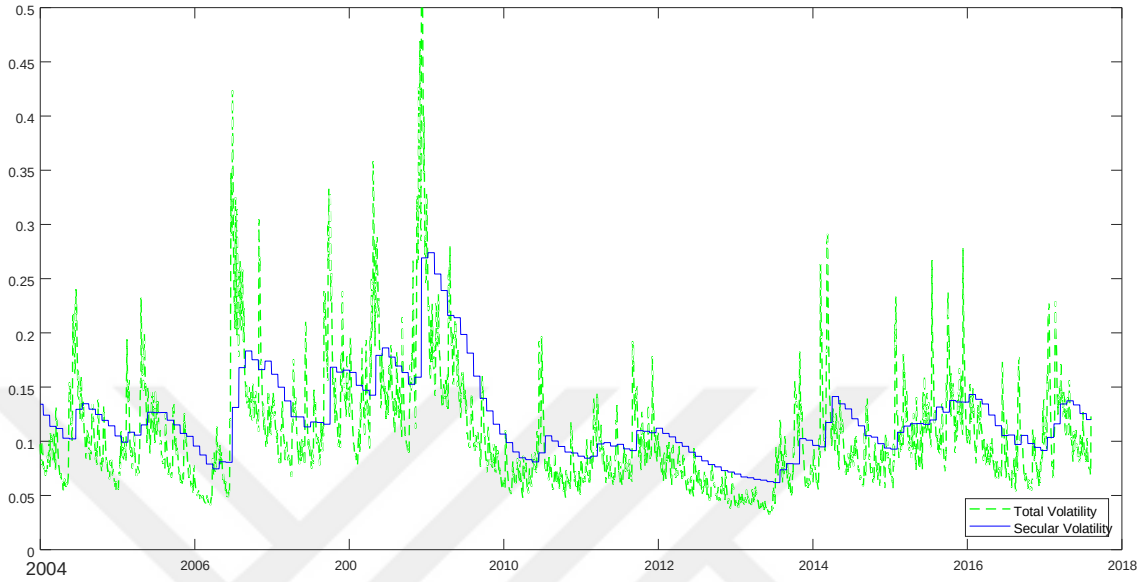
Note: Standard Errors are in paranthesis.
***,**,and * represent the significance level at 1%, 5%, and 10%, respectively.

Another important property is that in case of monthly fixed span RV, the sums of α and β are 0.942830 and 0.952870; while in case of rolling window, they are 0.931070 and 0.951460 for basket and dollar, respectively. These values indicate that the sum of α and β are close to but smaller than 1[15] (except euro). This feature indicates high degree of volatility persistence.

In figures 42 and 43, volatility components of model with exchange rate returns (basket); that is total and secular volatility, can be seen[16]. It is clear that for both specifications; i.e. fixed and rolling, long term (secular) components are smoother than total volatilities.

[15] Normally, in most GARCH type model, the sum of α and β is typically equal to 1.
[16] See Appendix F for Plot of GARCH-MIDAS model for Dollar and Euro Exchange rate return RVs.

Figure 42. GARCH-MIDAS with Fixed Span RV (Basket, same period with BHT CCI)



Also, in the rolling window case, long term volatility is smoother compared to fixed span; even though general pattern of long term component follows total volatility and captures dynamics well. This smoothness is obvious since the extracted τ component is of monthly frequency in fixed span; whereas it is of daily frequency in rolling window estimation. Here, a quick conclusion can be drawn; that is, for both specifications, secular volatility of RV has a crucial role in explaining total volatility in exchange rate returns. Especially until crisis period, contribution of secular component is quite high; whereas it loses its influence in later years.

Figure 43. GARCH-MIDAS with Rolling Window RV (Basket, same period with BHT CCI)

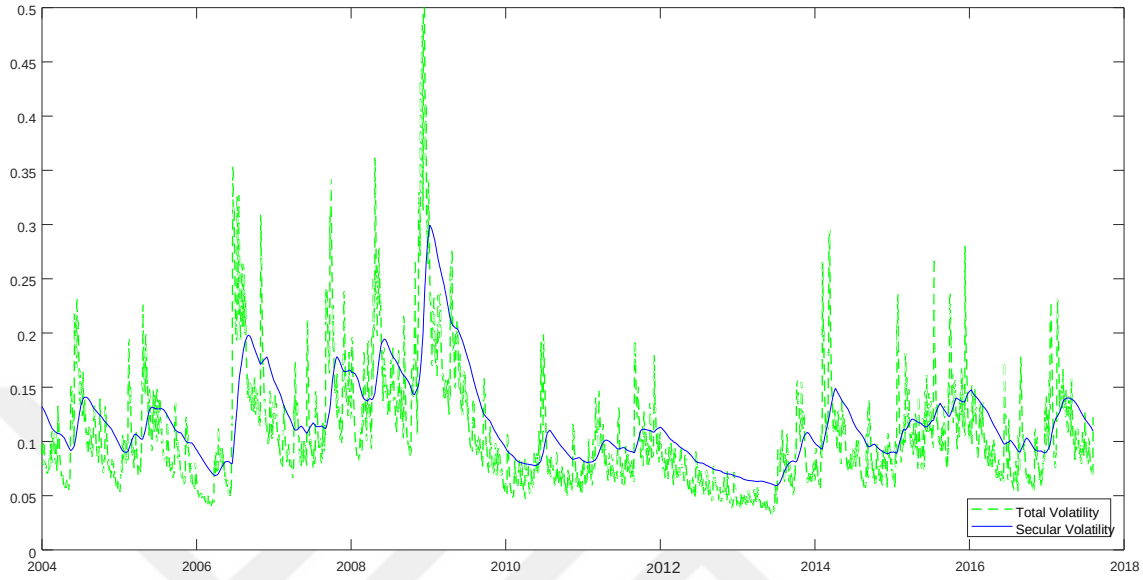


Table 16 provides the estimated coefficients of RV for gold price in which almost all coefficients are significant. In particular, θ estimates is not significant for rolling window span which can also be seen in Figure 45. Additionally, the GARCH parameters, α and β, sum to 0.957119 and 0.973868 for fixed span and rolling window, respectively; and they are within the stationarity boundary $\alpha_i + \beta_i < 1$, as well.

Table 16. Parameter Estimates for GARCH-MIDAS with Realized Variance of Gold Price Returns (same period with BHT CCI)

MIDAS Regressor	μ	α	β	θ	ω	m	*LLF/BIC*	RMSE
Fixed RV	0.00043442**	0.082669***	0.87445***	0.1072***	7.1936**	0.010637***	11484.00	0.000437
	(0.000173)	(0.007032)	(0.015340)	(0.023733)	(3.439200)	(0.000889)	-22918.30	
Rolling RV	0.00041278**	0.079638***	0.89423***	0.022433	4.671900	0.012561***	11482.90	0.000436
	(0.000172)	(0.006358)	(0.012652)	(0.224890)	(61.209000)	(0.001697)	-22915.90	

Note: Standard Errors are in paranthesis.
***,**,and * represent the significance level at 1%, 5%, and 10%, respectively.

The below figures 44 and 45 illustrate the long term and total variances estimated by MIDAS equation only includes realized volatility of daily returns of gold

price. In both figures, despite some large peaks in total variance (for example, due to the global financial crisis between 2008 and 2009), the long term volatility is smoother than total volatility in Figure 44. More interestingly, in Figure 45, secular volatility is very flat or equivalently long run component is close to constant which can also be supported by insignificant θ values reported in Table 16. As a result, explanation power of long run component for total volatility is in reasonable extent for fixed span; whereas there is almost no contribution of it for total variance in case of rolling window.

Figure 44. GARCH-MIDAS with Fixed Span RV (Gold Price, same period with BHT CCI)

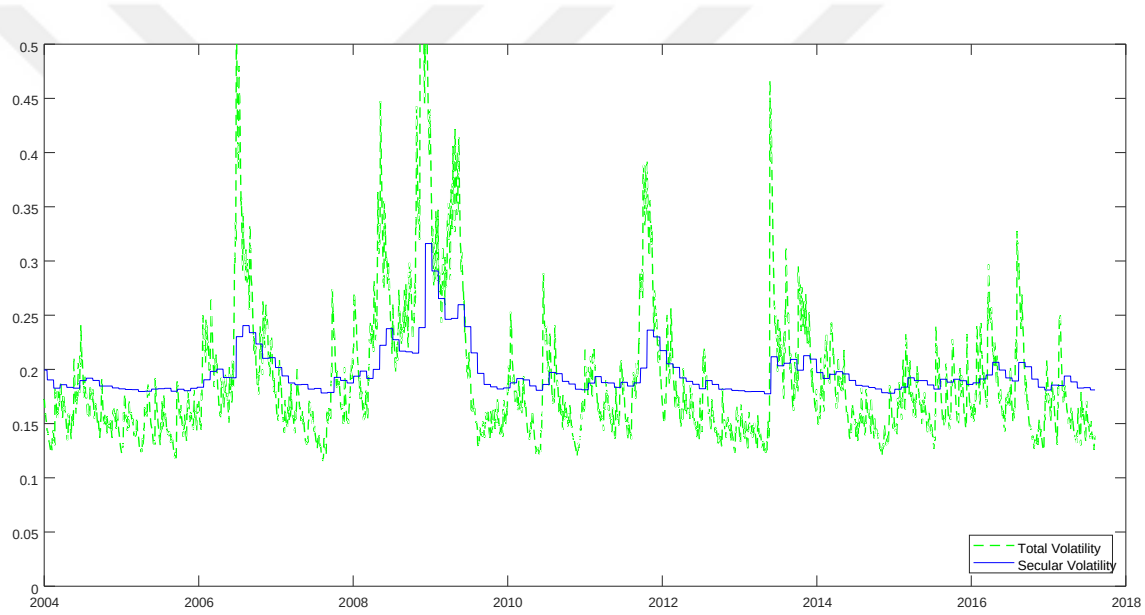


Figure 45. GARCH-MIDAS with Rolling Window RV (Gold Price, same period with BHT CCI)

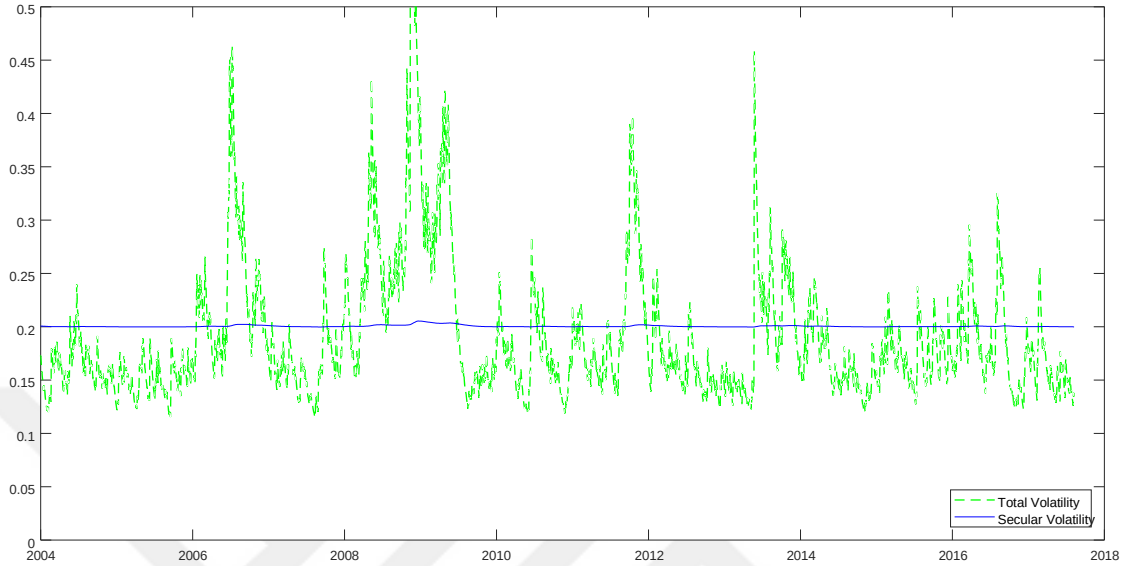


Table 17 and 18 below gives estimates of oil and stock price return volatilities for two specifications. Similar judgments can be made for oil and stock returns. The findings, in table 17 and 18, demonstrates that sums of α and β for fixed span are 0.972216 and 0.929900; while in case of rolling window, they are 0.947612 and 0.836450 for oil and stock price, respectively. Finally, θ estimates are positive and statistically significant for both variables with two specifications.

Table 17. Parameter Estimates for GARCH-MIDAS with Realized Variance of Oil Price Returns (same period with BHT CCI)

MIDAS Regressor	μ	α	β	θ	ω	m	*LLF/BIC*	RMSE
Fixed RV	0.000376	0.053516***	0.9187***	0.1941***	2.4487**	0.0092735***	9330.45	0.001131
	(0.000304)	(0.006381)	(0.014436)	(0.011610)	(1.102900)	(0.001954)	-18611.10	
Rolling RV	0.000353	0.056632***	0.89098***	0.19959***	4.871**	0.0080465***	9328.81	0.001134
	(0.000306)	(0.007835)	(0.026225)	(0.008348)	(2.034500)	(0.001502)	-18607.80	

Note: Standard Errors are in paranthesis.
***,**,and * represent the significance level at 1%, 5%, and 10%, respectively.

Table 18. Parameter Estimates for GARCH-MIDAS with Realized Variance of Stock Price Returns (same period with BHT CCI)

MIDAS Regressor	μ	α	β	θ	ω	m	*LLF/BIC*	RMSE
Fixed RV	0.0012313***	0.13189***	0.79801***	0.14734***	1.001***	0.0098844***	11130.9	0.000439
	(0.000187)	(0.009462)	(0.014719)	(0.012671)	(0.031684)	(0.000661)	-22211.90	
Rolling RV	0.0012387***	0.16091***	0.67554***	0.17308***	5.4804***	0.0078375***	11143.30	0.000438
	(0.000191)	(0.012822)	(0.026153)	(0.008318)	(1.199700)	(0.000536)	-22236.80	

Note: Standard Errors are in paranthesis.
***,**,and * represent the significance level at 1%, 5%, and 10%, respectively.

Figure 46-49 plots the long term and total variances for oil and stock prices in case of fixed span and rolling window. In figure 46 and 47, although the secular volatility of oil price returns in rolling window specification is smoother than fixed span; long term variances in both specification give relatively similar pattern with total variances most of the time. Also, it can be clearly observed that the contribution of secular volatility to total volatility is in a considerable extent for both specifications leaving very small place for short term volatility component.

Figure 46. GARCH-MIDAS with Fixed Span RV (Oil Price, same period with BHT CCI)

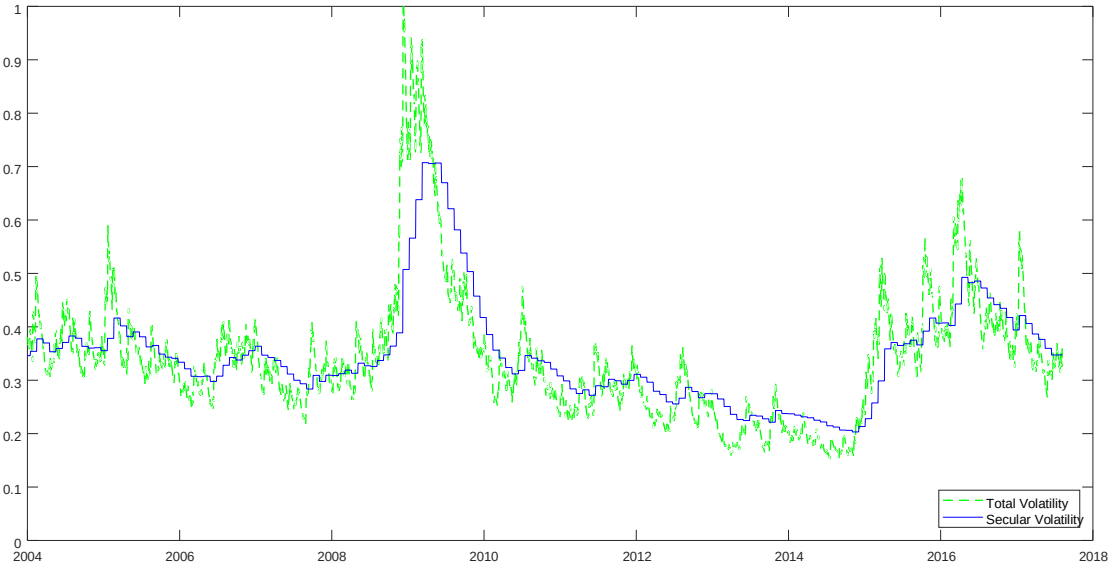
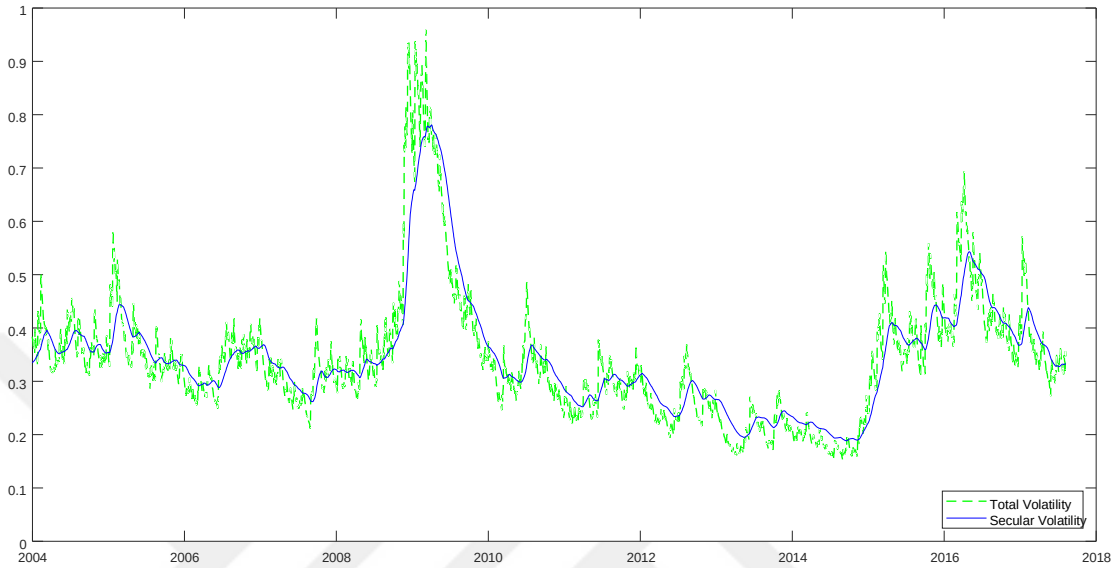


Figure 47. GARCH-MIDAS with Rolling Window RV (Oil Price, same period with BHT CCI)



As can be seen in figure 48 and 49, secular volatility is smoother compared to total volatility of stock price. Yet, it simply moves with total volatility in almost all periods. Especially in rolling window case, the interaction between them increases. To sum up, long term component appears as main driver of volatility of oil price; whereas the effect of short term variance on total variance of stock prices cannot be ignored for stock price volatility. In both specifications of oil and stock price realized volatilities, total and long run volatilities increase during the crisis period proving that they are experienced severity of this crisis.

Figure 48. GARCH-MIDAS with Fixed Span RV (Stock Price, same period with BHT CCI)

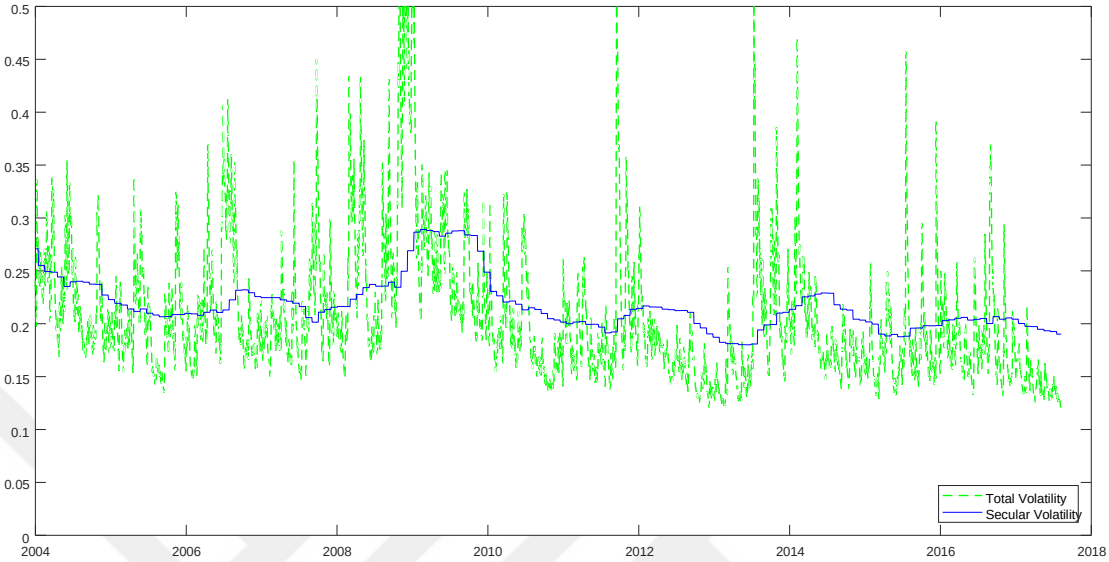
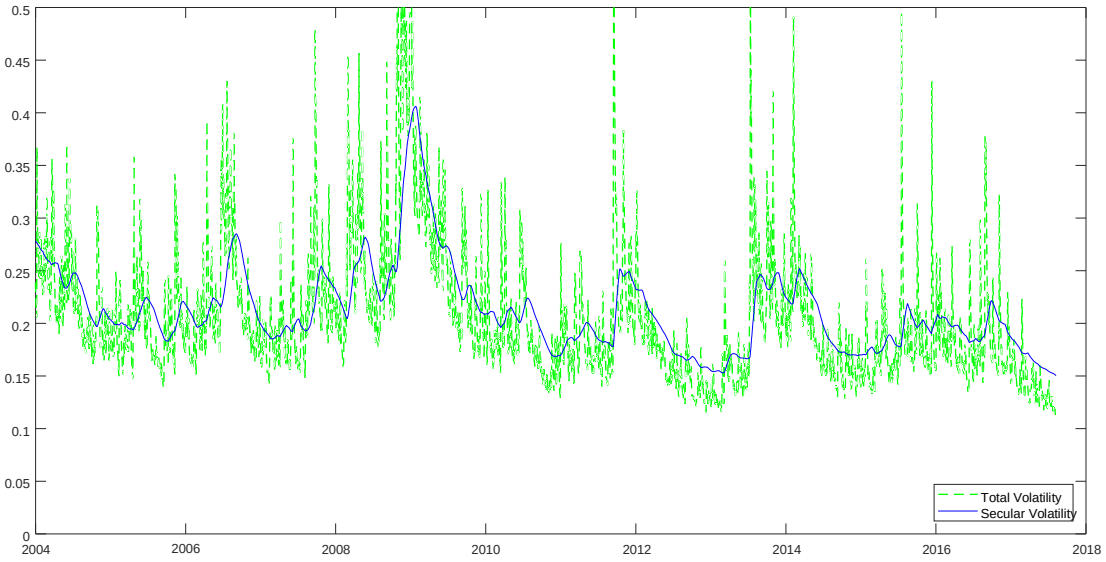


Figure 49. GARCH-MIDAS with Rolling Window RV (Stock Price, same period with BHT CCI)



In the following figure and tables, results are obtained by replacing the realized volatility by BHT CCI for four main high frequency variables. Here, the important question tried to be answered is that how much volatility is related to consumer sentiment and what is the direction of this relationship between related volatilities and indices. To answer this question, we start with models with daily returns and involving one of the single series of consumer sentiment, BHT CCI. The parameter estimates appear in Table 19 for GARCH-MIDAS with level of BHT CCI. In each case, we use one year of lag which is 12 months lags.

Before explaining how consumer sentiment index contributes to long term volatility of interested daily variables, evaluating other parameters is noteworthy. μ is statistically significant in the MIDAS equations with gold price and stock price. Furthermore, α and β values are strongly statistically significant and their sums for each daily variable (0.988580, 0.986600, 0.968800, 0.971632, 0.998165, and 0.940490) are smaller than and close to 1 which are within the stationarity boundary. It specifies that volatility clustering is the major component of daily variables' volatilities and information coming from monthly variables contribute to the long term component variance to some extent. Moreover, being closer to 1 depicts a higher level of persistence in the volatility.

Table 19. Parameter Estimates for GARCH-MIDAS with Level of BHTCCI

MIDAS Regressor		μ	α	β	θ	ω	m	*LLF/BIC*	RMSE
Exchange Rate	Basket	0.000037	0.17261***	0.81597***	-0.023135**	6.4378**	0.0011719**	12301.90	0.000193
		(0.000083)	(0.009520)	(0.008766)	(0.010003)	(3.032300)	(0.000498)	-24553.90	
	Dollar	0.000051	0.11591***	0.87069***	-0.015354***	46.81**	0.00079053***	11876.50	0.000274
		(0.000106)	(0.006953)	(0.006474)	(0.004397)	(18.693000)	(0.000218)	-23703.10	
	Euro	0.000039	0.14175***	0.82705***	-0.0089635***	11.943000	0.00047901***	11952.10	0.000175
		(0.000100)	(0.008122)	(0.008410)	(0.002180)	(8.814000)	(0.000104)	-23854.40	
Gold Price		0.00043464**	0.085092***	0.88654***	-0.010309**	43.947	0.00062893***	10156.8	0.000437
		(0.000182)	(0.006574)	(0.008090)	(0.004324)	(69.878000)	(0.000200)	-20263.8	
Oil Price		0.000342	0.045205***	0.95296***	-0.029225	40.404000	0.002113	8299.09	
		(0.000318)	(0.004720)	(0.004926)	(0.042743)	(114.080000)	(0.002106)	-16548.40	0.000441
Stock Price		0.0011862***	0.14388***	0.79661***	0.004196	43.123000	-0.000002	9929.84	
		(0.000199)	(0.010681)	(0.014774)	(0.003548)	(134.220000)	(0.000159)	-19809.90	

Note: Standard Errors are in paranthesis.
***,**,and * represent the significance level at 1%, 5%, and 10%, respectively.

Now, to describe the deterministic component of volatility of daily returns, sentiment index of Bloomberg HT is considered for each variable. The most important parameter is the slope parameter; i.e. θ for level of BHT CCI, revolving between 0,004196 and 0.029225. Consider values θ of daily returns for period of 2002M1-2017M6. Out of 6 cases for θ values, five of them have negative value and in all but one case they are statistically significant. For level specification of BHT CCI, this means that more consumer confidence accompanies less volatility in daily returns of variables; specifically, basket, dollar, euro, and gold price. However, the changes in the level of BHT CCI does not have explanatory power on oil price and stock price volatility indicating that these variables will be less affected by consumers' expectations. This indicates that these volatilities are disconnected from consumers' overall outlook of the economy.

In more detail, exchange rate volatility increases in times of financial and macroeconomic uncertainty, since it is directly linked to macroeconomic instability. There are studies in the literature showing the negative relationship between exchange rate volatility and, for example, output growth, industrial production and productivity. The effect of increase in these kinds of macroeconomic indicators are closely monitored by household and reflected positively to the consumer sentiment. When consumers have optimistic expectations about overall economy, this optimism, reflected to consumer confidence indices, can reduce uncertainty and decrease the volatility of exchange rate which means more stable economy. On the other hand, economic downturns can lead opposite effect. To illustrate, recall that in Figure 1, there is a sharp decline in BHT CCI during global financial crisis, while Figure 50-51 indicate high volatility in these periods. Therefore, it can be concluded that for exchange rate variable, the obtained coefficients are as they expected.

More importantly, it is possible to measure the magnitude of the change in the sentiment variable on the low frequency component by following a method proposed by Engle, Ghysels and Sohn (2013). The amount of contribution of changes in BHT CCI on volatility of daily variables can be calculated by using θ and ω values. The lower value of θ means that long term variance is smoother. Furthermore, the value of ω is

inversely related with contribution of secular component. To be more precise, the higher value of ω means that influence of CCI lessens quickly. In order to calculate the amount of contribution of BHT CCI on 4 daily indicators, the formula $e^{\theta*\varphi(\omega)}-1$ is used[17].

To be more specific, for basket variable, parameter estimate of θ is -0.023135 with 1% significance level. Since the weighting function ω=6.4378 which puts 0.01917on the first lag, it is found that one percent increase in the level of BHT CCI at the current month would change the long term component of the next month's basket volatility by $e^{-0.023135*0.01917}-1$= -0.0443 percent. Similarly, if the last month's confidence index increased by 1%, one would see 0.0354% decrease in long term dollar exchange rate volatility next month. For euro the weighting function are characterized by ω=11.94 and puts -0.000249326 on its first lag. In this case, one percent increase in the level of current month's sentiment index would lead to 0.0249% amount of decrease in long term volatility of euro exchange rate next month. These contributions support above claims, as well. Among three variant of exchange rates, basket variable is one mostly affected by the BHT HT sentiment index. As it is mentioned in the results of ADL-MIDAS approach, Turkey's exports are based on Euro, while imports are based on Dollar terms. Hence, these results reflecting the influence of sentiment indices on the volatility of exchange rate variables together, Dollar and Euro, is in line with expectations.

Similarly, Table 19 indicates negative relationship between volatility of gold price and consumer confidence. As known to everyone, increased consumer sentiment can be explained by growing economy. In times of economic upturn, there would be a steady demand for gold and due to relatively flexible supply of gold; increase in constant demand for gold will result in lower price volatility. On the other hand, general instability and uncertainty may increase gold prices due to its 'safe heaven' property in which people would like to invest in if uncertainty increases since it preserves the value of money during recession times. Therefore, the more uncertainty in the economy means the more volatile gold prices.

[17] See Engle,Ghysels and Sohn (2013) for further information.

Moreover, in the literature, consumer sentiment indices are considered as a proxy for investor sentiment. Accordingly, decrease in sentiment indices, for example in crisis times, cause 'investors to transmit the volatility from other markets to the gold market' (Baur, 2011, p.9) Therefore, sentiment induced investment decisions can easily be influenced by turbulent times and this financial uncertainty can lead an amplified volatility in gold prices, again.

Here, the contribution of changes in sentiment index on gold price volatility can be measured. For gold price, the weight parameter is ω=43.94, and it puts -0.000253245 on its first lag. Hence, one percent increase in the level of current month's sentiment index would lead to 0.0253% amount of decrease in long term volatility of gold price next month. In this case, this change is close to the values obtained in exchange rate cases. Therefore, it can be inferred that, even if there is an individual effect of BHT CCI on gold price volatility, the large part of it is coming from its effect on exchange rate volatility, since gold prices are in TRY form.

Finally, oil price volatility has negative relation, whereas there is positive relationship in case of stock price volatility. However, θ values are not significant in these instances indicating BHT CCI does not help to explain the long term component of oil price and stock price volatilities.

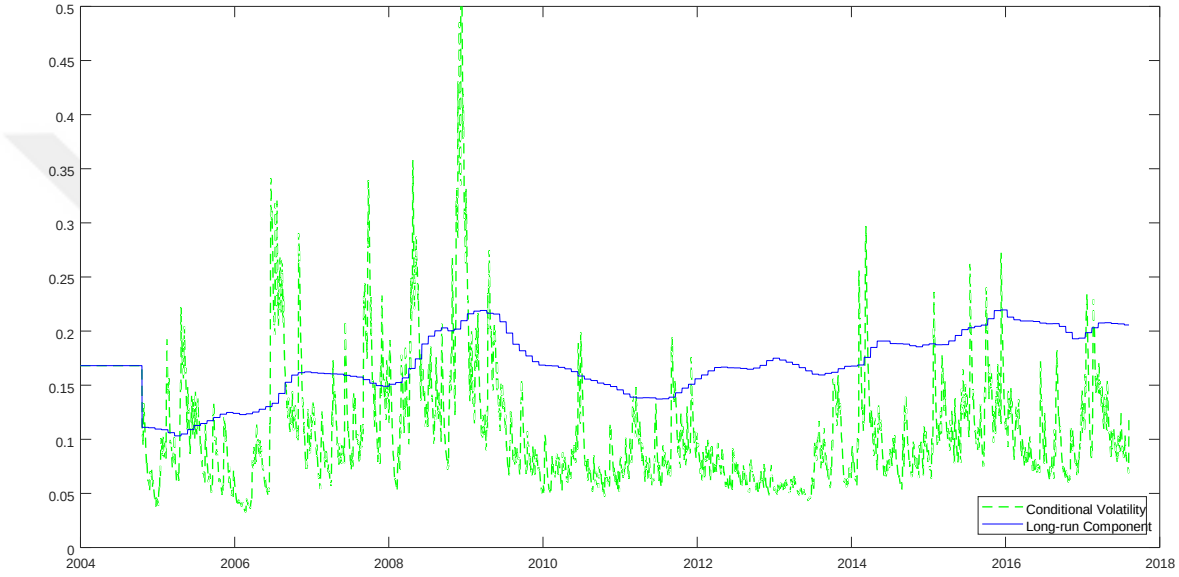
As a result, these percentages indicate that since low sentiment is indication of uncertainty, decrease in its value is accompanied by increased volatility in cases of exchange rate and gold price. Here, there are small amount of differences between significant variables in terms of BHT CCI's corresponding effect on the volatilities. Yet, basket variable is the one mostly affected by changes in confidence level compared to other variables.

For better understanding the behavior of volatility and obtained results in Table 19, it is also worth examining some figures plotted. Figure 50-53 are drawn to see conditional and secular volatilities of each variable, exchange rate of basket[18], gold price, oil price and stock price with BHT CCI. These figures show that long term

[18] See Appendix G for Plot of Total and Secular Volatilities of Dollar and Euro with CCI.

components are above the total volatilities in general except some peaks (except stock price). In line with the results for θ estimates, long term variance moves with conditional variance for exchange rate and gold price; however, the support of the long term component on conditional variance is lower in models constructed with gold price.

Figure 50. GARCH-MIDAS with BHT CCI Conditional Volatility and its Long Run component of Exchange Rate (Basket) Returns



For oil price and stock price returns, long term component is quite flat indicating that there is a little effect (almost none) of it on conditional variance. Although there are some fluctuations during the global financial crisis, for example, there is not worth mentioning movement of long term component in case of stock and oil prices compared to the previous two variables.

Figure 51. GARCH-MIDAS with BHT CCI Conditional Volatility and its Long Run Component of Gold Price Returns

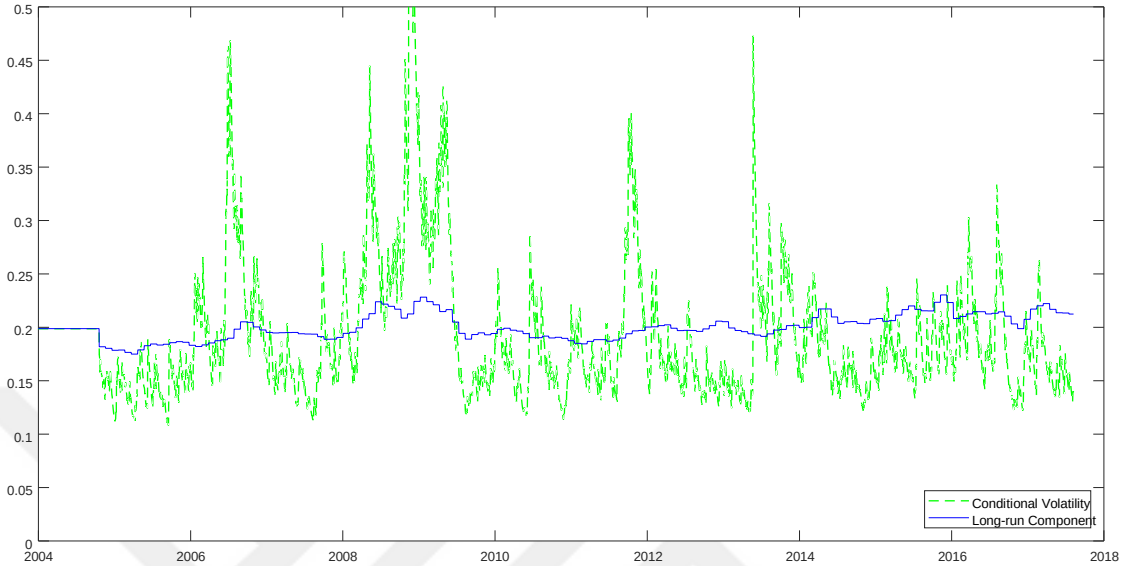


Figure 52. GARCH-MIDAS with BHT CCI Conditional Volatility and its Long Run Component of Oil Price Returns

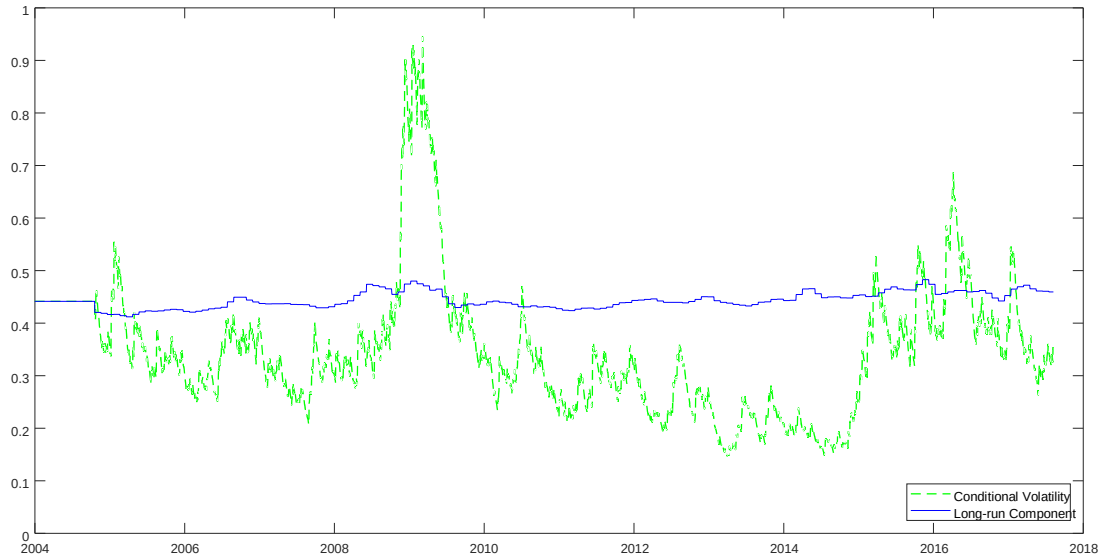
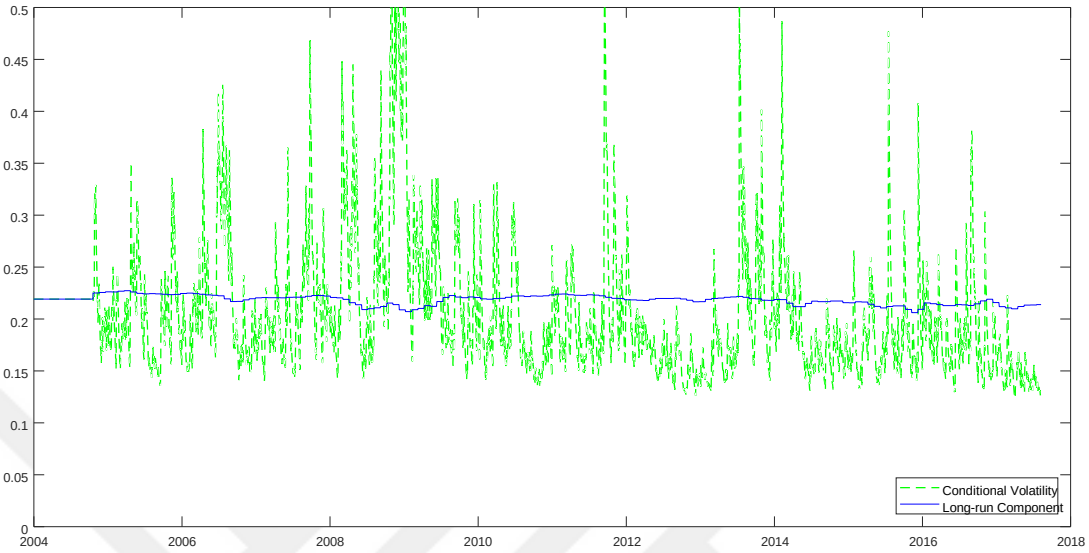


Figure 53. GARCH-MIDAS with BHT CCI Conditional Volatility and Its Long Run Component of Stock Price Returns



6.3.2. CBRT CCI

In this part, Table 20-23 demonstrate the parameter estimates for GARCH-MIDAS with Realized Variance for monthly fixed span and rolling window for the same period with CBRT CCI. Like the BHT CCI case, estimated parameters are shown in the column 3-8 with their standard errors in parenthesis. Also, ninth column demonstrates the LLF function and BIC values underneath with the following column indicating RMSEs. Like in BHT CCI, Table 20-23 show roughly similar values for LLF and BIC values obtained for CBRT CCI. It indicates that holding τ fixed for monthly time periods or allowing it to change daily does not have an important effect on likelihood behavior.

To begin with, Table 20 below gives parameter estimates of model constructed with daily exchange rate returns (basket, dollar and euro). The results indicate that almost all parameters apart from μ are strongly statistically significant.

Table 20. Parameter Estimates for GARCH-MIDAS with Realized Variance of Exchange Rate Returns (same period with CBRT CCI)

MIDAS Regressor		μ	α	β	θ	ω	m	*LLF/BIC*	RMSE
Fixed RV	Basket	0.000056	0.23625***	0.7582***	0.5828**	3.6476***	0.01001*	11996.10	0.000236
		(0.000085)	(0.012207)	(0.011492)	(0.289620)	(0.782390)	(0.005129)	-23943.20	
	Dollar	0.000095	0.12473***	0.83992***	0.19822***	2.757***	0.0044245***	11572.40	0.000289
		(0.000109)	(0.007419)	(0.007793)	(0.015104)	(0.594060)	(0.000622)	-23095.80	
	Euro	0.000031	0.17698***	0.69647***	0.18314***	6.7131***	0.0041773***	11672.10	0.000166
		(0.000102)	(0.011543)	(0.018816)	(0.007059)	(0.972030)	(0.000269)	-23295.10	
Rolling RV	Basket	0.000056	0.18609***	0.74714***	0.2151***	4.5093***	0.0030188***	12006.8	0.000195
		(0.000088)	(0.010790)	(0.013329)	(0.010706)	(0.812670)	(0.000395)	-23964.5	
	Dollar	0.000092	0.12575***	0.83316***	0.20185***	3.6864***	0.0040707***	11571.50	0.000293
		(0.000108)	(0.007600)	(0.008826)	(0.013464)	(0.868330)	(0.000570)	-23094.10	
	Euro	0.000031	0.17716***	0.68596***	0.18823***	7.6908***	0.0039006***	11672.40	0.000165
		(0.000102)	(0.011793)	(0.020791)	(0.007018)	(1.151600)	(0.000281)	-23295.70	

Note: Standard Errors are in paranthesis.
***,**,and * represent the significance level at 1%, 5%, and 10%, respectively.

Furthermore, the sums of α and β are 0.99445, 0.96465 and 0.87345 in case of monthly fixed span RV; while in case of rolling window, they are 0.93323, 0.95891 and 0.86312 for basket, dollar and euro returns, respectively. These values indicate that sum of α and β are close to but smaller than 1 indicating high degree of volatility persistence. In figures 54 and 55, volatility components of model; that is total and secular volatility of dollar exchange rate returns, can be seen[19]. It is clear that for both specifications, the long term components (secular) are smoother than total volatilities.

Also, in rolling window case, long term volatility is smoother compared to the fixed span, even though the general pattern of long term component follows total volatility in both figures. This smoothness is obvious, because τ component is of monthly frequency in fixed span; whereas it is of daily frequency in rolling window estimation. As it can be seen from both figures above, most of the changes in total volatility can be attributed to the changes in secular component of exchange rate of dollar RV.

[19] See Appendix F for Plot of GARCH-MIDAS model for Basket and Euro Exchange rate return RVs.

Figure 54. GARCH-MIDAS with Fixed Span RV (Dollar, same period with CBRT CCI)

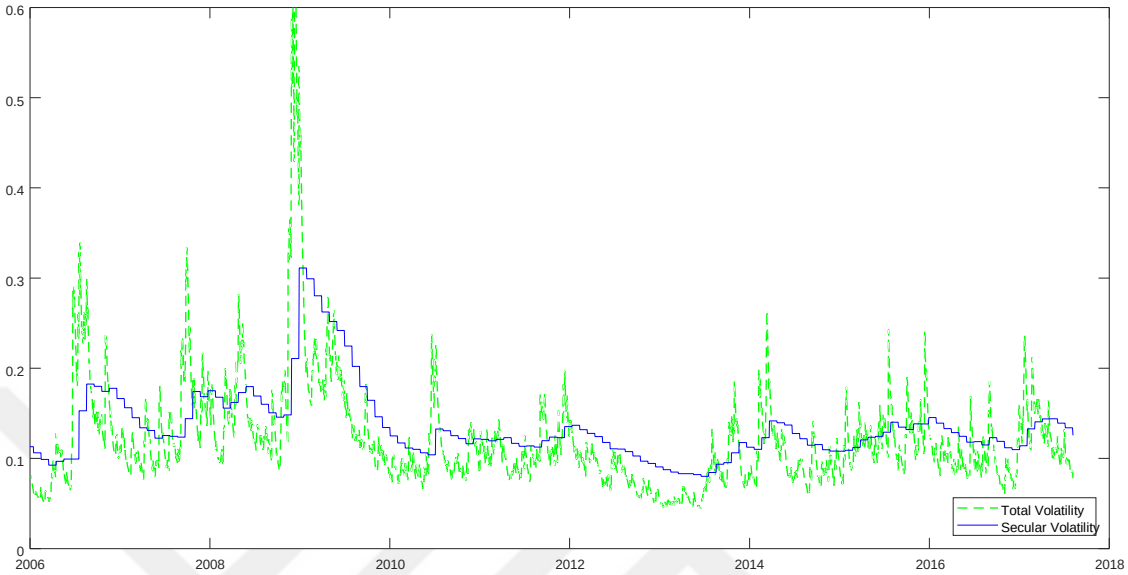
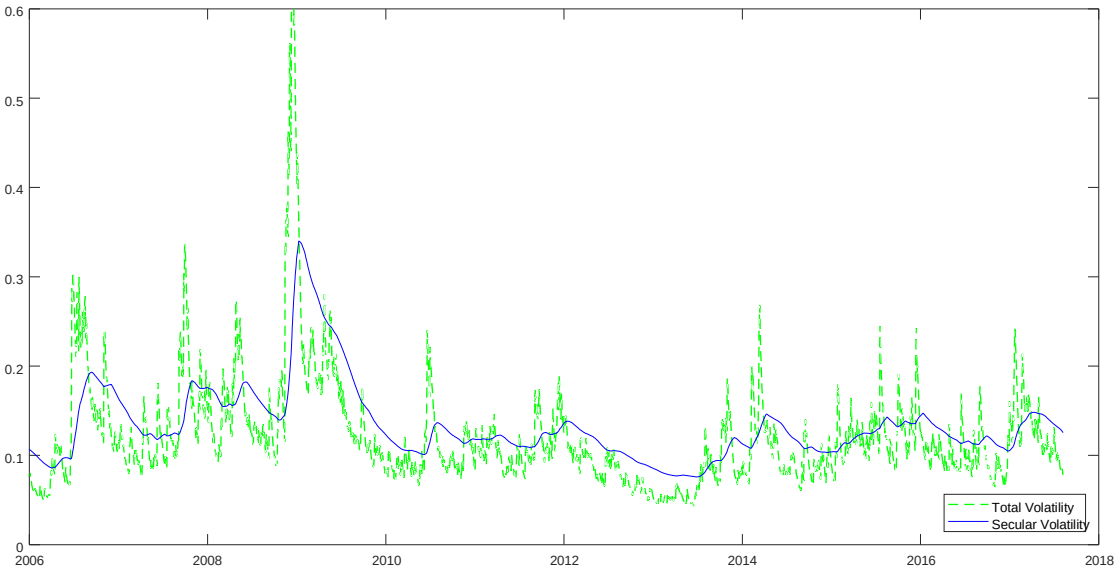


Figure 55. GARCH-MIDAS with Rolling Window RV (Dollar, same period with CBRT CCI)



Now, Table 21 provides estimated coefficients of RV for gold price where almost all coefficients are statistically significant. The sums of α and β are 0.951523 and 0.77394 for fixed span and rolling window, respectively and they are within the stationarity boundary $\alpha_i + \beta_i < 1$, as well. θ estimates are significant for both specifications.

Table 21. Parameter Estimates for GARCH-MIDAS with Realized Variance of Gold Price Returns (same period with CBRT CCI)

MIDAS Regressor	μ	α	β	θ	ω	m	*LLF/BIC*	RMSE
Fixed RV	0.00048794***	0.091213***	0.86031***	0.11991***	7.4349**	0.010311***	9888.48	0.000444
	(0.000188)	(0.008429)	(0.018452)	(0.022088)	(3.485400)	(0.000889)	-19728.00	
Rolling RV	0.00060439***	0.11934***	0.6546***	0.17245***	49.892***	0.0074922***	9889.19	0.000442
	(0.000192)	(0.012210)	(0.050511)	(0.006911)	(18.243000)	(0.000369)	-19729.40	

Note: Standard Errors are in paranthesis.
***,**,and * represent the significance level at 1%, 5%, and 10%, respectively.

The below figures 56 and 57 illustrate the long term and total variances estimated by GARCH-MIDAS model including RV of daily returns of gold price. In both figures, general pattern of secular volatility is following total variance. Especially for rolling window case, one can barely differentiate between secular and total variance which indicates the former's great contribution to the latter.

Table 22 and 23 below gives estimates of oil and stock price return volatilities for two specifications. Similar judgments can be obtained from oil and stock return volatilities. The findings, in table 22 and 233, demonstrates that sums of α and β for fixed span are 0.99801 and 0.85644; while in case of rolling window, they are 0.904057 and 0.80524 for oil and stock price, respectively. Finally, θ estimates are positive and statistically significant for both variables with two specifications (except one case).

Figure 56. GARCH-MIDAS with Fixed Span RV (Gold Price, same period with CBRT CCI)

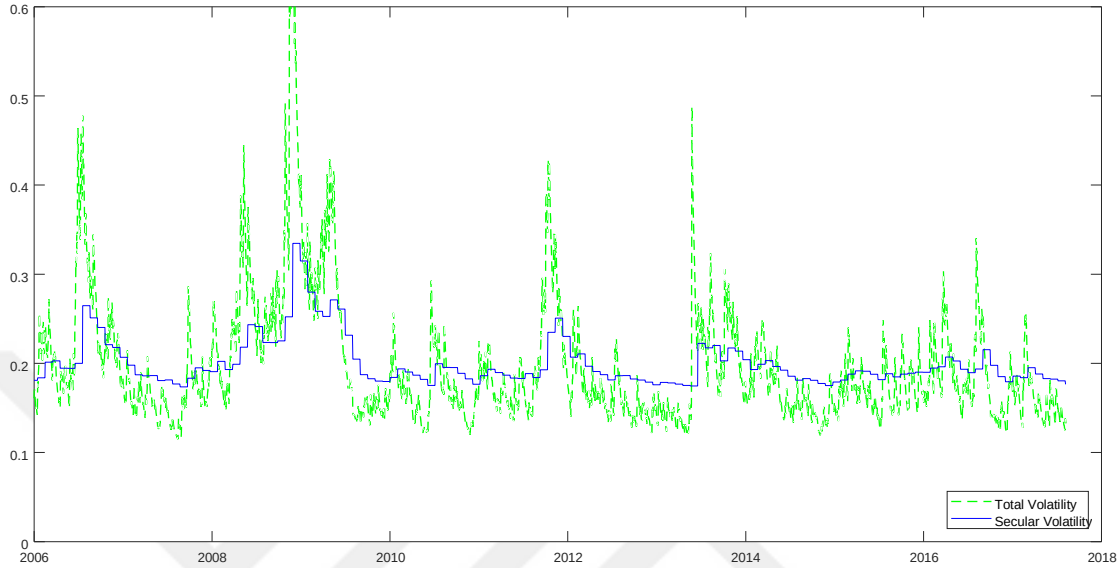


Figure 57. GARCH-MIDAS with Rolling Window RV (Gold Price, same period with CBRT CCI)

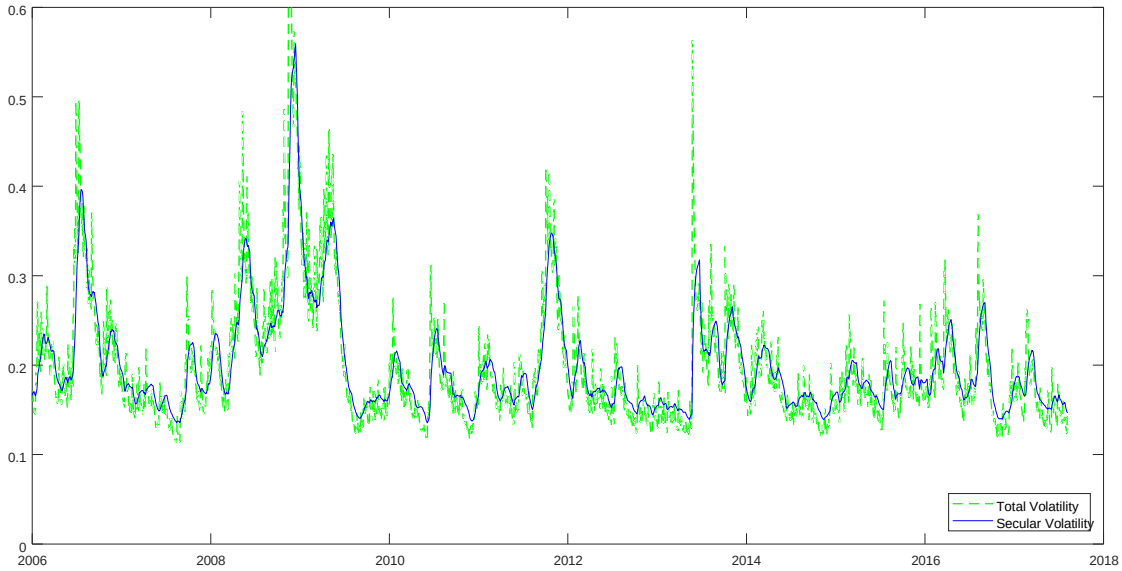


Table 22. Parameter Estimates for GARCH-MIDAS with Realized Variance of Oil Price Returns (same period with CBRT CCI)

MIDAS Regressor	μ	α	β	θ	ω	m	*LLF/BIC*	RMSE
Fixed RV	0.000349	0.04412***	0.95389***	0.043510	8.377000	0.026709***	8127.06	0.001161
	(0.000319)	(0.005150)	(0.005394)	(0.071454)	(49.580000)	(0.003546)	-16205.10	
Rolling RV	0.000284	0.061867***	0.84219***	0.20124***	8.7856***	0.0072927***	8127.73	0.001161
	(0.000320)	(0.011899)	(0.049243)	(0.006512)	(2.510000)	(0.001149)	-16206.40	

Note: Standard Errors are in paranthesis.
***,**,and * represent the significance level at 1%, 5%, and 10%, respectively.

Table 23. Parameter Estimates for GARCH-MIDAS with Realized Variance of Stock Price Returns (same period with CBRT CCI)

MIDAS Regressor	μ	α	β	θ	ω	m	*LLF/BIC*	RMSE
Fixed RV	0.0011886***	0.174***	0.68244***	0.16197***	4.4083***	0.0087801***	9706.89	0.000384
	(0.000196)	(0.014071)	(0.025708)	(0.012122)	(1.331000)	(0.000653)	-19364.80	
Rolling RV	0.0011931***	0.18825***	0.61699***	0.16295***	11.419***	0.0087116***	9708.81	0.000384
	(0.000200)	(0.015848)	(0.030384)	(0.010144)	(2.823100)	(0.000538)	-19368.60	

Note: Standard Errors are in paranthesis.
***,**,and * represent the significance level at 1%, 5%, and 10%, respectively.

Figure 58-61 plots the long term and total variances for oil and stock prices in case of fixed span and rolling window. In figure 58, long term variance indicating little support for total variance. This plot proves insignificance of θ value estimate of oil price returns with fixed span. On the other hand, in Figure 59, secular component appears as main driver of total volatility of oil price with small contribution coming from short term component.

Figure 58. GARCH-MIDAS with Fixed Span RV (Oil Price, same period with CBRT CCI)

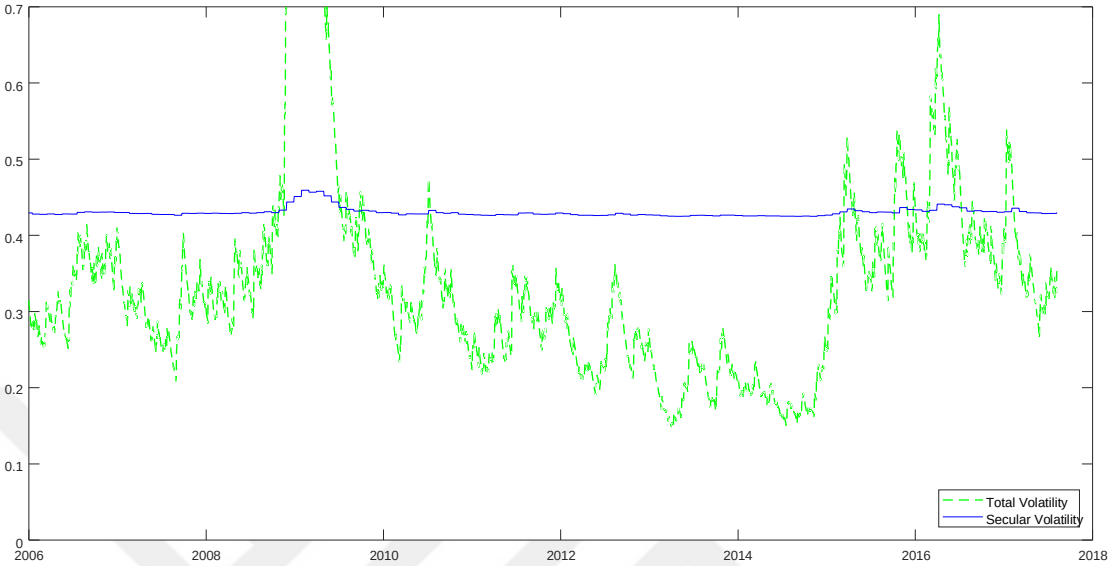
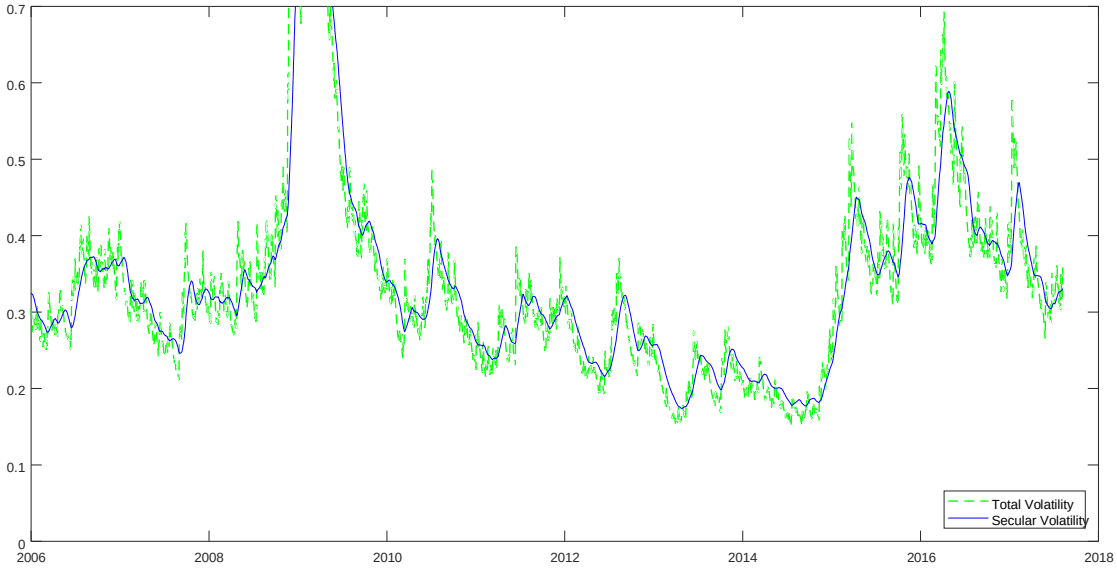
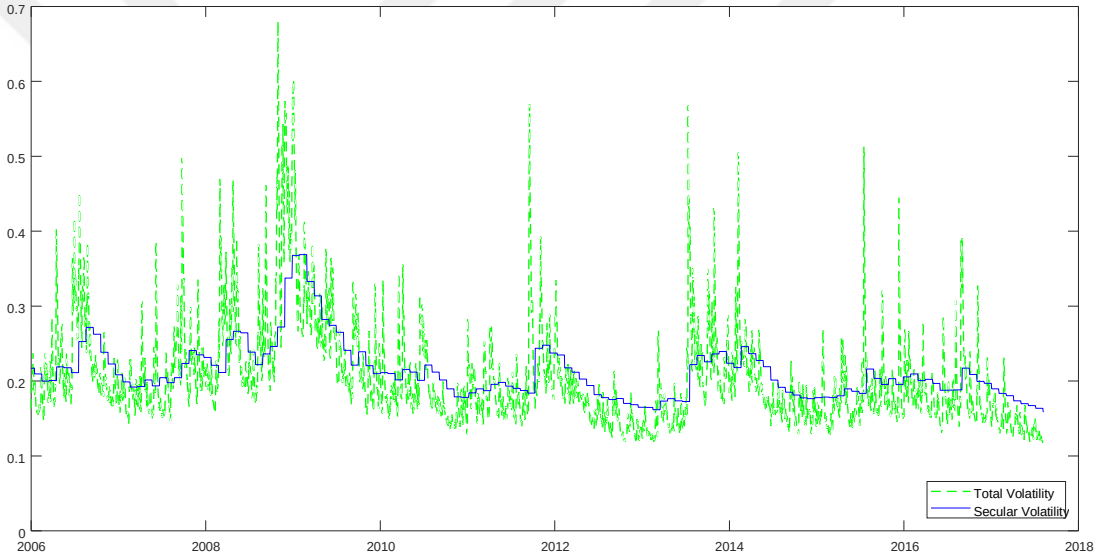


Figure 59. GARCH-MIDAS with Rolling Window RV (Oil Price, same period with CBRT CCI)



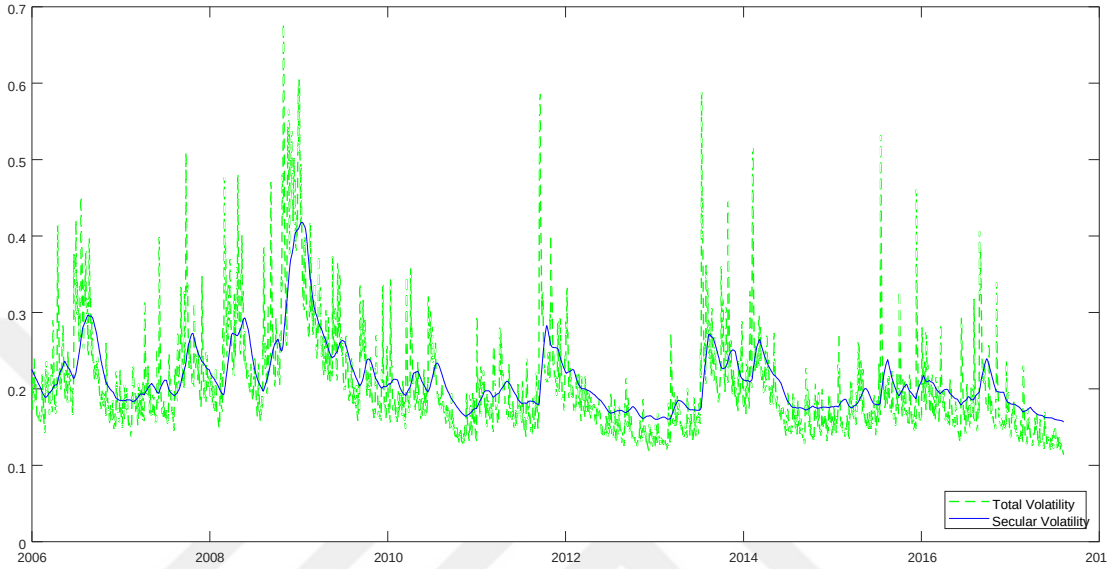
As can be seen in Figure 60 and 61, secular volatility is smoother compared to total volatility of stock price returns, especially in rolling case. Yet, it simply follows the trend of total volatility in almost all periods. As a result, long term component constitutes significant part of total volatility of stock returns; but influence of short term variance on total variance of stock prices cannot be ignored. Like almost all cases, for both specifications of oil and stock price realized volatilities, total and long run volatilities increase during global financial crisis.

Figure 60. GARCH-MIDAS with Fixed Span RV (Stock Price, same period with CBRT CCI)



After this point, models that directly use monthly time series data of CBRT CCI without changing its frequency are visited. Table 24 provides results for parameter estimates of GARCH-MIDAS with level of CBRT CCI. Seen from the table, μ is statistically significant in case of gold price and stock price. Furthermore, α and β values are strongly statistically significant and their sums for each daily variable (0.998340, 0.998260, 0.863120, 0.973700, 0.997647 and 0.935080) are smaller than and close to 1 indicates a higher level of persistence in the volatility. This justifies that information coming from monthly variables contributes to the long-term component variance to some extent.

Figure 61. GARCH-MIDAS with Rolling Window RV (Stock Price, same period with CBRT CCI)



Herein, influence of sentiment index on volatility of high frequency variables is estimated. The most important parameter is the slope parameter; i.e. θ for level of CBRT CCI. Consider values θ of daily returns for period of 2004M1-2017M6. Out of 6 cases for θ values, five of them have negative value. For level specification of BHT CCI, this means that more consumer confidence accompanies less volatility in the daily returns of the variables. Specifically, dollar, euro, oil price and stock price are significant with expected signs (except euro).

Table 24. Parameter Estimates for GARCH-MIDAS with Level of CBRTCCI

MIDAS Regressor		μ	α	β	θ	ω	m	*LLF/BIC*	RMSE
	Basket	0.00013043	0.13667***	0.86167***	-0.0096261	2.0163	0.00085964	10362.3	0.000261
		(0.000096)	(0.007790)	(0.007836)	(0.050562)	(21.935000)	(0.002266)	-20675.6	
Exchange Rate	Dollar	0.000169	0.10299***	0.89527***	-0.16632**	47.119**	0.0075132**	10001.10	0.000314
		(0.000116)	(0.006338)	(0.006390)	(0.067765)	(22.537000)	(0.002979)	-19953.20	
	Euro	0.000031	0.17716***	0.68596***	0.18823***	7.6908***	0.0039006***	11672.40	0.000165
		(0.000102)	(0.011793)	(0.020791)	(0.007018)	(1.151600)	(0.000281)	-23295.70	
Gold Price		0.00043681*	0.08724***	0.88646***	-0.016682	37.527	0.00088379	8549.59	0.000444
		(0.000204)	(0.007554)	(0.008544)	(0.012745)	(100.650000)	(0.000549)	-17050.2	
Oil Price		0.000264	0.043467***	0.95418***	-0.22529**	49.511000	0.010336**	7054.10	0.001158
		(0.000338)	(0.004988)	(0.005308)	(0.109730)	(48.502000)	(0.004873)	-14059.20	
Stock Price		0.0010176***	0.15296***	0.78212***	-0.022503**	7.122900	0.0011492**	8427.18	0.000386
		(0.000209)	(0.012115)	(0.016244)	(0.010927)	(9.638300)	(0.000473)	-16805.40	

Note: Standard Errors are in paranthesis.
***,**,and * represent the significance level at 1%, 5%, and 10%, respectively.

Here, exchange rate variables provide different results. The one that is in line with the results in BHT CCI case is the dollar exchange rate returns volatility which constitutes inverse relationship with CBRT CCI. Like in the previous section, the amount of the impact of CBRT CCI on six daily indicators variables can be measured by using θ and ω values with same formula; $e^{\theta*\varphi(\omega)}-1$. In more detail, for dollar exchange rate returns, parameter estimate of θ is -0.16632 with 5% significance level. Since the weighting function ω=47.119 which puts 0.0228661 on the first lag, it is found that one percent increase in the level of CBRT CCI at the current month would change the long-term component of the next month's dollar return volatility by $e^{-0.16632 *0.0228661} -1= -0.3796\%$. On the contrary, if the last month's confidence index increased by 1%, 0.4084% increase is seen in long term euro exchange rate volatility next month.

In case for oil and stock prices, negative relation is expected between changes in CBRT CCI and their volatility. Compared to exchange rate, oil and stock price demonstrate expected dynamics in case for CBRT CCI. Results suggest that optimistic expectations of investors on the overall economy reduce the uncertainty and therefore volatility of stock market returns[20]. This result confirms that there is counter cyclical

[20] See Sayim and Rahman (2015) for discussion.

behavior of stock price volatility[21]. It is observed that long term stock volatility is inversely related with the CBRT CCI. Similarly, Conrad and Loch (2012) included sentiment index to their research and confirm the counter-cyclical property of long-run volatility. Also, negative value of θ for oil price volatility confers the same pattern. In this case, the main reason of improved sentiment index, growing economy, can cause constant demand for oil due to increased investment activities and results in lower oil price volatility. For oil and stock price returns, the weighting functions are characterized by ω=49.51 and ω=7.12, and puts -0.02160 and 0.02057 on the first lags, respectively. In these cases, one percent increase in the level of current month's sentiment index would lead to 0.4854% and 0.0463% amount of decrease in long term volatility of oil and stock price returns next month, separately.

Closer look to the values of contributions of CBRT CCI on exchange rate (Dollar), oil price and stock price indicates that oil price volatility is influenced the most by the changes in consumer sentiment. Here, since regressions in this thesis are run by using brent oil prices in form of TL, most of its volatility seems stemming from the exchange rate fluctuations. Yet, there is a place for its own individual fluctuation. Finally, stock price volatility is influenced in a small amount by changes in sentiment index and CBRT CCI has no explanatory power on gold price volatility.

To capture the behavior of volatility, Figure 62-65 are plotted including conditional and long-term volatilities of each variable with CBRT CCI. These figures show that long term components are above the total volatilities in general except some peaks (except stock returns). In line with the results for θ estimates, the long-term variance moves with the total variance for exchange rate (dollar)[22] and oil price. Also, in Figure 62 and 63, they share very similar path supporting that most of the volatility of oil price stems from exchange rate fluctuations.

[21] This behavior is first observed by Schwert (1989).
[22] See Appendix G for Plot of Total and Secular Volatilities of Basket and Euro Exchange rate returns with CCI.

Figure 62. GARCH-MIDAS with CBRT CCI Conditional Volatility and its Long Run component of Exchange Rate (Dollar) Returns

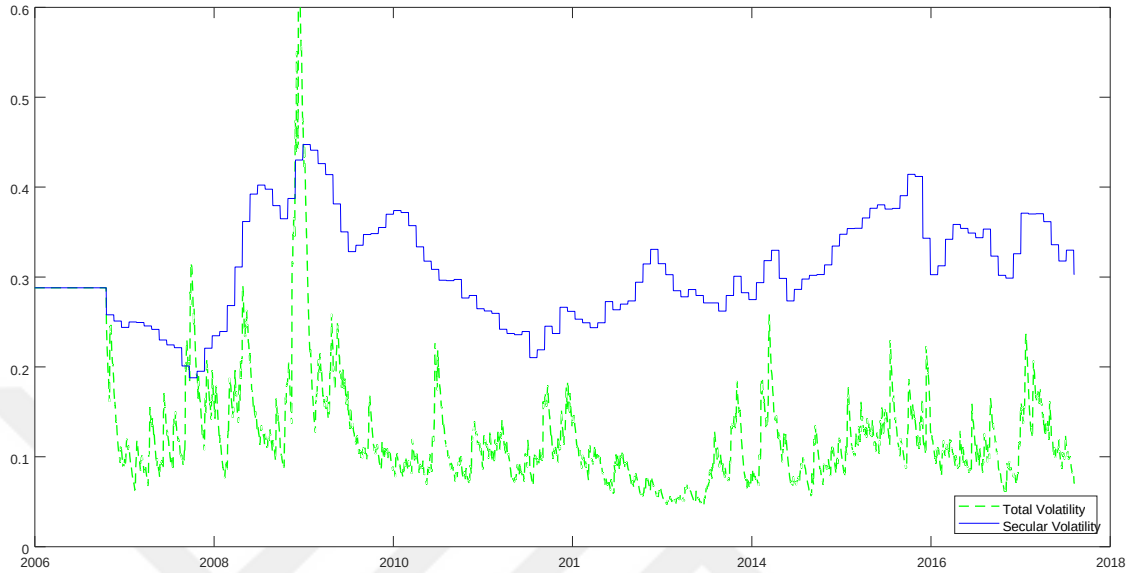
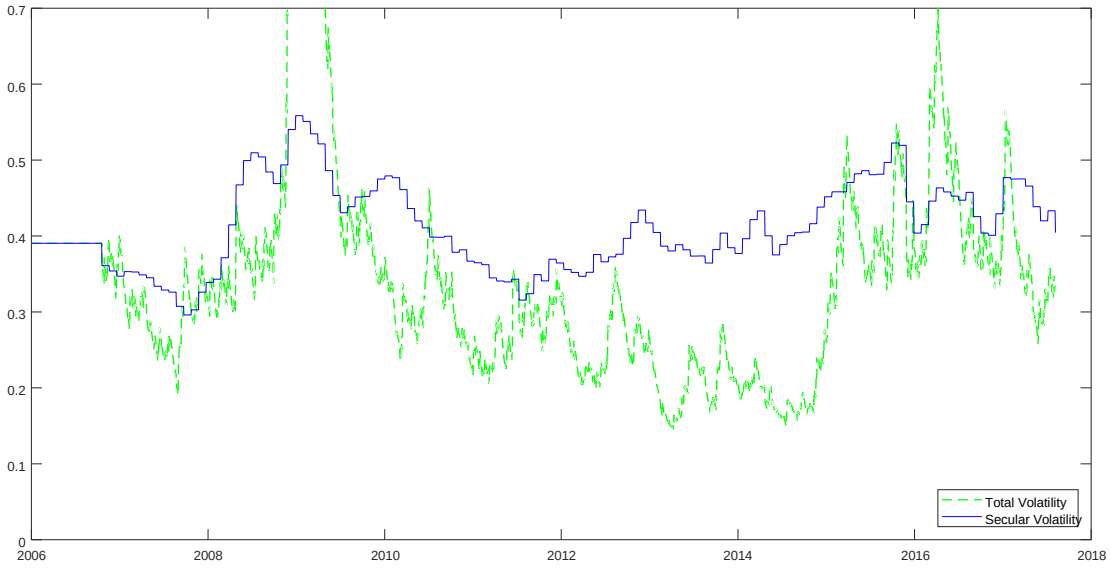
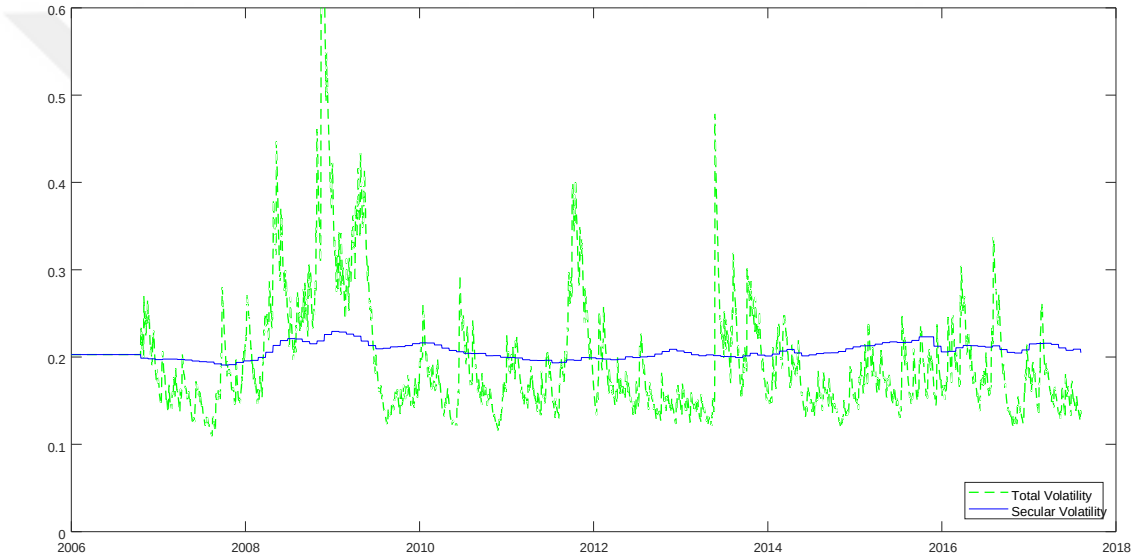


Figure 63. GARCH-MIDAS with CBRT CCI Conditional Volatility and its Long Run component of Oil Price Returns



On the other hand, long term component of gold and stock price are smoother which indicates there is little effect on total variance and support of them is lower compared to exchange rate and oil price variable. Of course, there are some fluctuations during the global financial crisis. Yet, they are not worth mentioning movements in cases plotted in Figure 64 and 65.

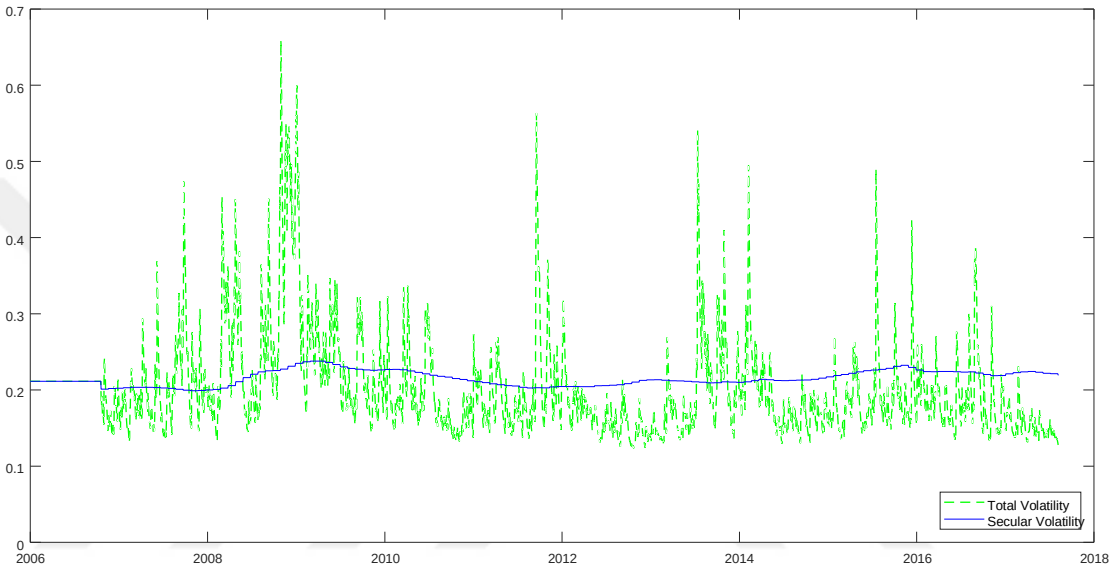
Figure 64. GARCH-MIDAS with CBRT CCI Conditional Volatility and its Long Run component of Gold Price Returns



As a general conclusion, the link between secular volatilities and sentiment indices reflecting macroeconomic environment is visited by using GARCH-MIDAS model. In general, results show that BHT CCI and CBRT CCI have their own contributions to exchange rate, gold price, oil price and stock exchange volatilities and their behavior is counter cyclical. Specifically, the former gives more balanced results in terms of predictive ability for long-term volatility of exchange rate and gold price variables; while oil and stock prices volatilities are explained well by the latter. Interestingly, both sentiment indices give complementary results for our four variables. Yet, volatilities of these four different variables can be captured by considering both indices displaying different dynamics since these volatilities are found that they are

driven by the information hidden in the sentiment measures which are very closely related to the current stance of the economy.

Figure 65. GARCH-MIDAS with CBRT CCI Conditional Volatility and its Long Run component of Stock Price Returns



7. CONCLUSION AND RECOMMENDATIONS

Throughout this study, the ultimate goal is to find the relationship between consumer sentiment and four important high frequency variables in an emerging economy, Turkey. Firstly, ADL-MIDAS regression models are used to obtain monthly forecasts for two consumer confidence indices in Turkey. This novel approach yields an adjustable setting by considering the contribution of each daily data to forecasting of monthly variable. Specifically, by exploiting highly frequent variables like exchange rate, stock exchange, oil price and gold price; nowcasting consumer sentiment by the flexible data-driven weighting scheme is achieved. Empirical results show that models with exchange rate variable outperform others. It is also shown that, for shorter horizons, BHT CCI estimations are better; whereas for longer horizons, there is an improvement over regressions with CBRT CCI.

Additionally, volatility of these interested high frequency returns given the information of monthly consumer confidence index is other side of the coin. The link between secular volatilities and sentiment indices reflecting macroeconomic environment is visited by using GARCH-MIDAS model. In general, empirical evidence suggests that BHT CCI and CBRT CCI have their own contributions to exchange rate, gold price, oil price and stock exchange volatilities and their behavior is counter cyclical. Specifically, it is found that the former gives more balanced results in terms of predictive ability for long-term volatility of exchange rate and gold price variables; while oil and stock prices volatilities are explained well by the latter. Interestingly, both sentiment indices give complementary results for four variables. Yet, volatilities of these four different variables can be captured by considering both indices displaying different dynamics since these volatilities are found that they are driven by the information hidden in the sentiment measures which are very closely related to the current stance of the economy.

At this point, it should be noticed that exchange rate variable is the most important channel which affects consumer sentiment in Turkey. On the other hand, its volatility is highly dependent on the changes in consumer confidence index level. This is not surprising result when Turkey's economic structure is examined, in detail. As

explained previously, basket variable explains sentiment indices better in ADL-MIDAS applications. The negative relationship between exchange rate and sentiment index shows Turkey's dependency to the foreign currency. Since, its imports and exports are based on dollar and euro terms, respectively; basket variable's role in explaining household's expectations can be understood easily. Moreover, Turkey has negative current account balance for many years[23]. According to the Moody's annual report in Nov 2017, Turkey's current account deficit corresponds 4.5 % of its GDP and it is highest current account deficit among 22 emerging economies. Hence, current account deficit can easily explain its dollar dependency and negative relation between sentiment indices and foreign currency. In a similar way of thinking, exchange rate volatility is affected by changes in household's perception of economy.

Another important conclusion that should be drawn is that all results confirm the use of consumer confidence index in understanding the stance of the economy. For full sample period with available data of sentiment indices and also subsample period corresponding before crisis and crisis period demonstrates that 4 high frequency variable can successfully forecast both sentiment indices. Indeed, there is little or no difference between actual and estimated variables in out of sample practices. This close interaction between frequently used economic variables and consumer confidence index supports the use of expectation surveys in forecasting growth related variables in countries. Specifically for an emerging economy, Turkey, consumer confidence index can constitute a basis for nowcasting GDP growth. Furthermore, its use in estimation of other expectation surveys can be beneficial as its close dynamic interaction with current state of the economy is considered.

The last but not the least, there can be some recommendations for future researches. First of all, question by question analysis of consumer confidence index can be done with same high frequency variables. Moreover, instead of one variable model, all variables can be included with different combinations to understand their joint relation with sentiment indices. Finally, variables like oil price and gold price can be

[23] See https://data.worldbank.org/indicator/BN.CAB.XOKA.GD.ZS?end=2016&locations=TR&start=1974&view=chart

included in USD form to obtain their own influence independent of exchange rate effect.

To sum up, the empirical results in this paper support the use of mixed frequency data, including monthly sentiment index and daily variables, in nowcasting consumer sentiment. Moreover, it is evident that there is a close relationship between sentiment indices and volatility of daily returns. With these two aspects of the study, the dynamic interaction between included variables is comprehended, in detail.

APPENDIX

APPENDIX A. Actual and Estimated Values of Consumer Confidence Indices (Out of Sample Estimation with Full Sample Period)

Table A1. BHT CCI between July 2016 and June 2017, (Fixed Window Scheme, 5 days horizon, 22 days Xlag)

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17
Actual Value	81.8309	94.1352	100.334	82.8277	69.2152	68.2807	65.1969	74.4795	78.4356	77.1584	78.5602	81.3325
Estimated Value by USD	78.7281	86.3838	92.8978	95.5357	77.8513	65.4378	64.7737	70.7109	75.4824	79.3922	83.2044	82.5992
Estimated Value byEUR	78.0617	84.0658	94.3772	98.0228	79.5909	69.4426	63.1429	70.7251	75.3995	79.9259	77.7501	81.9984
Estimated Value by BASKET	78.9567	85.5243	93.5504	95.9858	78.1946	66.8533	62.7087	71.1222	74.7463	79.5193	80.7534	82.4671
Estimated Value by GOLD	74.4033	85.8584	96.005	100.927	82.2612	73.5893	65.8777	69.4773	78.093	78.5865	81.8428	81.9001
Estimated Value by OIL	76.6999	84.1163	95.0592	101.382	82.1872	71.1365	69.6791	67.6197	77.1306	81.6303	78.406	81.9656
Estimated Value by BIST	78.6809	86.7734	93.9723	98.7508	80.7938	71.8298	71.9233	70.8383	77.0381	80.0299	79.7263	80.9717
Estimated by All Variables (USD)	77.4165	85.9358	94.2169	98.5437	80.3024	69.7348	67.6603	69.8884	76.7229	79.8061	81.1176	81.9247
Estimated by All Variables (EUR)	77.285	85.2169	94.3112	98.3468	79.9899	69.1584	65.4182	69.8884	76.2792	79.7901	80.5115	82.179
Estimated by All Variables (BASKET)	77.6103	85.6184	94.0569	97.6803	79.5273	68.3472	65.144	70.0564	76.0203	79.6705	81.3207	82.3106

Table A2. BHT CCI between July 2016 and June 2017, (Fixed Window Scheme, 5 days horizon, 44 days Xlag)

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17
Actual Value	81.8309	94.1352	100.334	82.8277	69.2152	68.2807	65.1969	74.4795	78.4356	77.1584	78.5602	81.3325
Estimated Value by USD	78.8936	84.1752	95.8707	93.8784	77.3159	65.0659	63.3326	70.4075	76.7689	80.5518	83.1212	83.1794
Estimated Value byEUR	79.862	82.2695	95.2876	97.1834	80.3105	67.6468	63.9435	68.3335	77.7112	80.6082	79.3128	80.5437
Estimated Value by BASKET	79.7822	83.0215	95.7461	95.1638	78.1164	65.6738	62.7024	69.4217	77.4397	80.7372	81.2069	81.8919
Estimated Value by GOLD	74.9184	82.5662	97.2709	101.758	83.6633	72.3851	67.6942	65.6213	78.5001	79.4716	80.5437	83.1877
Estimated Value by OIL	76.8073	82.8971	94.7934	99.6935	82.0723	69.0824	68.5319	67.2085	77.6025	81.2475	77.9291	82.4507
Estimated Value by BIST	78.4687	83.0963	94.3867	99.554	82.6736	71.4573	74.0766	74.5373	79.1306	80.7211	82.4754	82.8225
Estimated by All Variables (USD)	77.6336	83.3876	95.5739	97.651	80.5276	68.4771	67.3229	69.6442	77.7346	80.5437	81.3776	82.9468
Estimated by All Variables (EUR)	78.0539	83.1462	95.727	97.1737	80.0699	67.7077	65.2222	68.4087	77.463	80.5276	80.6162	82.3353
Estimated by All Variables (BASKET)	78.1398	83.3293	95.8419	96.5441	79.4081	67.0944	64.7543	68.7379	77.401	80.5759	81.1257	82.6488

Table A3. BHT CCI between July 2016 and June 2017, (Rolling Window Scheme, 5 days horizon, 22 days Xlag)

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17
Actual Value	81.8309	94.1352	100.334	82.8277	69.2152	68.2807	65.1969	74.4795	78.4356	77.1584	78.5602	81.3325
Estimated Value by USD	78.7281	88.6681	93.9723	93.7377	76.3021	68.1833	62.4271	72.0096	75.2714	77.7268	80.8827	83.1378
Estimated Value byEUR	78.0617	84.5548	94.4717	97.9248	79.6148	68.6211	62.3834	70.6544	75.2488	79.7582	78.1867	82.023
Estimated Value by BASKET	78.9567	85.5414	93.6346	95.794	77.9603	66.5198	62.1966	71.3003	74.5001	79.4319	80.423	83.3043
Estimated Value by GOLD	74.4033	85.0892	95.6791	100.988	81.761	72.7406	65.7527	69.1377	77.2232	77.6258	81.5079	79.862
Estimated Value by OIL	76.6999	84.1668	95.1924	101.85	82.2119	66.7664	67.9043	65.5229	77.2541	82.4754	77.2387	82.1955
Estimated Value by BIST	78.6809	86.7734	93.9723	98.8496	80.9717	71.7724	71.8801	70.4709	76.7536	79.4875	80.118	81.2556
Estimated by All Variables (USD)	77.6025	86.895	94.4717	97.3488	79.1623	69.512	65.7987	70.1124	76.241	78.8147	80.2543	81.9902
Estimated by All Variables (EUR)	77.494	86.3492	94.5662	97.1834	78.9094	68.841	63.7902	70.1685	75.8987	78.9015	79.7742	82.1544
Estimated by All Variables (BASKET)	77.7657	86.5394	94.3301	96.6214	78.4844	68.2379	63.6691	70.3653	75.6562	78.8542	80.3265	82.5001

Table A4. BHT CCI between July 2016 and June 2017, (Rolling Window Scheme, 5 days horizon, 44 days Xlag)

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17
Actual Value	81.8309	94.1352	100.334	82.8277	69.2152	68.2807	65.1969	74.4795	78.4356	77.1584	78.5602	81.3325
Estimated Value by USD	78.8936	84.2088	95.8515	93.6627	76.9919	64.7867	62.8279	70.8383	76.2868	80.3908	82.7728	83.0631
Estimated Value byEUR	79.862	82.2695	95.3353	97.0572	79.9659	67.1481	63.2377	68.1492	77.2387	80.5518	78.9488	80.6162
Estimated Value by BASKET	79.7822	83.0298	95.727	94.8788	77.5405	65.144	61.9235	69.6512	76.9226	80.6807	80.9474	81.982
Estimated Value by GOLD	74.9184	82.3024	97.1834	101.575	83.588	72.0096	67.4104	67.8568	75.4975	77.5405	82.1215	79.7503
Estimated Value by OIL	76.8073	82.9468	94.9547	100.444	80.8019	68.8479	67.8433	66.7531	77.6103	81.9492	77.432	82.8971
Estimated Value by BIST	78.4687	83.1462	94.4906	99.6735	82.7397	71.586	73.9878	73.8547	78.5472	80.3024	81.6956	82.1379
Estimated by All Variables (USD)	77.618	83.371	95.6217	97.7096	80.118	68.272	66.8666	69.9863	76.8765	80.1741	81.2637	82.2283
Estimated by All Variables (EUR)	78.0383	83.1295	95.7557	97.1737	79.5989	67.3767	64.6637	68.8066	76.6615	80.2462	80.5759	81.8264
Estimated by All Variables (BASKET)	78.1242	83.3126	95.8515	96.5055	78.8778	66.7464	64.1677	69.2207	76.6002	80.3105	81.0933	82.1708

Table A5. BHT CCI between July 2016 and June 2017, (Recursive Scheme, 5 days horizon, 22 days Xlag)

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17
Actual Value	81.8309	94.1352	100.334	82.8277	69.2152	68.2807	65.1969	74.4795	78.4356	77.1584	78.5602	81.3325
Estimated Value by USD	78.7281	88.6504	94.0287	95.5739	76.4166	68.313	62.5271	72.1466	74.173	77.9058	81.2394	83.421
Estimated Value byEUR	78.0617	84.5464	94.5	97.4754	79.7343	68.8479	62.5584	70.7038	75.0609	79.9499	78.6022	82.3271
Estimated Value by BASKET	78.9567	85.5243	93.6814	96.0338	78.0617	66.9335	61.5223	71.9305	75.0159	79.5591	80.7776	82.9137
Estimated Value by GOLD	74.4033	85.0892	95.7174	100.897	82.4424	73.6924	65.8777	69.4495	78.218	77.9525	81.9083	81.8837
Estimated Value by OIL	76.6999	84.1752	95.2019	101.596	83.9314	67.0206	68.313	65.97	77.1152	81.6058	79.0041	82.5331
Estimated Value by BIST	78.6809	86.7734	94.0099	98.8398	80.7938	71.7652	71.7652	70.6685	76.8611	79.8061	79.5591	80.8019
Estimated by All Variables (USD)	77.5482	86.7907	94.5284	98.2976	79.7503	69.8814	66.1682	70.2458	76.0279	78.9567	80.6001	82.3682
Estimated by All Variables (EUR)	77.432	86.194	94.6419	97.964	79.5114	69.193	64.0203	70.2739	75.5882	79.0278	80.3024	82.7149
Estimated by All Variables (BASKET)	77.7268	86.4183	94.3867	97.5046	79.0278	68.6005	63.631	70.6473	75.5504	78.9488	80.8746	82.8722

Table A6. BHT CCI between July 2016 and June 2017, (Recursive Scheme, 5 days horizon, 44 days Xlag)

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17
Actual Value	81.8309	94.1352	100.334	82.8277	69.2152	68.2807	65.1969	74.4795	78.4356	77.1584	78.5602	81.3325
Estimated Value by USD	78.8936	84.2004	95.9186	93.9347	77.1923	65.0594	63.0419	70.9092	76.6615	80.6969	83.2543	83.3793
Estimated Value byEUR	79.862	82.2777	95.3639	97.3196	80.3346	67.5927	63.631	68.6211	77.4242	80.8504	79.3525	80.7372
Estimated Value by BASKET	79.7822	83.0381	95.794	95.259	78.0539	65.6738	62.3523	69.9024	77.2232	80.9555	81.28	82.1544
Estimated Value by GOLD	74.9184	82.3024	97.1931	101.585	83.5462	72.1466	67.2556	64.9359	77.2696	79.3049	82.6488	82.5084
Estimated Value by OIL	76.8073	82.9468	94.9642	100.083	82.3847	68.8892	68.2379	67.0005	77.8357	81.5895	77.8279	82.7646
Estimated Value by BIST	78.4687	83.1378	94.5189	99.6835	82.7646	71.4787	74.047	74.1656	78.799	80.431	82.1379	82.4424
Estimated by All Variables (USD)	77.6569	83.3793	95.6408	97.7096	80.5115	68.3745	67.0474	69.6373	77.4552	80.584	81.7283	82.8971
Estimated by All Variables (EUR)	78.0773	83.1295	95.7844	97.232	80.0379	67.5859	64.871	68.5319	77.1923	80.6888	81.0203	82.4094
Estimated by All Variables (BASKET)	78.1555	83.3126	95.8898	96.6021	79.3446	66.9871	64.3862	68.9306	77.146	80.7292	81.5161	82.748

Table A7. CBRT CCI between July 2016 and June 2017, (Fixed Window Scheme, 22 days horizon, 22 days Xlag)

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17
Actual Value	67.0266	74.4414	74.2861	74.0366	68.9254	63.3802	66.9345	65.7287	67.8067	71.2869	72.8	70.0008
Estimated Value by USD	69.9234	67.5724	75.3768	74.3958	72.828	67.1212	63.8221	64.4378	67.5116	67.2287	70.9234	72.828
Estimated Value byEUR	69.9164	67.6265	74.6865	74.1804	73.8695	68.6623	63.803	66.2808	67.0742	67.7687	71.7509	72.6825
Estimated Value by BASKET	69.9723	67.7483	75.2639	74.2546	73.479	67.9519	63.752	65.7329	67.4779	67.5995	71.8011	73.0176
Estimated Value by GOLD	68.3608	67.2489	74.5821	74.7987	73.6998	68.6829	64.6896	66.6463	66.1351	68.313	71.229	72.2043
Estimated Value by OIL	69.5816	67.4239	74.4777	74.1507	73.973	69.2692	63.9947	67.3565	66.1682	68.1152	71.4216	72.8862
Estimated Value by BIST	69.0203	68.2925	74.6492	74.1285	73.8843	68.676	64.3348	68.1629	66.5331	68.3882	71.3288	73.0395
Estimated by All Variables (USD)	69.2069	67.64	74.7837	74.3735	73.5746	68.395	64.2126	66.593	66.6064	67.9995	71.2148	72.7333
Estimated by All Variables (EUR)	69.4356	67.4711	74.7987	74.3958	73.5673	68.3813	64.0843	66.1087	66.7397	67.8433	71.3145	72.6389
Estimated by All Variables (BASKET)	69.4565	67.5049	74.9409	74.4107	73.4717	68.2038	64.0651	65.97	66.8533	67.7958	71.3359	72.7261

Table A8. CBRT CCI between July 2016 and June 2017, (Fixed Window Scheme, 22 days horizon, 44 days Xlag)

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17
Actual Value	67.0266	74.4414	74.2861	74.0366	68.9254	63.3802	66.9345	65.7287	67.8067	71.2869	72.8	70.0008
Estimated Value by USD	69.8605	67.7416	75.4749	74.3958	73.0833	67.4374	63.6564	65.8514	67.3431	67.7551	71.7652	73.4717
Estimated Value byEUR	69.9374	67.6265	74.6119	74.1878	73.936	68.7791	63.8413	66.4799	67.0206	67.9043	71.8155	72.7115
Estimated Value by BASKET	69.9653	67.7687	75.136	74.2695	73.5525	68.0335	63.7392	65.9766	67.3835	67.7754	71.9305	73.0833
Estimated Value by GOLD	68.3198	67.2085	74.5075	74.8361	72.9665	68.7241	64.6702	66.7864	66.0096	68.3335	71.2931	72.1177
Estimated Value by OIL	70.3934	67.2018	74.0766	74.3586	73.936	69.5607	64.187	68.4771	66.7197	67.9791	71.1293	72.7188
Estimated Value by BIST	68.8548	68.0947	74.3735	74.1359	73.8991	68.7585	64.142	68.0675	66.8733	68.5594	71.2575	73.1637
Estimated by All Variables (USD)	69.3038	67.5792	74.6492	74.433	73.6261	68.5457	64.1549	67.2018	66.7464	68.1629	71.3787	72.8862
Estimated by All Variables (EUR)	69.5746	67.4577	74.7164	74.4554	73.6335	68.5525	64.0843	66.7998	66.7798	67.9927	71.5145	72.7697
Estimated by All Variables (BASKET)	69.5955	67.4981	74.8436	74.4703	73.5378	68.3745	64.0523	66.6597	66.88	67.9587	71.5502	72.8644

Table A9. CBRT CCI between July 2016 and June 2017, (Rolling Window Scheme, 22 days horizon, 22 days Xlag)

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17
Actual Value	67.0266	74.4414	74.2861	74.0366	68.9254	63.3802	66.9345	65.7287	67.8067	71.2869	72.8	70.0008
Estimated Value by USD	69.9234	67.5522	75.3995	74.4033	72.6461	66.8399	63.7583	63.9563	67.9587	67.1145	71.0298	72.9811
Estimated Value byEUR	69.9164	67.5995	74.7164	74.2027	73.8104	68.5388	63.7201	65.7264	67.37	67.0608	71.758	72.697
Estimated Value by BASKET	69.9723	67.7145	75.294	74.2695	73.3322	67.7145	64.0715	65.2483	67.1011	67.613	71.3217	72.53
Estimated Value by GOLD	68.3608	67.2354	74.6343	74.8361	73.7145	68.6829	64.8061	66.6263	66.1748	68.3882	71.2005	72.0457
Estimated Value by OIL	69.5816	67.5049	74.7463	73.9582	73.9656	70.0353	63.9052	67.3431	66.2013	68.1356	71.9952	72.2766
Estimated Value by BIST	69.0203	68.2788	74.709	74.1582	73.8769	68.6211	64.3927	68.4224	66.633	68.4155	71.3288	73.0833
Estimated by All Variables (USD)	69.2069	67.6468	74.881	74.3586	73.5231	68.4566	64.2255	66.5132	66.7664	67.9995	71.3573	72.6098
Estimated by All Variables (EUR)	69.4217	67.4644	74.8885	74.3735	73.5011	68.4361	64.0587	65.825	66.9469	67.6671	71.4644	72.5082
Estimated by All Variables (BASKET)	69.4426	67.4981	75.0234	74.3884	73.3836	68.2311	64.0715	65.2483	67.1011	67.613	71.3217	72.53

Table A10. CBRT CCI between July 2016 and June 2017, (Rolling Window Scheme, 22 days horizon, 44 days Xlag)

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17
Actual Value	67.0266	74.4414	74.2861	74.0366	68.9254	63.3802	66.9345	65.7287	67.8067	71.2869	72.8	70.0008
Estimated Value by USD	69.8605	67.7009	75.5126	74.4107	72.9081	67.1481	63.5229	65.2026	67.7822	67.5657	71.715	73.5452
Estimated Value byEUR	69.9374	67.5995	74.6417	74.2101	73.8843	68.6898	63.7201	65.9964	67.2758	67.728	71.8298	72.7261
Estimated Value by BASKET	69.9653	67.728	75.1586	74.2918	73.4276	67.884	63.5991	65.2809	67.7822	67.5589	71.9233	73.1418
Estimated Value by GOLD	68.3198	67.1951	74.5895	74.851	73.6998	68.7379	64.7867	66.7664	66.1021	68.4087	71.2646	71.9305
Estimated Value by OIL	70.3934	67.1816	74.0988	74.3512	73.7072	69.8605	64.0459	67.5454	66.3007	68.0063	71.9808	72.2621
Estimated Value by BIST	68.8548	68.0743	74.4256	74.1507	73.8991	68.7241	64.2062	68.3403	66.9737	68.5731	71.2575	73.215
Estimated by All Variables (USD)	69.3038	67.5522	74.694	74.4479	73.5378	68.5319	64.1356	66.8934	66.8198	68.1356	71.5359	72.7624
Estimated by All Variables (EUR)	69.5816	67.4307	74.7538	74.4628	73.5231	68.5182	64.0139	66.3073	66.8934	67.9247	71.6792	72.6389
Estimated by All Variables (BASKET)	69.5955	67.4644	74.881	74.4852	73.4129	68.313	63.9819	66.1153	67.0273	67.8772	71.7078	72.7479

Table A11. CBRT CCI between July 2016 and June 2017, (Recursive Scheme, 22 days horizon, 22 days Xlag)

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17
Actual Value	67.0266	74.4414	74.2861	74.0366	68.9254	63.3802	66.9345	65.7287	67.8067	71.2869	72.8	70.0008
Estimated Value by USD	63.5801	65.6344	67.5116	67.6806	71.8083	73.5378	63.5801	65.6344	67.5116	67.6806	71.8083	73.5378
Estimated Value byEUR	69.8605	67.7009	75.5277	74.4182	73.0979	67.3633	63.7074	66.155	67.1279	67.7687	71.8298	72.7624
Estimated Value by BASKET	69.9653	67.728	75.1736	74.2992	73.5525	68.0131	63.6373	65.6541	67.5522	67.6603	71.9593	73.1345
Estimated Value by GOLD	68.3198	67.1884	74.597	74.866	73.7514	68.7516	64.7025	66.7798	66.0492	68.3677	71.2931	72.0601
Estimated Value by OIL	70.3934	67.1749	74.1285	74.3586	73.9434	69.7906	64.1036	67.64	66.3604	67.9587	71.9233	72.3199
Estimated Value by BIST	68.8548	68.0743	74.433	74.1582	73.9286	68.7241	64.1805	68.2311	66.8533	68.5114	71.2717	73.215
Estimated by All Variables (USD)	69.3038	67.5522	74.709	74.4554	73.6556	68.5799	64.1356	67.0139	66.7197	68.1356	71.5574	72.8134
Estimated by All Variables (EUR)	69.5816	67.4239	74.7687	74.4703	73.6556	68.5799	64.0203	66.4866	66.7798	67.9451	71.7007	72.697
Estimated by All Variables (BASKET)	69.5955	67.4644	74.896	74.4926	73.5599	68.395	63.9947	66.3537	66.8934	67.9111	71.7365	72.7916

Table A12. CBRT CCI between July 2016 and June 2017, (Recursive Scheme, 22 days horizon, 44 days Xlag)

	Jul-16	Aug-16	Sep-16	Oct-16	Nov-16	Dec-16	Jan-17	Feb-17	Mar-17	Apr-17	May-17	Jun-17
Actual Value	67.0266	74.4414	74.2861	74.0366	68.9254	63.3802	66.9345	65.7287	67.8067	71.2869	72.8	70.0008
Estimated Value by USD	63.5801	65.6344	67.5116	67.6806	71.8083	73.5378	63.5801	65.6344	67.5116	67.6806	71.8083	73.5378
Estimated Value byEUR	69.8605	67.7009	75.5277	74.4182	73.0979	67.3633	63.7074	66.155	67.1279	67.7687	71.8298	72.7624
Estimated Value by BASKET	69.9653	67.728	75.1736	74.2992	73.5525	68.0131	63.6373	65.6541	67.5522	67.6603	71.9593	73.1345
Estimated Value by GOLD	68.3198	67.1884	74.597	74.866	73.7514	68.7516	64.7025	66.7798	66.0492	68.3677	71.2931	72.0601
Estimated Value by OIL	70.3934	67.1749	74.1285	74.3586	73.9434	69.7906	64.1036	67.64	66.3604	67.9587	71.9233	72.3199
Estimated Value by BIST	68.8548	68.0743	74.433	74.1582	73.9286	68.7241	64.1805	68.2311	66.8533	68.5114	71.2717	73.215
Estimated by All Variables (USD)	69.3038	67.5522	74.709	74.4554	73.6556	68.5799	64.1356	67.0139	66.7197	68.1356	71.5574	72.8134
Estimated by All Variables (EUR)	69.5816	67.4239	74.7687	74.4703	73.6556	68.5799	64.0203	66.4866	66.7798	67.9451	71.7007	72.697
Estimated by All Variables (BASKET)	69.5955	67.4644	74.896	74.4926	73.5599	68.395	63.9947	66.3537	66.8934	67.9111	71.7365	72.7916

APPENDIX B. Plot of Out of Sample Estimation with 2 months value of Xlag for Full Sample Period

Figure B1. Out of Sample Estimation Results for BHT CCI between July 2016-June 2017 (Fixed Window Scheme, 1 weeks horizon, 2 month Xlag)

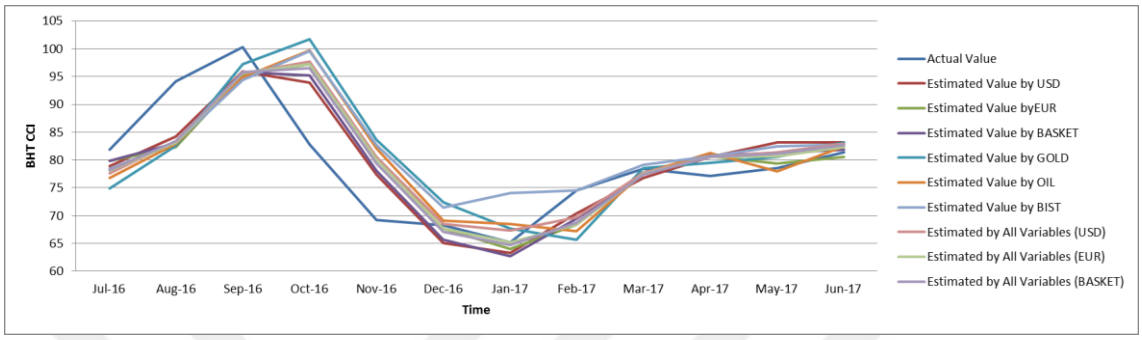


Figure B2. Out of Sample Estimation Results for BHT CCI between July 2016-June 2017 (Rolling Window Scheme, 1 weeks horizon, 2 month Xlag)

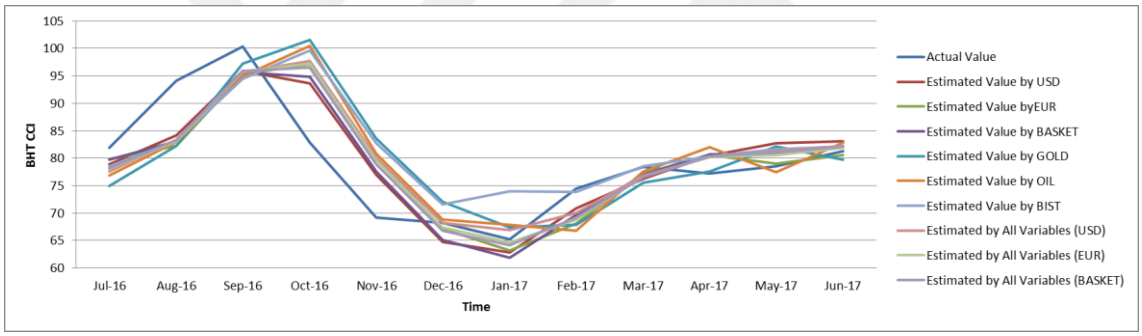


Figure B3. Out of Sample Estimation Results for BHT CCI between July 2016-June 2017 (Recursive Scheme, 1 weeks horizon, 2 month Xlag)

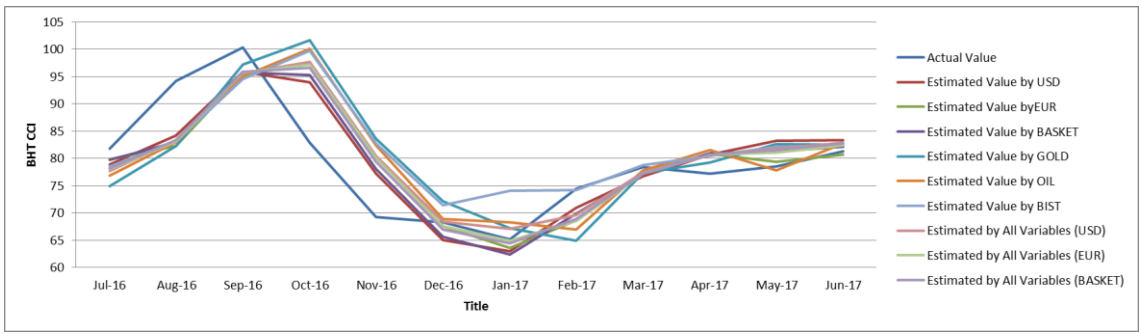


Figure B4. Out of Sample Estimation Results for CBRT CCI between July 2016-June 2017 (Fixed Window Scheme, 4 weeks horizon, 2 month Xlag)

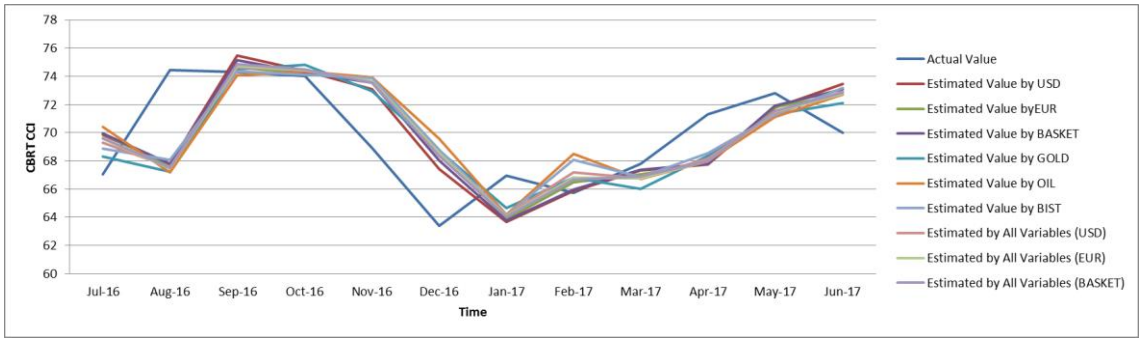


Figure B5. Out of Sample Estimation Results for CBRT CCI between July 2016-June 2017 (Rolling Window Scheme, 4 weeks horizon, 2 month Xlag)

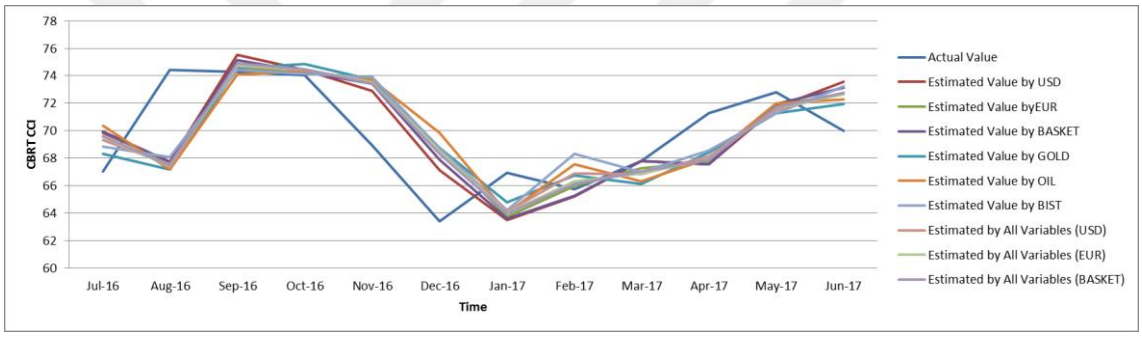
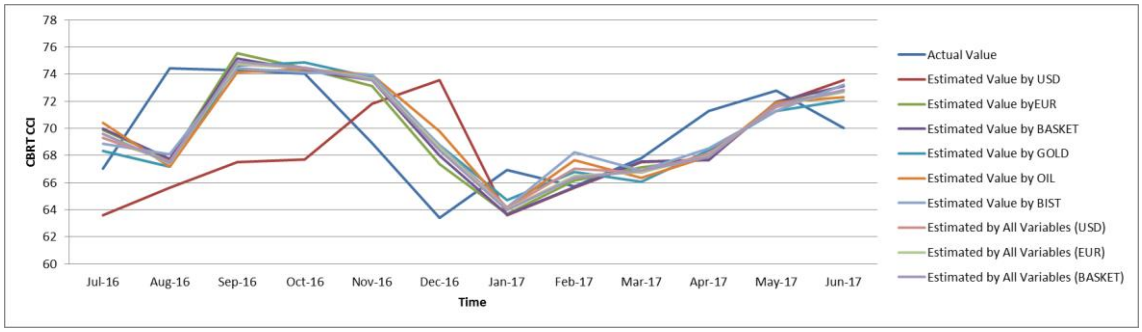


Figure B6. Out of Sample Estimation Results for CBRT CCI between July 2016-June 2017 (Recursive Scheme, 4 weeks horizon, 2 month Xlag)



APPENDIX C. Out of Sample Estimation with Subsample Period with Xlag=Ylag=1

Table C1. ADL-MIDAS Regression Results for by Fixed Window for Subsample

		BHT CCI with 1 month Xlag		CBRT CCI with 1 month Xlag	
HF Variables		**ADL-MIDAS R Square**	**ADL-MIDAS Slope**	**ADL-MIDAS R Square**	**ADL-MIDAS Slope**
Exchange Rate	**USD/TL**	0.67988	**-0.2182***** (-4.1381)	0.92195	**-0.0636***** (-3.5673)
	EUR/TL	0.70678	**-0.2169***** (-4.5518)	0.9351	**-0.0639***** (-5.5722)
	BASKET	0.70209	**-0.2402***** (-4.6533)	0.93141	**-0.0689***** (-3.1360)
Gold Price		0.64188	**-0.0316***** (-2.8276)	0.87907	**-0.0314***** (-2.1005)
Oil Price		0.69799	**-0.0908***** (-4.5410)	0.9089	**-0.0265***** (-3.7700)
Stock Exchange		0.71746	**0.1171***** -4.9934	0.9113	**0.0292***** -4.4114

Source: Author's Estimations.

Note: t-statistics are in parenthesis and significant values are shown in bold.

***, ** and * denotes significance at 1, 5 and 10% level.

Table C2. ADL-MIDAS Regression Results for by Rolling Window for Subsample

HF Variables		BHT CCI with 1 month Xlag		CBRT CCI with 1 month Xlag	
		ADL-MIDAS R Square	ADL-MIDAS Slope	ADL-MIDAS R Square	ADL-MIDAS Slope
Exchange Rate	USD/TL	0.9123	**-0.2993*** **	0.94273	**-0.0705*** **
			(-7.5751)		(-4.2553)
	EUR/TL	0.90175	**-0.2986*** **	0.95062	**-0.0828*** **
			(-6.6136)		(-4.7433)
	BASKET	0.91435	**-0.3325*** **	0.94916	**-0.0833*** **
			(-7.7705)		(-4.7499)
Gold Price		0.87441	**-0.0694*** **	0.93104	**-0.0640*** **
			(-3.6322)		(-3.9676)
Oil Price		0.8421	0.0067	0.91817	**-0.0094***
			-0.655		(-1.8266)
Stock Exchange		0.90799	**0.1400*** **	0.9419	**0.0448*** **
			-6.9166		-4.9108

Source: Author's Estimations.

Note: t-statistics are in parenthesis and significant values are shown in bold.

*** , ** and * denotes significance at 1, 5 and 10% level.

Table C3. ADL-MIDAS Regression Results for by Recursive for Subsample

HF Variables		BHT CCI with 1 month Xlag		CBRT CCI with 1 month Xlag	
		ADL-MIDAS R Square	ADL-MIDAS Slope	ADL-MIDAS R Square	ADL-MIDAS Slope
Exchange Rate	USD/TL	0.85816	**-0.3069*** **	0.96173	**-0.0639*** **
			(-7.3271)		(-4.6621)
	EUR/TL	0.84751	**-0.2919** **	0.96778	**-0.0791*** **
			(-6.6767)		(-5.6386)
	BASKET	0.85845	**-0.3301*** **	0.96623	**-0.0775*** **
			(-7.4571)		(-5.4123)
Gold Price		0.81931	**-0.0838*** **	0.95271	**-0.0516*** **
			(-3.7947)		(-3.6951)
Oil Price		0.77237	0.0023	0.94897	**-0.0099** **
			(NaN)		(-2.1413)
Stock Exchange		0.86243	**0.1461*** **	0.96103	**0.0399*** **
			-7.7131		-5.2619

Source: Author's Estimations.

Note: t-statistics are in parenthesis and significant values are shown in bold.

*** , ** and * denotes significance at 1, 5 and 10% level.

APPENDIX D. Plot of Out of Sample Estimation Results for CCI with Xlag=1, Crisis Period

Figure D1. Out of Sample Estimation Results for BHT CCI (Rolling Window Scheme)

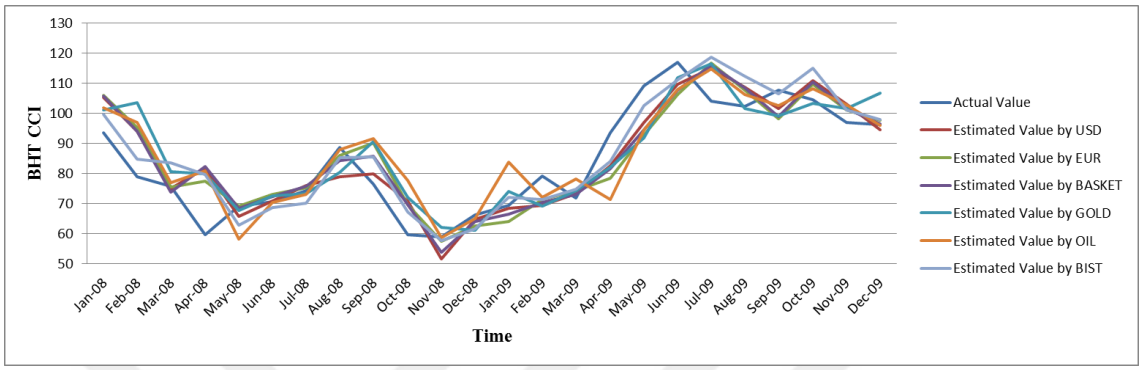


Figure D2. Out of Sample Estimation Results for BHT CCI (Recursive Scheme)

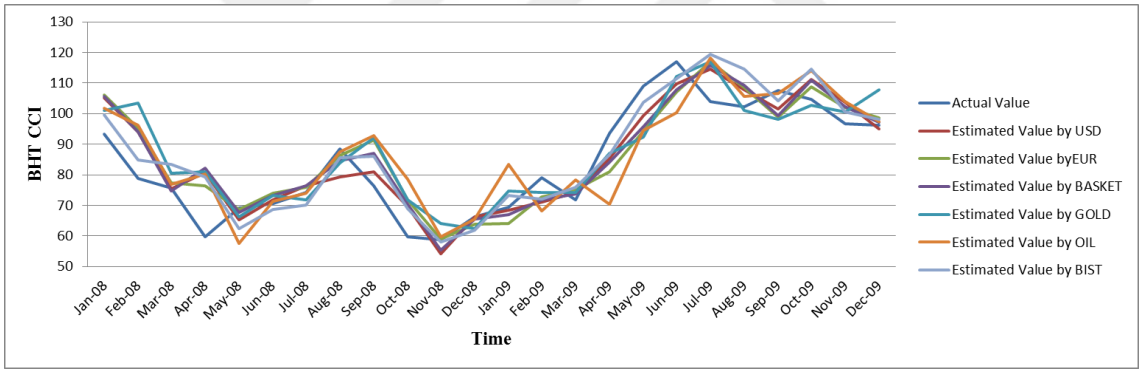


Figure D3. Out of Sample Estimation Results for CBRT CCI (Rolling Window Scheme)

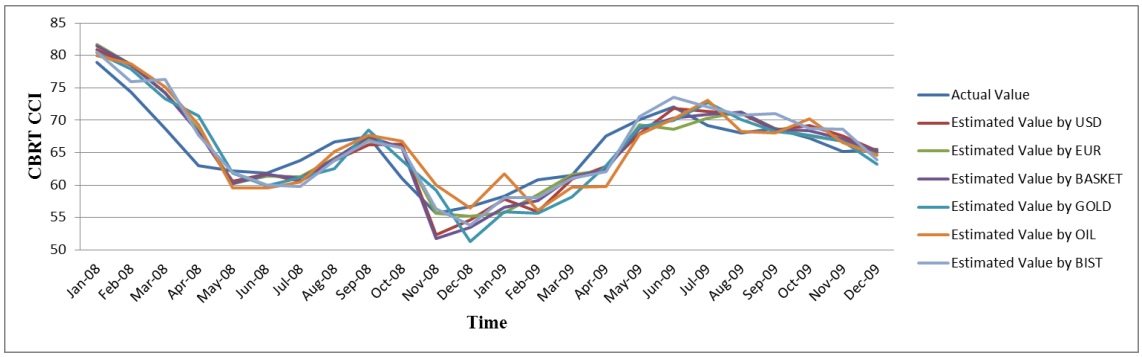
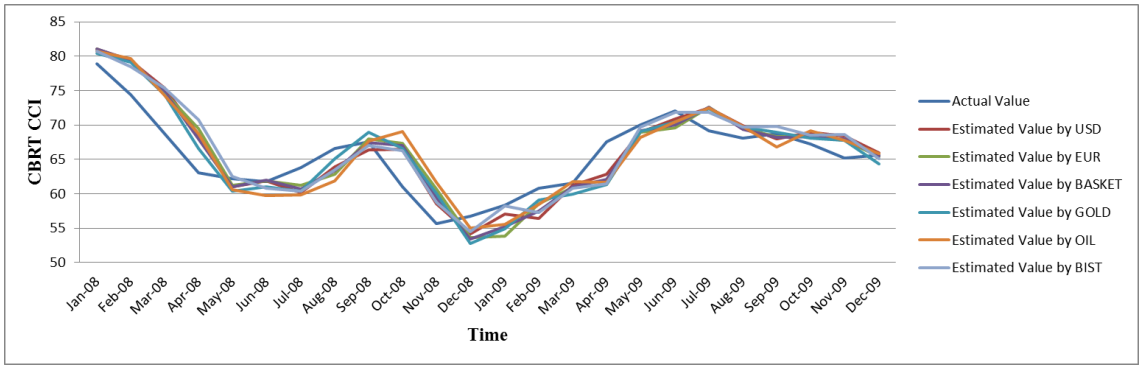


Figure D4. Out of Sample Estimation Results for CBRT CCI (Recursive Scheme)



APPENDIX E. Actual and Estimated Values of Consumer Confidence Indices (Out of Sample Estimation with Subsample Period)

Table E1. BHT CCI between January 2008 and December 2009, (Fixed Window Scheme, 11 days horizon, 22 days Xlag)

	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08	Jul-08	Aug-08	Sep-08	Oct-08	Nov-08	Dec-08	Jan-09	Feb-09	Mar-09	Apr-09	May-09	Jun-09	Jul-09	Aug-09	Sep-09	Oct-09	Nov-09	Dec-09
Actual Value	93.4073934	78.7846	75.7263	59.7017	69.0361	70.629	74.1971	88.5535	76.3125	59.6699	58.7536	66.1528	69.2712	78.9758	71.7569	93.5234	109.021	116.928	103.95	102.203	107.654	104.539	96.7725	96.0976
Estimated Value by USD	105.235427	91.8907	81.9984	78.4216	69.29	77.015	79.2573	83.4377	87.6192	73.1784	61.6455	67.8026	74.8585	73.582	78.9409	89.6488	98.6226	111.085	116.594	109.881	103.286	110.3	105.763	98.2583
Estimated Value byEUR	106.017057	95.4688	79.1385	79.2415	72.024	78.736	79.6387	87.9176	95.593	76.6539	68.2447	69.5607	70.1054	78.1164	79.9659	86.4011	98.7706	108.755	117.003	110.079	103.11	108.788	104.043	100.223
Estimated Value by BASKET	105.678345	94.151	79.099	78.4295	71.3074	77.9837	79.3208	86.8168	92.4345	73.1272	65.9304	68.7585	72.2983	76.1268	77.6413	88.323	98.6916	109.826	116.723	110.974	103.049	109.738	104.47	99.3849
Estimated Value by GOLD	100.917162	102.987	87.2869	78.0227	70.7887	74.3215	77.789	84.0406	87.5229	85.9272	70.4146	67.2758	74.9559	76.9303	85.234	87.7946	98.4452	111.642	116.164	103.835	99.3352	109.497	101.911	102.956
Estimated Value by OIL	101.798971	96.409	78.8069	82.4671	62.9034	74.2992	76.5543	90.6313	93.8408	81.6793	72.2188	71.8801	78.8384	72.559	85.5243	76.5007	96.5152	103.296	122.352	94.6892	108.061	110.753	99.5938	101.382
Estimated Value by BIST	99.5042145	85.0977	83.9986	80.584	66.8132	71.6004	73.2589	87.1996	87.2171	71.8227	62.4459	65.7001	75.9671	75.2864	79.6068	87.252	103.41	111.464	119.474	114.847	103.441	113.092	102.248	99.554

Table E2. BHT CCI between January 2008 and December 2009, (Rolling Window Scheme, 11 days horizon, 22 days Xlag)

	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08	Jul-08	Aug-08	Sep-08	Oct-08	Nov-08	Dec-08	Jan-09	Feb-09	Mar-09	Apr-09	May-09	Jun-09	Jul-09	Aug-09	Sep-09	Oct-09	Nov-09	Dec-09
Actual Value	93.4073934	78.7846	75.7263	59.7017	69.0361	70.629	74.1971	88.5535	76.3125	59.6699	58.7536	66.1528	69.2712	78.9758	71.7569	93.5234	109.021	116.928	103.95	102.203	107.654	104.539	96.7725	96.0976
Estimated Value by USD	105.235427	94.0475	74.8585	81.6956	65.7855	70.7534	75.8836	78.9173	79.9339	70.8171	51.5937	64.6443	68.3472	69.2345	73.2296	82.624	96.7955	109.673	114.801	108.484	101.443	110.797	102.873	94.5284
Estimated Value by EUR	106.017057	95.2019	75.3768	77.4165	69.2207	72.9957	75.1811	85.9444	90.1793	69.6164	57.3	62.5083	63.9179	71.2148	74.1582	78.4138	92.7586	106.219	116.746	107.544	98.0914	109.519	101.109	97.6315
Estimated Value by BASKET	105.678345	93.8784	73.6556	82.1955	68.3745	72.2477	75.6714	84.2004	85.6526	69.6303	53.6564	63.9883	66.46	70.2387	73.0833	81.5161	94.415	107.619	115.908	108.408	98.8101	110.41	101.555	96.2838
Estimated Value by GOLD	100.917162	103.379	80.5034	79.9339	67.728	72.6316	73.3249	80.3667	90.4864	71.9377	62.0413	61.1421	73.9434	69.0824	74.2027	81.982	91.6613	111.642	116.501	101.474	99.1665	103.152	101.484	106.74
Estimated Value by OIL	101.798971	96.8439	76.815	80.8423	58.0962	70.4005	72.9811	87.7946	91.4416	77.6569	58.7094	64.9813	83.7051	72.0889	78.0227	71.3145	94.4906	107.943	114.744	106.07	102.391	108.159	102.709	95.9858
Estimated Value by BIST	99.5042145	84.6733	83.4794	79.5273	62.7903	68.4908	70.1264	85.0807	85.4559	67.0541	57.7198	61.5777	72.0673	71.2575	74.7987	83.9314	102.371	111.03	118.57	112.325	106.421	114.996	101.069	97.778

Table E3. BHT CCI between January 2008 and December 2009, (Recursive Scheme, 11 days horizon, 22 days Xlag)

	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08	Jul-08	Aug-08	Sep-08	Oct-08	Nov-08	Dec-08	Jan-09	Feb-09	Mar-09	Apr-09	May-09	Jun-09	Jul-09	Aug-09	Sep-09	Oct-09	Nov-09	Dec-09
Actual Value	93.4073934	78.7846	75.7263	59.7017	69.0361	70.629	74.1971	88.5535	76.3125	59.6699	58.7536	66.1528	69.2712	78.9758	71.7569	93.5234	109.021	116.928	103.95	102.203	107.654	104.539	96.7725	96.0976
Estimated Value by USD	105.235427	93.9629	75.3015	80.7776	65.3593	71.6863	76.325	79.3922	81.0365	69.7	54.2498	66.2344	68.4771	71.044	74.1433	85.3534	99.4246	109.706	114.583	107.889	101.433	111.152	103.586	95.0877
Estimated Value byEUR	106.017057	95.1543	77.4707	76.2716	68.5868	73.8769	75.8305	86.194	91.4598	71.8227	58.9153	63.7392	64.1356	72.7624	75.2488	80.9474	94.3018	107.125	116.874	108.429	98.8496	108.777	102.013	98.593
Estimated Value by BASKET	105.678345	94.0099	74.5821	82.253	67.6603	73.3175	76.2792	84.5464	87.0776	70.3723	55.3624	65.4182	66.9871	71.7939	73.7514	84.1163	95.6791	107.781	115.862	109.213	99.3948	111.03	102.279	97.1251
Estimated Value by GOLD	100.917162	103.368	80.5276	81.0527	66.3405	73.2223	71.758	83.8391	92.0195	71.8298	64.1485	62.3647	74.6791	74.1507	74.2101	86.9036	92.2406	112.168	116.886	101.119	98.0718	102.771	100.534	107.716
Estimated Value by OIL	101.798971	96.226	76.8227	80.3667	57.6275	71.4073	74.0766	87.5929	92.805	78.6573	59.716	65.5491	83.4711	68.1016	78.265	70.316	94.5284	100.223	118.203	105.562	106.506	114.194	103.855	97.3293
Estimated Value by BIST	99.5042145	84.7919	83.371	79.4001	62.3149	68.628	70.1545	85.6184	86.1336	68.8755	58.0555	61.8864	73.3542	72.0745	75.8153	86.6087	103.627	111.397	119.498	114.572	104.23	114.469	100.655	98.1798

Table E4. CBRT CCI between January 2008 and December 2009, (Fixed Window Scheme, 16 days horizon, 22 days Xlag)

	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08	Jul-08	Aug-08	Sep-08	Oct-08	Nov-08	Dec-08	Jan-09	Feb-09	Mar-09	Apr-09	May-09	Jun-09	Jul-09	Aug-09	Sep-09	Oct-09	Nov-09	Dec-09
Actual Value	78.8926604	74.3768	68.739	63.0132	62.139	61.7916	63.7864	66.6269	67.498	61.017	55.6574	56.6763	58.3345	60.7838	61.5508	67.5313	70.0534	72.0461	69.1456	68.0791	68.7013	67.2368	65.1552	65.5678
Estimated Value by USD	80.8988816	78.5708	74.6567	69.117	64.1036	63.8349	63.4721	65.4051	67.9791	68.2174	54.6145	56.9458	59.5074	58.7388	61.9979	64.6314	68.3813	72.0961	71.7652	71.7509	69.3315	69.9304	68.2993	66.3405
Estimated Value by EUR	81.7119289	78.7202	74.7164	70.0634	64.6831	63.4784	64.4636	66.7063	69.1515	67.222	56.7923	57.7025	58.7388	60.6609	63.1239	64.4829	69.5885	70.0704	71.672	72.0745	69.8954	69.2138	67.9927	66.3604
Estimated Value by BASKET	81.4997539	78.6887	74.7164	69.3177	64.2383	63.7201	63.9691	65.9832	68.9168	67.5927	55.5176	57.6909	58.9624	59.9074	62.7463	64.528	69.3038	70.9588	71.5717	71.9736	69.6512	69.387	68.1016	66.3405
Estimated Value by GOLD	80.4792993	77.9369	73.8178	71.0156	65.4051	62.8217	63.631	66.0426	68.3813	66.0096	62.5459	55.4954	58.2474	58.7446	60.5095	64.0651	67.9791	70.2247	73.2882	70.5838	69.1584	69.5607	68.0879	65.0073
Estimated Value by OIL	79.9978693	78.7596	74.9484	70.895	63.7392	62.715	63.2313	67.2489	69.3454	67.7212	63.4023	57.5354	62.7275	59.1632	62.9915	62.1344	68.2379	70.7392	72.3995	69.3385	69.6791	71.9377	67.1481	67.5589
Estimated Value by BIST	80.5920492	76.1039	76.1572	69.2276	65.2287	62.7275	62.6147	66.6397	67.4981	67.8568	58.7329	55.5231	59.3232	59.1928	61.2461	64.9229	69.7279	72.5155	73.1272	71.3288	71.0654	70.6049	69.1584	65.4443

Table E5. CBRT CCI between January 2008 and December 2009, (Rolling Window Scheme, 16 days horizon, 22 days Xlag)

	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08	Jul-08	Aug-08	Sep-08	Oct-08	Nov-08	Dec-08	Jan-09	Feb-09	Mar-09	Apr-09	May-09	Jun-09	Jul-09	Aug-09	Sep-09	Oct-09	Nov-09	Dec-09
Actual Value	78.8926604	74.3768	68.739	63.0132	62.139	61.7916	63.7864	66.6269	67.498	61.017	55.6574	56.6763	58.3345	60.7838	61.5508	67.5313	70.0534	72.0461	69.1456	68.0791	68.7013	67.2368	65.1552	65.5678
Estimated Value by USD	80.8988816	78.4295	74.2695	68.0947	60.5579	61.6763	60.5337	63.7711	66.1881	66.2808	52.3107	54.6364	57.8816	55.8685	60.9223	62.8342	67.9247	71.8227	71.4144	71.0369	68.484	69.1723	67.5724	65.3201
Estimated Value by EUR	81.7119289	78.6337	74.2695	68.5594	60.2619	61.424	61.3196	64.1485	67.1481	65.7264	55.6343	55.1469	55.7122	58.5453	61.5839	62.3336	69.3107	68.5525	70.309	71.2789	68.7585	67.5859	66.7864	64.871
Estimated Value by BASKET	81.4997539	78.5472	74.2695	68.1424	60.2197	61.6393	61.0932	63.9947	67.5184	65.7527	51.7643	53.5063	56.5542	57.5814	61.2828	62.4708	68.7104	70.3301	70.9234	71.2931	68.6142	68.3745	67.1615	65.144
Estimated Value by GOLD	80.4792993	77.8668	73.2589	70.6402	61.874	59.9434	61.1237	62.5333	68.5319	63.7966	59.258	51.2441	55.8238	55.6121	58.1427	63.0293	68.9858	70.0143	72.7115	70.1335	68.2993	67.6942	66.7798	63.2124
Estimated Value by OIL	79.9978693	78.673	75.1135	69.3038	59.5431	59.5074	60.4067	65.131	67.6739	66.8065	59.9973	56.4751	61.7195	56.1092	59.6563	59.7698	67.7754	70.2598	73.0541	68.2311	68.0199	70.2668	66.5797	64.6443
Estimated Value by BIST	80.5920492	75.9899	76.2563	67.6603	61.9359	60.0213	59.7877	63.7711	66.7597	65.6869	56.289	53.8176	58.102	58.0671	61.0443	62.0785	70.5838	73.5378	72.0312	70.7534	71.0227	68.7447	68.5662	63.8924

Table E6. CBRT CCI between January 2008 and December 2009, (Recursive Scheme, 16 days horizon, 22 days Xlag)

	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08	Jul-08	Aug-08	Sep-08	Oct-08	Nov-08	Dec-08	Jan-09	Feb-09	Mar-09	Apr-09	May-09	Jun-09	Jul-09	Aug-09	Sep-09	Oct-09	Nov-09	Dec-09
Actual Value	78.8926604	74.3768	68.739	63.0132	62.139	61.7916	63.7864	66.6269	67.498	61.017	55.6574	56.6763	58.3345	60.7838	61.5508	67.5313	70.0534	72.0461	69.1456	68.0791	68.7013	67.2368	65.1552	65.5678
Estimated Value by USD	80.8988816	78.3903	74.1582	68.1697	60.9406	61.5285	61.0199	63.7711	66.1285	66.6997	53.3994	53.6242	57.4894	56.7128	60.9406	62.8468	67.8772	71.6147	71.3359	71.0085	68.5319	69.117	67.4779	65.3071
Estimated Value by EUR	81.7119289	78.6101	74.1878	68.7447	60.9102	61.467	61.7504	64.2126	68.1356	65.3462	53.3727	55.512	55.9132	58.6097	61.6085	62.5959	69.2761	68.6005	70.2809	71.229	68.8066	67.6062	66.7864	64.8385
Estimated Value by BASKET	81.4997539	78.5158	74.173	68.2584	60.7702	61.4916	61.4117	63.9947	67.4374	65.8909	51.9406	52.3682	56.6108	57.8643	61.3442	62.6899	68.6623	70.1826	70.7675	71.2646	68.6829	68.2993	67.0877	65.0854
Estimated Value by GOLD	80.4792993	77.8435	73.1857	70.6685	62.1034	61.1237	61.7072	62.6022	68.4361	65.0854	59.4479	52.4363	55.9971	56.2384	58.6155	62.8028	68.841	70.1124	72.5663	69.9653	68.3267	67.9247	66.9469	63.6437
Estimated Value by OIL	79.9978693	78.6966	74.8585	69.4148	60.0513	59.9493	60.7156	65.2548	67.9859	66.8132	60.6913	55.5954	60.9406	56.3003	60.0694	59.9134	67.6333	70.3582	72.7333	68.3813	68.5251	70.612	66.8867	65.1049
Estimated Value by BIST	80.5920492	75.9063	76.142	67.7754	62.7024	60.2077	60.3162	64.6572	66.4068	65.9106	56.4356	53.2714	57.7198	57.6506	60.5579	62.8217	69.9863	72.8862	72.2693	70.4991	70.7675	69.0203	68.354	63.854

APPENDIX F. Plot of GARCH-MIDAS model for Exchange Rate RV

Figure F1. GARCH-MIDAS with Fixed Span RV (Dollar, same period with BHT CCI)

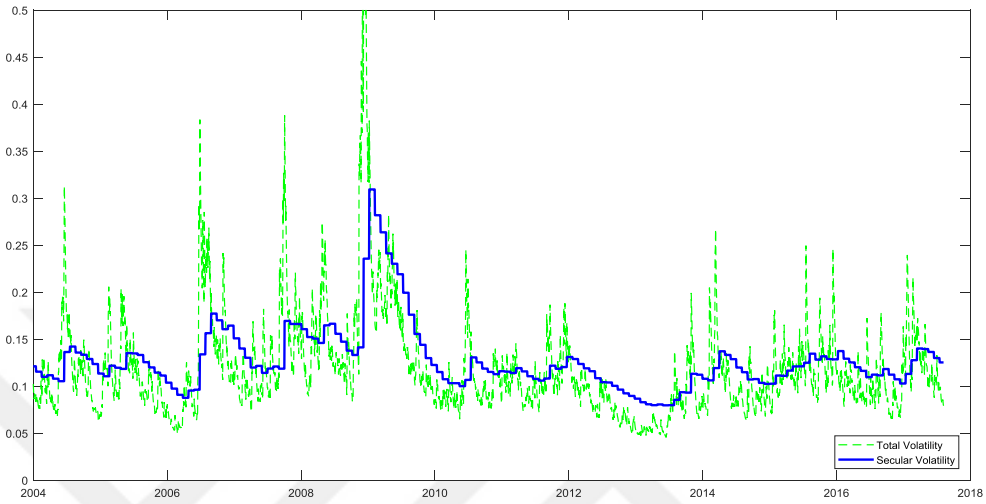


Figure F2. GARCH-MIDAS with Rolling Window RV (Dollar, same period with BHT CCI)

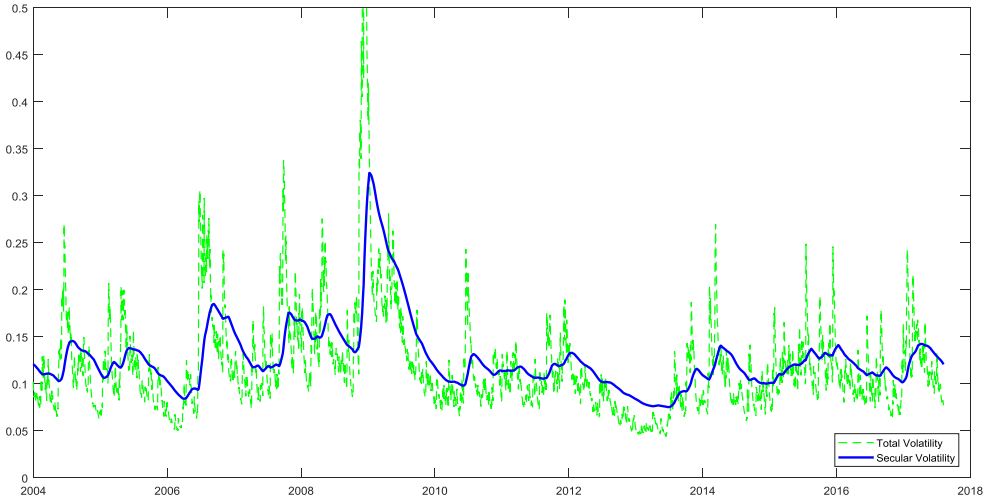


Figure F3. GARCH-MIDAS with Fixed Span RV (Euro, same period with BHT CCI)

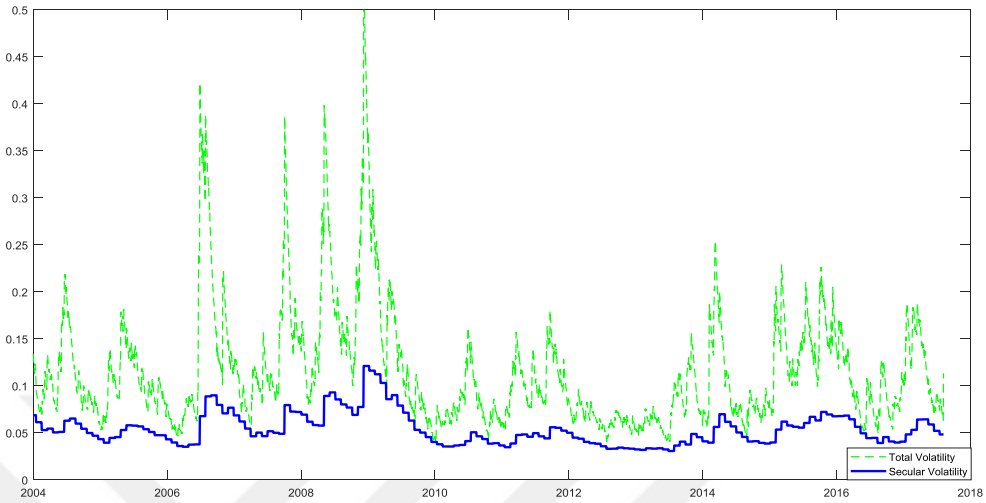


Figure F4. GARCH-MIDAS with Rolling Window RV (Euro, same period with BHT CCI)

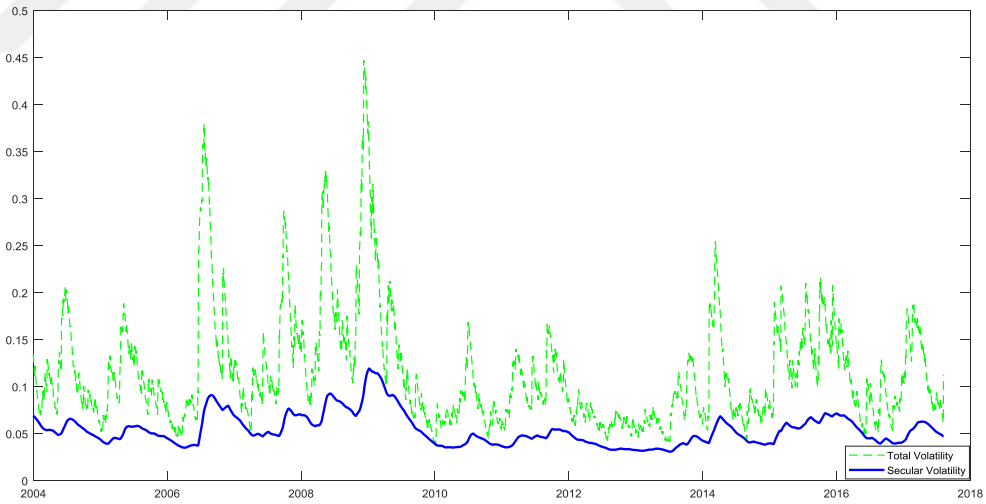


Figure F5. GARCH-MIDAS with Fixed Span RV (Basket, same period with CBRT CCI)

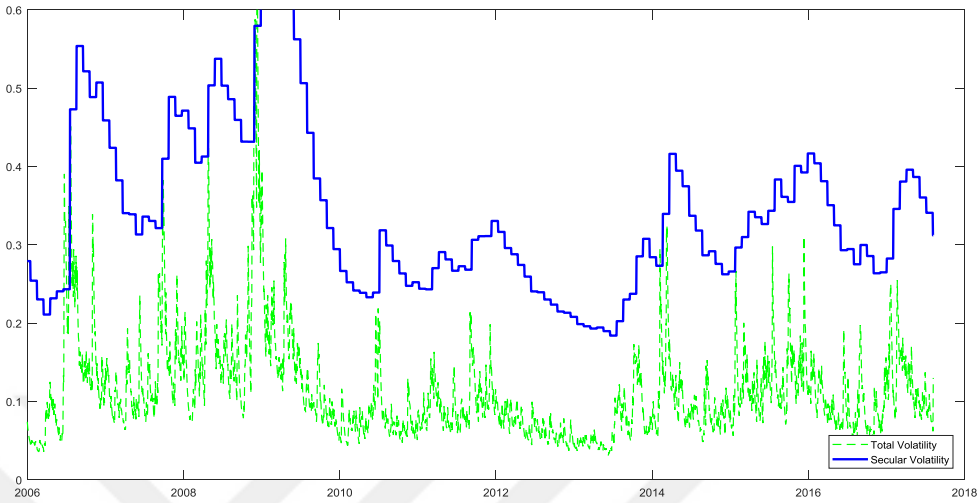


Figure F6. GARCH-MIDAS with Rolling Window RV (Basket, same period with CBRT CCI)

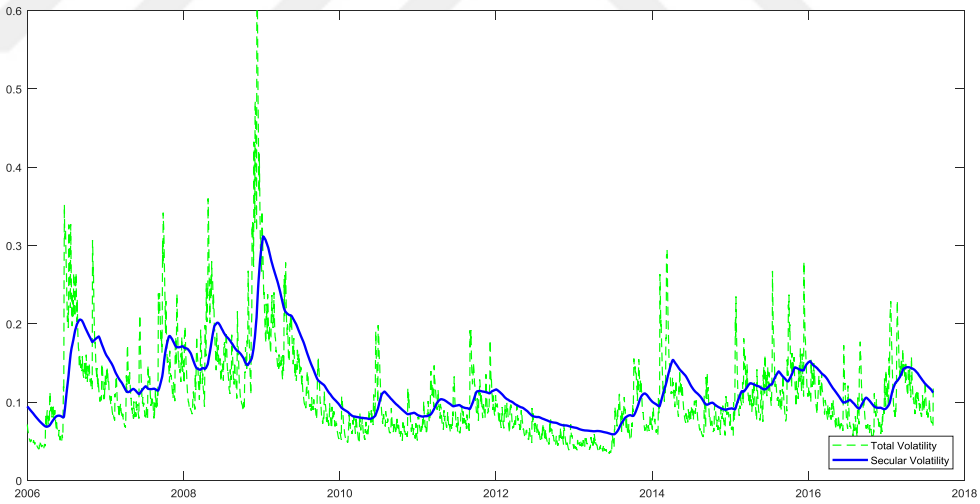


Figure F7. GARCH-MIDAS with Fixed Span RV (Euro, same period with CBRT CCI)

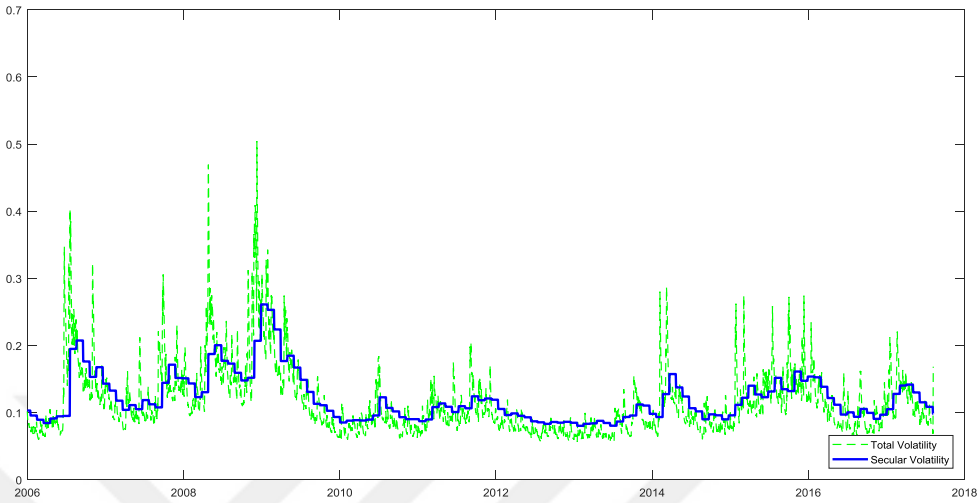
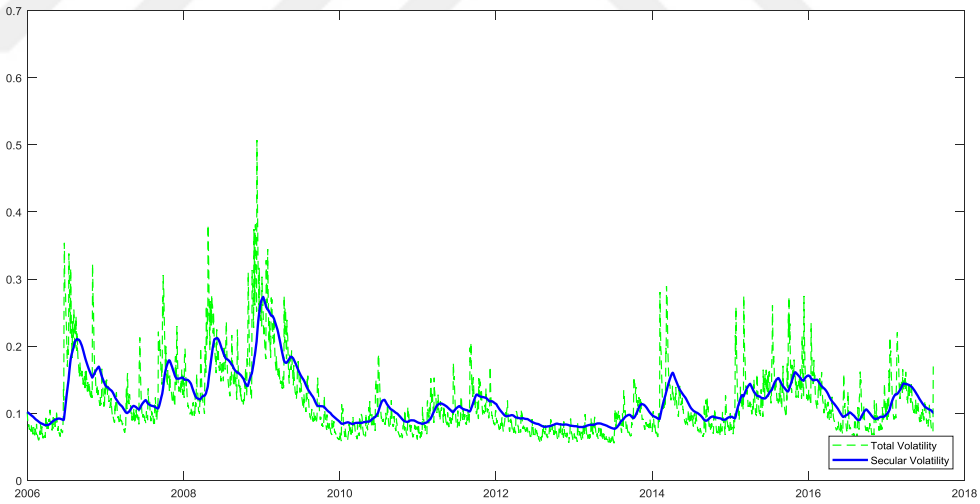


Figure F8. GARCH-MIDAS with Rolling Window RV (Euro, same period with CBRT CCI)



APPENDIX G. Plot of Total and Secular Volatilities with CCI

Figure G1. GARCH-MIDAS with BHT CCI Conditional Volatility and its Long Run component of Exchange Rate (Dollar) Returns

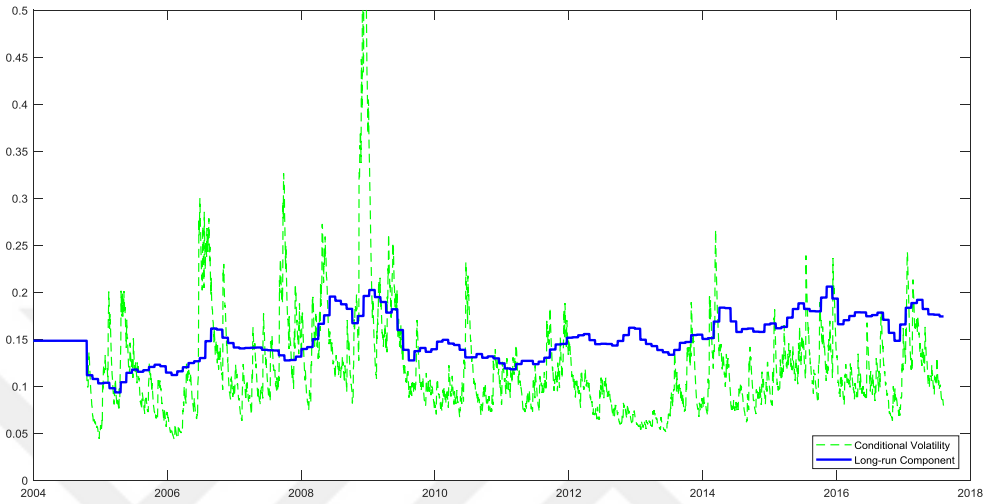


Figure G2. GARCH-MIDAS with BHT CCI Conditional Volatility and its Long Run component of Exchange Rate (Euro) Returns

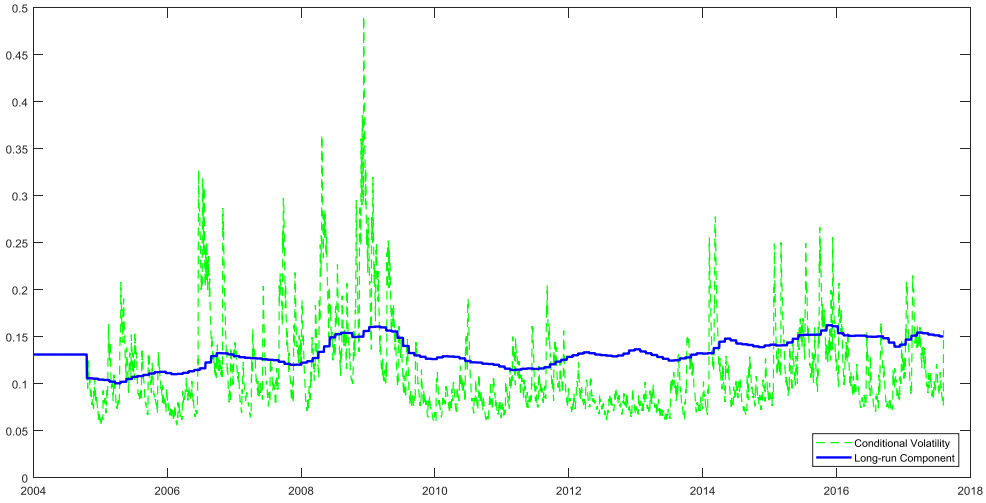


Figure G3. GARCH-MIDAS with CBRT CCI Conditional Volatility and its Long Run component of Exchange Rate (Basket) Returns

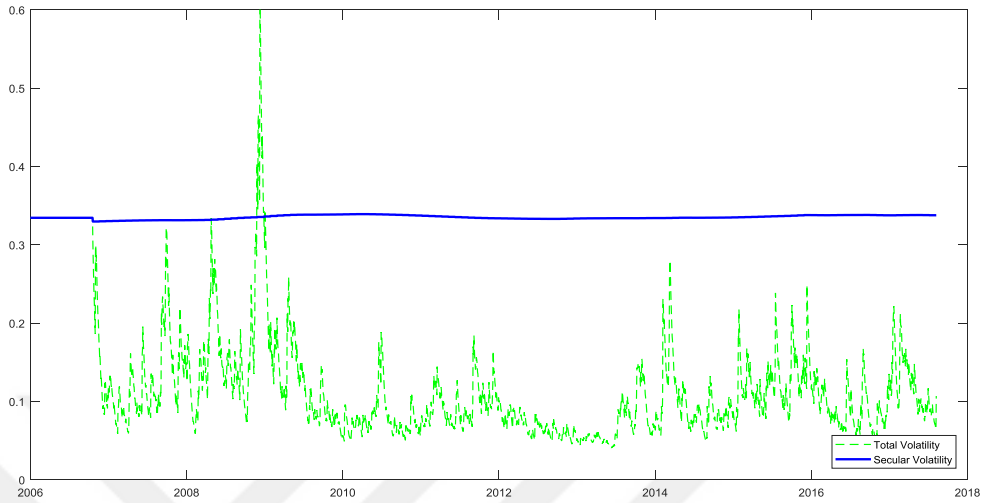
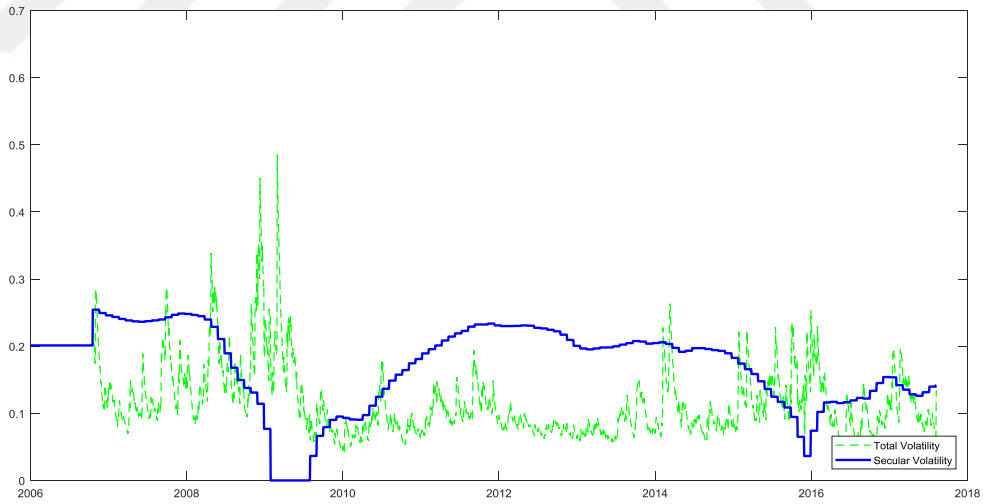


Figure G4. GARCH-MIDAS with CBRT CCI Conditional Volatility and its Long Run component of Exchange Rate (Euro) Returns



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