T.C.
MARMARA ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
İKTİSAT ANA BİLİM DALI
İKTİSAT (İNG) BİLİM DALI

ESSAYS ON DIVISIA MONETARY AGGREGATES AND MONETARY POLICY

Doktora Tezi

UMURCAN POLAT

İstanbul, 2020

T.C.
MARMARA ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
İKTİSAT ANA BİLİM DALI
İKTİSAT (İNG) BİLİM DALI

ESSAYS ON DIVISIA MONETARY AGGREGATES AND MONETARY POLICY

Doktora Tezi

UMURCAN POLAT

Danışmanı: Dr. Öğr. Üyesi PINAR DENİZ

İstanbul, 2020

GENEL BİLGİLER

İsim ve Soyadı :Umurcan Polat
Anabilim Dalı :İktisat
Programı :İktisat (İngilizce)
Tez Danışmanı :Dr. Öğr. Üyesi Pınar Deniz
Tez Türü ve Tarihi :Doktora, 28 Ağustos 2020
Anahtar Kelimeler :Para Politikası, Divisia Endeksi, Divisia Parasal Toplamlar, Basit Toplamlı Parasal Toplamlar, Parasal Aktarım Mekanizması, FAVAR Modeli, Döviz Kuru Oynaklığı, GARCH-MİDAS Modeli

ÖZET

DİVİSİA PARASAL TOPLAMLAR VE PARA POLİTİKASI ÜZERİNE YAZILAR

Bu tez, Türkiye para politikasına ilişkin üç farklı bölümden oluşmaktadır. Birinci bölümde, Türkiye için Divisia endekse dayalı parasal toplamlar 2006:1–2018:4 dönemi için oluşturulmuş ve enflasyon hedeflemesi rejimi altında basit toplamlı parasal toplamlar ile tahmin performanslarına göre karşılaştırılmıştır. Temel Divisia endeksin yanında, katılım bankalarının eklendiği ve kur beklentilerinin dahil edildiği endeksler oluşturularak Türkiye ekonomisinin farklı yönlerinin yansıtılması hedeflenmiştir. Uygulanan tanı testleri, çoklu wavelet analizi ve örneklem dışı tahminler sonucunda temel Divisia endeksin, basit toplamlı endeks karşısında enflasyon ve üretim değişimlerini tahmin etmede benzer sonuçlar oluşturduğu görülmüştür. Bunun yanında katılım bankalarının eklendiği Divisia endeks üzerinden varlık sayısının arttırılması ile Divisia parasal toplamların daha güçlü tahminler oluşturduğu gözlemlenmiştir. İkinci bölümde ise Türkiye para politikası için etkinlik analizi gerçekleştirilmiştir. Bu çerçevede politika şoklarının farklı piyasalara ve sektörlere geçiş etkisinin kapsamlı bir analizi için *faktör donanımlı VAR (FAVAR) modelinden yararlanılmıştır. Analizde 2006:1-2018:4 dönemi için 113 seriden faydalanmıştır. Temel tartışma, politika faizinin çoklu araç politikası çerçevesinde ve diğer politika araçları karşısındaki geçiş etkinliğinin incelenmesini içermektedir. Bu kapsamda periyodik olarak ilan edilen politika faizi değişimlerinin piyasaya geçiş etkisinin çoklu araç politikası altında görece olarak zayıf gerçekleştiği görülmektedir. Üçüncü bölümde, GARCH-MIDAS modelini temel alarak Türkiye ekonomisi için dalgalı kur rejimi altında döviz kuru oynaklığının uzun dönemli dinamikleri ve bu dinamiklerin ne ölçüde yurtiçi makroekonomik kaynaklar tarafından belirlendiği incelenmektedir. Çalışmada, Türkiye kur piyasasının, model tarafından iyi bir şekilde temsil edildiği görülmekte, döviz kuru oynaklığının süreklilik gösterdiği ve makroekonomik değişkenlerin kur oynaklığının uzun dönemli bileşenini etkileme gücüne sahip olduğu izlenmektedir. Ayrıca, politika yapıcıların kontrolünde olan politika araçlarındaki değişimlerin uzun dönemli kur oynaklığını azaltmadaki etkinliğine dair gözlemler oluşmaktadır.*

GENERAL KNOWLEDGE

Name and Surname :Umurcan Polat

Field :Economics

Program :Economics (English)

Supervisor :Asst. Prof. Pınar Deniz

Degree Awarded and Date :PhD, August 28, 2020

Keywords :Monetary Policy, Divisia Index, Divisia Monetary Aggregates, Simple-sum Monetary Aggregates, Monetary Transmission Mechanism, FAVAR Model, Exchange Rate Volatility, GARCH-MIDAS Model

ABSTRACT

ESSAYS ON DIVISIA MONETARY AGGREGATES AND MONETARY POLICY

This dissertation includes three chapters on the monetary policy stance of Turkey. In Chapter 1, Divisia index based monetary aggregates are constructed for Turkey between 2006:1-2018:4 and compared to simple-sum aggregates for their predictive abilities under the inflation-targeting regime. Beside to the benchmark Divisia index, the index with participation banks and expectations-augmented index are constructed to feature different aspects of Turkish economy. Applying diagnostic tests, multiple wavelet and out-of-sample forecasting analyses it is revealed that the Divisia index generates similar results with its simple-sum counterpart in predicting the variations in inflation and production. Still, it is observed that increasing the number of assets by introducing the participation banks to calculations leads Divisia index to give more robust predictions. In Chapter 2, an efficiency analysis is employed for Turkish monetary policy. In this regard, it is used a factor-augmented VAR (FAVAR) model for *an exhaustive analysis of the transmission of policy shocks through different markets and sectors. It is used 113 series in estimation for the period 2006:1-2018:4. The main discussion is upheld on the transmission of policy rate shocks relative to other instruments and under multiple policy environment. It is found, accordingly, that the transmission of the periodically announced policy rate changes is relatively weak under the multiple policy framework. In Chapter 3, it is examined the dynamics of long-term exchange rate volatility under the floating regime for Turkey and the extent to which these dynamics are determined by domestic macroeconomic sources grounded on the GARCH-MIDAS model. It is found that the Turkish exchange rate market is well-fitted by the model, the volatility features persistence and macroeconomic variables significantly affect the long-term component of the volatility. Besides, it is observed a potential functioning of the instruments controlled by policy makers in mitigating the long-term volatility.*

To Tülin and my Family

PREFACE

First and foremost, I would like to thank to my advisor, Asst. Prof. Pınar Deniz for her support, help and encouragements throughout the thesis process. I am deeply grateful to the assistance that Prof. Deniz gave at every turn of my thesis.

I would also like to thank to Prof. Mahmut Tekçe, Assoc. Prof. Barış Tekin and Asst. Prof. Seçil Yıldırım Karaman for accepting being members of thesis committee and making critical contributions during the thesis process which prevents to lose my bearings. I would also like to thank to Prof. Kamil Yılmaz for his valuable comments on my thesis. I am also grateful to Prof. Jürgen von Hagen for inviting me to continue my PhD researches at University of Bonn and for his valuable comments. I am also deeply indebted to all members of Economics Department at Marmara University for their assistance during my PhD. I would also like to thank to Asst. Prof. Kutay Bolkol, Res. Asst. Cemil Faruk Durmaz and Res. Asst. Altan Bozdoğan for their assistance and encouragement during my thesis.

Lastly, I would like to express my gratitude to my family, foremost to my father and mother Engin Polat and Çiçek Polat, for motivating and encouraging me, without any hesitation, during my entire life.

TABLE OF CONTENT

Page No:

CHAPTER 2

MONETARY POLICY EFFECTIVENESS IN TURKEY: DOES THE POLICY RATE STILL WORK WELL?

LIST OF TABLES

Page No:

CHAPTER 1

CHAPTER 2

CHAPTER 3

LIST OF FIGURES

CHAPTER 3

LIST OF ABBREVIATIONS

CBRT	Central Bank of Republic of Turkey
TKBB	Participation Banks Association of Turkey
TUIK	Turkish Statistical Institute
MTF	Ministry of Treasury and Finance of the Republic of Turkey
FRED	Federal Reserve Bank of St. Louis;
TBB	the Banks Association of Turkey
ROM	Reserve Option Mechanism
TRLibor	Turkish lira Reference Interest Rate

CHAPTER 1

INFORMATION CONTENT OF MONETARY AGGREGATES UNDER INFLATION TARGETING REGIME

1. INTRODUCTION

The claims on the lameness of money consolidated in the post-1980 period in its inability to serve as a policy indicator, an information variable or a reference value in a policy rule, or equivalently an intermediate target in the stance of monetary policy. The commonly held argument is that under a Taylor-type rule, the equilibrium paths of output and inflation can be observed without a reference to any path of money supply (Friedman and Kuttner, 1996 and Woodford, 2003). There is not equivalently a well-established consensus on what is the true measure of money supply in an economy that would act as a reliable indicator in the monetary policy conduct. Hereby, the aforesaid lameness of the money is attributed largely to the simple summation method used in computation of the monetary aggregates (Belongia and Ireland, 2014) with a claim that the monetary policy and monetary research have been plagued by bad (simple-sum) monetary aggregates data (Barnett and Chauvet, 2011). All assets included in the simple sum monetary aggregates are assumed to feature perfect substitution in between and, thus, are summed with the same weights. This assumption implies linear indifference curves for the asset owners and requires holding either the asset that has the lowest opportunity cost or an indeterminate group of assets in which each asset shares the same opportunity cost (Schunk, 2001). Acknowledging the increasing richness of assets in the monetary system with different rates of return and liquidities, however, such an assumption seems quiet inconsistent. Additionally, in the empirical sphere, the targeted growth rates of officially announced money supply have been defended to be of *no avail* to correlate with economic state variables and demand for money (Belongia and Ireland, 2015). More specifically, simple-sum aggregates are argued to result in puzzling behaviors during the pass through of monetary policy (Keating et al., 2016), over-state the total stock of money (Barnett, et al., 2008) and hide the expected liquidity effects following a change in the money supply (Kelly et al., 2011). Hereby, the problematic elements of the simple-sum aggregation paved the way for formation of Divisia index based monetary aggregates as the alternative summation method with the purpose of encouraging research on monetary economics, providing alternative monetary measures and facilitating transparent discourse on construction of money and aggregation methods (Matsonn, 2013). In provision of a more accurately measured "money", the seminal contribution is made by W. Barnett (Barnett, 1978, 1980) who puts forward the utilization of the (Tornqvist-Theil) Divisia index to measure the overall quantity of money. In its theoretical ground, the Divisia index does not impose a strong assumption on elasticities of substitution between assets and rather distinguish them with respect to their user costs (or discounted spreads). In this way, any transmission from one asset to another in the Divisia type aggregates is able to capture the change in the weights of each asset, reflect the change in the liquidity conditions and, thus, track inflation and output (Kelly et al, 2011). True to form, it is missing in the simple-sum aggregation.

For the developed economies with increasing varieties of financial assets, innovations in banking sector and under the zero-lower bound constraints (Fischer, 2016), Divisia aggregates are markedly constructed and advocated as being a signaling instrument in the monetary policy stance (Belongia and Ireland, 2018). However, for the emerging economies with relatively low varieties of assets in their monetary system and their idiosyncratic dynamics, the Divisia type summation is not constructed and tested sufficiently to see whether it contains a notable information in the stance of monetary policy. Emerging economies operating under policy rules similar to those in advanced economies can be faced with frequent regime switches with dramatic reversals in fiscal, monetary and trade policies (Aguiar and Gopinath, 2007). Turkey arises as a good case of emerging markets with its high potential in economic growth coming with high foreign indebtedness, variability in policy rate and inflation, short business cycle durations with more volatile trend term and relatively low richness in its financial assets (Alp et al., 2012). The monetary policy in Turkey operates under inflation targeting regime since

2006 making money become more out of sight as the nominal anchor. Still, as the Turkish economy features high inflation variability and inflationary gap during this period, the Central Bank of Republic of Turkey (CBRT) called on a more of cluttered policy stance giving financial stability as a secondary objective beside to price stability. It also adopted multiple policy framework and allowed the interest rates prevailing in the market to diverge from the officially announced rate in this framework (CBRT, 2012; Binici et al., 2019). Also, although the vigorous use of different instruments under the multiple policy environment brings the impacts of policy-induced changes into view, it brings direct impacts on different economic state variables (CBRT, 2012) making the conduct of policy more to more blurred to track.

In broad strokes, this chapter makes a discussion on the relevance of a Divisia type monetary aggregates for an emerging economy with a low richness of assets in its monetary system and operating under an inflation targeting regime. We construct, accordingly, Divisia money under different specifications for Turkish economy to see whether it includes any additional information content compared to its simple-sum counterpart and has at least a reference value in the policy stance during an inflation targeting regime. In this regard, Divisia monetary aggregates are obtained at M1 and M2 levels for Turkey. The time period is from 2005:12 through 2018:4. The construction of the Divisia index is upheld under three main specifications: i) benchmark index, ii) benchmark index that includes the participation banks beside to the deposit banks and iii) expectations-augmented index. In the following sections, we provide an in-sample dispersion dependency diagnostic test to control for existence of any statistical aggregation error contained in the Divisia monetary aggregates for Turkish data. Also, we employ a wavelet coherence analysis to examine strength of alternative monetary aggregates in predicting the variations in output and prices in both time and frequency domain. In the last section, we employ out-of-sample forecasting of inflation and production with monetary aggregates in an unrestricted VAR model over one- and three-months ahead horizons to measure the relative performance of alternative monetary statistics.

2. DIVISIA INDEX

2.1 Theoretical Foundation of Divisia Index

Following Handa (2009, p. 211) the monetary aggregation function of simple-sum aggregates can be defined as

$$M = M_1 + \Sigma_i a_i X_i \quad i = 2,3,\dots,m \quad a_i = (0,1) \tag{1}$$

where M stands for the value of the monetary aggregate in nominal terms, M_1 for the currency in circulation plus sight deposits held in banks and the central bank, X_i for the value of the ith liquid monetary asset and the weight a_i is the *degree of moneyness*[1] of a particular asset. This general functional form assumes that

i. The weight a_i can take only the value zero or one which causes all other values to be excluded.

ii. There exists an *infinite elasticity of substitution* among the assets with a non-zero coefficient, which in turn makes the included assets perfect substitutes.

Assuming perfect substitution among all assets implies an aggregation in which all the components are summed up with equal weights or, put it differently, all the assets are assumed to share the same value of "moneyness". However, such an aggregation is "only consistent with microeconomic theory in the case where economic decision makers hold *only one* monetary asset" (Anderson et al., 1997a, p.34).

By strictly following Anderson et al. (1997a, 1997b, 1997c) we explicate the notational and conceptual underlying of Divisia monetary aggregation below. We can at first define the relation between real and nominal holdings of monetary aggregates as follows:

[1] Degree of moneyness corresponds to the liquidity of a monetary asset or, putting it differently, the transaction cost of transforming asset to the cash holdings.

Let m_{it}^{real} stands for the stock of monetary asset i in real terms for period t such that $m_t^{real} = (m_{1t}^{real} \dots m_{nt}^{real})$ arise as the vector of real stocks and m_{it}^{nom} is the nominal stock of asset i for period t such that $m_t^{nom} = (m_{1t}^{nom} \dots m_{nt}^{nom})$. In this regard, stocks of monetary assets in real and nominal terms are linked by the identity:

$$m_{it}^{real} = (m_{it}^{nom}/P_t^*) \tag{2}$$

where P_t^* shows the true cost of living index of the consumer.

Notice that nondurable assets completely depreciate during the decision period of agents. For such assets the user costs equal to the price. Durable assets, however, do not purely depreciate during the decision period and the corresponding user costs become the opportunity cost of holding such assets. Hereby, monetary assets are presumed to be counted as durable goods. The user cost of any asset can be defined as "the discounted value of the interest foregone by holding a particular asset" (Anderson et al., 1997a, p.26). It shows, equivalently, a discounted spread between the return on a benchmark asset and particular asset the agents hold. Hereby, the benchmark asset corresponds to "a risk-free asset that can be used only for intertemporal transfer of wealth and provides no more services and […] has no default risk" (Anderson et al., 1997c, p.55). Barnett and Spindt (1982) advocate to use $R_t = max[r_{baa}, r_{it}, i = 1,2 \dots, n]$ to determine the best attainable indicator for the benchmark return where r_{baa} is the Moody's series of Baa corporate bond rates[2] and r_{it} is the rate of return on each individual monetary assets. In Anderson et al. (1997b; 1997c) this way of determining a benchmark return is redefined as $R_t^* = max[r_{baa}, r_{it}, i = 1,2 \dots, n] + c$ with c as a small constant number. The constant c is included to guarantee that the rate of return on the benchmark asset is strictly higher than any asset included in computation of the index. We follow this latter way to guarantee a strictly high benchmark rate.

In defining the user cost of assets, let π_{it}^{nom} shows the nominal user cost of asset i in period t, r_{it} denotes the nominal return on asset i in period t and R_t shows the nominal return on the benchmark asset in period t. Then, the user cost of asset i in period t is equal

[2] Moody's Baa corporate bond rates correspond to yields on long term corporate bonds that are rated as Baa by the credit rating agency of Moody's. Note that the Baa rating comprises low risk investment bonds.

to the value of a return forgone due to holding this particular asset i.e., $p_t^*(R_t - r_{it})$, discounted by the term $(1 + R_t)$ (Anderson et al., 1997c). That is,

$$\pi_{it}^{nom} = \frac{p_t^*(R_t - r_{it})}{(1+R_t)} \tag{3}$$

In pursuit of nominal user cost, it can be defined the real user cost of any asset *i* simply as follows:

$$\pi_{it}^{real} = \frac{R_t - r_{it}}{1+R_t}. \tag{4}$$

Thus, similar to identity (2), the user cost of assets in nominal and real terms can be linked using the identity:

$$\pi_{it}^{real} = (\pi_{it}^{nom}/P_t^*). \tag{5}$$

In the next step the total expenditure on each monetary asset (Y_t) is calculated. It is obtained by multiplying the real stock of each asset with the corresponding nominal user cost or, equivalently, multiplying the nominal stock with the corresponding real user cost prevailing in period t. That is,

$$Y_t = \sum_{i=1}^{n} \pi_{it}^{nom} m_{it}^{real}$$

$$= \sum_{i=1}^{n} P_t^* \pi_{it}^{real} \, (m_{it}^{nom}/P_t^*)$$

$$= \sum_{i=1}^{n} \pi_{it}^{real} m_{it}^{nom}. \tag{6}$$

It implies that the total expenditure function is not contingent upon P_t^* and is reached using solely stocks and user costs.

Then, the share of each asset in the total expenditure function is as follows:

$$w_{it} = \left(\frac{\pi_{it}^{real} m_{it}^{nom}}{y_t}\right) = (R_s - r_{is}) m_{is}^{nom} / \sum_{i=1}^{n} (R_s - r_{js}) m_{js}^{nom}. \tag{7}$$

Hereby, using the nominal money stocks and the corresponding rates of returns, the (Törnqvist-Theil)[3] nominal Divisia index of monetary services DM_t^{nom} is measured as

$$DM_t^{nom} = DM_{t-1}^{nom} \prod_{i=1}^{n} \left(\frac{m_{it}^{nom}}{m_{it-1}^{nom}}\right)^{\overline{w}_{it}} \quad (8)$$

where $\overline{w}_{it} = \frac{1}{2}(w_{it} + w_{it-1})$. Notice that the Divisia weights $\overline{w}_{it}$ are not obtained intuitively or via an ad hoc way (Barnett and Serletis, 1990). They are, rather, aggregated to one as the aggregation is made for each i at time t. Besides, simple sum index, SS_t can simply be provided as:

$$SS_t = \sum_{i=1}^{n} m_{it}^{nom}. \quad (9)$$

Expenditure shares of agents may be expressed as either real or nominal shares. Hence, in obtainment of the index defined in (8), the Törnqvist-Theil quantity index is defined for the nominal stocks. In a similar vein, it can be defined as real user cost index, Π_t^{real}, as follows:

$$\Pi_t^{real} = \Pi_{t-1}^{real} \left(\frac{y_t / y_{t-1}}{DM_t^{nom} / DM_{t-1}^{nom}}\right), \quad (10)$$

so that it will be dual to DM_t^{nom}.

Then, the Divisia indexes under real and nominal terms and their corresponding dual user cost indexes are associated by

$$\Delta \log(DM_t^{nom} / P_t^*) = \Delta \log\left(DM_t^{real}\right)$$

(11)

$$\Delta \log\left(\Pi_t^{real}\right) = \Delta \log(\Pi_t^{nom} / P_t^*) \quad (12)$$

[3]Anderson et al. (1997c, p.55) point out that "the Törnqvist-Theil index number is the only one known among *superlative* index numbers to retain its second-order tracking properties when some common aggregation theoretic assumptions are violated" and, thus, gives good statistical approximations to the unknown monetary aggregates.

Besides, we follow Anderson et al. (1997b) to convert /adjust all the rates of return series belonging a variety of different maturities to annualized 1–week and 1–month yield calculated on a bond equivalent basis, respectively:

$$r^{adj} = \left[\left(1 + \frac{(r/_{100})}{365}\right)^{7} - 1\right] \times \left(\frac{365}{7}\right) \times 100 \tag{13}$$

and

$$r^{adj} = \left[\left(1 + \frac{(r/_{100})}{365}\right)^{30} - 1\right] \times \left(\frac{365}{30}\right) \times 100 \tag{14}$$

where r and r^{adj} are the unadjusted and adjusted own rates of return for a particular asset, respectively. For the 1-week yield adjustment, (identity (13)), firstly, the annual effective rate is converted to the daily rate, then, compounded to the weekly rate and, lastly, is annualized assuming a 7-day week. The same rule applies for the (identity (14)) that is provided for 1-month yield adjustment.

2.2 Expectations-Augmented User Cost of Money

Assets in the form of foreign exchange deposits (FXD) have a significant place for Turkish economy. The share of FXD in total money holdings held in deposit banks is remarkable and has gradually increased over the sample period of 2006:1 – 2018:4 (even though share of FXD in total money holdings is around 35% on average for the sample period it rises from 32% in the beginning of 2006 to 42% in the beginning of 2018).[4] The scaling up of the holdings of exchange deposits of residents can be attributed, among others, to the high volatility in the exchange market accompanied by the persistent depreciation of domestic currency (Turkish Lira – TL) and ever-increasing external debt stock of Turkey. Henceforth, though the rates of return on those exchange deposits were relatively low, over-lasting disturbances on domestic currency had resulted in agents to hold their assets at a significant portion in the form of foreign currencies in the wake of

[4] https://www.tcmb.gov.tr/

precautionary attitudes during the sample period. This, in turn, paves the way for the inclusion of expectations into the analysis in means of re-calculating the user costs favoring foreign currency holdings and, thus, to reach more accurate rates of return on foreign currencies. In this regard, acknowledging that (low) returns on foreign exchange deposits do not capture accurately the true rate of return on assets in foreign currency, we include the expected rate of depreciation / appreciation of deposits in foreign currency in the analysis as an extension. To do so, following a similar procedure in Karaman (2009), we add the expected rate of depreciation of FX deposits to the related interest rate for sight and time deposits with all maturities. Notice that such an attempt corresponds to the obtainment of a hypothetical definition of money supply as we change the user costs of all assets notionally.

To specify the expected rate of depreciation, the arithmetic means of backward and forward expectations of FX rates are employed. For sight deposits, for instance, we calculate the rate of depreciation of TL with respect to both previous week and next week and for 1-month time deposits, we calculate the rate of depreciation of TL with respect to previous month and next month. The same procedure is employed for the remaining assets. Then, the arithmetic mean of the two rates is taken so as to denote expected rate of depreciation of foreign deposits. For 1-month time deposits, when the calculation results in an expected appreciation of TL, then the return on 1-month foreign deposits is just set to the return on 1-month TL deposits. As previously stated, even if the FX deposits are less liquid and the rates of return on them are low, they serve as barriers, to certain extent, in leaning against the volatilities in the domestic currency. By setting them equal to the returns on TL deposits with the same maturity in the case of depreciation, we aim at containing inflated user costs of assets held in foreign currency. In the case of appreciation, we set the new "*expectations-augmented*" rate as the interest rate on TL deposits that have the same maturity with the foreign assets plus the rate of appreciation multiplied by the interest rate on the same TL deposits. In either cases, i.e., depreciation or appreciation, we favor holding FXD compared to domestic deposits by adding additional returns on the former in computation of the corresponding Divisia aggregates.

In Figure 2.1, we give the average rates of return on FXD adjusted for expectations (Adjusted Returns on FXD), the average rates of return on FXD (Unadjusted Returns on FXD) and the share of FXD in total money holdings (Share of FXD in Total Deposits) for the sample period. From the figure we see that even though the average unadjusted return on foreign exchange deposits is less than 5% and slightly decreases over the sample period, the share of FXD in total holdings rises particularly after certain period of time. In alleviating this contradiction, the adjusted returns on FXD that are more in line with the changes in the share of FXD in total deposits compared to unadjusted returns are incorporated in calculating Divisia indexes.

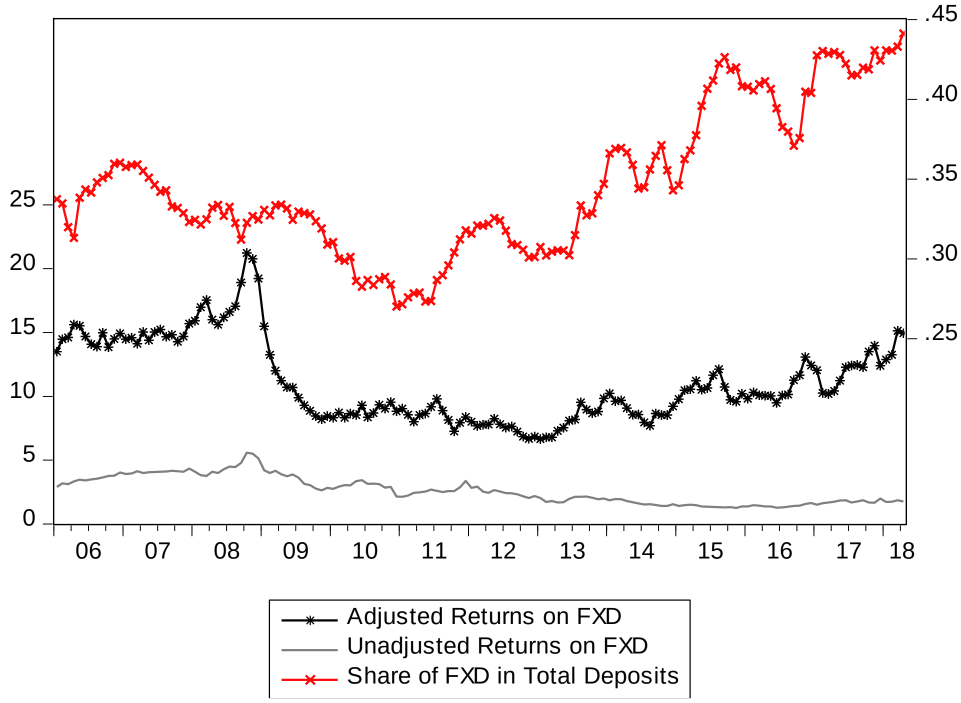

Figure 2.1: Annual Growth Rates of the Simple-sum M1, Divisia M1 under Benchmark Index and the Benchmark Interest Rate

2.3 Monetary Assets and Interest Rate Data in Computation of Divisia Index

The monetary system in Turkey consists of a low variety of monetary assets. That is, besides the currency in circulation, there exist sight and time deposits held under domestic and foreign unit of currencies and with various maturities. At the end of 2005, the CBRT revised the definition of monetary aggregates to accommodate itself to international standards of monetary system. In this regard, monetary aggregates at different levels (M1, M2 and M3) were revised as follows:

$$\mathrm{M1} = \text{Currency in circulation} + \text{Sight deposits (TL, FX)}$$
$$\mathrm{M2} = \mathrm{M1} + \text{Time deposits (TL, FX)}$$
$$\mathrm{M3} = \mathrm{M2} + \text{Repo} + \text{Money market fund}$$

Definitions of aggregates are expanded to cover participation (Islamic) banks besides the deposit money banks with the amendments made on January 2007. In this regard, besides the benchmark index that only includes deposits money banks in calculation of the Divisia indexes, we also provide Divisia indexes with participation banks. Note that there exists a relatively small but growing share (around 6% in the beginning of 2018)[5] of participation banks in the Turkish monetary system with respect to their deposit holdings in volume compared to deposit banks. Being different from the conventional banking mechanism, the participation banks deliver the resultant profit shares or losses on funds raised in their deposits accounts. The amendments made by CBRT in compliance with international standards, however, render the inclusion of the monetary assets and profit shares belonging to the participation banks into the monetary aggregates possible.[6] Accordingly, deposits accounts denominated in Turkish lira and foreign currency held in those banks and their corresponding profit shares (or participation rates) with different maturities are added to monetary aggregates.[7]

Besides, acknowledging that the low yields on deposits in foreign currency may not represent accurately the true rate of return on foreign assets, the expected rate of depreciation / appreciation of FX deposits is included in the analysis as an extension and named as the expectations-augmented index (see Section 2.2). The information on the data of monetary assets and corresponding rates of return is displayed in Tables 2.1 and 2.2, respectively.

[5] The share of participation banks in total deposit holdings rises form 3% in the beginning of 2006 to 6% in the beginning of the 2018.
[6] The related arrangement can be reached from: http://www.tcmb.gov.tr.
[7] The related data is taken from: http://www.tkbb.org.tr/ (accessed 18/11/2018).

In this regard, we compute the Divisia type monetary aggregates under three different specifications to approach the dynamics of Turkish economy in different perspectives: i) the benchmark index that excludes participation banks and any form of expectations in calculating the money supply, ii) the index that includes the participation banks and iii) expectations-augmented index that includes the formation of expectations on exchange market while calculating the user cost of assets. We aim at constructing Divisia type monetary aggregates for M1 and M2 under different specifications keeping M3 out as it is problematic to reach good proxies for the returns on assets in M3 and the subcomponents of M3 are quite small in total money stock.

In obtainment of Divisia type monetary aggregates under different specifications, following the official definitions settled by the CBRT, monetary assets and their corresponding returns are collected and grouped with respect to their maturities and unit of currency.[8] Hence, the deposits held in both deposit money and participation banks are collected according to their maturities (i.e., up to one-month, three-month, six-month and one-year and more) and to their unit of currency (i.e., in Turkish Lira and in U.S. Dollar). We collect the series weekly from 2005:12 through 2018:4. Also, in collection of the rate of returns corresponding to aforesaid deposits held in domestic currency we use the weighted average returns for the deposits in Turkish lira. In collection of rate of returns held in foreign currency i.e., U.S. Dollar and Euro, the rates of returns on deposits are expressed in the form of Turkish lira transformed by the end of month basket exchange rate. Notice that as in the case of TL deposits, we differentiate the rates of return on foreign currency deposits with respect to their maturities (i.e., up to one-month, three-month, six-month and one-year and more).

With respect to the determination of the benchmark rate of return to be used in obtaining the user costs of all assets, following the literature (Anderson et al., 1997b; 1997c and Anderson and Jones, 2011) we determine the benchmark rate as the highest rate among 2-year government bonds r_{bond}[9] and all monetary assets denominated in TL in each period plus a premium of 100 basis points. That is, $R_t = (max[r_{bond}, r_{it}, i =$

[8] The related data is taken from: https://evds2.tcmb.gov.tr/ (accessed 18/01/2020).

[9] 2-year government bond returns are selected to serve as the long-term low risk asset returns and taken as a natural candidate for the benchmark asset yields.

$1,2 \ldots, n] + 1)$ arise as the benchmark rate of return where r_{it} arise as the rate of return on each of individual monetary asset. Still, as stated also by Anderson and Jones (2011) while the definition of the benchmark monetary asset and the corresponding rate of return are straightforward, measuring that concept is not at all so. For the related series used in the analysis, there exist certain periods of time in which the sight deposits have higher returns than longer term deposits e.g., during the 2008-2009 financial crisis. Besides, due to existence of highly volatile FX markets and variability of inflation, economic agents may prefer to hold the money mostly in terms of foreign currency though they bear low interest rates serving as barriers to expected further depreciation of domestic currency.

Regarding the Divisia literature on Turkey we see a limited number of studies that construct and analyze Divisia monetary aggregates for Turkey. Kunter (1993) constructs Divisia monetary aggregates at M1, M2 and M2Y for the period between 1986 – 1993 and provides a descriptive analysis for Turkey. Çelik (1999) makes a significant contribution to the related literature by investigating how the Divisia type monetary aggregates constructed for the period 1986 – 1999 are relevant for Turkey for the period 1986 – 1999 and recommend Divisia M1 as the monetary target for the short-run. Lastly, in Karaman (2009) Divisia aggregates are constructed for the period from 1986 through 2006 and it is found superiority of Divisa money in predicting inflation and output.

Table 2.1: Monetary Assets Used in Computation of Monetary Aggregates

Monetary Assets	Frequency	Sample Period
M1		
Currency in Circulation (Deposit Banks)	Weekly	2005.M12-2018.M6
Sight Deposits Denominated in Turkish Lira (Deposit Banks)	Weekly	2005.M12-2018.M6
Sight Deposits Denominated in Foreign Currency (Deposit Banks)	Weekly	2005.M12-2018.M6
Sight Deposits Denominated in Turkish Lira (Participation Banks)	Monthly	2005.M12-2018.M5
Sight Deposits Denominated in Foreign Currency (Participation Banks)	Monthly	2005.M12-2018.M5
M2 = M1 +		
Time deposits denominated in Turkish Lira with different maturities (Deposit Banks)*	Weekly	2005.M12-2018.M6
Time deposits denominated in Foreign Currency with different maturities (Deposit Banks)	Weekly	2005.M12-2018.M6
Time deposits denominated in Turkish Lira with different maturities (Participation Banks)*	Monthly	2005.M12-2018.M5
Time deposits denominated in Foreign Currency with different maturities(Participation Banks)	Monthly	2005.M12-2018.M5

Note: *Time deposits are divided among one-month, three-month, six-month and one-year and more and with respect to their unit of currency.

Table 2.2: Interest Rate Series Used in Computation of User Costs

Interest Rate Series	Frequency	Sample Period
Deposit Banks		
Interest Rates on Sight Deposits Denominated in Turkish Lira and Foreign Currency*	Weekly	2005.M12-2018.M6
Interest Rates on (up to) 1-Month Time Deposits Denominated in Turkish Lira and Foreign Currency**	Weekly	2005.M12-2018.M6
Interest Rate on (up to) 3-Month Time Deposits Denominated in Turkish Lira and Foreign Currency	Weekly	2005.M12-2018.M6
Interest Rate on (up to) 6-Month Time Deposits Denominated in Turkish Lira and Foreign Currency	Weekly	2005.M12-2018.M6
Interest Rate on (up to and more than) 1-Year Time Deposits Denominated in Turkish Lira and Foreign Currency	Weekly	2005.M12-2018.M6
2-Year Government Bond Yields***	Weekly	2005.M12-2018.M6
Participation Banks		
The Profit Share on (up to) 1-Month Time Deposits Denominated in Turkish Lira and Foreign Currency****	Monthly	2005.M12-2018.M5
The Profit Share on (up to) 3-Month Time Deposits Denominated in Turkish Lira and Foreign Currency	Monthly	2005.M12-2018.M5
The Profit Share on (up to) 6-Month Time Deposits Denominated in Turkish Lira and Foreign Currency	Monthly	2005.M12-2018.M5
The Profit Share on (up to) 1-Year Time Deposits Denominated in Turkish Lira and Foreign Currency	Monthly	2005.M12-2018.M5

Note: * Yields on sight deposits that deposit banks bear, correspond to the weighted average of rate of returns for sights in TL and foreign currency. The rates of returns series are flow variables and correspond to observations at the end of the period. Note that starting from December 2010 the effective maximum interest rates for sight deposits were obligated by Central Bank to be set to 0.25%.

**Yields on time-deposits that the deposit banks bear with different maturities, correspond to weighted average of rate of return for deposits in TL and foreign currency.

***The rate of return on two-year government bonds that encounter coupon payments in each three or six months is selected as the benchmark rate.

****The profit shares on the funds raised in the deposits accounts in Turkish lira and foreign currency correspond to weighted averages of resultant profit or loss shares of five participation (Islamic) banks in Turkey i.e., Albaraka, Kuveyt Türk, Türkiye Finans, Vakıf Participation and Ziraat Participation.

2.4 Constructed Divisia Monetary Aggregates

The time series of the simple sum and constructed Divisia monetary aggregates are displayed in the Figures 2.2 to 2.5. The series are normalized to 100 at the first observation of the sample and the growth rates of the aggregates are calculated with year-on-year change that contains seasonality and gives smoother but still informative observations. It is also given the year-on-year change in 2-year government bond yields that stands for the benchmark interest rate. The time period is from 2007:1 through 2018:4 as a relatively short but elucidative period for its inclusion of pre-crisis, financial crisis and post-crisis episodes. Firstly, it is observed a neck and neck relationship between the year-on-year growth rates of narrowly defined monetary aggregates particularly starting from the end of 2011 while in the case of broadly defined aggregates, it arises significant divergence among the series. Besides, under all the specifications we observe convergence of growth rates of simple sum and Divisia aggregates for both M1 and M2 during the great moderation that had taken effect from the 2008:9 through 2010:10 (roughly denoted by the grey boxes in the figures below). Note that in this period, starting with the collapse of Lehman Brothers, the detrended industrial production series turns incessantly negative for Turkish economy. Such a convergence is explicated in the literature by a compression of returns in the relatively low interest-rate structure which in turn leads to the convergence in the user costs and thus weights of monetary assets in the Divisia aggregates (Scharnagl and Mandler, 2015). From the figures it is also revealed that the growth rate of money measured by Divisia index in pre-crisis episode was lower than money growth series measured by the simple sum index. That is, monetary policy when measured by Divisia was more contractionary just before the recession had begun. Measuring the money with Divisia index, thus, signals for overestimating the true amount of money circulating in the economy during this period. This observation does not conform with the findings that the money growth when measured by Divisia money was higher than observed in the pre-crisis period, so that the excessive money creation may have prompted the financial crisis and fed the bubbles (Barnett and Chauvet, 2011 and Chen and Nautz, 2015). Besides, after the great moderation episode, the Divisia and simple sum money growth rates diverge to some extent (except for the expectations-augmented index) in which the Divisia money growth moves above its simple-sum counter-parts. Thus, in the post-crisis episode, it signals that monetary policy when measured by the Divisia index, has been indeed more expansionary and fluctuated more than was announced by the central bank. In Figure 2.5, Divisia monetary aggregates are specified under the expectations-augmented index to give more emphasis on the precautionary attitudes of the agents towards the deposits in foreign currency at the cost of high returns in domestic currency. In this case, as opposed to other cases, the fluctuations of the Divisia money in the post-crisis years, particularly after the end of 2013 are smaller in size and does not follow strictly its simple-sum counterpart.

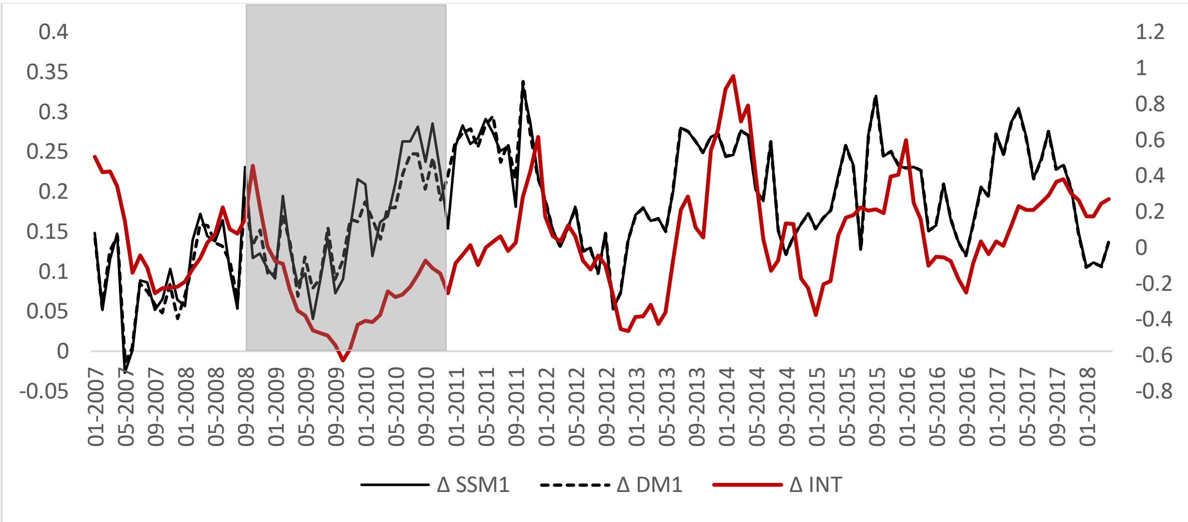

Figure 2.2: Annual Growth Rates of the Simple-sum M1, Divisia M1 under Benchmark Index and the Benchmark Interest Rate

Note: The figure indicates the year-on-year change in simple sum and Divisia aggregates under the benchmark index (Δ SSM1 and Δ DM1) on the left-axis and year-on-year change in 2-year government bond yields (Δ INT) on the right-axis. The period is from 2007:1 through 2018:4.

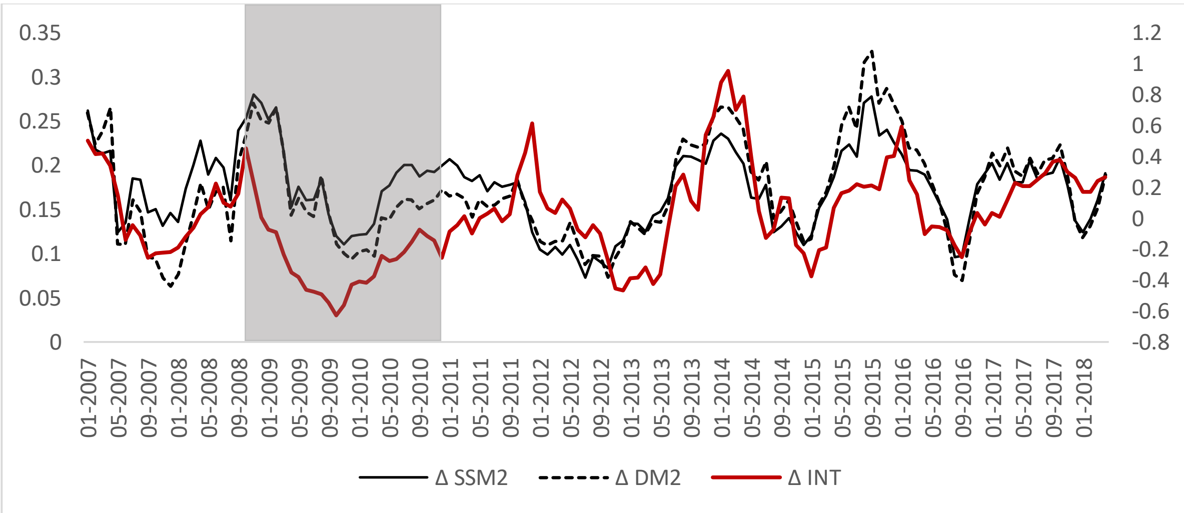

Figure 2.3: Annual Growth Rates of the Simple-sum M2, Divisia M2 under Benchmark Index and the Benchmark Interest Rate

Note: The figure indicates the year-on-year change in simple sum and Divisia aggregates under the benchmark index (Δ SSM2 and Δ DM2) on the left-axis and year-on-year change in 2-year government bond yields (Δ INT) on the right-axis. The period is from 2007:1 through 2018:4.

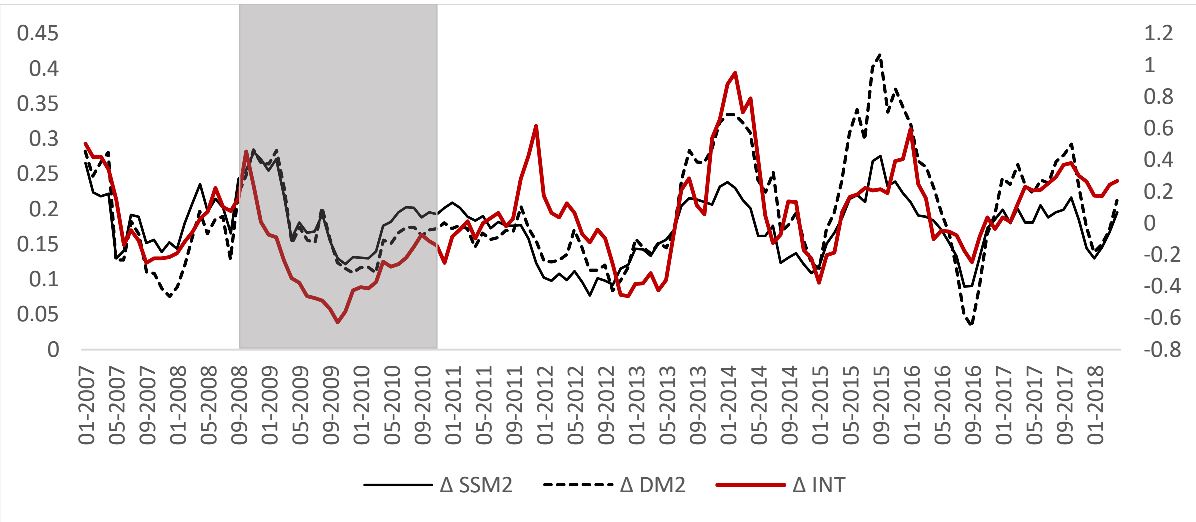

Figure 2.4: Annual Growth Rates of the Simple-sum M2, Divisia M2 under Benchmark Index with Participation Banks and the Benchmark Interest Rate

Note: The figure indicates the year-on-year change in simple sum and Divisia aggregates under the benchmark index (Δ SSM2 and Δ DM2) with participation banks on the left-axis and year-on-year change in 2-year government bond yields (Δ INT) on the right-axis. The period is from 2007:1 through 2018:4.

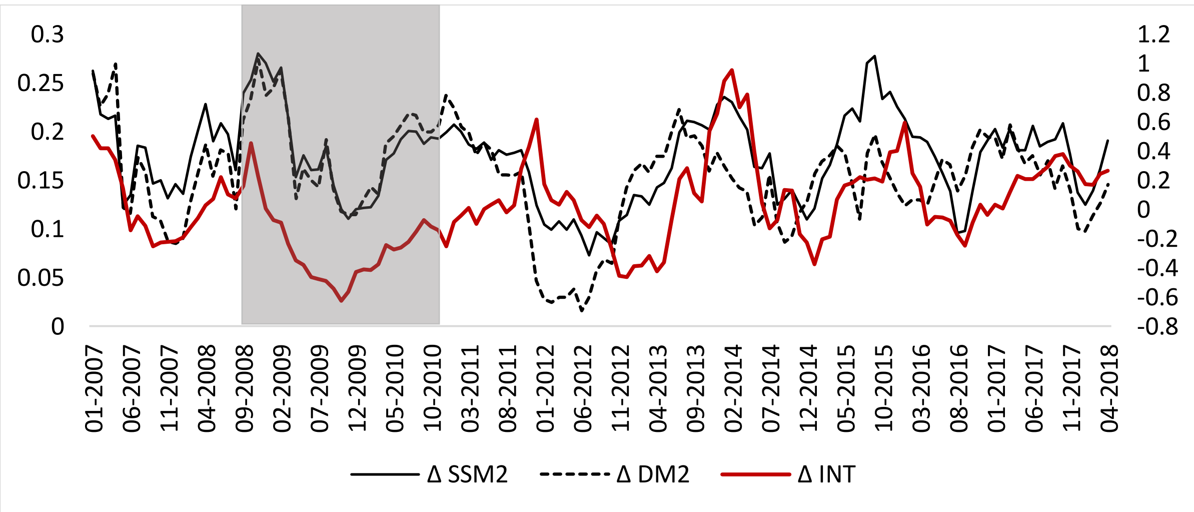

Figure 2.5: Annual Growth Rates of the Simple-sum M2, Divisia M2 under Expectations-Augmented Index and the Benchmark Interest Rate

Note: The figure indicates the year-on-year change in benchmark simple sum aggregates (Δ SSM2) and Divisia aggregates under the expectations-augmented index (Δ DM2) on the left-axis and year-on-year change in 2-year government bond yields (Δ INT) on the right-axis. The period is from 2007:1 through 2018:4.

3. A DISPERSION-DEPENDENCY DIAGNOSTIC TEST FOR AGGREGATION ERROR

As stated by Serletis (2007) the exact aggregation (over monetary assets) necessitates the existence of weak separability and linear homogeneity of aggregator function. That the conditions for the exact aggregation are broken may signal for the existence of an aggregation error. Hereby, we use the Divisia variance to measure the remainder term in the Divisia index and, thus, see whether the exact aggregation holds in our case. Grounded on the Divisia second moments (variances) due to Theil (1967), a dispersion dependency diagnostic test (DDT) is advocated by Barnett and Serletis (1990) to provide a useful measure of the amount of statistical aggregation error that the constructed aggregates include. As the Divisia money growth is in effect a mean and its dispersion measures are the relevant Divisia second moments, the argument is that the dispersion of assets' growth rates does not contain additional information, if the agents have already conditioned upon the information included in the aggregates themselves (Barnett and Serletis, 1990).

Hereby, we can empirically test whether the Divisia second moments may contain some worth-mentioning information (e.g., during some periods of financial change) that is not totally captured by the first moments of the monetary aggregates. In this respect, the Divisia quantity-growth rate variance is obtained as follows:

$$K_t = \sum_{i=1}^{n} \overline{w_{it}} \, [\Delta \log(m_{it}^{nom}) - \Delta \log(DM_t^{nom})]^2. \tag{15}$$

In Figure 3.1 it is given the Divisia quantity-growth rate variances of M1 and M2 under benchmark indexes. The special case is that the quantity variance will be zero if equal growth rates of all included assets are not fulfilled. True to form, it is also evident from the figure that the measure of broad monetary aggregation with higher number of components results in higher dispersion than that of narrow monetary aggregation.

We use the dispersion dependency diagnostic test due to Barnett and Serletis (1990) for the well-known St. Louis-type reduced form equation in order to see the presence of any approximation errors contained in the constructed monetary aggregates.

The sample is quarterly and between 2006:Q1 – 2018:Q2. In St. Louis-type reduced form equation the growth rate of nominal GDP is related to lagged GDP growth, current and lagged growth rates of monetary aggregates, the current and lagged growth rates of a fiscal policy indicator and Divisia variance variable:

$$Dz_t = a_0 + \sum_{i=1}^{1} b_i Dz_{t-i} + \sum_{k=0}^{2} c_i Dg_{t-k} + \sum_{j=0}^{1} d_i Q_{t-j} + e_i K_{t-l} + u_t \qquad (16)$$

where the term D stands for the logarithmic operator, Dz_t is the logarithm of GDP at month t, Dg_t is the logarithm of the central government spending at month t, Q_t is the logarithmic change of the Divisia (first-moment) broad monetary aggregate at quarter t and K_t is the variance of Divisia growth rate at month t. By including the term $e_i K_{t-l}$ in the St. Louis model we apply the afore-said DDT in measuring the aggregation error.

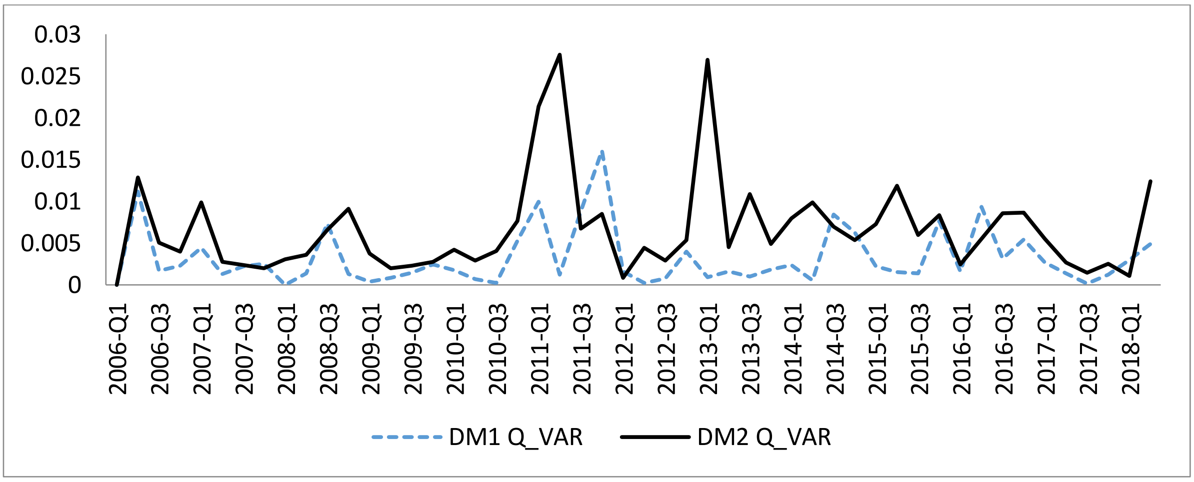

Figure 3.1: Divisia Quantity-Growth Rate Variances for M1 and M2 Level

The seasonality for the series of logarithm of GDP and logarithm of government spending is revealed by utilizing the Tramo-Seats method and the cyclical components of the series are obtained using Hodrick-Prescott Filter. The detrended series are found to be stationary. It is only the Divisia quantity variance that is found to be I(0). Regarding the selection of optimal lag lengths, it is revealed one-lag for nominal GDP, two-lags for nominal government spending, one-lag for the monetary aggregates and zero-lag for Divisia quantity variance measure. Since the heteroscedasticity is observed for SSM2 and DM2 under benchmark case, robust standard errors are used. We control for the existence of autocorrelation using the Cumby-Huizinga test statistics provided by Baum and Schaffer (2013) for more efficiently controlling autocorrelation at high orders and the settings that include weakly exogenous or endogenous regressors (Baum and Schaffer, 2013). It allows us also to take the overlapping series as well as conditional heteroscedasticity into account. From the Cumby-Huizinga test statistic it is revealed no serial correlation at different orders and the result does not change when we consider the conditional heteroscedasticity.

We estimate the parameters of the St. Louis type equation (16) and display the results in the tables from 3.1 to 3.4.[10] We estimate this equation also by imposing the constraint that the coefficients d_i are summed up to 1. Such a constraint is necessary for steady-state (long run) superneutrality (Barnett and Serletis, 1990). Besides, the estimates of both unconstrained and constrained St. Louis type equations are obtained under different specifications of monetary aggregates of i) the benchmark index at M1 and M2 levels, ii) benchmark index with participation banks, iii) expectations-augmented index. For all specifications we apply the DDT test by Barnett and Serletis (1990) with the inclusion of corresponding Divisia variance variables (DM1 with Q_VAR and DM2 with Q_VAR). Note that we confine ourselves with in-sample predictions in capturing the aggregation error, so that the adjusted R^2, root mean square errors (RMSE) as well as the information criteria of AIC and BIC are reported. For convenience it is only given the results on *constrained* St. Louis type equation under benchmark index. The constrained St. Louis type equations under other specifications yield similar results.

It is evident from alternative model specifications that the high persistence of nominal GDP accounts for the good-fit of model settings. That is, in all specifications, the nominal GDP is significantly affected by its lagged value and both monetary and fiscal actions are far from having significant impacts on the nominal GDP. In determining the optimal aggregation measure, in-sample predictions reveal mixed results. That is, simple-sum type monetary aggregates slightly outperform their Divisia type counterparts for M1 and M2 levels under the benchmark and the expectations-augmented indexes (Tables 3.1,

[10] We use also quarterly change of logarithm of GDP, logarithm of government spending and monetary aggregates in estimation instead of detrended series. The findings on the existence of the aggregation errors contained in constructed aggregates do not change in this case either.

3.2 and 3.4) while when participation banks are incorporated into the benchmark index (Table 3.3) it arises that the Divisia M2 predominates the conventional measures of M2.

Table 3.2 provides the estimation results with the imposed constraint that the sum of the coefficients of money variables equals one for the sake of upholding the super-neutrality condition. We observe that the condition is held and the changes in monetary aggregates are found to have significant effects on nominal GDP under most of the cases.

To the test if any potential aggregation error is contained in Divisia indexes it is included the Divisia quantity variance terms i.e., DM1 with Q_VAR and DM2 with Q_VAR in different model specifications. For narrowly defined monetary aggregates, we obtain that the inclusion of the Divisia second moments does not improve the model performance and the model fits are even deteriorated for most of the cases. This results lead us to argue for no aggregation error contained in constructed Divisia M1.

Also, as the aggregation error is likely to grow as the aggregation level rises with an increasing variety of components, we can expect certain potential gains from including the dispersion measure at the broad monetary aggregates (Barnett and Serletis, 1990; Barnett et al., 2008). We observe, in this regard, that when the Divisia quantity variances at M2 are included the model fits tend to improve, but slightly. Even if the adjusted R^2 and RMSE increase due to inclusion of Divisia quantity variances at M2 the overall effect, however, does not turn out to be significant. The only exception is the model under expectations-augmented index at M2. As denoted at Table 3.4, The Divisia quantity variance of M2 defined by expectations-augmented index includes additional information at 10% significance level. This signals for the existence of missing information that the first moments of expectations-augmented index at M2 cannot capture which in turn leads us to be less confident in using this definition of money supply.

Table 3.1: Estimates of the Unconstrained St. Louis Type Equation with the Benchmark Index

VARIABLES	SSM1	DM1	DM1 with Q_VAR	SSM2	DM2	DM2 with Q_VAR
b_1	0.643***	0.685***	0.688***	0.697***	0.703***	0.692***
	(0.120)	(0.120)	(0.120)	(0.114)	(0.118)	(0.118)
c_0	0.0242	0.0318	0.0150	0.0169	0.0252	0.0406
	(0.0805)	(0.0826)	(0.0852)	(0.0798)	(0.0793)	(0.0799)
c_1	-0.140	-0.145	-0.130	-0.123	-0.135	-0.162*
	(0.0844)	(0.0865)	(0.0887)	(0.0826)	(0.0851)	(0.0876)
c_2	0.170*	0.175*	0.174*	0.139	0.144	0.149*
	(0.0877)	(0.0909)	(0.0912)	(0.0837)	(0.0862)	(0.0858)
d_0	0.129	0.0702	0.0600	0.0189	-0.0164	-0.0293
	(0.137)	(0.131)	(0.132)	(0.182)	(0.121)	(0.121)
d_1	0.118	0.0897	0.0770	-0.242	-0.0840	-0.0602
	(0.123)	(0.122)	(0.123)	(0.186)	(0.119)	(0.120)
e_0			0.914			0.727
			(1.090)			(0.598)
a_0	0.000510	0.000330	-0.00247	7.06e-05	0.000159	-0.00471
	(0.00317)	(0.00325)	(0.00467)	(0.00320)	(0.00326)	(0.00515)
Observations	48	48	48	48	48	48
Adj. R-squared	0.539	0.5165	0.5130	0.526	0.509	0.515
RMSE	.02181	.02235	.02244	.02213	.02251	.02238
AIC	-224.5795	--222.2176	--221.0544	-223.197	-221.5631	-221.3056
BIC	-211.4811	-209.1192	-206.0848	-210.0986	-208.4647	-206.336

Note: *Standard errors are given in parentheses such that *** p<0.01, ** p<0.05, * p<0.1.

Table 3.2: Estimates of the Constrained St. Louis Type Equation with the Benchmark Index

VARIABLES	SSM1	DM1	DM1 with Q_VAR	SSM2	DM2	DM2 with Q_VAR
b_1	0.361**	0.414**	0.416**	0.864***	1.051***	1.028***
	(0.146)	(0.158)	(0.160)	(0.170)	(0.211)	(0.211)
c_0	-0.00625	0.0172	0.0272	-0.0142	0.00640	0.0330
	(0.107)	(0.116)	(0.121)	(0.121)	(0.148)	(0.150)
c_1	-0.0991	-0.0993	-0.109	-0.154	-0.174	-0.221
	(0.112)	(0.121)	(0.126)	(0.125)	(0.159)	(0.164)
c_2	0.158	0.178	0.178	0.232*	0.372**	0.377**
	(0.117)	(0.128)	(0.129)	(0.126)	(0.155)	(0.155)
d_0	0.587***	0.549***	0.547***	0.603**	0.550***	0.518**
	(0.150)	(0.152)	(0.154)	(0.250)	(0.201)	(0.202)
d_1	0.413***	0.451***	0.453***	0.397	0.450**	0.482**
	(0.150)	(0.152)	(0.154)	(0.250)	(0.201)	(0.202)
e_0			-0.535			1.239
			(1.510)			(1.116)
a_0	0.00184	0.00163	0.00325	0.000252	-0.000137	-0.00841
	(0.00423)	(0.00455)	(0.00649)	(0.00487)	(0.00608)	(0.00962)
Observations	48	48	48	48	48	48
RMSE	.0292	.0314	.0318	.0336	.0420	.0419
AIC	-197.5626	-190.3382	-188.485	-183.8459	-162.4718	-161.8918
BIC	-186.3354	-179.111	-175.3866	-172.6187	-151.2446	-148.7934

Note: *Standard errors are given in parentheses such that *** p<0.01, ** p<0.05, * p<0.1.

Table 3.3: Estimates of the Unconstrained St. Louis Type Equation with the Benchmark Index Including Participation Banks

VARIABLES	SSM1	DM1	DM1 with Q_VAR	SSM2	DM2	DM2 with Q_VAR
b_1	0.688***	0.695***	0.694***	0.697***	0.703***	0.691***
	(0.116)	(0.113)	(0.114)	(0.122)	(0.118)	(0.117)
c_0	0.0168	0.0178	0.00401	0.0293	0.0252	0.0466
	(0.0761)	(0.0777)	(0.0821)	(0.0850)	(0.0793)	(0.0802)
c_1	-0.143*	-0.142*	-0.129	-0.138	-0.135	-0.164*
	(0.0779)	(0.0791)	(0.0831)	(0.0846)	(0.0851)	(0.0872)
c_2	0.167**	0.166**	0.167**	0.150*	0.144	0.147*
	(0.0805)	(0.0814)	(0.0821)	(0.0874)	(0.0862)	(0.0854)
d_0	0.229*	0.213*	0.207	-0.0708	-0.0164	-0.0333
	(0.115)	(0.123)	(0.124)	(0.194)	(0.121)	(0.120)
d_1	-0.0448	0.00143	-0.00848	-0.136	-0.0840	-0.0609
	(0.107)	(0.115)	(0.117)	(0.196)	(0.119)	(0.120)
e_0			0.927			0.742
			(1.641)			(0.556)
a_0	0.000646	0.000574	-0.00182	-2.58e-05	0.000159	-0.00547
	(0.00315)	(0.00317)	(0.00531)	(0.00553)	(0.00326)	(0.00531)
Observations	48	48	48	48	48	48
R-squared	0.543	0.539	0.531	0.504	0.509	0.519
RMSE	.02172	.02182	.0220	.02263	.02251	.0223
AIC	-224.9997	-224.5456	-222.9272	-220.2236	-221.5631	-221.6544
BIC	-211.9013	-211.4472	-207.9576	-205.254	-208.4647	-206.6848

Note: *Standard errors are given in parentheses such that *** p<0.01, ** p<0.05, * p<0.1.

Table 3.4: Estimates of the Unconstrained St. Louis Type Equation with the Expectations-Augmented Index

VARIABLES	SSM1	DM1	DM1 with Q_VAR	SSM2	DM2	DM2 with Q_VAR
b_1	0.643***	0.703***	0.702***	0.692***	0.700***	0.663***
	(0.120)	(0.118)	(0.118)	(0.119)	(0.119)	(0.119)
c_0	0.0242	0.0298	0.0108	0.0128	0.0496	0.0720
	(0.0805)	(0.0823)	(0.0847)	(0.0847)	(0.0819)	(0.0812)
c_1	-0.140	-0.145*	-0.127	-0.123	-0.155*	-0.185**
	(0.0844)	(0.0847)	(0.0867)	(0.0836)	(0.0842)	(0.0842)
c_2	0.170*	0.177*	0.177*	0.136	0.165*	0.164*
	(0.0877)	(0.0882)	(0.0883)	(0.0870)	(0.0843)	(0.0825)
d_0	0.129	0.0733	0.0649	0.0187	-0.187	-0.235
	(0.137)	(0.112)	(0.112)	(0.185)	(0.211)	(0.209)
d_1	0.118	0.0492	0.0428	-0.247	-0.00541	-0.0433
	(0.123)	(0.106)	(0.107)	(0.190)	(0.210)	(0.206)
e_0			1.044			1.012*
			(1.079)			(0.600)
a_0	0.000510	0.000364	-0.00283	-0.000640	0.000228	-0.00647
	(0.00317)	(0.00327)	(0.00465)	(0.00551)	(0.00325)	(0.00509)
Observations	48	48	48	48	48	48
Adj. R-squared	0.539	0.509	0.508	0.514	0.512	0.533
RMSE	.02181	.02253	.0225	.0224	.02244	.0219
AIC	-224.5795	-221.4706	-220.581	-221.2276	-221.8392	-223.1363
BIC	-211.4811	-208.3722	-205.6114	-206.2579	-208.7408	-208.1666

Note: *Standard errors are given in parentheses such that *** p<0.01, ** p<0.05, * p<0.1.

4. WAVELET ANALYSIS

The macroeconomic series arise as combination of components operating on different frequencies and some remarkable links may prevail between two macroeconomic series at different frequencies (Aguiar-Conraria et al., 2008). In the side of policy making, the monetary actions result in different impacts on the fundamentals at different frequencies i.e., short run and long run. Due to institutional or policy shifts, the impact of policy actions may also get intensified over time or come into existence with some delay. In this regard, we apply the wavelets to contribute our discussion on alternative formations of monetary aggregates by explaining the relation between money and economic state variables in both time and frequency. Notice here that contrary to spectral analysis, in the wavelet analysis, the time dimension is not missing.

We apply the wavelet methodology to analyze in depth the information content of Divisia monetary aggregates compared to their simple-sum counterparts for Turkish economy. This methodology enables us to observe the very abstract of the relationship between time series in both time and frequency domains. That is, on the one hand, it gives information on how the coherence between the series evolves over time at given frequency bands. On the other hand, it informs about whether the link between series changes at different frequencies at a given period of time. Besides, the used wavelet methodology enables us to report the lead and lag relations between selected series again in different time-frequency domains.

More specifically we use the multiple wavelet methodology developed by Aguiar-Conraria et al. (2018). The “beauty” of this approach is its structure that enables us to track the partial coherencies between two series after controlling any third series in a time-frequency space. Such an analysis is particularly beneficial given the empirical evidence that the coherence of money growth with inflation and output would be spurious with the omission of the short-term interest rates utilized as primary tools to transmit through the state variables in the short-run or medium-run (Schreiber, 2009). In this regard, in our study, we aim at tracing the link across money, inflation and output controlling for selected interest rate. That is, grounded on this approach, we analyze whether the Divisia money includes any further information for the state variables compared to the conventionally measured money controlling the interest rate. In other case, we execute the wavelet analysis on the relation among the interest rate, inflation and production controlling different formations of money to see to what extent, if any, Divisia aggregates differ from simple-sum aggregates in contributing to this relation.

We use the cross-wavelet spectrum to observe local covariance between the related series, the wavelet coherence to see the localized degrees of correlation in time-frequency space and the wavelet phase difference to obtain information on the delay between oscillations of the two series. We follow particularly Aguiar-Conraria et al. (2018) that estimate an equation relating more than two series in a time-frequency domain. Besides, in controlling the significance of multiple and partial coherencies, contrary to the existing literature assuming that the economic time series strictly follow white noise or red noise (AR1), using Aguiar-Conraria et al. (2018) we are able to assume that the economic time series may follow ARMA processes. In this regard, we fit both (AR1) and (ARMA(1,1)) models.

4.1 Methodology: The Continuous Wavelet Transform (CWT)

We employ the wavelet coherence analysis using the Morlet's specification to control the aforesaid difference between simple sum and Divisia aggregates in affecting macroeconomic fundamentals. It is strictly followed Grinsted et al. (2004) and Yang et al. (2016) to define underlying details of the wavelet methodology. The continuous wavelet transform builds mainly on the intrinsic limitations of the fourier transform. The latter serves as a tool for obtaining local frequency notices of a signal and is taken as an inaccurate and inefficient way of localization as it does not have any time component of the signal and thus cannot explain the spectral features over time (Torrence and Compo, 1998, p. 63). Thus, unlike the fourier transform under which the time information of a time series is purely missing, the wavelet transform enables us to employ local analysis in a manner that the length of wavelets (narrow and wide windows) changes endogenously and optimally. For instance, in order to capture abrupt changes, very short basis functions (narrow windows) are needed while, very long basis functions (wide windows) are used to isolate slow and persistent movements (Raihan et al., 2005).

Wavelet analysis hereby arises as an approach of time-frequency localization that does not impose any restriction on the scaling. Thus, the wavelets provide a visualization of the signal in both time and frequency and "are characterized by finite energy such that they grow and die out within a period" (Kumar et al., 2017, p. 3234).

The wavelet can be identified under two forms determined by corresponding normalization rules: the wavelet ϕ that integrates to 1 ($\int \phi(t)dt = 1$) is named as father wavelet whereas the wavelet ψ that integrates to 0 ($\int \psi(t)dt = 0$) is named as mother wavelet. The father wavelet displays the smooth and low frequency part of a signal or the raw data while the mother wavelet displays the detailed and the high-frequency part.

When any (signal) function $y(t)$ in $L^2(\mathbb{R})$ that serves as the space for square integrable functions is converted into various frequency parts via a resolution oriented to the scale, then the wavelet function can be obtained as a sequence of projections onto the father and mother wavelets resulted from ϕ and ψ via scaling and translation (Yang et al., 2016). That is,

$$\phi_{j,k}(t) = 2^{-j/2}\phi(2^{-j}t - k), \tag{17}$$

$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t - k), \tag{18}$$

where j shows the scaling parameter in a J-level decomposition with $j = 1,2, \dots, J$ and k shows a translation parameter. Hereby, the representation of the signal function $y(t)$ in $L^2(\mathbb{R})$ can be given in a wavelet form as:

$$y(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \sum_k d_{1,k}\psi_{1,k}(t) \tag{19}$$

where $s_{J,k} = \int y(t)\phi_{J,k}(t)dt$ and $d_{J,k} = \int y(t)\psi_{J,k}(t)dt$. The term $s_{J,k}$ shows the smooth coefficients and $d_{J,k}$ shows the detail coefficients. The coefficients $s_{J,k}$ and $d_{J,k}$ measure the share of the corresponding wavelet compared to the total signal. The term 2^j is the scale factor and shows the dilation element that controls the length of the wavelet and the term $2^j k$ is the translation factor and stands for the location element. As the index j gets larger, then the scale factor 2^j becomes larger in value which makes the function to more spread out. The decomposed signals can also be defined as follows:

$$S_J(t) = \sum_k S_{J,k}\phi_{J,k}(t) \quad (20)$$

$$D_J(t) = \sum_k d_{J,k}\psi_{J,k}(t) \quad (21)$$

so that $S_J(t)$ and $D_J(t)$ show smooth signals and detail signals, respectively, and provide the decomposition of a signal $y(t)$ into orthogonal components at different scales (Yang et al., 2016). The extent of localization in time domain (Δt) and frequency $(\Delta\omega)$ domain features the wavelet function. One of mostly used wavelets is the Morlet wavelet. The Morlet wavelet can be given as

$$\psi(t) = \pi^{-1/4}e^{i\omega_0 t}e^{-\frac{1}{2}t^2}, \quad (22)$$

where ω_0 is taken as the central frequency parameter while t is taken as time parameter without imposing any dimension. The parameter ω_0 is usually taken as 6 to have the admissibility property that the wavelet function has zero mean and is localized in both time and frequency space (Torrence and Compo, 1998; Grinsted et al., 2004).

The wavelet function in CWT is stretched out in time by variation and normalization of its scale (s) to get unit energy. The CWT of any $x(t)$ given the wavelet ψ is given as

$$W_x(\mathrm{t},\mathrm{s}) = \frac{1}{\sqrt{\mathrm{s}}}\int_{-\infty}^{\infty} x(t)\,\bar{\psi}\left(\frac{t-\mathrm{t}}{s}\right)dt\ . \quad (23)$$

$W_x(\mathrm{t},\mathrm{s})$ is obtained by projecting the specific wavelet $\psi(\cdot)$ onto selected time series. Hence, the CWT can decompose and then reconstruct the function $x(t)$ (Yang et al., 2016).

4.2 Univariate and Bivarite Tools

4.2.1 The Wavelet Power Spectrum

The term $(WPS_x) = W_x\overline{W}_x = |W_x|^2$ corresponds to wavelet power spectrum and gives a measure of the local variance. That is, “by varying the *wavelet scale* s and translating along the *localized time index* t one can construct a picture showing both the amplitude of any features versus the scale and how this amplitude varies with time" (Torrence and Compo, 1998, p.64). For a complex-valued wavelet ψ, the wavelet transform W_x is complex-valued as well. In such a case, the transform can be put as $W_x = |W_x|e^{i\phi_x}$, $\phi_x \in (-\pi, \pi]$ where the term ϕ_x is named as the wavelet phase.

4.2.2 Cross Wavelet Tools

A cross wavelet transform of two time series $y(t)$ and $x(t)$ can be defined as $W_{yx} = W_y \bar{W}_x$ and absolute value of it, $|W^{xy}|$, is called as the cross wavelet power. Note that the cross wavelet transform detects regions in time frequency space in which the series show high joint power. Putting it differently, the time frequency space gives the local covariance between the two signals at each frequency or scale (Yang et al., 2016). The complex wavelet coherence of y and x is given by

$$\varrho_{yx} = \frac{S(W_{yx})}{\left[S(|W_x|^2)S\left(|W_y|^2\right)\right]^{1/2}} \tag{24}$$

where S shows the smoothing parameter in both time and scale. If the smoothing is not applied, the coherence turns to equal to 1 at all scales and times. To provide the smoothing of the time series, the convolution in time with a Gaussian window and in scale with rectangular window is used (Aguiar-Conraria et al., 2008). The smoothed cross-wavelet transform of y and x can be denoted as $S_{yx} = S(W_{yx})$. Besides, the square root of the smoothed wavelet powers of x and y can be denoted as $\sigma_x = \sqrt{S(|W_x|^2)} = \sqrt{S_{xx}}$ and $\sigma_y = \sqrt{S\left(|W_y|^2\right)} = \sqrt{S_{yy}}$, respectively. Thus, the complex wavelet coherence can be denoted as $\varrho_{yx} = \frac{S_{yx}}{\sigma_x \sigma_y}$. Also, the wavelet coherence, R_{yx}, arises as the complex wavelet coherence in absolute value. That is, $R_{yx} = |\varrho_{xy}| = \frac{|S_{xy}|}{\sigma_x \sigma_y}$. By using a complex-valued wavelet, we can obtain the phase diagram of the wavelet transform of series and by obtaining phase differences between two series we can capture the phase delay between oscillations in these series as a function of frequency (Bloomfield et al., 2004). Putting it differently, the phase difference displays the relative positions of two series in a pseudo-cycle (Aguiar-Conraria et al., 2008). We define the complex wavelet gain of y over x as $\mathcal{g}_{yx}$ such that $\mathcal{g}_{yx} = \frac{|S_{yx}|}{S_{xx}} = R_{yx}\frac{\sigma_y}{\sigma_x}$ and the wavelet gain as $G_{yx} = \frac{|S_{yx}|}{S_{xx}} = R_{yx}\frac{\sigma_y}{\sigma_x}$ that stands for the modulus of the complex wavelet gain. Here, the wavelet gain can be interpreted as the modulus of the regression coefficient in the regression of y on x at each time and frequency (Aguiar-Conraria et al., 2018).

4.3 Multivariate Wavelet Tools

In this section we define the multivarite tools i.e., multiple wavelet coherence, partial wavelet coherence, partial wavelet phase-difference and partial wavelet gain in the case of three series x, y and z. The square of multiple wavelet coherence between the series y and other series, x and z is given by $R^2_{y(xz)} = \frac{R^2_{yx}+R^2_{yz}-2R(\varrho_{yx}\,\varrho_{xz}\,\overline{\varrho_{yx}})}{1-R^2_{xz}}$ and the positive square root of it gives the multiple wavelet coherence, denoted by $R_{y(xz)}$. The complex partial wavelet coherence between y and x, after controlling for z, is given by $\varrho_{yx,z} = \frac{\varrho_{yx}-\varrho_{yz}\overline{\varrho_{xz}}}{\sqrt{(1-R^2_{yz})(1-R^2_{xz})}}$. The absolute value of $\varrho_{yx,z}$ is named as the partial wavelet coherence between y and x, after controlling for z and denoted by $R_{yx,z}$. Also, the angle of $\varrho_{yx,z}$ is named as the partial wavelet phase-difference between y and x, after controlling for z and denoted by $\phi_{yx,z}$. The complex partial wavelet gain between y and x, after controlling for z, $\mathcal{g}_{yx,z}$ is defined as $\mathcal{g}_{yx,z} = \frac{\varrho_{yx}-\varrho_{yz}\overline{\varrho_{xz}}}{(1-R^2_{xz})}\frac{\sigma_y}{\sigma_x}$ and the partial wavelet gain corresponds to absolute value of the complex partial gain and is denoted by $G_{yx,z}$, such that $G_{yx,z} = \frac{|\varrho_{yx}-\varrho_{yz}\overline{\varrho_{xz}}|}{(1-R^2_{xz})}\frac{\sigma_y}{\sigma_x}$.

In interpreting the partial phase-difference between y and x after controlling for z, $\phi_{yx,z}$, a phase difference of zero denotes that the time series move together at the related frequency. When $\phi_{yx,z}$ is between 0 and $\frac{\pi}{2}$ i.e., $\phi_{yx,z} \in \left(0,\frac{\pi}{2}\right)$, then both series are in-phase meaning that they are positively-related and y leads x. When $\phi_{yx,z} \in \left(-\frac{\pi}{2},0\right)$, then both series are in-phase but now x leads y. Besides, an π (or $-\pi$) phase difference shows an *anti-phase* relationship. When $\phi_{yx,z} \in \left(\frac{\pi}{2},\pi\right)$, then x leads y and when

$\phi_{yx,z} \in \left(-\pi, -\frac{\pi}{2}\right)$, then y leads x. It is given the corresponding phase difference diagram in Figure 4.1.

4.4 Notes on Significance Testing, Edge Effects and Frequency Intervals

Testing significance arises as a remarkable step in discussion of the wavelet measures. As pointed out by Ge (2008) that in the wavelet analysis, "even large peaks could be merely artifacts resulting from randomness due to the nature of the problem and errors in the measurements" (Ge, 2008: 3825). Here, to reject those artificial values with certain degrees of freedom, an exhaustive effort has been devoted to the significance testing. In evaluating the statistical significance of a wavelet power of economic series, the commonly held assumption is that the wavelet power spectrum is either white noise corresponding to a flat fourier spectrum or red noise corresponding to rising power with decreasing frequency (Torrence and Compo, 1998).

In evaluating the significance of the wavelet power spectrum we follow this sampling distribution. In testing the significance of multiple and partial coherencies, however, instead of relying only on the assumption that time series strictly follow white noise or red noise (AR1) we assume also that the economic time series may follow ARMA processes.[11] In this regard we follow Aguiar-Conraria et al., (2018) that define an alternative null hypothesis for testing significance. That is, they fit an ARMA$(1,1)$ model to each series and obtain new samples by drawing errors from a Gaussian distribution with a variance being equal to that of estimated error terms. We perform Monte-Carlo surrogates for 5000 times to reach critical values with 5% and 10% significance levels. The 5% and 10% significance levels are denoted by black and gray contours in the figures below, respectively.

Also, in computation of the continuous wavelet transform of the time series, since the values transformed at the start and the end of the series include missing or repeating values, the corresponding results may suffer from edge effects. Hence, it is

[11]We report the computed wavelet measures under only the ARMA$(1,1)$ significance testing. The results with AR(1) gives slight differences of significance contours.

identified the cone-of-influence (COI) by drawing a black line in the plots of wavelet transforms to carefully interpret the results. The wavelet coherencies and wavelet powers are plotted as heat-maps, with colors drawing up from blue (giving small coherence) to red (high coherence).

Lastly, we determine two frequency intervals instead of three as assumed by Aguiar-Conraria et al. (2018) as our sample encounters a relatively short period of time and report the partial phase-difference and gain diagrams for each intervals. Note that Turkey has short-winded recessions and relatively short expansions and tends to face with sharp falls in output during recessions followed by strong subsequent recoveries (Altuğ and Bildirici, 2012). Because of Turkey's idiosyncratic experiences, thus, the time durations are set to be strictly shorter compared to those of business cycles in developed countries. Following Alp et al., (2012) and Altuğ and Bildirici (2012) we set the intervals of the business cycles for Turkish economy as follows: short end of business cycles (high business cycles) is between 1 to 3 years and long run end of cycles (medium cycles) is between 3 to 8 years given the findings that the maximum cycle length is 30 quarters (Alp et al., 2012).

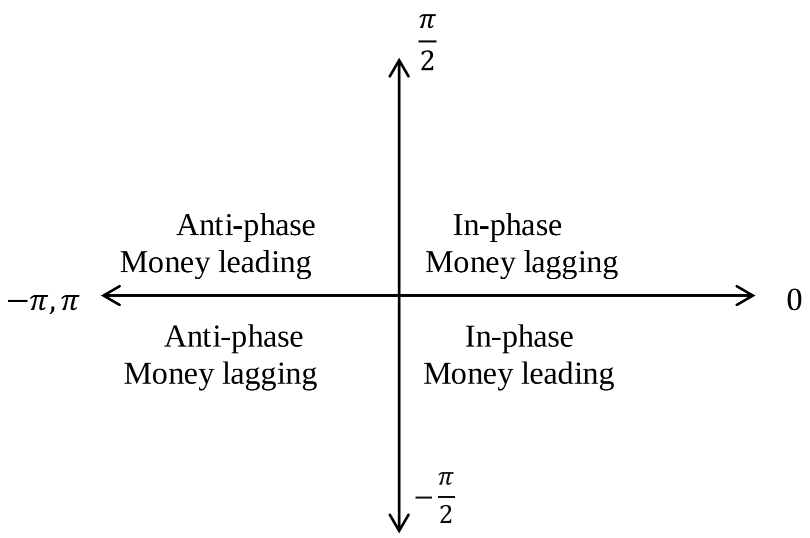

Figure 4.1:Phase-difference Diagram ψ_{xy}

4.5 Data

The data set consists of monthly series of industrial production index (IPI), consumer price index (INF), TRlibor rate (INT) and both narrowly and broadly defined monetary aggregates (SSM1, DM1, SSM2, DM2). The data sources are CBRT[12], TUIK[13], TBB[14] and TKBB[15]. The time period is from 2007:1 through 2018:4. All the series except for the TRlibor rate are used in the form of year-over-year percentage changes.[16] The transformed series are close to have normal distribution, so that we confine ourselves to Monte Carlo simulation methods in assessing the statistical significance against AR(1) and ARMA(1,1). The indexed series of industrial production index, consumer price index and monetary aggregates are normalized to 100 at the start of the sample period. The year-over-year industrial production growth is taken as a proxy for output growth while the yearly change in the CPI inflation is used to capture the dynamics of aggregated prices. TRLibor rate (Turkish lira Reference Interest Rate) is taken as a reference interest rate to summarize the central bank's policy set (see Alp et al., 2010; Gürkaynak et al., 2015).[17,18] The TRlibor rate is used in its level. The monetary aggregates are defined and used under different specifications: i) the benchmark indexes of simple-sum and Divisia monetary aggregates at M1 and M2 levels, ii) benchmark index with participation banks and iii) expectations-augmented index.

In Tables 4.1 and 4.2 below the Pearson correlation coefficients are given along with their significance level to suggest a course of action prima facie on the link between the money and macroeconomic fundamentals. Still we should bear in mind that the correlation coefficients reported below give the degree of the correlation between variables with solely a single value and hide a great deal of the information content across time and frequency domains. This is where the wavelet coherence comes into action. For instance, while it is determined a negative but insignificant link between the monetary

[12] https://evds2.tcmb.gov.tr/
[13] http://www.turkstat.gov.tr/
[14] http://www.trlibor.org/
[15] http://www.tkbb.org.tr/
[16] The results are robust to using monthly changes in series.
[17] The Banks Association of Turkey (TBB) established the TRlibor market in August 2002 to set a reference interest rate among the banks and their clients.
[18] We also use the 2-year government bond returns to stand for the interest rate that summarizes the CBRT's policy stance and reach quite similar results with respect to partial-coherencies between monetary aggregates and state variables.

aggregates ($SSM2$ and $DM2$) and IPI from the Pearson correlation coefficients, the wavelet analysis provides below that during the crisis episode it arises a significantly negative link between monetary aggregates and IPI while in the post-crisis episode the link becomes consistently positive. Besides, even though the Divisia and simple-sum monetary aggregates are positively correlated with the CPI inflation they differ in respect to their significance. The partial wavelet analysis reported below, however, draws different pictures on co-movements of monetary aggregate with the CPI inflation at different time periods and frequencies.

Table 4.1: The Pearson Correlation Coefficients among IPI, INF, INT and Simple-sum M2 under the Benchmark Index

	IPI	INF	INT	MS
IPI	1			
INF	-0.0486 (0.572)	1		
INT	-0.2270 (0.076)	0.5233 (0.000)	1	
MS	-0.0863 (0.315)	0.0962 (0.263)	0.3579 (0.000)	1

Note: The numbers in parentheses are p-values for the correlations based on the permutation test.

Table 4.2: The Pearson Correlation Coefficients among IPI, INF, INT and Divisia M2 under the Benchmark Index

	IPI	INF	INT	MS
IPI	1			
INF	-0.0486 (0.572)	1		
INT	-0.2270 (0.076)	0.5233 (0.000)	1	
MS	-0.0828 (0.336)	0.1451 (0.090)	0.2484 (0.003)	1

Note: The numbers in parentheses are p-values for the correlations based on the permutation test.

4.6 Results

In this section we estimate and discuss the multiple wavelet coherencies, partial coherencies, partial phase-differences and partial gains between money growth, industrial production growth, CPI inflation and the reference interest rate.[19] In the left-hand side of the figure 4.2 we plot the year-over-year percentage change of industrial production,

[19] All estimations were made using the toolbox (ASToolbox2018) for MATLAB developed by Aguiar-Conraria and Soares. (https://sites.google.com/site/aguiarconraria/joanasoares-wavelets). We are grateful to the authors for providing the codes.

inflation and Divisia M2 under benchmark case and the TRlibor rate in its level. Other specifications of monetary aggregates under benchmark case are displayed in Appendix A. The right-hand side of the figure denotes the corresponding wavelet power spectra which display the measure of the variance distribution of variables in the time and frequency plane.

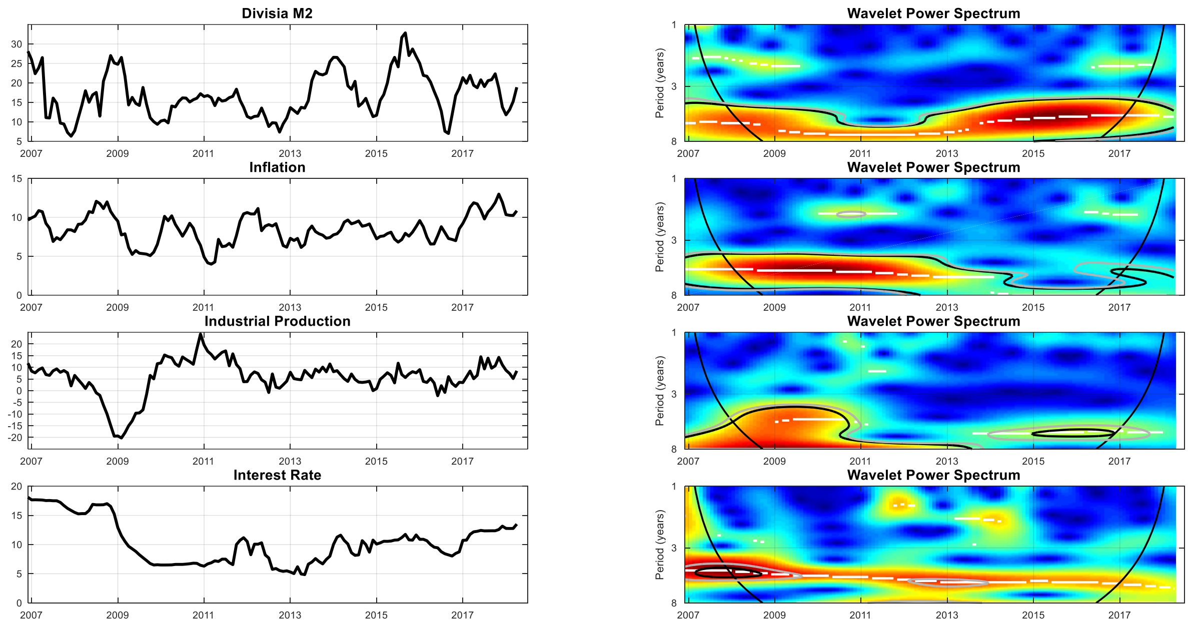

Figure 4.2: Wavelet Power Spectrum of DM2, INF, IPI and INT

From the wavelet power spectra of the time series we can deduce at first glance that all of the time series have significant variability occurring at relatively low frequencies i.e., larger than three years. The wavelet power spectrum of Divisia monetary aggregate for M2 level gives significant variance during the whole sample period prevailing for the long-run end of cycles. Besides, starting from the year of 2013 the variability goes towards higher frequencies (from 8 years to 4 or 5 years). The wavelet power spectrum of inflation denotes firstly significant variability until the year of 2013 with highest variance during the crisis years. Besides, the variability of inflation persists but weakens thereafter. Note here that the significant variance of the inflation that we encounter prevails in the long period. It is only the years of 2011 and 2017 around which the inflation features high variance but for the short-end of cycles. Hereby, the inflation variability of medium cycles is not in the first glance confirm with the intentions of a policy making operating under the inflation targeting regime. Regarding the variability of the industrial production index, the wavelet power spectrum shows significant variance during the financial crisis episode occurring at long cycles. It shows also high variability around the year of 2016 that vanishes away thereafter. The power spectrum provides also that the variability of the reference interest rate is significantly high during the whole sample period and occurs at long end of cycles. However, it is observed that the highest variance of the interest rate occurs in the beginning of the crisis in 2008 being in rapport with the counter-cyclicality of the policy rates with the onset of the crisis.

4.6.1 The Link between Inflation and Alternative Measures of Monetary Aggregates

On the top of the Figure 4.3 the multiple coherence among the series of inflation, interest rate and simple-sum M1 is given under the benchmark case.[20] Note that the multiple coherence can be taken as a time-frequency analog of the R^2 in a regression and measures the overall fit of the explanatory variables in the time-frequency domain (Aguiar-Conraria et al., 2018). Accordingly, the areas with a high multiple coherence imply that the selected monetary aggregate and the interest rate jointly and significantly explain the CPI inflation for those regions.

The Figures 4.3 and 4.4 provide that narrowly measured monetary aggregates and policy rate jointly explain the inflation until the year of 2012 and that significant multiple coherencies arise for both high and medium business cycles during this period. Replacing the simple-sum aggregates with their Divisia counterparts at M1 (see Figure 4.4) does not improve the overall coherence. Also, using the monetary aggregates at M2 results multiple coherence to arise only at low frequency band and for the pre-2012 period. It arises a significant coherence among inflation, interest rate and money when it

[20] As previously stated we construct Divisia aggregates under different specifications. For convenience we discuss the results of multiple wavelet analysis with monetary aggregates under the benchmark index and report the remaining two specifications of monetary aggregates i.e., aggregates based on the Divisia index with participation banks and expectations-augmented index in Appendix A (Figures A.2 and A.3, respectively) to avoid any confusion in interpreting the results.

is used M2 for the post-2015. Besides, using Divisia aggregates at M2 provides relatively long-lasting multiple coherence in the post-2015 period.

In the next step we provide partial coherencies between the monetary aggregates and the inflation filtering out the impact of the interest rate to observe the strength of the co-movement between money and inflation in an interest-rate oriented policy environment and whether the Divisia type aggregates include any additional information compared to simple-sum money in explaining inflation. Also, we interpret the partial phase-differences for regions for which there occur significant partial coherencies to comment on the direction of the causality between time series.[21] Lastly, following Aguiar-Conraria et al. (2018), we add the partial gains to obtain parametric estimations over time-frequency domains in comparing the information gained from alternative monetary aggregates. In interpreting the partial gains as a measure of reaction of the inflation to monetary aggregates we do not compare the partial gains with an estimated baseline value obtained from a linear time-series model. Instead, we compare the partial gains from inflation and industrial production to alternative specifications of money. Note also that we provide the partial phase-difference and gain diagrams for two frequency intervals: 1~3 year frequency band for the short end of business cycles and 3~8 year for the long-run end of cycles.

When the money is narrowly defined (SSM1 and DM1), it arises significant partial coherence for the short end of business cycles (1~3 years) between the period of 2009 – 2011 where the phase differences are unexpectedly located in the interval $(-\pi, -\frac{\pi}{2})$, showing an anti-phase link between money and inflation with the former precedes. However, for the same period and at longer cycles we observe an in-phase link between money and inflation where the phase difference points that the inflation leads the money. Lastly, for the post-2016 period and at high frequency we observe a partial coherence in which the money leads the inflation. As previously stated we assess the time-frequency partial gains for regions in which the partial coherencies are significant so as to see extent to which inflation is responsive to alternative formations of monetary aggregates. In this regard, we observe similar partial gains from both simple-sum or

[21] No contribution has been made so far in controlling directly the significance of the phase differences.

Divisia M1 for the regions of significant partial coherence. Considering the post-2016 period, among others, the gains from inflation due to simple-sum M1 and Divisia M1 are similar and around 0.5 during this period.

When the money supply is measured by SSM2 or DM2, a less penetrating partial coherence between money supply and inflation arises after controlling the impact of interest rate. At the short end of business cycles i.e., 1~3 year frequency band we do not observe any worth-mentioning coherence between broadly defined aggregates and inflation. At the long run end of cycles i.e., 3~8 year frequency band, a worth-mentioning partial coherence between money defined either by SSM2 or DM2 and inflation that becomes visible between the years 2010 and 2012. As the phase differences are located in the interval $(0, \frac{\pi}{2})$ during this period we see an in-phase relation and causality from inflation to monetary aggregates. Besides, the partial gains are almost the same across SSM2 and DM2 and quite low (less than 0. 5) during this sub-period.

These observations lead us to sum up firstly that using the multiple wavelet coherence analysis we fail to observe diffusive partial coherencies between yearly money growth and yearly CPI inflation at least for the long-run end of cycles controlling for the reference interest rate for the sample period that witnesses a direct adoption the inflation-targeting policy stance. Besides, the use of Divisia type monetary aggregates does not give a substantially different partial coherence with the inflation compared to the official aggregates.

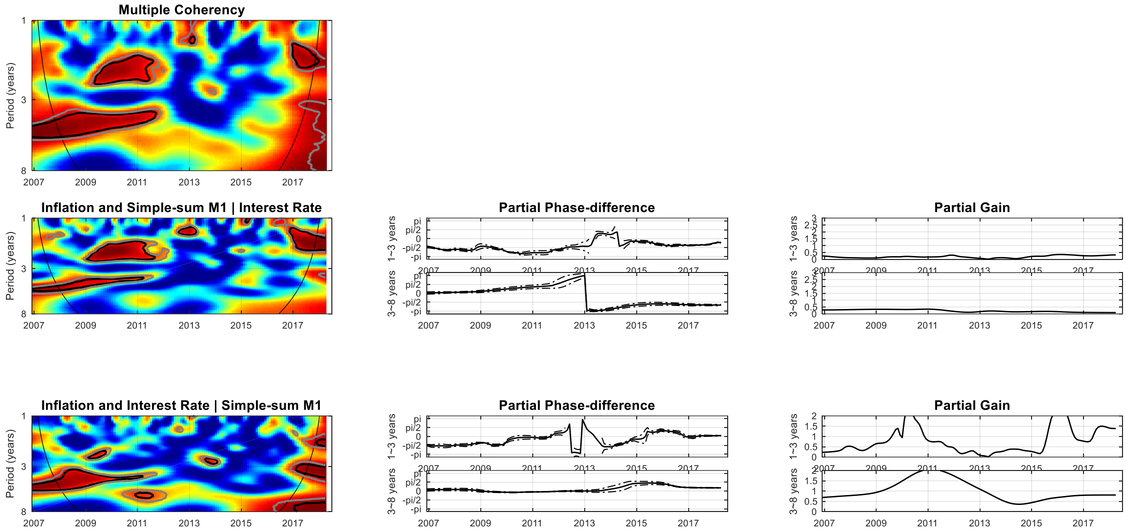

Figure 4.3: Multiple and Partial Coherencies, Partial Phase Differences and Partial Gains among Inflation, SSM1 and Interest Rate

Note: On the top of the figure it is given the multiple coherencies among three series Y, X and Z. On the left of the figures it is given the partial coherence between series Y and X, controlling for Z. For both multiple and partial coherencies, the black and grey contours refer to the 5% and 10% significance levels obtained from Monte Carlo simulations using phase randomized surrogate series, respectively. The color scale for the wavelet coherencies ranges from blue (low coherence) to red (high coherence). The cone of influence that shows regions with edge effects is denoted by curved-black line. On the middle of the figures it is given phase-difference diagrams between the series Y and X, controlling for Z under two different frequency bands. On the right of the figures it is given the partial gain from Y due to X, controlling for Z under two different frequency bands. In the vertical axis the period is expressed in terms of years. The horizontal axis contains the sample period i.e., between 2006:12 and 2018:4.

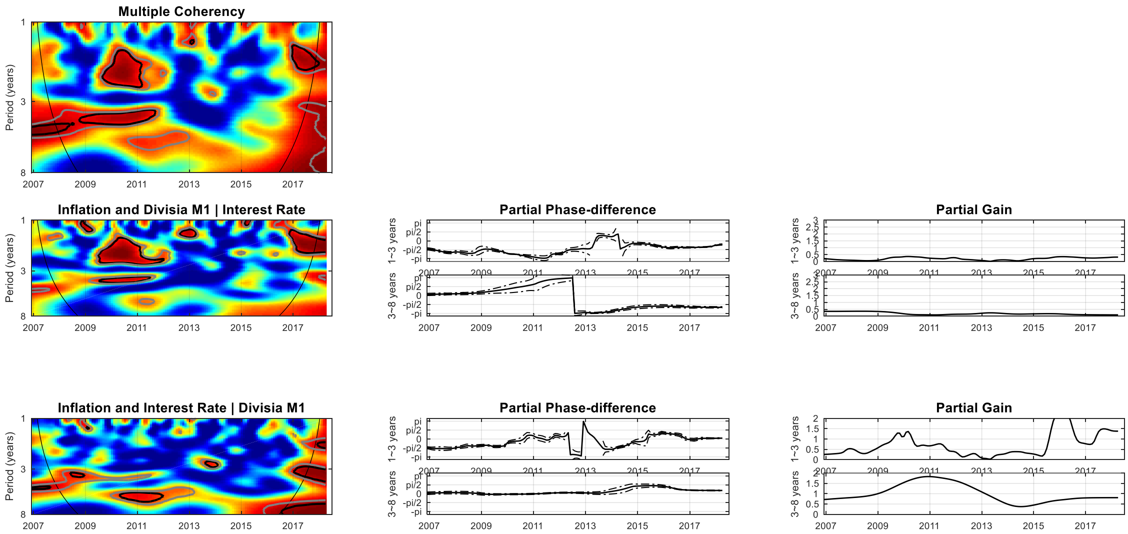

Figure 4.4: Multiple and Partial Coherencies, Partial Phase Differences and Partial Gains among Inflation, Divisia M1 and Interest Rate

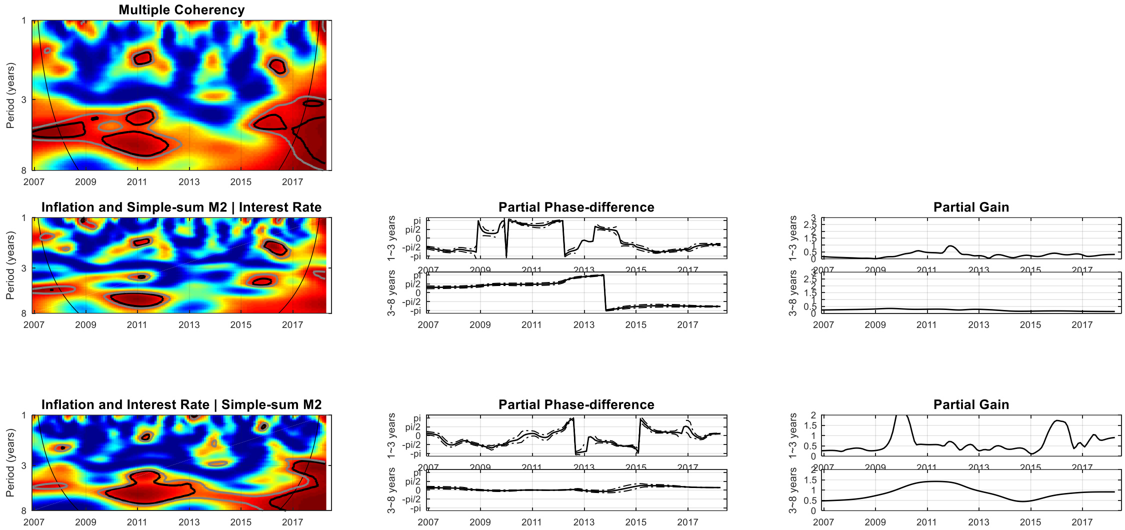

Figure 4.5: Multiple and Partial Coherencies, Partial Phase Differences and Partial Gains among Inflation, SSM2 and Interest Rate

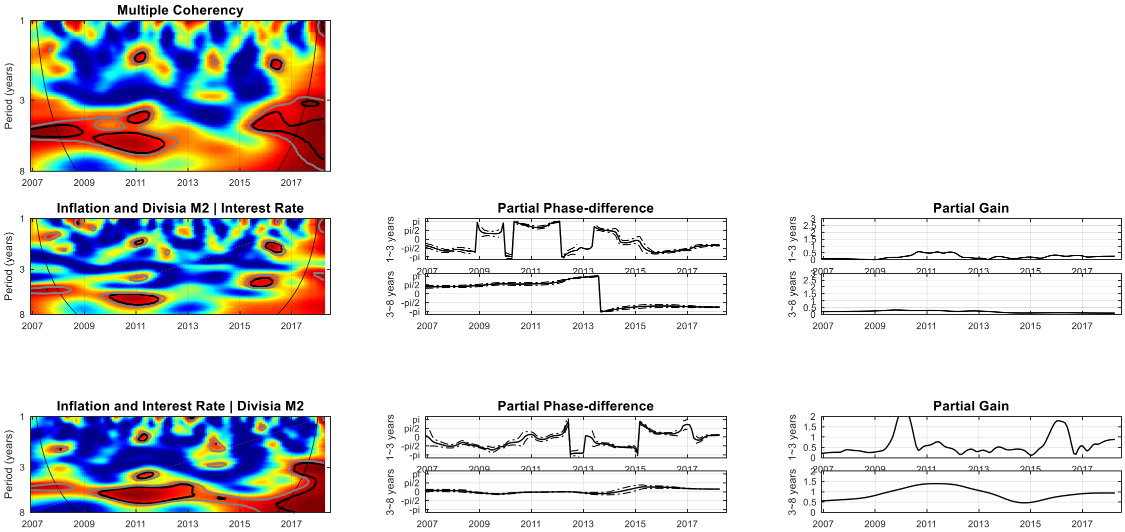

Figure 4.6: Multiple and Partial Coherencies, Partial Phase Differences and Partial Gains among Inflation, Divisia M2 and Interest Rate

4.6.2 The Link between Industrial Production and Alternative Measures of Monetary Aggregates

In this section we report the multiple – partial coherencies, phase-differences and partial gains between alternative formations of monetary aggregates and industrial production after controlling for the interaction of interest rate with the industrial production. Firstly, Figures 4.7 and 4.8 give multiple coherencies for simple-sum M1 (SSM1) and Divisia M1 (DM1), respectively. It is observed from the figures that along with the interest rate, both SSM1 and DM1 co-move with the industrial production at different frequency bands. Prevailing for both SSM1 and DM1, the multiple coherence among money, interest rate and industrial production is significant for i) the period 2008 and 2010 particularly at 3∼8 year of business cycles and ii) the period between 2014 and 2018 at both high and low frequency bands. Besides, as in the case of inflation we do not observe any worth mentioning difference in between SSM1 and DM1 in multiple coherence.

When the narrowly defined monetary aggregates are replaced with the broadly defined ones i.e., with SSM2 and DM2, (Figures 4.9 and 4.10, respectively) we observe similar penetrating patterns for both multiple coherencies among monetary aggregates, interest rate and industrial production. That is, the multiple coherence is significant for the periods between i) 2008 and 2011 and ii) 2013 and 2018 particularly at 3∼8 year of business cycles. Measuring money by DM2, however, makes the multiple coherence less persistent for the latter period. Notice here that the high multiple coherence of monetary aggregates with interest rate and industrial production does not necessarily mean partial causation. For analyzing the latter, we use partial phase differences and partial gains below.

At first glance, the Figures 4.7 and 4.8 show significant partial coherence between narrowly defined monetary aggregates and industrial production during the crisis years at 3∼8 year of cycles. In this time-frequency domain, the phase differences are located in $(\frac{\pi}{2}, \pi)$ implying unexpectedly an *anti-phase* relationship between money and industrial production where the response of the latter comes with a delay. The partial gain due to a change in Divisia M1 is more than 1.5 points during this period and higher than the simple-sum M1. We also observe a robust partial coherence between money and industrial production for the period between 2013 and 2016 at low frequencies. Even though it arises *in-phase* relationship between money and industrial production as the partial phase difference is consistently located at (0) we cannot interpret on any lead-lag relationship.

Regarding the partial coherencies for broadly defined aggregates, we track a robust *anti-phase* co-movement of SSM2 with industrial production beginning from 2008 and spreading to 2011 for the long-run end of cycles. Replacing SSM2 with DM2 gives a similar pattern of an unexpected *anti-phase* coherence but occurring between 2008 and 2010. The corresponding phase difference for SSM2 is consistently located in $(\frac{\pi}{2}, \pi)$ while that for the DM2 is located in (π) which denotes a more delayed impact of Divisia M2 on the industrial production compared to officially announced M2. During this period the partial gain from the SSM2 is higher than the DM2. As opposed to the crisis years, in more tranquil periods i.e., between 2014 – 2017 the partial phase difference diagram lies in (0) and thus signals for in-phase relation between M2 and industrial production. Besides, it does not arise any lead-lag relation across these series. Lastly, using broadly defined monetary aggregates we are unable to draw conclusions on the link with the industrial production for the short-run end of cycles given that the partial coherencies dies quickly at high frequencies.

Grounded on above mentioned observations it arises different partial coherencies of monetary aggregates with the industrial production across crisis and post-crisis episodes. Besides, Divisia and simple-sum monetary aggregates differ with respect to their partial-coherencies during the crisis episode while they do behave along similar lines during more tranquil times. Lastly, partial coherence of monetary aggregates with industrial production is quite limited at high frequency bands.

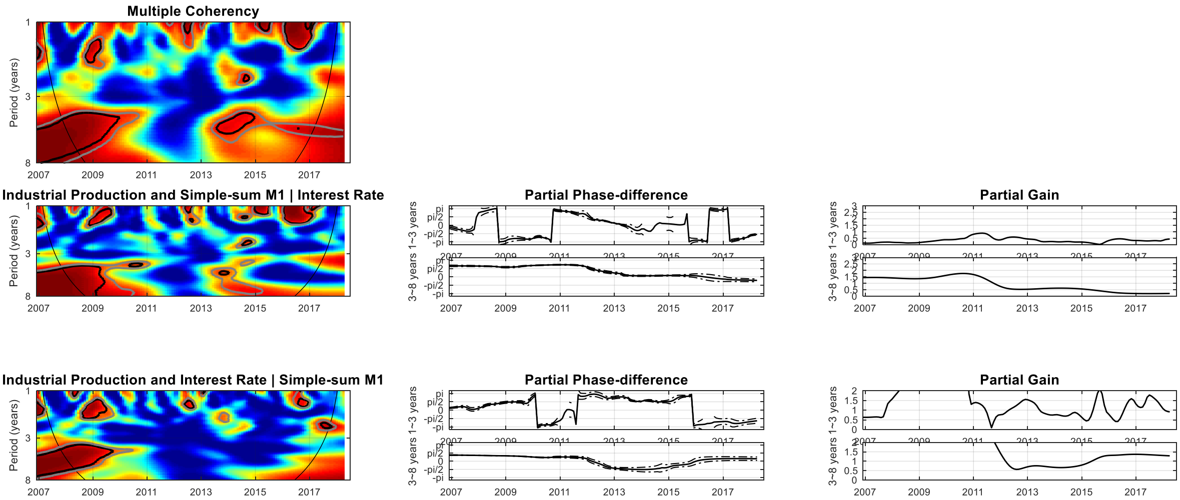

Figure 4.7: Multiple and Partial Coherencies, Partial Phase Differences and Partial Gains among Industrial Production, SSM1 and Interest Rate

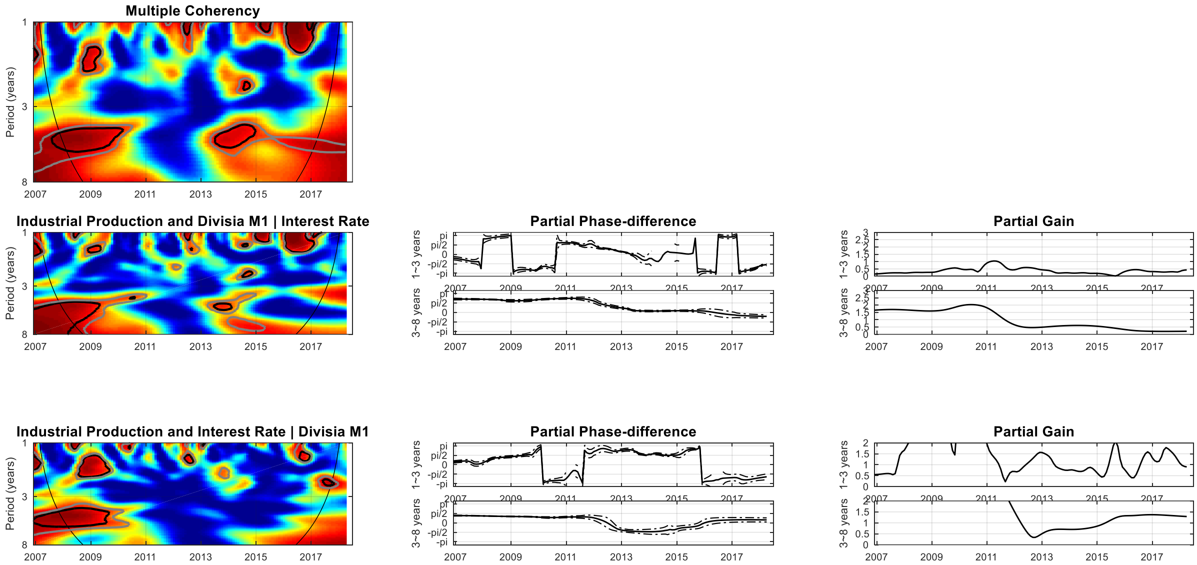

Figure 4.8: Multiple and Partial Coherencies, Partial Phase Differences and Partial Gains among Industrial Production, Divisia M1 and Interest Rate

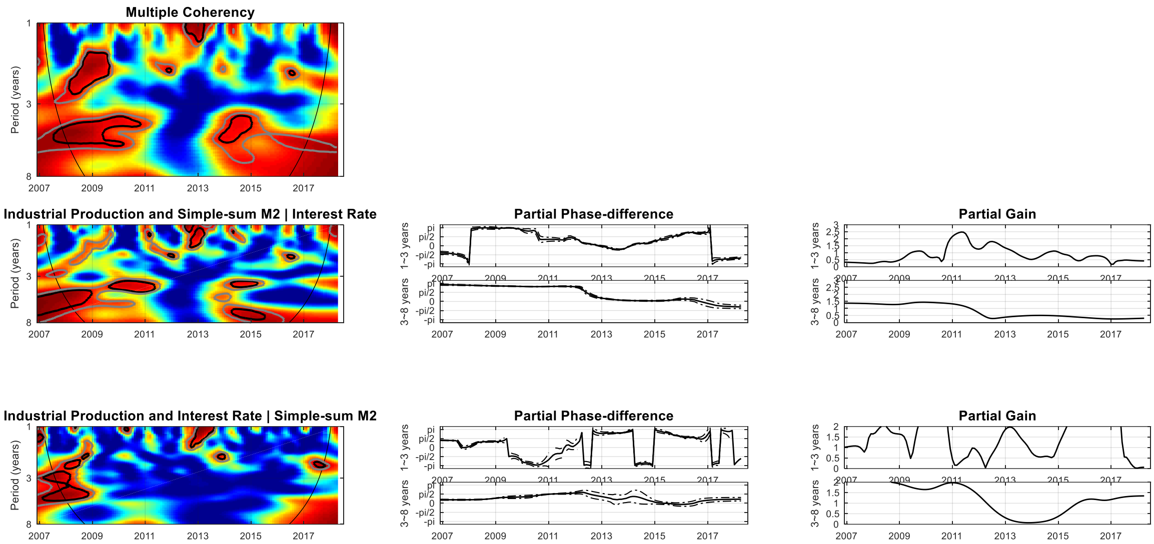

Figure 4.9: Multiple and Partial Coherencies, Partial Phase Differences and Partial Gains among Industrial Production, SSM2 and Interest Rate

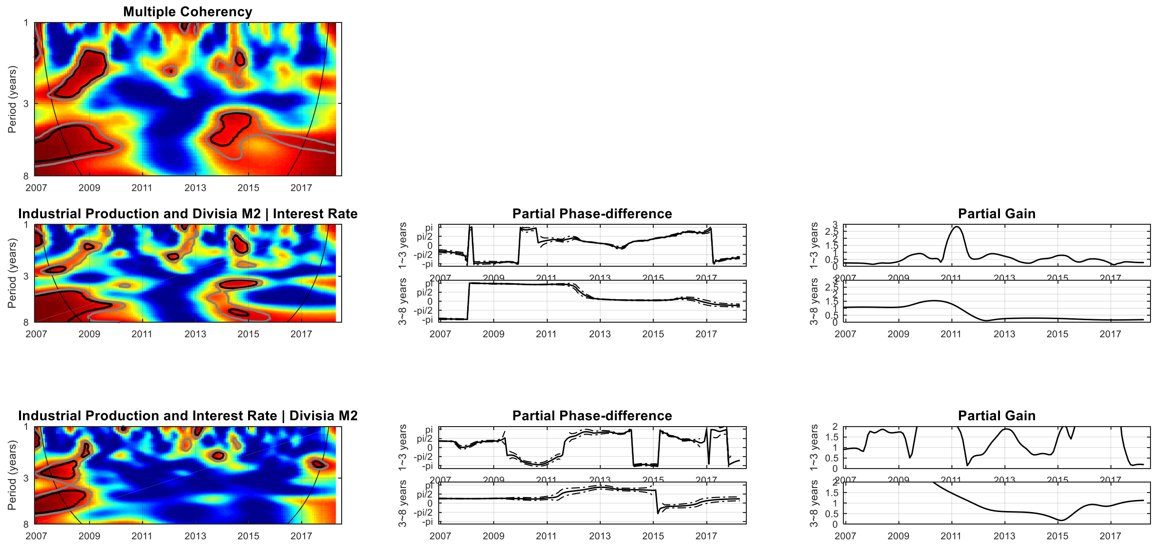

Figure 4.10: Multiple and Partial Coherencies, Partial Phase Differences and Partial Gains among Industrial Production, Divisia M2 and Interest Rate

4.6.3 The Link between Inflation, Industrial production and Interest Rate under Inflation Targeting Regime

In this section, we report the partial coherencies, phase-differences and partial gains between the benchmark interest rate, the inflation and industrial production controlling for the interaction of monetary aggregates with state variables to draw information on the policy making preferences in the stance of monetary policy.[22]

Firstly, the partial coherencies between interest rate and inflation point a shift in the policy at around the year of 2011 under narrowly defined aggregates and of 2013 under broadly defined aggregates after which the significant coherence between the interest rate and the inflation diminishes in the long run end of cycles. This conclusion is expected as this period, indeed, bears witness to a policy shift from an objective of price stability *per se* to that of price and financial stability with a re-designation of policy instruments using reserve requirements, asymmetric interest rate corridor and a reserve options mechanism (ROM) along with the policy rate (Uysal, 2017). In such a multiple-rate environment, different instruments under an unconventional monetary policy stance brought the impacts of policy-induced changes into view but making the link between the policy rate and the inflation to be more blurred. Still, when we control for the Divisia M2 it arises a significant partial coherence between the reference rate and the CPI inflation after 2013 and for a certain period of time, which is lacking when the simple-sum aggregates are used to measure money. Further, we do not observe any robust partial coherence between these two series in the short-run end of the series

Regarding the partial-phase difference analysis, after controlling narrowly defined aggregates (SSM1 and DM1) the phase differences are located consistently in (0) implying an in-phase co-movement between the interest rate and inflation for the long-run end of business cycles and between 2009 – 2011 (Figures 4.3 and 4.4). However, as it is located in (0) we cannot interpret on any lead-lag relationship between inflation and interest rate. The same result is also valid for broadly defined monetary aggregates (SSM2 and DM2), as the phase differences are consistently located at (0) starting from the year

[22] We interpret the partial coherencies among CPI inflation, production and interest rate controlling monetary aggregates belonging to the benchmark case.

of 2009 through 2013, it arises no lagging link between the interest rate and inflation after controlling SSM2 or DM2. One exception is the period between 2013 and 2015 through which the partial phase difference is located in the interval $(0, \frac{\pi}{2})$ when it is used Divisia M2 to measure the money. In this case, the inflation leads the reference rate (Figur 4.6). For this period the partial gain diagram provides 0.5 point of coefficient of the inflation on the interest rates at low frequency bands.

Regarding the partial coherence between industrial production and the interest rate after controlling alternative measures of money, it is revealed a less penetrating coherence over time and frequency. That is, the partial coherencies between the reference rate and annual industrial production growth become weak throughout the sample period except for the pre-crisis years at low frequency bands. Further, we observe robust partial coherencies between these two series at 1~3 years frequency band which quickly die out. When we control narrowly defined aggregates, the partial coherence is located in the interval $(-\pi, -\frac{\pi}{2})$ from 2016 through 2018, so that the industrial production growth leads but negatively the reference rate and the corresponding partial gain from industrial production growth becomes more than 1 points. Further, the use of Divisia money as the control variable does not change the partial coherence and causality between the industrial production and interest rate series.

5. OUT-OF-SAMPLE FORECASTING

In Section 3 we estimate the St. Louis type reduced-form model which serves as an in-sample- estimation. In this section, we employ out-of-sample forecasting of inflation and economic activity with monetary aggregates in an unrestricted VAR model. We forecast the industrial production and CPI inflation over one- and three-months ahead horizons to measure the relative performance of alternative monetary statistics. For the training sample we define two estimation periods: i) the period between 2006:1 and 2008:9 and ii) the period between 2006:1 and 2016:12. In the first case, out-of-sample forecasting is upheld for the period 2008:10 – 2010:10 in which Turkish economy operated largely under a turbulent regime. In the forecasting period, starting from last quarter of 2008 that coincides with the collapse of Lehman Brothers, the Turkish economy confronted with a sudden tumble in its industrial production and employment rate, fall in export volume, sizable net capital outflows and depreciation of its domestic currency (Uygur, 2010). By using this period, we evaluate the relevance of the argument that the Divisia type monetary aggregates diverge from their simple-sum competitors in the pre-crisis episodes and outperform better in capturing the changes in economic activity and prices during the crisis years. In the second case, the estimation period is extended to include the post-crisis episode i.e., from 2006:1 through 2016:12 and the forecasting over one- and three-months ahead horizons is upheld between 2017:1 and 2018:4 to forecast for a relatively tranquil period of time.

In determining the time series included in the VAR model we largely follow the related literature (Barnett et al., 2006 and Elger et al., 2006, among others). Accordingly, we use a small-scale unrestricted VAR model containing industrial production index (Y), consumer price index (P), 2-year government bond returns (R) and monetary aggregates (M). The monetary aggregates are defined for different levels (narrow and broad definitions) and methods of aggregation (simple-sum and Divisia aggregates). Besides, Divisia type monetary aggregates are defined and tested against their simple-sum counterparts under three specifications (benchmark index, the index that includes participation banks and expectations-augmented index). The logarithmic differences of the series (i.e., $100 * \left(ln(x_t) - ln(x_{t-1})\right)$ are used in the VAR model.[23] The series are found to be stationary using standard unit-root tests (i.e., augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests). Using the Akaike (AIC) and Schwarz (SIC) information criteria we determine that the VAR model has one lag ($p = 1$) with a maximum lag-length of 3 months for the turbulent period and two lags ($p = 2$) with a maximum lag-length of 8 months for the tranquil period.

For forecast evaluation we utilize three information criteria: root mean squared errors (RMSE), mean absolute errors (MAE) and Theil's U (Theil) statistics. These

[23]We use the first difference of the interest rate variable. For the robustness check, we use i) detrended seasonally adjusted versions of monthly series; ii) quarterly series replacing the industrial production with nominal GDP growth and iii) real GDP growth, real interest rate and real money supply adjusted for the CPI inflation. In all these specifications we obtain largely similar results with a few exceptions.

criteria are defined as follows: Assume that x_{t+h} is the value of a series at time $t+h$ and $\hat{x}_{t+h}$ is the forecasted value of this series at time t. Then,

$$\text{RMSE} = \sqrt{\frac{1}{T_h}\sum_{t=1}^{T_h}(x_{t+h} - \hat{x}_{t+h})^2},$$

$$\text{MAE} = \frac{1}{T_h}\sum_{t=1}^{T_h}|x_{t+h} - \hat{x}_{t+h}|,$$

$$\text{Theil} = \frac{\text{RMSE (model)}}{\text{RMSE (No−change)}} = \sqrt{\frac{\sum_{t=1}^{T_h}(x_{t+h}-\hat{x}_{t+h})^2}{\sum_{t=1}^{T_h}(x_{t+h}-x_t)^2}},$$

where the term h denotes the forecast horizon and T_h denotes the total number of out-of-sample forecasts for the horizon h. In our case, for the forecast period 2008:10 – 2010:10, T_h is equal to 24 and 22 for one- and three months ahead forecasts, respectively and for the forecast period 2017:1 – 2018:4, equal to 16 and 14. RMSE and MAE both measure the magnitude of the forecast errors without indicating whether those errors are positive or negative. However, RMSE criterion measures the magnitude of the error giving higher weights to large but rare errors compared to the mean while MAE measures the magnitude of the errors on average. Besides, true to form, the smaller values these measures have, the better h-ahead forecasts the models make. Also, Theil compares the RMSE of forecasted model with that of a no-change model. In the case of a less than one Theil U coefficient, the estimated model outperforms the naive no-change model and can be taken as a good predictor.

In provision of the forecast evaluation we use the modified version of the test statistic developed by Diebold and Mariano (1995, DM henceforth) to compare the forecast accuracy of the models with alternative definitions of money. The forecasting abilities of two non-nested models are judged under certain specifications of loss functions. In the case of DM test, only the forecast errors are used to determine the loss function. Let $d_t = g(e_{1t}) - g(e_{2t})$ shows the loss differential from the forecast errors, $g(e_{1t})$ and $g(e_{2t})$, of two competing models. The null hypothesis of the DM test is $H_0 = E[d_t] = 0$, meaning that the mean squared forecast errors of two competing models are equal, on average. The alternative, thus, turns out to be choosing the forecasts that yield the smallest error. Hereby, the DM test is defined as

$$\mathrm{DM} = \frac{\bar{d}}{\sqrt{\frac{2\pi\hat{f}_d(0)}{T}}},$$

where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$ denotes the mean of the loss differential and $\frac{2\pi\hat{f}_d(0)}{T}$ is the asymptotic variance estimate of $\bar{d}$ using the heteroscedasticity and autocorrelation-consistent (HAC) estimator due to Newey and West (1994) and truncated kernel with a data-determined bandwidth of $(h-1)$ for h-ahead forecasts (Luger, 2004). Under the null, then the DM test statistic is asymptotically normally distributed given certain regularity assumptions that ensure the central limit theorem to be applicable. Empirical applications, however, show that having normal distribution under the null may lead the DM test to suffer from the small-sample bias and over-reject the null quite a bit. One reason is that "the forecast errors, and hence loss differentials, may be serially correlated…Hence the standard error in the denominator of the DM statistic should be calculated robustly." (Diebold, 2012, p.3). In this regard, Harvey et al. (1997) propose a modified DM test with a small-sample distortion correction to original test statistic. They adjust the DM statistic by the term $\sqrt{\frac{T+1-2h+h(h-1)/T}{T}}$, so that the modified DM test becomes

$$\text{Modified DM} = \sqrt{\frac{T+1-2h+h(h-1)/T}{T}}\,\mathrm{DM},$$

where h denotes the forecast horizon and T denotes the rounds of forecasts for each horizon. In the forecasting exercises, for convenience, we report only one-month ahead forecast horizon i.e., $h = 1$ for both the great moderation period (2008:10 – 2010:10) and the extended period (2017:1 – 2018:4) which implies $T = 25$ and $T = 16$, respectively. Note that under the modified DM test, the statistic values are compared to critical values obtained from a t-distribution instead of a normal distribution. Since we have a relatively small sample size for forecast exercises we implement the modified DM test in controlling the accuracy of forecasts.

5.1 The Unrestricted VAR Model

Let x_t is a n-dimensional vector of dependent series at time t. Assume for a VAR(p) model in which the series x_t are determined by the following process: $\boldsymbol{x}_t = \boldsymbol{A}_0 + \mathbf{A}_1\boldsymbol{x}_{t-1} + \cdots + \mathbf{A}_p\boldsymbol{x}_{t-p}\boldsymbol{\varepsilon}_t$ where $\mathbf{A}_0$ stands for the vector of intercepts, $\mathbf{A}_i$, $i = 1, \dots, p$, denote coefficient matrices and $\boldsymbol{\varepsilon}_t$ is a white-noise disturbance vector. Hereby, the coefficients are estimated grounded on ordinary least squares. Also, the conditional forecast of $\boldsymbol{x}_t$ at $t+1$ is defined as $E_t(\boldsymbol{x}_{t+1}) = \boldsymbol{A}_0 + \mathbf{A}_1\boldsymbol{x}_t + \cdots + \mathbf{A}_p\boldsymbol{x}_{t-p+1}$ for each t. The term E_t provides that the expected value of $\boldsymbol{x}_t$ at $t+1$ is obtained conditional on the set of information $\boldsymbol{X}_t = \{\boldsymbol{x}_t, \boldsymbol{x}_{t-1}, \dots\}$. The conditional forecast for $t+1$ can be generalized for the dynamic forecast at $t+\tau$, defined as $E_t(\boldsymbol{x}_{t+\tau})$.

5.2 Empirical Results: Out-of-Sample Forecasts and Evaluation

Tables 5.1 through 5.4 give the out-of-sample forecasting results with alternative specifications of monetary aggregates in our small-scale VAR model. Though we report the results corresponding to the dynamic stochastic forecasts, conditional forecasts also produce more or less the same results, true to form with smaller forecast errors. Tables 5.1 and 5.2 summarize the one- and three- months forecasts of P and Y for the crisis episode with a short estimation period whereas Tables 5.3 and 5.4 summarize that for the extended period. We exercise the forecasts with simple-sum and Divisia monetary aggregates under the benchmark index ($\mathrm{SSM1}, \mathrm{SSM2}, \mathrm{DM1}$ and $\mathrm{DM2}$), the benchmark index including participation banks $\left(\mathrm{SSM1_P}, \mathrm{SSM2_P}, \mathrm{DM1_P}\text{ and }\mathrm{DM2_P}\right)$ and the expectations-augmented index $\left(\mathrm{DM1_{EXP}}\text{ and }\mathrm{DM2_{EXP}}\right)$.[24] At first glance, it is observed from the tables that RMSE and MAE are smaller for forecasts of CPI inflation than for industrial production at different forecast horizons. Also, prevailing for all specifications of the monetary aggregates, the Theil U statistic is quietly below one that shows up the outperforming of the model compared to the naive no-change model. Besides, true to

[24] We also compare the VAR forecasts with monetary aggregates to an AR(4) model forecasts for CPI inflation and industrial production and obtain that the small-scale VAR model reveals better forecasts than the AR model in most cases.

type, RMSE and MAE get larger as the forecasts are upheld for three-months ahead forecasts compared to one-month ahead forecasts.

Tables 5.1 and 5.2 tabulate that in forecasting industrial production during the crisis episode the smallest RMSE and MAE are generated by the model SSM1 that includes participation banks. The use of alternative Divisia-type aggregates, hereby, does not improve the forecasting performance of industrial production during the so-called great moderation. This result is contrary to findings in the literature that the forecasts of production during the great recession are most accurately obtained from models including Divisia-type money (see Barnett and Chauvet, 2011, among others). Note that the related literature concentrates largely on the developed economies with exhaustive varieties of financial assets and find considerable level of divergence between Divisia and simple-sum aggregates before the great depression episode proposing the Divisia money for better capturing the excessive money creation and the dynamics of income during the great moderation.

In VAR forecasting of CPI inflation in the crisis episode, however, DM2 provides the smallest RMSE and MAE for both one-and three-ahead forecasts. Though the inclusion of participation banks into the Divisia indices ($\mathrm{DM1_P}$ and $\mathrm{DM2_P}$) improves the VAR forecasts of inflation, expectations-augmented index does not significantly contribute to the forecasting ability of Divisia aggregates.

Tables 5.3 and 5.4 denote errors from forecasting inflation and industrial production with alternative monetary aggregates for the period from 2006:1 through 2016:12. This extended period corresponds to a sample that includes both crisis and post-crisis episode and provides a larger training period. Prevailing for both one- and three ahead forecasts, the simple-sum M2 money that includes participation banks, $\mathrm{SSM2_P}$, produces the smallest RMSE and MAE in forecasting the dynamics of CPI inflation. In the extended period, Divisia money under alternative specifications does not show any superiority in forecasting the prices[25] being quite contrary to forecasting P during the great moderation in which DM2 produces the smallest errors. In forecasting the industrial

[25] The results are robust for slight changes in estimation sample e.g., from 2006:1 through 2015:12.

production during the extended period, however, it arises that the smallest RMSE and MAE are generated by the Divisia M2 that includes the participation banks – $\mathrm{DM2_P}$. Note also that when the money is measured as expectations-augmented Divisia aggregates we do not observe any significant improvement in the forecast of industrial production compared to the benchmark Divisia index. These results can be taken as signal for the regime-switching or time-varying behavior of alternative definitions of money aggregates with respect to their forecasting abilities of price and production dynamics. However, to control "whether the differences between competing forecasts are statistically significant or due to sampling variability" (Luger, 2004, p. 1) we apply the modified DM test. Tables 5.5 and 5.6 give the modified DM test results at one-month horizon for the great moderation period (2008:10 – 2010:10) and the extended period (2017:1 – 2018:4), respectively.

At first glance, it can be argued that the modified DM test results partly justify the forecasting performance of monetary aggregates under two different regimes. Firstly, the aforesaid forecasting superiority of broadly defined Divisia aggregate ($\mathrm{DM2}$) compared to its simple-sum counterpart ($SSM2$) in forecasting CPI inflation during the great moderation vanishes away once we control for the accuracy of the forecast. In forecasting the industrial production during the great moderation, however, the null of equal forecast accuracy between $\mathrm{SSM1_P}$ and $\mathrm{DM1_P}$ is rejected at 1% significance level, implying a strong evidence that the simple-sum money M1 including the participation banks forecasts better the production compared to alternative formations of money during the crisis years. Besides, when the returns on foreign assets are adjusted in accordance with the expectations on FX rates it arises that the broadly defined expectations-augmented Divisia index ($\mathrm{DM2_{EXP}}$) outperform SSM2 in forecasting the production during the great recession.

From Table 5.6 we evaluate the results on the accuracy of forecasting P and Y with alternative monetary aggregates during the extended period. Firstly, the modified DM test statistic cannot reject the null hypothesis that in forecasting inflation the mean squared forecast errors of the models with $\mathrm{SSM2_P}$ and $\mathrm{DM2_P}$ are equal, on average. That is, our modified DM test does not justifies the finding that $\mathrm{SSM2_P}$ shows superiority in forecasting the prices compared to $\mathrm{DM2_P}$ during the tranquil period. Overall, prevailing for both small and extended estimation samples, the forecast accuracy test statistic cannot reveal significant forecasting ability of neither conventional simple-sum nor alternative Divisia aggregates in forecasting inflation. It may signal rather the sampling variability that results in incidental difference between alternative aggregates. In explaining the industrial production during the extended period, however, the modified DM test rejects the null at 1% significance level and gives strong evidence that Divisia money including participation banks $\mathrm{DM2_P}$ outperforms its simple-sum counter-part $\mathrm{SSM2_P}$ in forecasting the dynamics of the production.

Table 5.1: One-month Ahead Forecasts of Inflation and Industrial Production (2008:12-2010:10)

	P			**Y**		
	RMSE	**MAE**	**Theil**	**RMSE**	**MAE**	**Theil**
SSM1	0.782	0.661	0.298	3.545	2.313	0.230
SSM2	1.033	0.854	0.366	3.755	2.535	0.250
$\mathbf{SSM1_P}$	0.785	0.664	0.298	**3.539**	**2.308**	**0.229**
$\mathbf{SSM2_P}$	1.027	0.846	0.364	3.751	2.533	0.249
DM1	0.779	0.643	0.301	3.568	2.332	0.232
DM2	**0.771**	**0.642**	**0.299**	3.603	2.362	0.235
$\mathbf{DM1_P}$	0.794	0.657	0.305	3.567	2.330	0.232
$\mathbf{DM2_P}$	0.775	0.646	0.290	3.604	2.365	0.235
$\mathbf{DM1_{EXP}}$	0.901	0.744	0.332	3.641	2.387	0.240
$\mathbf{DM2_{EXP}}$	0.948	0.796	0.345	3.695	2.466	0.245

Table 5.2: Three-month Ahead Forecasts of Inflation and Industrial Production (2008:12 – 2010:10)

	P			**Y**		
	RMSE	**MAE**	**Theil**	**RMSE**	**MAE**	**Theil**
SSM1	0.809	0.696	0.329	2.125	1.847	0.137
SSM2	1.065	0.893	0.396	2.433	2.080	0.161
$\mathbf{SSM1_P}$	0.812	0.698	0.329	**2.118**	**1.841**	**0.137**
$\mathbf{SSM2_P}$	1.058	0.884	0.394	2.422	2.077	0.161
DM1	0.802	0.672	0.332	2.157	1.868	0.140
DM2	**0.786**	**0.660**	**0.325**	2.196	1.897	0.143
$\mathbf{DM1_P}$	0.817	0.685	0.335	2.156	1.866	0.140
$\mathbf{DM2_P}$	0.790	0.665	0.325	2.198	1.899	0.143
$\mathbf{DM1_{EXP}}$	0.936	0.788	0.372	2.291	1.941	0.150
$\mathbf{DM2_{EXP}}$	0.979	0.829	0.379	2.367	2.016	0.156

Table 5.3: One-month Ahead Forecasts of Inflation and Industrial Production (2017:01 – 2018:04)

	P			**Y**		
	RMSE	**MAE**	**Theil**	**RMSE**	**MAE**	**Theil**
SSM1	1.035	0.827	0.300	3.044	2.101	0.504
SSM2	0.876	0.764	0.248	2.943	2.572	0.540
$\mathbf{SSM1_P}$	1.015	0.815	0.294	2.846	1.980	0.485
$\mathbf{SSM2_P}$	**0.857**	**0.749**	**0.241**	2.764	2.422	0.518
DM1	1.051	0.843	0.304	3.009	2.077	0.504
DM2	0.888	0.755	0.254	2.300	1.963	0.473
$\mathbf{DM1_P}$	1.030	0.826	0.298	2.870	2.047	0.491
$\mathbf{DM2_P}$	0.886	0.737	0.254	**2.061**	**1.755**	**0.440**
$\mathbf{DM1_{EXP}}$	1.001	0.816	0.290	2.346	1.729	0.447
$\mathbf{DM2_{EXP}}$	0.965	0.797	0.279	2.398	1.986	0.478

Table 5.4: Three-month Ahead Forecasts of Inflation and Industrial Production (2017:03 – 2018:04)

	P			Y		
	RMSE	MAE	Theil	RMSE	MAE	Theil
SSM1	1.093	0.886	0.299	3.186	2.180	0.515
SSM2	0.923	0.813	0.246	3.105	2.774	0.544
$\mathbf{SSM1_P}$	1.069	0.867	0.293	2.967	2.022	0.496
$\mathbf{SSM2_P}$	**0.902**	**0.796**	**0.239**	2.914	2.612	0.522
DM1	1.109	0.899	0.303	3.140	2.137	0.515
DM2	0.937	0.808	0.252	2.428	2.108	0.477
$\mathbf{DM1_P}$	1.084	0.874	0.296	2.980	2.079	0.502
$\mathbf{DM2_P}$	0.939	0.800	0.254	**2.182**	**1.902**	**0.445**
$\mathbf{DM1_{EXP}}$	1.051	0.857	0.288	2.495	1.880	0.457
$\mathbf{DM2_{EXP}}$	1.013	0.837	0.276	2.544	2.179	0.486

Table 5.5: Forecast Accuracy Results: Great Moderation Period

One-month ahead forecasts	P	Y
SSM1 - DM1	-1.117	1.948*
SSM2 - DM2	-4.845	-0.903
$\mathbf{SSM1_P}$ **-** $\mathbf{DM1_P}$	-1.591	-1.849**
$\mathbf{SSM2_P}$ **-** $\mathbf{DM2_P}$	-4.912	0.672
SSM2 - $\mathbf{DM2_{EXP}}$	-4.747	3.594***

Note: H_0: The forecast errors from simple-sum and Divisia monetary aggregates are equal. $(*)$, $(**)$ and $(***)$ show the rejection of the null at 10%, 5% and 1%, respectively.

Table 5.6: Forecast Accuracy Results: Extended Period

One-month ahead forecasts	P	Y
SSM1 - DM1	-0.504	0.367
SSM2 - DM2	1.893**	-2.251***
$\mathbf{SSM1_P}$ **-** $\mathbf{DM1_P}$	0.354	-0.805
$\mathbf{SSM2_P}$ **-** $\mathbf{DM2_P}$	0.368	2.645***
SSM2 - $\mathbf{DM2_{EXP}}$	3.795***	-0.093

Note: H_0: The forecast errors from simple-sum and Divisia monetary aggregates are equal. $(*)$, $(**)$ and $(***)$ show the rejection of the null at 10%, 5% and 1%, respectively.

6. CONCLUSION

It has been a long inquiry among economists to understand the extent to which the overall quantity of money supply, or its growth, has a role in monetary policy regularly following the oscillations in output or prices over time. In order to base monetary stance process on the very abstract of money it has been advocated various empirical musts on the link between money and the macroeconomic fundamentals. As pointed out by Friedman and Kuttner (1992) setting the money growth possibly ex ante and choosing it as the intermediate target in the policy rule result in being close to optimal point if the demand for money is close to being non-stochastic and interest inelastic. Or setting the money as the information indicator and adjusting policy actions accordingly within some band in response to departures of growth of money from its ex ante levels may be taken as a looser requirement which does not in any case necessitate a restoration of money growth to its predetermined level. It is essential, however, for both of the ways of policy making to get reliable connections with income or inflation in a manner that any departures from the money growth path induce systematic responses for income and inflation at next periods. Though the existence of a positive comovement of money supply and the economic activity over the course of economic fluctuations is mostly taken as an empirical fact (see King and Watson, 1996), almost a consensus has arisen in the related literature for deficiency of monetary aggregates to fulfill the duty of an information variable or instrument in a policy rule. The afore-said inability of monetary aggregates in the conduct of monetary policy has been identified largely with the use of theoretically weak simple sum monetary aggregates. Hereby, the Divisia type monetary aggregation due to Barnett (1978, 1980) has been highly proposed to serve at least as a supportive tool to the with short-term interest rates in the policy rule.

Grounded on the aforesaid discussion we analyze the information content of alternative formations of Divisia and simple-sum monetary statistics in predicting the variations of price and quantity variables. In doing so, we construct and test Divisia aggregates against the officially measured aggregates for Turkish economy as an emerging market with relatively low varieties of financial assets and its idiosyncratic features. Based on in-sample estimations using the DDT test, multiple wavelet analyses and out-of-sample UVAR forecasting exercises at first glance we reach that the simple-sum and Divisia monetary aggregates give similar information in predicting the dynamics of prices and production. However, as the number of heterogeneous assets rises by introducing new components and their corresponding returns into the definitions of money, the Divisia and simple-sum monetary aggregates diverge and the former dominates. In this regard, the incorporation of participation banks into the Divisia index significantly improves the ability of Divisia aggregates in predicting the dynamics of inflation and industrial production. Also, though the expectations-augmented Divisia index performs better compared to official one, still it does not improve upon the benchmark Divisia index. Another point is that the recent literature explores the information content of alternative monetary statistics in the conduct of monetary policy largely for advanced economies (Barnett and Chauvet, 2011 and Belongia and Ireland, 2014). In these groups of economies that suffer from the zero-lower bound condition, the empirical evidence considerably favors the Divisia type aggregates opposed to both simple-sum ones and short-term interest rates and are advocated as the intermediate target in the conduct of monetary policy. However, that the short-term policy rates have never reached to zero lower bound (Varlık et al., 2015) and there exist limited varieties of financial assets in Turkish economy prevent the Divisia aggregates to diverge significantly from simple-sum aggregates. Still, we can acknowledge the relatively better predictive power of Divisia aggregates for the production. Still, its impact on the prices does not differ from the simple-sum aggregates particularly during the crisis years. Lastly, the wavelet analysis and forecast exercises both signal for a time-varying feature of the link among monetary statistics, inflation and production in which both direction and strength of the relation between monetary aggregates and macroeconomic fundamentals differ in crisis years and post crisis years.

REFERENCES

Aguiar-Conraria, L., N. Azevedo and M. J. Soares. (2008). Using Wavelets to Decompose the Time–Frequency Effects of Monetary Policy. *Physica A*. 387.12, 2863–2878.

Aguiar-Conraria, L., M. M. F. Martins and M. J. Soares. (2018). Estimating the Taylor Rule in the Time-Frequency Domain. *Journal of Macroeconomics*. 57, 122–137.

Aguiar, M. and G. Gopinath. (2007). Emerging Market Business Cycles: The Cycle is the Trend. *Journal of Political Economy*. 115.1, 69–102.

Alp, H., R. Gürkaynak, H. Kara, G. Keleş, and M. Orak. (2010). Türkiye'de Piyasa Göstergelerinden Para Politikası Beklentilerinin Ölçülmesi. *İktisat İşletme ve Finans*. 25.295, 21-45.

Alp H., Y. S. Başkaya, M. Kılınç and C. Yüksel. (2012). Stylized Facts for Business Cycles in Turkey. *Working Papers* 1202, Research and Monetary Policy Department, Central Bank of the Republic of Turkey.

Altuğ, S. and M. Bildirici. (2012). Business Cycles in Developed and Emerging Economies: Evidence from a Univariate Markov Switching Approach. *Emerging Markets Finance and Trade*. 48.6, 4-38.

Anderson, R. G., B. E. Jones and T. D. Nesmith. (1997a). Introduction to the St. Louis Monetary Services Index Project, *The Federal Reserve Bank of St. Louis Review*. 79.1, 25-29.

Anderson, R. G., B. E. Jones and T. D. Nesmith. (1997b). Monetary Aggregation Theory and Statistical Index Numbers. *The Federal Reserve Bank of St. Louis Review*. 79.1, 31-51.

Anderson, R. G., B. E. Jones and T. D. Nesmith. (1997c). Building New Monetary Services Indexes: Concepts Data and Methods. *The Federal Reserve Bank of St. Louis Review*. 79.1, 53-82.

Anderson, R. and B. Jones. (2011). A Comprehensive Revision of the US Monetary Services (Divisia) Index. *Federal Reserve Bank of St. Louis Review*. 93.5, 325-359.

Barnett, W. A. (1978). The User Cost of Money. *Economics Letters*. 1, 145-149.

Barnett, W. A. (1980). Economic Monetary Aggregates: An Application of Index Number of Aggregation Theory. *Journal of Econometrics*. 14, 11-48.

Barnett, W. A. and P. A. Spindt. (1982). Divisia Monetary Aggregates: Compilation, Data, and Historical Behavior. *Staff Study*. 116, Board of Governors of the Federal Reserve System, May 1982.

Barnett, W. A. and A. Serletis. (1990). A Dispersion-Dependency Diagnostic Test for Aggregation Error: With Applications to Monetary Economics and Income Distribution. *Journal of Econometrics.* 43, 5-34.

Barnett, W. A., J. W Keating and U. Chae. (2006). The Discounted Economic Stock of Money with VAR Forecasting. *Annals of Finance.* 2, 229–258.

Barnett, W. A., B. E. Jones and T. D. Nesmith. (2008). Divisia Second Moments: An Application of Stochastic Index Number Theory, *MPRA Paper*. 9111, University Library of Munich, Germany.

Barnett, W. and M. Chauvet. (2011). How Better Monetary Statistics Could Have Signaled the Financial Crisis, *Journal of Econometrics*. 161, 6-23.

Baum, C. F. and M. E. Schaffer. (2013). A General Approach to Testing for Autocorrelation. *Paper presented at the Stata Conference,* New Orleans, LA.

Belongia, M. T. and P. N. Ireland. (2014). The Barnett Critique after Three Decades: A New Keynesian Analysis. *Journal of Econometrics.* 183.1, 5 – 21.

Belongia, M. T. and P. N. Ireland. (2015). Interest Rates and Money in the Measurement of Monetary Policy, *Journal of Business & Economic Statistics*, Taylor & Francis Journals. 33.2, 255-269.

Belongia, M. T. and P. N. Ireland. (2018). Targeting Constant Money Growth at the Zero Lower Bound. *International Journal of Central Banking*. 14, 159–204.

Binici, M., H. Kara and P. Özlü. (2019). Monetary Transmission with Multiple Policy Rates: Evidence from Turkey. *Applied Economics*. 51.17, 1869-1893.

Bloomfield, D., R. McAteer, B. Lites, P. Judge, M. Mathioudakis and F. Keena. (2004). Wavelet Phase Coherence Analysis: Application to a Quiet-Sun Magnetic Element, *The Astrophysical Journal*. 617, 623–632.

Central Bank of the Republic of Turkey. (2012). *Monetary and exchange rate policy for 2013*. 25 December 2012, Ankara.

Chen, W. and D. Nautz. (2015). The Information Content of Monetary Statistics for The Great Recession: Evidence from Germany. *SFB 649 Discussion Paper*. 2015-027.

Çelik, S. (1999). Divisia Monetary Aggregates: An Empirical Investigation of Their Usefulness for Turkey. *Unpublished PhD Dissertation*: University of Nebraska.

Diebold, F. X. and R. S. Mariano (1995). Comparing Predictive Accuracy. *Journal of Business and Economic Statistics*. 13, 253-63.

Diebold, F. X. (2012). A Personal Perspective on the Origin(s) and Development of 'Big Data': The Phenomenon, the Term, and the Discipline. *PIER Working Paper*. Second Version (November 26, 2012). 13-003.

Elger, T., B. E. Jones and B. Nilsson. (2006). Forecasting with Monetary Aggregates: Recent Evidence for the United States. *Journal of Economics and Business,* 58.5–6, 428-446.

Fischer, S. (2016). Monetary Policy, Financial Stability, and the Zero Lower Bound. (Speech to the Annual Meeting of the American Economics Association, San Francisco, California, January 12). Retrieved July 28, 2020, from https://www.federalreserve.gov/newsevents/speech/fischer20161005a.htm

Friedman, B. and K. Kuttner. (1992). Money Income, Prices, and Interest Rates, *American Economic Review*. 82.3, 472–492.

Friedman, B. and K. Kuttner. (1996). A Price Target for U.S. Monetary Policy? Lessons from the Experience with Money Growth Targets. *Brookings Papers on Economic Activity*. 27.1, 77-146.

Ge, Z. (2008). Significance Tests for The Wavelet Cross Spectrum and Wavelet Linear Coherence. *Annales Geophysicae*. 26.12, 3819-3829.

Grinsted, A., J. C. Moore and S. Jevrejeva. (2004). Application of The Cross Wavelet Transform and Wavelet Coherence to Geophysical Time Series. *Nonlinear Processes in Geophysics,* European Geosciences Union (EGU). 11.5/6, 561-566.

Gürkaynak, R., Z. Kantur, M. A. Taş and S. Yıldırım. (2015). Monetary policy in Turkey after Central Bank independence. *CFS Working Paper Series*. 520. Center for Financial Studies.

Handa, J. (2009). *Monetary Economics*. Routledge, Second Edition, New York.

Harvey, D., S. Leybourne and P. Newbold. (1997). Testing the Equality of Prediction Mean Squared Errors. *International Journal of Forecasting*. 13, 281-91.

Karaman, D. (2009). An Empirical Study of Simple Sum and Divisia Monetary Aggregation: A Comparison of Their Predictive Power Regarding Prices and Output in Turkey. *Unpublished PhD Dissertation*. Kansas University.

Keating, J. W., J. K. Logan, A. L. Smith, and V. J. Valcarcel. (2016). A Model of Monetary Policy Shocks for Financial Crises and Normal Conditions. *Research Working Paper* 14-11. Federal Reserve Bank of Kansas City.

Kelly, L., W. Barnett and J. Keating. (2011). Rethinking the Liquidity Puzzle: Application of A New Measure of the Economic Money Stock. *Journal of Banking and Finance*. 35.4, 768–774.

King, R. and M. Watson. (1996). Money, Prices, Interest Rates and the Business Cycle. *The Review of Economics and Statistics*. 78.1, 35–53.

Kumar, S., R. Pathak, A. K. Tiwari and S. M. Yoon. (2017). Are Exchange Rates Interdependent? Evidence Using Wavelet Analysis, *Applied Economics*. 49.33, 3231-3245.

Kunter K. (1993). Turkiye'deki Parasal Buyuklukler icin indeks ve Bileşim Teorisinin Bir Uygulaması: Divisia ve Fisher indeksi. *CBRT Discussion Papers*. Central Bank of Republic of Turkey.

Luger, R. (2004). Exact Tests of Equal Forecast Accuracy with an Application to the Term Structure of Interest Rates. *Staff Working Papers* 04-2, Bank of Canada.

Matsonn, R. (2013). Essays on Broad Divisia Monetary Aggregates: Admissibility and Practice. *Unpublished PhD Dissertation*. Kansas University.

Newey, W. K. and K. D. West. (1994). Automatic Lag Selection in Covariance Matrix Estimation. *The Review of Economic Studies*. 61.4, 631-653.

Raihan, S., Y. Wen and B. Zeng. (2005). Wavelet: A New Tool for Business Cycle Analysis. *Working Paper.* 2005-050A, Federal Reserve Bank of St. Louis.

Scharnagl, M. and M. Mandler. (2015). The Relationship of Simple Sum and Divisia Monetary Aggregates with Real GDP And Inflation: A Wavelet Analysis For the US. *Annual Conference 2015* (Muenster): Economic Development - Theory and Policy 112879, Verein für Socialpolitik / German Economic Association.

Schreiber, S. (2009). Low-frequency determinants of inflation in the euro area. *Working paper*-6/2009. Macroeconomic Policy Institute.

Schunk, D. L. (2001). The Relative Forecasting Performance of the Divisia and Simple Sum Monetary Aggregates. *Journal of Money, Credit, and Banking*. 272-283.

Serletis, A. (2007). *The Demand for Money, Theoretical and Empirical Approaches*. Elsevier, Second Edition.

Theil, H. (1967). *Economics and Information Theory. Amsterdam*. North-Holland Publishing Company; New York: Elsevier, North-Holland.

Torrence, C. and G. P. Compo. (1998). A Practical Guide to Wavelet Analysis. *Bulletin of the American Meteorological Society*. 79.1, 61–78.

Uygur, E. (2010). The Global Crisis and the Turkish Economy. *TWN Global Economy Series.* no. 21.

Uysal, M. (2017). Financial Stability and Macroprudential Policy in Turkey. *Macroprudential policy frameworks, implementation and relationships with other policies*. Bank for International Settlements. 94, 349-364

Varlık, S., N. B. Ceylan, and M. H. Berument. (2015). Assessing the Effects of A Policy Rate Shock on Market Interest Rates: Interest Rate Pass-Through with A FAVAR Model—the Case of Turkey for the Inflation-Targeting Period. *Journal of Money, Investment and Banking*, 30.

Woodford, M. (2003). *Interest and Prices: Foundations of a Theory of Monetary Policy*. Princeton: Princeton University Press.

Yang, L., X. J. Cai, H. Zhang and S. Hamori. (2016). Interdependence of Foreign Exchange Markets: A Wavelet Coherence Analysis. *Economic Modelling*. 55, 6–14.

APPENDIX A

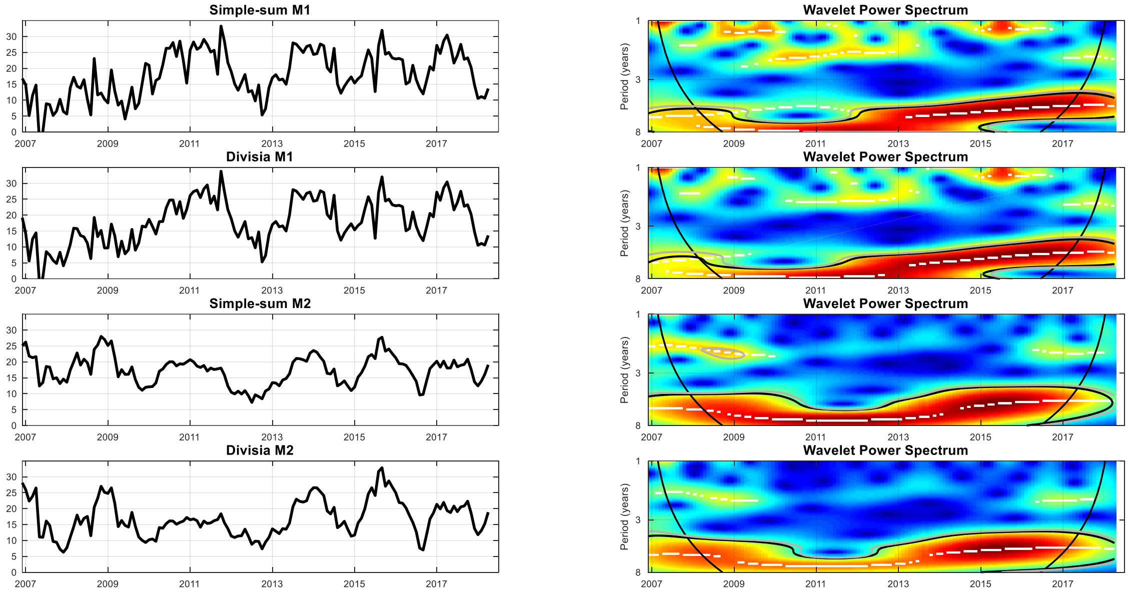

Figure A.1: Wavelet Power Spectrum of SSM1, DM1, SSM2 and DM2 under Benchmark Index

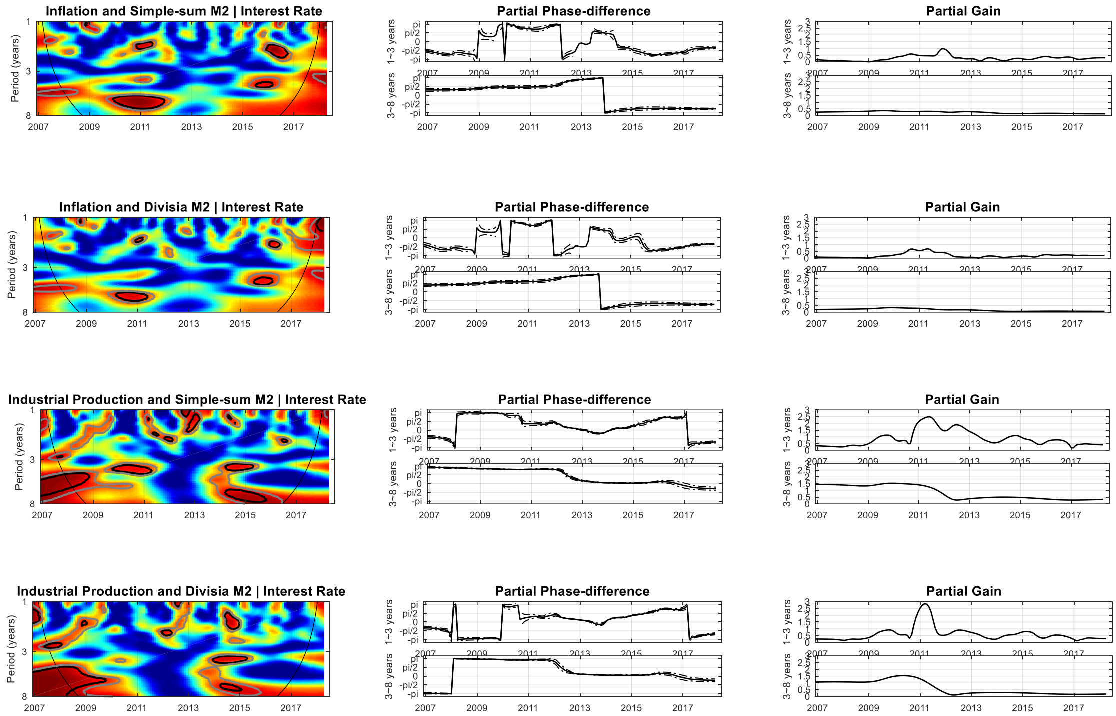

Figure A.2: Partial Coherencies, Partial Phase Differences and Partial Gains Among Inflation, IPI and Monetary Aggregates at M2 including Participation Banks

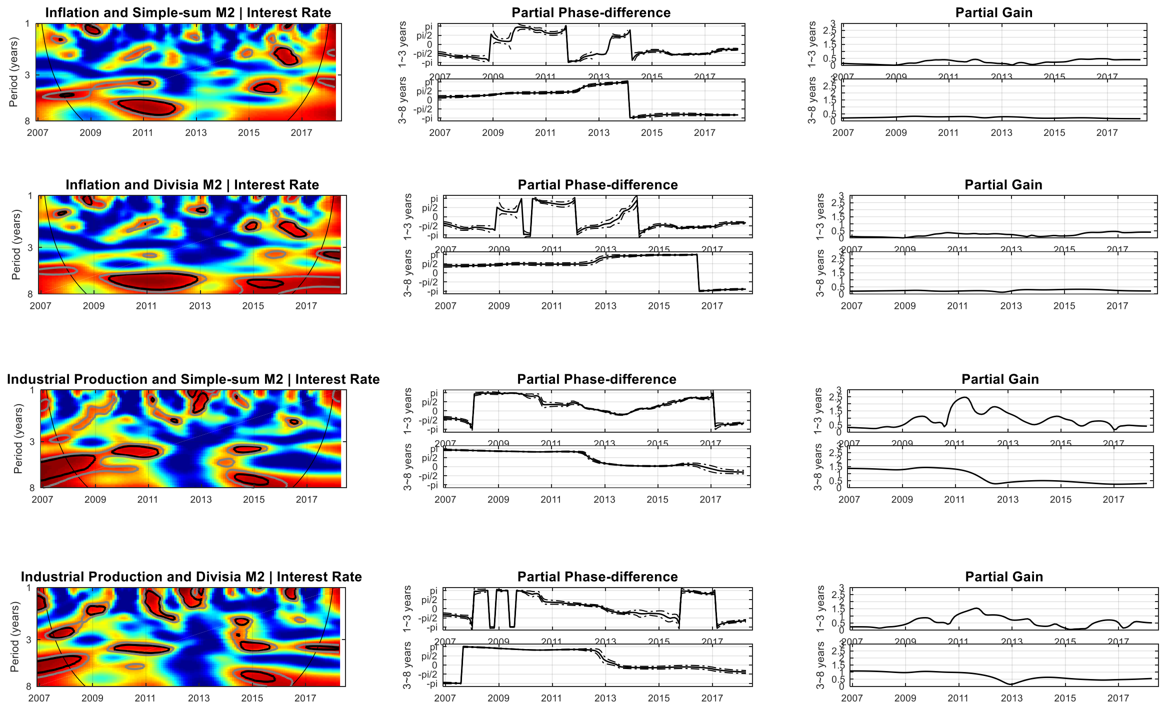

Figure A.3: Partial Coherencies, Partial Phase Differences and Partial Gains Among Inflation, IPI and Monetary Aggregates at M2 belonging Expectations-Augmented Divisia Index

CHAPTER 2

MONETARY POLICY EFFECTIVENESS IN TURKEY: DOES THE POLICY RATE STILL WORK WELL?

1. INTRODUCTION

The transmission of the policy rate changes ringed by monetary authorities to the state of economy is of importance for understanding the efficiency of these changes on the policy objectives as well as on well-being of economies. The importance attributed to the policy rates has undergone changes in the last decade with the articulation of the financial crisis and become more blurred in the monetary policy stance of many economies operating under multiple policy framework. Turkish economy is not an exception to this case. On the one hand, using the periodically announced policy rate changes, the Central Bank of Republic of Turkey (CBRT) shoots for containing the deterioration in the inflation outlook, operating the liquidity conditions and expectations and counteract external disturbances (CBRT, 2015; 2019). The CBRT, on the other hand, benefits from varieties of policy instruments to manage different state variables which is particularly the case in the new monetary policy episode i.e., in the aftermath of the financial crisis (Aysan et al., 2014; Binici et al., 2018). These additional instruments beside to the policy rate are needed in handling the trade-off that might occasionally realize between different objectives (Kara, 2013). At this stage, the critiques arise essentially on the inefficiency of the officially announced policy rate as being uninformative about the conduct of monetary policy (Gürkaynak, 2015; Çatık and Akdeniz, 2019) as well as on the divergence of the efficient interest rates from the policy rates that could result in different equilibria in the policy making (Küçük et al., 2016).

Thereby, it arises a considerable uncertainty on the extent to which the policy rate is de-potentiated in the policy making in the case of Turkey.

In this chapter, with an attempt to reduce the aforesaid uncertainty on the effectiveness of the policy rate and to capture the strength of the transmission of monetary policy disturbances to disaggregated or sectoral series we use a Factor Augmented VAR (FAVAR) model. More specifically, we estimate a two-stage principal components (PC) FAVAR model developed by Bernanke et al. (2005). Utilization of this model enables us to use all the available set of information and allows us to obtain direct responses of all of the variables included in the data set (Soares, 2013). In this regard, we use more than a hundred of series for the period spanning from 2005:12 through 2018:4. To present how the policy shocks pass through different components of the economy we go through certain indicators standing for the real activity, exchange market, prices, credit market, expectations and market interest rates. Besides, we include an external factor drawn from a set of foreign series to track the external shocks as Turkish economy is considered among the most fragile emerging economies with its high foreign indebtedness and its vulnerabilities against the external forces.

The FAVAR models are highly implemented in the empirical macroeconomics in solving drawbacks of the small-scale VAR models e.g., in mitigating anomalies like the price puzzles á la Sims (1992) and giving *ad hoc* decisions on which data to include in a VAR or which not (Fernald et al., 2014). Regardless of the specifications used, they are found to outperform the traditional VAR models (see, Eickmeier et al., 2015). Besides, this model setting is particularly well-suited in exploring the effectiveness of monetary policy for imperfectly observed latent variables as of inflation, credit conditions and real activity. That is, under a dynamic factor model, given a number of factors drawn from the set of all available data, all the series and their response functions to a policy shocks are reconstructed by weights of corresponding factor loadings.

In this regard, in analyzing the effectiveness of the selected policy rate for Turkish economy we consider the FAVAR model as a good candidate in solving the puzzling behaviors in prices and exchange rates observed in the VAR literature on Turkey (Erdoğan and Yıldırım, 2010; Çatık and Martin, 2012). Since this model specification allows for including all relevant sectoral and disaggregated variables into the analysis, we can also assess consistently the pass through of policy rate disturbances to disaggregated variables including consumer and financial loans separately in the credit market. Also, the FAVAR model is extended by including the monetary policy factors beside to the policy rate to control for the vigorous use of various monetary policy instruments by the CBRT. Lastly, being intrinsic to the FAVAR model, the performance of the common factors is evaluated with respect to different policy shocks i.e., to the policy rates, effective rates and Divisia M2.

Firstly, we make a discussion on finding consistent estimates for pervasive forces and interpretation of factors to reveal the potential links across the rotated factors and macroeconomic series. Then, we proceed with estimating the model under the baseline specification. The policy rate is assumed to represent the monetary policy stance in this specification. In the later part, the model is extended to consider the multiple policy framework employed by the CBRT. That is, we consider estimated monetary policy factors beside to the policy rate to stand for the policy making and control other instruments while evaluating the effectiveness of the policy rate. In following part, we compare shocks to the policy rate with a money supply shock. Hereby, we consider Divisia aggregates at M2 as a hypothetical instrument and assume shocks to the Divisia M2 to visualize the relative performance of the policy rate in transmission to selected variables. In the last part, firstly, we compare transmission of the officially announced interest rate with that of effective interest rate for the new monetary policy episode that witnesses a vigorous use of multiple policy instruments with the end of 2010. During this episode the central bank allowed the policy rate and the market rates to diverge (Binici et al., 2018) and use more actively other instruments beside to the policy rate under the asymmetric interest rate corridor. Also, as a robustness check, we control whether our results are robust to changes in number of factors used in estimation.

2. MODEL

2.1 Baseline Model

Let Y_t and X_t be two $M \times 1$ and $N \times 1$ vectors of observable economic variables, respectively, with a time index t; $t = 1,2, \dots, T$. Note that the number of variables can be larger than the number of observations, i.e., $N \gg T$. Following the monetary VAR literature, Y_t stands for pervasive forces that characterize the dynamics of the economy. In other words, Y_t is a vector that contains a policy variable and a number of observable indicators of prices and real activity (Bernanke et al., 2005). Besides, suppose an available number of informative series, X_t, being larger than Y_t, used by the central banks, that is relevant with the dynamics of the economy and used to capture additional information, not fully provided by Y_t. To capture this additional information, Bernanke et al. (2005) propose a $K \times 1$ vector of unobservable factors, F_t and consider the policy rate as only observable indicator, Y_t, in their setting. These unobservable factors are used to measure "theoretically motivated concepts such as economic activity, price pressures, or credit conditions that cannot easily be represented by one or two series but rather are reflected in a wide range of economic variables" (Bernanke et al., 2005, p.392). Note that the number of available informational time series, X_t is much greater than the number of factors and observed series, so that $N \gg M + K$. Hereby, the dynamics of Y_t and F_t can be jointly expressed in a state-space representation using the following transition equation,

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \nu_t, \quad E(\nu_t{}'\nu_t) = \mathrm{Q} \tag{1}$$

where $\phi(L)$ is a lag polynomial of finite order d, ν_t is error term with zero mean and covariance Q, $\nu_t \sim i.i.d. N(0, Q)$. Equation (1) can be reduced to a standard VAR model which includes only Y_t if terms of $\phi(L)$ are equal to zero, otherwise it becomes a factor augmented vector autoregressive model (FAVAR) developed by Bernanke et al. (2005). As F_t contains an additional valuable information, the VAR model in Y_t will probably result in biased estimates of coefficients and impulse responses. However, since the factors F_t are not observables, one cannot estimate Equation (2.1) directly. To capture the "information content" of unobserved factors, one can relate available informational time series, X_t, to unobserved factors, F_t and observed time series, Y_t using the observation equation below,

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t, \quad E(e_t' e_t) = \mathrm{R} \tag{2}$$

where Λ^f is an $N \times K$ matrix of factor loadings, Λ^y is a $N \times M$ matrix, and e_t is $N \times M$ vector of error terms with zero mean and that are uncorrelated or weakly correlated depending on whether estimation is made using likelihood methods or principal components. The error terms in equations (1) and (2) are assumed to be independent and error terms in equation (2) are assumed to be diagonal. Notice that the observation equation implies for a static formation of the dynamic factor model in which X_t depends only on the current value of F_t.[1]

2.2 Extended Model

We follow principally the model defined in equations (1) and (2) but now partitioning the large data set, X_t, off two sub-groups, i.e., ${X_t}^1$ and ${X_t}^2$ with ${X_t}^i$ is a $W_i \times 1$ vector such that $\sum_i W_i = W$. Notice, however, that X_t now includes additional informational time series, say ${X_t}^2$, that correspond to the policy instruments used by the monetary authority beside to the existing observable economic variables, i.e., ${X_t}^1$. We still preserve the assumption on Y_t as a $M \times 1$ vector that contains a policy variable and/or a number of observable indicators. Following Belviso and Milani (2006), however, we make the assumption that ${X_t}^i$ is merely explained by the underlying the factor, ${F_t}^i$ with a $Z_i \times 1$ vector such that $\sum_i Z_i = Z$ and $Z_i < W_i$, $i = 1, 2$. It implies a restriction in our case that unobserved "monetary policy factors" are drawn from ${X_t}^2$ to capture the main components of the policy agenda set by the monetary authority and not fully provided by Y_t (in our case, the policy rate) in a multi-policy framework. As in Varlık and Berument (2017) we include monetary policy factors beside to an (observable) policy rate to mimic

[1] See Stock and Watson (1998, 2002a, 2002b) for details on static and dynamic approaches of a dynamic factor model.

better the policy stance in Turkey in which the monetary authority calls vigorously on multiple policy tools and track the transmission mechanism more realistically compared to one policy tool case. As the policy instruments are simultaneously used in most of the changes in the policy choices, through this way, we can control the common variations in the (mostly countercyclical behaviors) in the monetary policy factor, while analyzing a policy shock to a single policy tool. Thus, we have in the matrix form

$$\begin{bmatrix} {X_t}^1 \\ R_t \\ {X_t}^2 \end{bmatrix} = \begin{bmatrix} \Lambda^{f1} & 0 & 0 \\ 0 & \Lambda^r & 0 \\ 0 & 0 & \Lambda^{f2} \end{bmatrix} . \begin{bmatrix} {F_t}^1 \\ R_t \\ {F_t}^2 \end{bmatrix} + \varsigma_t,$$

implying the observation equation

$$X_t = \Lambda^{f1} {F_t}^1 + \Lambda^r R_t + \Lambda^{f2} {F_t}^2 + \varsigma_t, \qquad E({\varsigma_t}' \varsigma_t) = \mathrm{P} \tag{3}$$

where $\varsigma_t \sim i.i.d.N(0, \mathrm{P})$. The corresponding transition equation can be defined as follows

$$\begin{bmatrix} {F_t}^1 \\ R_t \\ {F_t}^2 \end{bmatrix} = \varphi(L) \begin{bmatrix} {F_{t-1}}^1 \\ R_{t-1} \\ {F_{t-1}}^2 \end{bmatrix} + \chi_t, \quad E({\chi_t}' \chi_t) = \Upsilon \tag{4}$$

where $\varphi(L)$ is a lag polynomial of finite order d, $\chi_t \sim i.i.d.N(0, \Upsilon)$ and the error term χ_t requires

$$E\left(\chi_t \middle| {F_t}^1, R_t, {F_t}^2\right) = 0. \tag{5}$$

The restriction that each subgroup in X_t interacts with economy merely with its factors implies no contemporaneous covariance across different subgroups, conditional on the factors i.e., $E\left({X_{wt}}^1, {X_{zt}}^2 \middle| {F_t}^1\right) = 0$ for all $w, z = 1,2 \ldots, N$ with $w \neq z$. However, explaining the relation of the macroeconomic series completely by corresponding factors may not be empirically so consistent if there exist some contemporaneous effects among series. In our case, it may be highly possible to get worth-mentioning impacts of the monetary policy tools on short-term interest rates prevailing in the market or on the asset prices. In extracting the factors from some subsets of X_t, thus, we re-calculate rotated factors but now including the fast moving monetary policy factors beside to the observed variables into the model. This enables us to remove the direct dependence of $\hat{C}\left(F_t{}^1, F_t{}^2, Y_t\right)$ on $F_t{}^2$ and Y_t and provides the theoretical consolidation of orthogonal factors both within and across subsets of X_t i.e., $E\left(X_{wt}{}^1, X_{zt}{}^2 \middle| F_t{}^1\right) = 0$. Accordingly, the estimated factors are obtained after removing the impact of high likelihood of contemporaneous covariance between fast-moving series and the monetary policy factors. It prevents also a potential over-estimation of responses of time series to a selected policy shock under consideration.

3. ESTIMATION

In estimation of the models[2] we follow the non-parametric two-stage PC approach, developed by Bernanke et al. (2005) instead of fully-parametric one-stage maximum likelihood approach. The former is computationally simple, requires a few of precise distributional assumptions in the observation equation (2), allows for small cross-correlations in the error terms, e_t and provides estimated factors that carry more information due to its low level of structural assumptions (Bernanke et al. 2005). These features make this approach advantageous compared to Bayesian joint estimation by maximum likelihood approach. However, the previous literature reaches mostly larger confidence intervals on the impulse response functions under the two-stage approach (see, Bağzıbağlı, 2014). Hereby, the existence of rotated factors in the second-stage may imply for a "generated regressors" problem. Firstly, as our N is large enough compared to T, using PC estimators can avoid this problem. Also, we implement a recursive-design residual bootstrap algorithm to obtain more consistent confidence intervals.[3]

Notice that the equations (1) and (2) are estimated separately. The first stage consists of estimating pervasive forces in observation equation (2), using principal components, prior to the estimation of the transition equation (1). The space covered by factors is obtained using the first $M + K$ principal components of X_t, shown by $\hat{C}(F_t, Y_t)$. The underlying rationale is that both F_t and Y_t encompas pervasive impacts throughout

[2] In the estimation and identification parts it is referred to the baseline model but the same formation applies to the extended model.
[3] See Appendix A for the bootstrapping steps used to derive confidence bands.

the economy and capture largely the common variations of all the variables in X_t (Soares, 2013). As stated by Stock and Watson (2002a), when N is large relative to number of observations and the number of principal components is sufficiently large to capture the true number of factors, then the PC consistently recover the space spanned by both F_t and Y_t. In the second stage, the equation (1) is estimated in a standard VAR fashion by replacing F_t with rotated factors, $\hat{F}_t$ that correspond to the part of $\hat{C}(F_t, Y_t)$ that is not explained by Y_t.

4. IDENTIFICATION AND EMPIRICAL IMPLEMENTATION

Following the structure of the standard VAR model, FAVAR methodology allows us to impose additional identifying restrictions. That is, though the identifying restrictions on the monetary policy shocks to the transition equation is defined as in standard VAR setting, e.g., restricting the covariance matrix of the VAR shocks, the FAVAR model requires us to identify restrictions on either the factor loadings or factors.[4] In this section, we briefly explain the identifying restrictions on the factors, the VAR model and contemporaneous time restrictions and cover the empirical implementation of both the baseline and extended models.

4.1 Identification of Factors

Firstly, as factors are not observed directly, the FAVAR model described by equations (1) and (2) cannot be estimated. For this reason, leaving the transition equation as in a standard VAR fashion, Bernanke et al. (2005) impose identifying restrictions on factors and factor loadings in observation equation.

Assume that coefficient matrix $\widehat{\Lambda}^f$ and factors $\hat{F}_t$ together are solutions to the model estimation given by equations (1) and (2). Let $\widetilde{\Lambda}^f = \widehat{\Lambda}^f L$ and $\tilde{F}_t = \hat{F}_t L$ satisfy also the estimation, where L is a $K \times K$ nonsingular matrix. Bernanke et al. (2005) are

[4] We follow the terminology used by Bernanke et al. (2005).

able to impose, accordingly, a normalization by replacing $\hat{F}_t$ with $\tilde{F}_t$ as it does not change the information content of the estimated factors. The identification of factors can be provided by imposing factors, $F^{i'}F^i/T = I$ or imposing factor loadings, $\Lambda_i^{f'}\,\Lambda_i^f/N = I$ for the first k number of factors, such that $i = 1,2,\dots,k$.

4.2 Identification of the VAR

According to conventional arguments, a rise in the policy rate resulted from a monetary contraction will lower prices and reduces the real output (Christiano et al., 1999; Uhlig, 2005). When any particular identification scheme is not well-organized, the expected responses may turn out to be false i.e., puzzling or theoretically less-convincing. In identification of the macroeconomic innovations, we will assume a recursive scheme following Stock and Watson (2005) and Bernanke et al. (2005). That is, the first k numbers of rotated factors estimated in the observation equation will respond to an unanticipated policy shock with a lag (within a month or quarter in accordance with the frequency of the data) in the transition equation. While macroeconomic indicators do not contemporaneously respond to monetary policy shocks, the contemporaneously feedback in the reverse direction is allowed (Favero, 2001). Since the true structural model is not directly observed, a reduced-form of the underlying structural model can be tracked using a VAR model. Following the pioneering study of Sims (1980) the identification of the VAR setting is determined under this recursive scheme grounded on the Cholesky decomposition of the reduced form variance-covariance matrix of residuals, in our case, $E(\nu_t{}'\nu_t) = \mathrm{Q}$ in equation (1).

Consider again the FAVAR setting as a reduced-from model described by the following transition equation (1)[5]:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \nu_t.$$

By using an orthogonal invertible matrix A with a dimension $[(K+M) \times (K+M)]$, structural FAVAR model can be reached from a reduced form. Hence, we define the

---

[5] For this part we follow Bağzıbağlı (2014).

relationship link between the (not observed) structural disturbances (ψ_t) and (observed) VAR residual (v_t) as

$$\psi_t = Av_t. \tag{6}$$

In this setting, the monetary policy shock as being one dimension of the matrix A will be used to identify the model. The Identification is operationalized by setting an appropriate block of elements of the A matrix equal to zero (Favero, 2001).

In this regard, as assumed by Sims (1980), A can be defined as a lower triangular matrix,

$$A = \begin{pmatrix} 1 & 0 & \dots & 0 \\ \alpha_{2,1} & 1 & \ddots & 0 \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{n,1} & \dots & \alpha_{n,n-1} & 1 \end{pmatrix}, \tag{7}$$

with a maximum number of $\frac{n(n+1)}{2}$ different unrestricted parameters, $\alpha_{i,j}$[6] to make A just-identified. Assuming also that structural disturbances have orthonormality condition, such that $E(\psi_t\psi_t') = I$, the relation between the variance-covariance matrices of v_t and ψ_t can be obtained as:

$$E(v_t v_t') = AE(\psi_t\psi_t')A'$$

$$E(v_t v_t') = AA'\,. \tag{8}$$

4.3 Identification of the Exclusion Restrictions

Following a VAR in F_t and Y_t we essentially examine the effect of the monetary policy shocks upon our estimated factors. In the baseline model, e.g., we define only the nominal interest rate / policy instrument, R_t, to stand for the observable series, Y_t, and as it is expected for R_t to react to factors, F_t, it would be the case that R_t contemporaneously responds to some variables in X_t. In such a case, a recursive VAR scheme in F_t and Y_t will

[6] It implies $\frac{n(n-1)}{2}$ restrictions in (5).

be inaccurate and needs for an additional exclusion restrictions. For this reason, we follow Bernanke et al. (2005) that use timing restrictions to avoid potential contemporaneous links between some of the variables in the large data set from which we draw principal components and the observable policy instrument. That is, they benefit from the identifying assumption of strict causal ordering of the series in the VAR setting with which the variable ordered last reacts simultaneously to all preceding variables whereas these variables are predetermined i.e., they do not react simultaneously to the last variable (Soares, 2013). Bernanke et al. (2005) trace a "Slow-R-Fast" scheme for timing restrictions under which "slow-moving" variables correspond to series that are predetermined before the current period (e.g., output, wages and prices) and monetary policy innovations (R) are assumed not to influence the "slow-moving" series within the same period. Besides, "fast moving" series (e.g., asset prices and variables of expectations) are assumed to react contemporaneously to all innovations. We will estimate recursively a VAR in $F_{new,t}$ and Y_t with a Cholesky identification structure in which the policy instrument is ordered after rotated factors and consider the innovations on the policy instrument as the policy shocks.

4.4 Empirical Implementation

In its empirical implementation of the model we cover the first-stage under four steps: firstly, we divide X_t into slow- and fast-moving series following the "slow-R-fast" scheme (see Bernanke et al. 2005; Boivin et al., 2009; Soares, 2013) and following Stock and Watson (2016) we order the series from slowest to fastest in our large data set, X_t; then, we estimate the matrix of common factors, F_t using all the series in X_t[7]; in the following step we apply PC to the slow-moving series to obtain the matrix of slow-moving factors ($F_{slow,t}$); lastly, we estimate the following regression:

$$F_t = \alpha + D \times (F_{slow,t}) + B \times Y_t + \varepsilon_t \tag{9}$$

[7] Note that Bernanke et al. (2005) do not assume that the short term interest rate that stands for Y_t is one of the common forces in the observation equation. Then, they remove the potential information provided by the interest rate from the space spanned by the PCs by using "rotated factors". In Boivin et al. (2009), however, this constraint is imposed in the way that the interest rate is one of the common factors in the first-step estimation. They compare their estimates with that of Bernanke et al. (2005) and find similar results.

equation by equation for each factor where Y_t stand for the matrix of observable series.[8] That is, for the first K number of PC, it becomes

$$F_t^1 = \alpha_1 + \beta_1 \times \left(F_{slow,t}^1\right) + \cdots + \beta_K\left(F_{slow,t}^K\right) + \gamma_1 Y_t + u_t,$$

$$F_t^2 = \alpha_2 + \beta_2 \times \left(F_{slow,t}^1\right) + \cdots + \beta_K\left(F_{slow,t}^K\right) + \gamma_2 Y_t + v_t,$$

$$\vdots$$

$$F_t^K = \alpha_K + \beta_K \times \left(F_{slow,t}^1\right) + \cdots + \beta_K\left(F_{slow,t}^K\right) + \gamma_K Y_t + z_t,$$

We use the overnight lending rate until 2010:5; one-week repo rate thereafter to obtain the policy rate. To avoid from any potential contemporaneous correlations between fast-moving series ($F_{fast,t}$) and the selected policy tool and, thus, to define the VAR setting accurately in a standard recursive fashion, we estimate the rotated factor ($F_{new,t}$) from the equation $F_{new,t} = F_t - B \times Y_t$. With this way, we remove the direct dependence of $\hat{C}(F_t, Y_t)$ on Y_t i.e., to remove any of the linear group of $\hat{C}(F_t, Y_t)$ that may relate to the policy instrument (see Bernanke et al., 2005). For this aim, for the first K number of factors, corresponding rotated factors are estimated as

$$F_{new,t}^1 = F_t^1 - \gamma_1 Y_t,$$

$$F_{new,t}^2 = F_t^2 - \gamma_2 Y_t,$$

$$\vdots$$

$$F_{new,t}^K = F_t^K - \gamma_K Y_t,$$

where the estimated coefficients on the selected policy tool Y_t are obtained from the equation (3). We subtract, thus, our observed variable, Y_t, multiplied with the corresponding estimated coefficients from each of the principal components of $\hat{C}(F_t, Y_t)$. In the second-stage, accordingly, we estimate a VAR setting in $F_{new,t}$ and Y_t.

[8] Notice that in the baseline model the policy rate is selected as only observable indicator which implies $R_t = Y_t$.

In its implementation of the extended model we build upon the baseline model. The extended model is not a fully structural FAVAR model in which the vector of economic variables is partitioned to derive structural factors in an ad hoc manner (see, Belviso and Milani, 2006). We define only a group of structural "monetary policy factor", so that it is not assumed any ordering on the series included in X_t^2. For the remaining large data set X_t^1, we divide X_t^1 into slow- and fast-moving series following the "slow-R-fast" scheme and order them from slowest to fastest. Then, it is estimated the matrix of common factors, F_t^i, using X_t^1 and "monetary policy factors" using X_t^2.[9] Next, we obtain the matrix of slow-moving factors $\left(F_{slow,t}^1\right)$ from slow-moving series in X_t^1. Lastly, we regress

$$F_t = \alpha + D \times \left(F_{slow,t}^1\right) + C \times (F_t^2) + B \times Y_t + \varepsilon_t \tag{10}$$

equation by equation for each factor.[10] To avoid from possible contemporaneous relations among fast-moving series and the policy rate, we estimate the rotated factor $(F_{new,t})$ from the linear equation: $F_{new,t} = F_t - C \times F_t^2 - B \times Y_t$.

In the second stage we estimate a VAR in $F_{new,t}$ and Y_t where, being in line with Stock and Watson (2016), with an ordering that rank the slow-moving factors first, followed by the observed policy rate and the fast-moving monetary policy factor last in estimation.[11]

5. PRIMARY ANALYSIS

In this section we introduce the data set and explain how we determine the number of factors and lag-length before moving into model estimation under different specifications.

[9] In the extended model the policy rate and the monetary policy factor(s) are selected as observable indicators $(R_t, monetary\ policy\ factors = Y_t)$.
[10] We detect no multicollinearity among monetary policy factors and the policy rate.
[11] We obtain significant causality from monetary policy factors to selected policy rates but the reverse is not the case. Thus, we assume for a feedback from the monetary policy instruments to the policy rate and slow-moving macroeconomic series in our FAVAR setting.

5.1 Data

The data set consists of a balanced panel of 113 disaggregated macroeconomic series for the period spanning from 2005:12 through 2018:4.[12] The choice of the starting date is mostly due to situation that the sample period bears witnesses to an episode that is idiosyncratically consistent in the policy making side. That is, the monetary authority announced to pursue an *explicit* inflation targeting policy setting with the beginning of 2006 and thereafter gradually succeeded a relatively low inflationary environment, featuring still high inflation variability and inflationary gap. Besides, all the definitions on monetary aggregates are revised at the end of 2005 to conform with international standards in the monetary sector, so that Divisia-type monetary aggregates are constructed starting from this date.

Following the literature on factor models (Stock and Watson, 2002a, 2005; Bernanke et al., 2005; Barhoumi et al., 2010; Soares, 2013; Varlık and Berument, 2017) and in accordance with the availability of the Turkish data we collect the macroeconomic series from the following categories: industrial production indexes, expenditures, employment, balance of payments, external trade, external debt, reserves, retail sales and turnovers, prices, confidence indicators, expectations, risk indicators, interest rates, exchange rates, credit and deposit aggregates, monetary aggregates, foreign series and policy instruments. Following the policy agenda set by the CBRT we include a variety of instruments to obtain the “monetary policy factors” to be used in the extended model setting. As Turkish economy is considered among the most fragile emerging markets with its high foreign indebtedness and its vulnerabilities against the external forces we include a set of foreign series to track the external impacts via an external factor.[13] Before drawing the factors and proceeding with the estimation we organize the data as follows:

Firstly, we make seasonal adjustments to better capture the true dynamics of the series. For removing seasonal patterns, in this regard, we rely on the X-12-ARIMA

[12] See Appendix B for the detailed description of the data set.
[13] Constructed external factor does not feature a high and significant correlation with any individual domestic series. We also control for certain number of dummies including a crisis dummy starting from 2008:9 and a financial stability dummy starting from 2011:1. The results are, however, robust to those dummies.

approach with multiplicative decomposition for non-negative series and with additive decomposition for the remaining series.

Secondly, we transform the series taking logarithm, first difference or first difference of logarithm to obtain approximate stationarity in the data set.[14] We apply the first difference of logarithms for the non-negative series except for the series that are already defined in percentages or rates. The interest rate series are expressed in terms of first difference. We take the first difference of the policy rate (see, Kelly et al., 2011) instead of using the series in level (see Sims, 1992) which induce stationarity and leads to narrower confidence bands of the response functions.

Thirdly, we correct the transformed series for the outliers following the commonly held procedure in the empirical literature (see Stock and Watson, 2005; Breitung and Eickmeier, 2011). That is, we define outliers as the observations of transformed series with median deviations (in absolute terms) larger than six times the inter-quartile range and correct for the outliers by replacing by the median value of the preceding five observations.

Finally, we normalize all the series used in computation of factors to have zero-mean and unit variance. For robustness control of the data sets, we also use the correlation matrix preceding the computation of factors which makes this formation of scaling unimportant.

5.2 Factor Determination

In estimation of the FAVAR model under two-stage PC approach, the first stage of finding pervasive forces in observation equation requires consistent estimates of the number of factors. In determining the number of potentially useful static factors, the related literature essentially benefits from “a combination of the a priori knowledge, visual inspection of a scree plot, and the use of information criteria and other statistical

---

[14] We also transform the series in the form of level (instead of logarithm) and percentage changes (instead of first difference and logarithmic difference) for controlling if any meaningful difference arises due to a particular choice of transformation. We do not confront with worth-mentioning differences in estimations.

measures" (Stock and Watson, 2016, p.435). In Table 1 we report some of the literature on monetary FAVAR models that use 2-stage method in estimation along with an information on the determination of factors, country and data statistics. We observe firstly that except for Holguín and Uribe (2019) the literature sticks largely to original 2-stage PC estimation due to Bernanke (2005). It arises also that the literature essentially grounds on Bai and Ng (2002) with different panels of information criteria ($IC_p(k)$ and/or $PC_p(k)$) to derive the number of static factors while a few of them uses Bai and Ng (2007) to obtain the dynamic factors.[15] It is only Holguín and Uribe (2019) that use the BIC criteria. Some of the studies also benefit from the scree plot analysis.

In this regard, firstly, following the related literature we apply a panel of information criteria $IC_p(k)$ and $PC_p(k)$ due to Bai and Ng (2002). Secondly, acknowledging the critiques on the criteria suggested Bai and Ng (2002)[16], [17], we employ the usual BIC and AIC information criteria as further test–statistics. Thirdly, to better observe the marginal contributions of first k factors to the average R^2 of the large data set and, thus, to better decide on the number of factors we use the scree plot analysis. Lastly, we estimate the model with different number of factors to control whether altering the number of factors in the model setting changes significantly the monetary transmission over the impulse response functions.

[15] For other but less employed approaches in determining the number of factors in FAVAR models, see Onatski (2010) and Ahn and Horenstein (2013).

[16] One argument is that information criteria in Bai and Ng (2002) may not give the optimal number of factors and overstate the factors as the maximum number of potential factors raises (Bağzıbağlı, 2014). Besides, Bernanke et al. (2005) set the number of factors using information criteria proposed by Bai and Ng (2002) but as they increase the number of factors used in their transition equation they find no qualitative change in responses of the series of interest.

[17] Ng (2002) information criteria are highly sensitive to the choice of maximum number of factors, so that the number of factors (K) may tend to be equal K_{max} in both studies.

Table 5.1: Studies on the Monetary FAVAR Models with Two-stage Estimation

Study	Estimation Method	Number of Factors	Country and the Data
Bernanke et al. (2005)	2-stage PC	3-static factors (from 120 series) Bai and Ng (2002)	US 1959:M1 – 2001:M8
Gupta et al. (2010)	2-stage PC	2- dynamic factors (from 246 series) Bai and Ng (2007)	South Africa 1980:M1 – 2006:M4
Benkovskis et al. (2011)	2-stage PC	3- dynamic factors for Poland, 4 for Czech Republic and Hungary (from 200 series) Bai and Ng (2002)	Poland, Czech Republic and Hungary 1999:Q2 – 2010:Q3
Soares (2013)	2-stage PC	7-static factors (explains 59% of 150 series Bai and Ng (2002), scree plots	16-country EA 1999:M1 – 2009:M3
Fernald et al. (2014)	2-stage PC	2-factors (explains 28% of 35 series) No information on how they set number of factors	China 2000:M1 – 2013:M9
Varlık and Berument (2017)	2-stage PC	5-factors (explains 99% of 59 series) Bai and Ng (2002)	Turkey 2001:M12 – 2016:M4
Holguín and Uribe (2019)	2-stage PC with time Restrictions	5-factors (explains 42% of 99 series Bai and Ng (2002), scree plots, BIC	U.S. 2001:M1 – 2016:M4

Below, we introduce briefly the methodology of information criteria used in determining the number of estimated factors (k). Bai and Ng (2002) define essentially a model selection problem over a class of criteria in setting the number of static factors to achieve asymptotically consistent estimates of true number of factors (r) when $N, T \rightarrow \infty$. In their setting, the resulting panel criteria depend on a trade-off between goodness-of-fit and parsimony. That is, in general form they define a class of criteria

$$IC(k) = ln\left(V\left(k, \hat{F}_k\right)\right) + kg(N,T)$$

in consistently estimating r. The term $V(k, \hat{F}_k)$ stands for the sum of squared residuals divided by NT $\left(\text{i.e., } V(k, \hat{F}_k) = \min_{\Lambda}(NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(X_{it} - \lambda_i^{k\prime} \hat{F}_{kt}\right)^2\right)$ and corresponds to the goodness-of-fit side. The term $g(N, T)$ is a penalty function for overfitting which increases with N and T. They specify, accordingly, the penalty as a function of both dimension. In consistently estimating r, it is crucial to achieve penalty function that vanishes at an appropriate rate. In this regard, Bai and Ng (2002) introduce a set of criteria, $IC_p(k)$ and $PC_p(k)$, as being specific formulations of the penalty factor. In detecting the number of static factors we will use all the set of criteria $(PC_{p1}, PC_{p2}, PC_{p3}, IC_{p1}, IC_{p2}, IC_{p3})$ proposed by Bai and Ng (2002) as well as BIC_3 and AIC_3. We prefer to include the usual AIC_3 and BIC_3 as they take into account both N and Tdimensions in estimation.

Hence, assuming $\hat{\sigma}^2$ as a consistent estimate of $(NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} E(e_t)^2$ the following criteria can be defined:

$$PC_{p1} = V(k, \hat{F}_k) + k\hat{\sigma}^2 \left(\frac{N+T}{NT}\right) \ln\left(\frac{NT}{N+T}\right),$$

$$PC_{p2} = V(k, \hat{F}_k) + k\hat{\sigma}^2 \left(\frac{N+T}{NT}\right) \ln C_{NT}^2,$$

$$PC_{p3} = V(k, \hat{F}_k) + k\hat{\sigma}^2 \left(\frac{\ln C_{NT}^2}{C_{NT}^2}\right),$$

$$IC_{p1} = ln\left(V(k, \hat{F}_k)\right) + k\left(\frac{N+T}{NT}\right) \ln\left(\frac{NT}{N+T}\right),$$

$$IC_{p2} = ln\left(V(k, \hat{F}_k)\right) + k\left(\frac{N+T}{NT}\right) \ln C_{NT}^2,$$

$$IC_{p3} = ln\left(V(k, \hat{F}_k)\right) + k\left(\frac{\ln C_{NT}^2}{C_{NT}^2}\right),$$

$$AIC_3 = V(k, \hat{F}_k) + k\hat{\sigma}^2 \left(2\,\frac{N+T-k}{NT}\right),$$

$$BIC_3 = V(k, \hat{F}_k) + k\hat{\sigma}^2 \left(2\,\frac{(N+T-k)\ln(NT)}{NT}\right),$$

where $C_{NT}^2 = min\{N, T\}$ is used under some criteria to set the average rate of convergence between k and r. Bai and Ng (2002) argue that the panel criteria are equivalent asymptotically $\left(\text{since } C_{NT}^{-2} \approx \left(\frac{N+T}{NT}\right) \to 0 \text{ as } N, T \to \infty\right)$ but may behave differently in finite sample $\left(\text{since } C_{NT}^{-2} \leq \left(\frac{N+T}{NT}\right) \text{ in finite time}\right)$. Besides, under IC_p panel criteria the choice of K_{max} becomes irrelevant by removing $\hat{\sigma}^2$.

Employing a panel of information criteria $IC_p(k)$ and $PC_p(k)$ in Bai and Ng (2002) reveals that the estimated number of factors is sensitive to the choice of maximum number of factors only in PC_{p3}, IC_{p3} and BIC_3. For these criteria, in Table 2, when the number of static factors is calculated for $k = 3, 4, \dots, 10$, increasing k results in the number of optimal static factors to rise with the same rate. Applying PC_{p1}, PC_{p2}, IC_{p1} and IC_{p2} criteria, however, gives $k = 5$ even if the maximum number of factors is increased to 10. Besides, AIC_3 determines the number of factors as two while in BIC_3 the number of factors is sensitive to the choice of maximum number of factors.

Table 5.2: Panel of Criteria in Determining the Number of Factors

Cr.	$K_{max} = 3$	$K_{max} = 4$	$K_{max} = 5$	$K_{max} = 6$	$K_{max} = 7$	$K_{max} = 8$	$K_{max} = 9$	$K_{max} = 10$
PC_{p1}	3	4	5	5	5	5	5	5
PC_{p2}	3	4	5	5	5	5	5	5
PC_{p3}	3	4	5	6	7	8	9	10
IC_{p1}	3	4	5	5	5	5	5	5
IC_{p2}	3	4	5	5	5	5	5	5
IC_{p3}	3	4	5	6	7	8	9	10
AIC_3	1	1	1	1	1	2	2	2
BIC_3	3	4	5	6	7	8	9	10

We also report scree plots that show the marginal contribution of kth factor to the average R^2 of the N regressions of the large data set X_t against the first k factors. The marginal contribution corresponds to the additional explanatory value on average of the kth factor (Stock and Watson, 2016). The Figure 5.1, thus, simply displays a bar graph of the marginal contributions of each factor against total number of factors. This implies for the eigenvalues arranged in order of principality. The scree plot displays a kink point in the 5th factor in which first five factors explain 42% of the total variance in X_t, where including the 6th factor contribute only 3% to R^2. Note also that the marginal gain from including 10 factors instead of 5 factors is around 13%. Hereby, grounded on different sets of information criteria denoted above and the scree plots on marginal contributions of factors we set the number of the factors as five. We also control whether altering the number of the factors changes the results in section 6.5 and find no evidence on significant improvement in response functions as we increase the number of factors. As static factors are estimated directly without having any model specification or any parametric constraints and as it is estimated the space spanned by the common factors rather than the factors themselves, any economic interpretation of those factors will be an informal one. Still, we provide an interpretation of the factors in Appendix C to be elucidative in revealing the potential relation across our rotated factors and macroeconomic series, otherwise lacking in the analysis. We also determine one external factor extracted separately from a group of foreign variables to encompass the potential external impacts on Turkish economy and consider it as an exogenous variable to the system.[18] The first factor explains about 47% of the total variance in foreign variables.

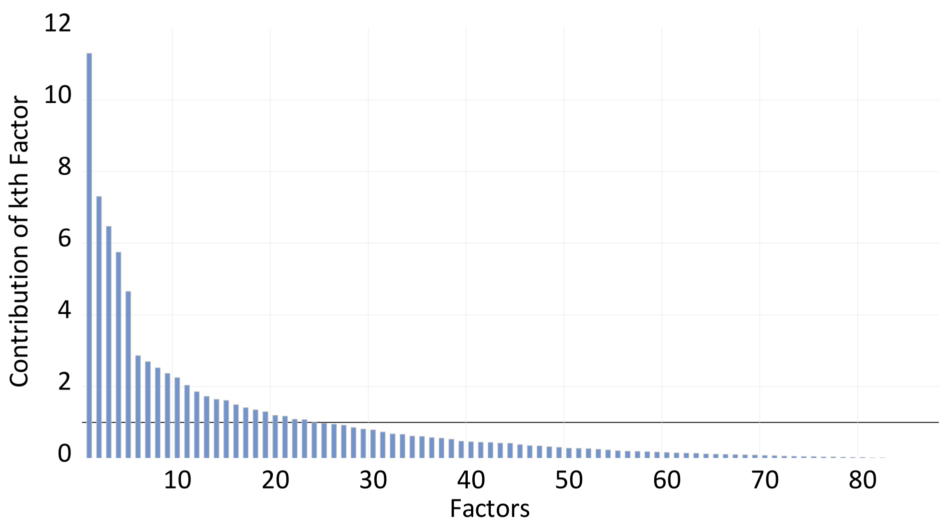

Figure 5.1: Scree Plots for Contribution of Factors

Note: The horizontal line gives a value, which is 1 in our case, being equal to the average of the calculated eigenvalues.

[18] Being in line with the previous findings (see Soares, 2013) when the foreign and domestic variables are considered together in extracting the factors with relatively low number of foreign variables (in our case, the number is seven), the resulting correlations among the factors and external series turn out to be subdued. In better capturing the foreign policy changes, thus, the corresponding external factor is extracted separately from foreign variables.

5.3 Lag-Length Determination

Following the estimation of the factors we proceed with determination of the lag-length of the transition equation. The decision on the optimal lag-length (p) to be used in any formation of VAR models is of importance in achieving consistent estimates of impulse response functions and variance decompositions from these models. To solve the trade-off of improved fit by including more lags against over-fitting problem and reduction in the degrees of freedom we apply standard test statistics of likelihood ratio test, the Akaike information criterion (AIC), the Schwarz criterion (SC) and the Hannan-Quinn criterion (HQ). Note that in the FAVAR literature there exist no specific preferred information criteria (Bağzıbağlı, 2014). In the seminal work of Bernanke et al. (2005), the number of lags is chosen as thirteen in an ad hoc manner to capture the main dynamics of the economy. In our study, however, to determine the lag-length used in our model we follow Bağzıbağlı (2014), so that using our estimated five factors, one external factor and the selected policy rate we estimate the baseline FAVAR model with seven variables $(n = 7)$ and determine the number of lags based on the criteria given above. The lag-order turns out to be two in the baseline FAVAR model.[19] In this regard, we prefer to use two lags in our model that benefits also us to encounter the relatively short length of the data (149 observations) and the high number of estimated parameters.[20] Lastly, we control whether the selected lag-length results in any problem of autocorrelation; non-normality and instability of residuals in the model using autocorrelation LM test, square root of correlation (Doornik – Hendry) test statistics and AR roots tables, respectively and find estimated residuals to be well-behaved.[21]

[19] We also estimated our baseline FAVAR model with 3, 4, 5, and 6 lags and observed that the selecting the lag-order as two results in similar responses of the variables in models with higher lag-orders.
[20] With $n = 7, p = 2$ in $n(1 + np)$ we have 105 parameters to be estimated in our baseline FAVAR
[21]The residuals of selected policy rate featuring non-normality are the only exception but the related series are found as stable.

5.4 Impulse Response Functions in the FAVAR Model

The FAVAR model enable us to obtain the impulse response functions of all the variables by manipulating the weights (factor loadings) with which the series are reconstructed from the estimated factors and observable series. The impulse response functions of the estimated factors and the observable variables are obtained as follows:

$$\begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} = \hat{\Psi}(L)\varepsilon_t \tag{11}$$

where $\hat{\Psi}(L) = \left(\hat{\psi}_t\right)^{-1} = \hat{\Psi}_0 - \hat{\Psi}_1 L - \cdots - \hat{\Psi}_h L^h$ is a matrix of polynomials in finite order h, in the lag of L and $\hat{\Psi}_i$ $(i = 0,1,\dots,h)$ is the coefficient matrix. Using the estimated factor loadings in the observation equation i.e., $\hat{X}_t = \hat{\Lambda}^f \hat{F}_t + \hat{\Lambda}^y Y_t$, the impulse response function of any variable included in the data set can be obtained as follows:

$$X_{j,t}^{IRF} = [\hat{\Lambda}^f \quad \hat{\Lambda}^y] \begin{bmatrix} \hat{F}_t \\ Y_t \end{bmatrix} = [\hat{\Lambda}^f \quad \hat{\Lambda}^y] \hat{\Psi}(L)\varepsilon_t. \tag{12}$$

6. RESULTS

6.1 Baseline Model

In this part we estimate the impulse response functions of selected variables to one-standard-deviation contractionary shock to the policy rate under baseline model (Figure 6.1).[22] Even though the FAVAR model setting allows us to obtain direct responses of all of the variables included in the data set (Soares, 2013), we select the response functions of 20 variables to reflect different aspects of Turkish economy (real activity, exchange market, prices, credit market, expectations and market interest rates) to avoid

[22] We also report the cumulative response functions of selected variables to a shock to the policy rate in Figure D.1 in Appendix D and observe that the cumulative responses are considerably in line with the impulse responses with respect to direction and significance of responses.

any confusion due to multitude. Note that impulse response functions are provided in the form of standard errors. Besides, the statistical significance of the impulse responses is evaluated with 90% confidence bands (dashed lines) which are obtained using the bootstrapping with a number of 1000 iterations.

The baseline model replicates Bernanke et al. (2005), so that the policy rate is considered to be only observable variable. The policy rate corresponds to the lending rates announced periodically in policy statements of CBRT (Binici et al., 2018) and is assumed to summarize the central bank's policy set. More specifically we see the overnight lending rate and one-week repo rate as two lending rates at which the central bank meet the liquidity needs of the banking system. We use the lending rate until 2010:5 and weekly repo rate thereafter to set the policy rate.[23, 24] It should be acknowledged that the weekly repo rate changes more passively and with a delay under the unconventional policy framework of the CBRT compared to the average funding cost interest rate which is determined by a combination of the amounts of quotations and auctions along with their corresponding costs and, thus, captures better the funding decisions of the participants. Still, as the CBRT clamorously announce its loyalty to the policy rate (CBRT, 2015; 2019) we take the repo rate in introducing the policy rate for the period between 2010:5 and 2018:4.

As a result of a contractionary monetary policy with a positive shock to the policy rate we observe largely expected negative impact on economic activity (with a fall in the employment rate, industrial production index, capacity utilization rate and number of new firms) with certain exceptions. One exception is the response of capacity utilization rate which is initially positive and become persistently negative only after fourth period. Note also that even though the response of the industrial production index is mostly negative, the resulting significance is quite low. This result is consistent with the recent findings (Çatık and Akdeniz, 2019) that the responses of the industrial production are not highly sensitive the interest rate shocks for Turkey. The current

[23] See CBRT (2011) for the adjustment made in April 2010 that determines the one-week repo auction rate as the policy rate which was previously used as more of a passive tool.
[24] The lending rate series are replaced with overnight borrowing rate series for the period from 2005:12 through 2010:5 for robustness check and no meaningful difference in estimation results is captured.

account balance improves insignificantly starting from the second quarter with a positive shock to the policy rate. Also, as a response to the policy shock, the domestic currency measured by a fall in the basket exchange rate[25] appreciates which signals for absence of exchange rate anomalies being contrary to Varlık and Berument (2017) that find exchange rate puzzle following a shock to the lending rates. Evaluating responses of current account balance and exchange rate together it can be stated that even if the contractionary shock suppresses the aggregate domestic demand and thus imports, the appreciation of the domestic currency potentially relocates the existing demand of firms and consumers toward more on the imported goods (Uysal, 2017).

With regard to response of the prices, Figure 6.1 reveals that the producer price index (PPI) is affected negatively and pronouncedly by a positive policy innovation starting from the second period while the negative response of the consumer price index (CPI) is quite modest. This result is not compatible with some strand of the literature that reaches significant and adverse impacts on CPI inflation of a shock to policy rate in Turkey (Varlık and Berument, 2017; Küçükefe and Demiröz, 2018). The impulse response functions of CPI[26], in our case, may signal for more of an indeterminacy state (see, Belaygorod and Dueker, 2007) where the monetary policy is passive in the way of raising the policy rate less than proportionately in response to an increase in prices of consumer goods (Castelnuovo and Surico, 2010) rather than price anomalies a la in Sims (1992). Such an indeterminacy state can be attributed to the existence of a policy mix that deals with a trade-off in provision of price stability, financial stability and economic growth (Uysal, 2017). Relatedly, it can be emphasized a relatively low growth and inflationary period of post-2009 that is featured by expansionary fiscal policy and weak monetary policy that allow inflation to rise and remain high and financial markets to suffer high volatility contrary to an aggressive attempt in controlling inflation (Gürkaynak et al., 2015).

A positive innovation to the policy rate in the baseline model passes through bank credit and deposit interest rates: a policy disturbance positively affects credit interest

[25] Basket exchange rate corresponds to the arithmetic average of US Dollar and Euro against Turkish Lira.
[26] Note that subgroups of consumer price indices reveal the similar patterns of the responses.

rates and credit loans (consumer credits, housing credits and financial credits) decreases. This result is not in line with the findings that discredit the policy rate for pricing of loan/deposit rates (Binici et al., 2018). The figure displays that the consumer loans (consumer and housing credits) are more responsive to the unexpected policy shock compared to corporate loans (financial credits). A contractionary shock to the policy rate, surprisingly, leads the foreign currency reserves and time deposits to be negatively and significantly affected even though deposit interest rates hike. Besides, short term adverse relation between the policy rate and the money stock signals for functioning of liquidity effect (see Kelly et al., 2011).

Regarding the responses of expectations of agents, the related policy shock affects negatively but modestly the expectations on end of year exchange rate. Besides, the expected CPI inflation for the end of year rises significantly as a response to a policy shock.[27] Thus, being different from the response of CPI inflation, a positive shock to the policy rate prompts agents to expect higher inflation at the end of the year in the Turkish economy. Lastly, agents' confidence to the economy, measured by real sector confidence index,[28] is negatively but insignificantly affected by a positive policy shock.

[27] The positive response of the expected CPI inflation to a positive policy rate shock is still reached when we use the expected inflation of twelve months later.
[28] Note that the consumer confidence index follows a similar response pattern with that of real sector confidence index.

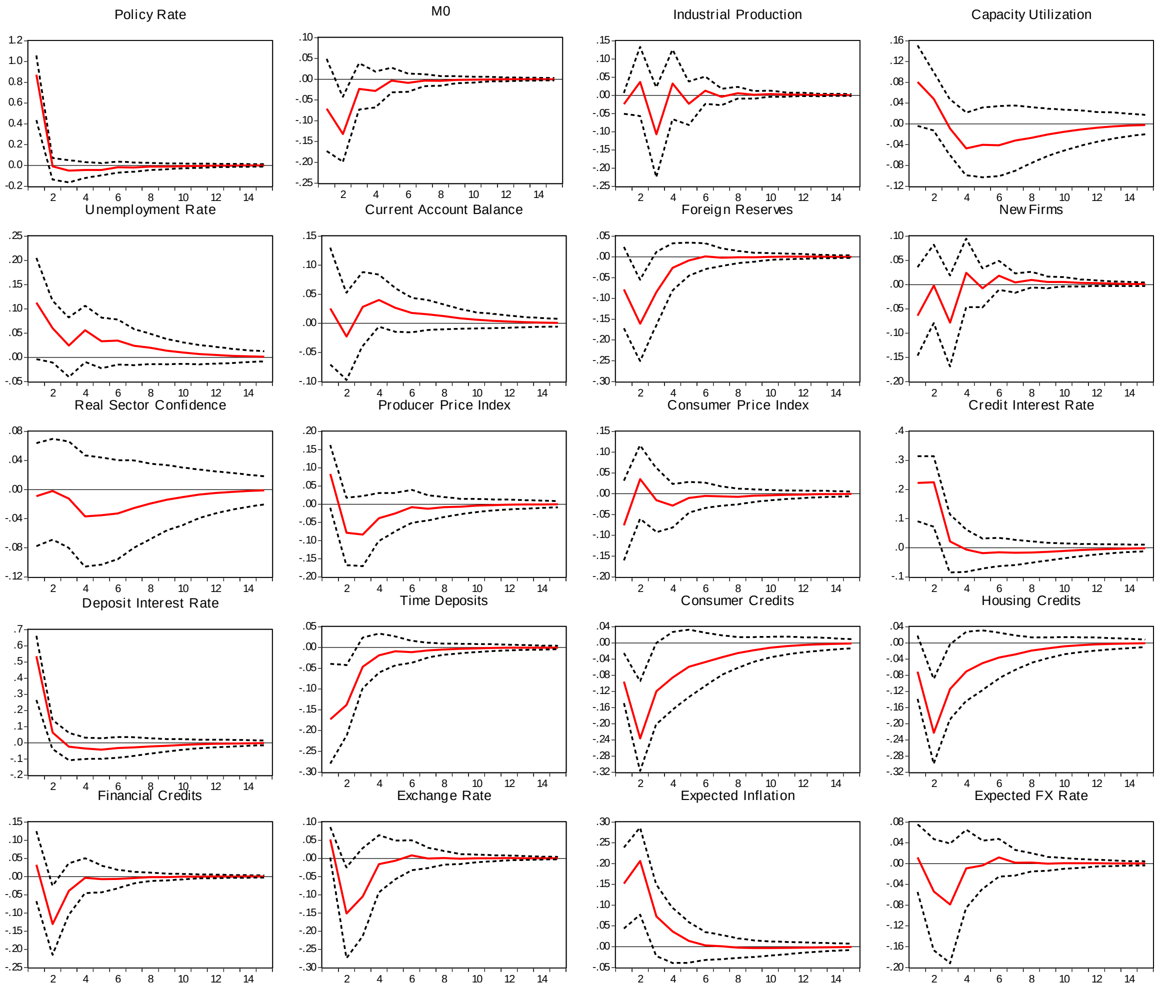

Figure 6.1: Impulse Response Functions to a Shock to the Policy Rate under Baseline Model

6.2 Comparison with Different Model Specifications

We proceed by estimating i) the extended model that takes monetary policy factors as observable variables beside to the policy rate ($Y_t = R_t$, Policy Factors) and ii) the baseline model replacing the policy rate with TRlibor rate ($Y_t =$ TRlibor Rate) and iii) the baseline model replacing the policy rate with Divisia M2 ($Y_t =$ Divisia M2). The comparison of the impulse response functions under alternative policy instruments and models is given to assess essentially whether the policy rate is alone a complete indicator of the monetary policy stance and whether money innovations improve the consistency of the transmission of the monetary policy to the economic indicators.

The extended model builds upon Varlık and Berument (2017)[29] that estimate the effects of different short term policy rates under a multiple-monetary policy framework in Turkey. Following Varlık and Berument (2017), we consider the monetary policy factors beside to the policy rate in representing the multiple-policy environment of the CBRT. In this regard we impose the identifying assumption that the monetary policy factors are drawn separately from a set of monetary policy instruments.[30] However, differing from Varlık and Berument (2017), in estimating the rotated factors we remove any impact of monetary policy factors beside to that of policy rate following the procedure explained in section 2.2. In this way, we eliminate the likelihood of contemporaneous covariance between fast-moving series (e.g., asset prices) and the monetary policy factors and, thereby, build weights correctly which are used to reconstitute all the variables from the estimated factors.

In determining the optimal number of related factors to be used in the extended model, among a panel of information criteria, PC_{p1}, PC_{p2}, IC_{p1}, IC_{p2} and AIC suggest the number of factors as two while the remaining criteria are sensitive to the choice of the maximum value (in our case, $k = 5$). Accordingly, we determine the number of the monetary policy factors as two that explain 58% of the total variation in the data set.

The Figure 6.2 displays the results of the baseline model and the extended model. Thus, as opposed to the existing FAVAR literature (Bernanke et al. 2005; Boivin, 2009; Soares, 2013) we examine the effectiveness of the policy rate controlling for also the common components of policy instruments applied by the central bank. In broad strokes, we reach that the officially announced interest rate becomes weaker in affecting economic state variables under a multiple-policy environment. This result considerably promotes

[29]In Varlık and Berument (2017) the cumulated variance share of all the principal components for the state variables is quite high i.e., around 99%. If not a typo, it may signal for a problem of the scale differences among the series, so that we standardize the series before drawing the factors.

[30]The related set of instruments includes rediscount rate, advance interest rate, overnight borrowing rate, overnight lending rate (for the period between 2010:5 – 2018:4), late lending rate, late borrowing rate, one-week repo rate (for the period between 2005:12 – 2010:4), CB average funding rate, overnight interbank repo rate, base money, open market operations, required reserves on foreign and domestic currencies, reserve option coefficient on foreign currencies (for the period between 2012:1 – 2018:4).

the findings that the policy rate is a poor indicator of the policy stance in Turkey operating under an asymmetric corridor (Binici et al., 2018; Şahin and Çiçek, 2018).

Following a positive innovation to the policy rate, the response of the real activity under the extended model does not feature a different pattern from the baseline model. The impact on the industrial production, among others, is limited and insignificant. The impact of a positive policy shock on the basket exchange rate under the extended model, however, is unexpectedly positive and insignificant. Regarding the response of aggregate price indexes, we observe that both responses of the PPI and CPI inflation to a policy shock materialize with a delay under the extended model. Note also that even though the impacts on the aggregate price indexes are negative, there occurs still no improvement on significance of the responses when the policy shock is evaluated under a multiple-policy environment. Besides, the pass-through impact on loans and deposits markets is quite low compared to that in the baseline model. Both consumer and financial credits respond less to a positive shock to the policy rate controlling for the multiple policy environment. This result now confirms the opposing arguments on the effectiveness of the policy rate for the successively penetrating the credit markets in Turkish economy (Binici et al., 2018). With regard to the response of expectations, we observe firstly that the positive response of expected CPI inflation for the end of year vanishes away and becomes insignificant under the extended model. Besides, the expected exchange rate responds surprisingly positive to a positive policy shock being inconsistent with the economic theory. The surprising negative impact on the foreign currency reserves and time deposits of a policy rate shock in the baseline model vanishes away evaluated under multiple policy environment.

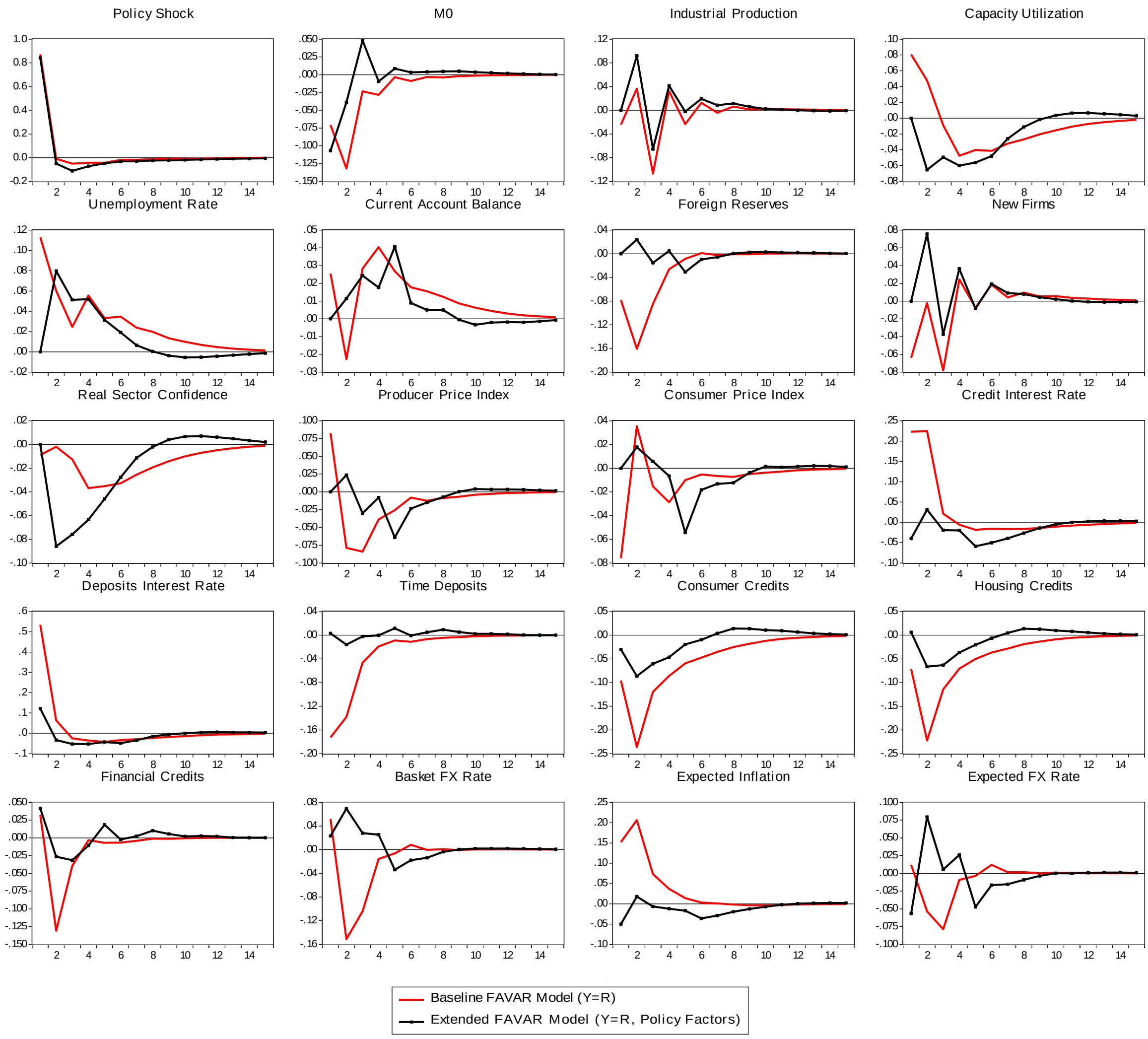

Figure 6.2: Impulse Response Functions to a Shock to the Policy Rate under Baseline and Extended Models

A number of studies advocates to use TRLibor rate (Turkish lira Reference Interest Rate) as a reference rate instead of using the policy rate announced periodically in policy statements of CBRT to summarize the central bank's policy set (see Alp et al., 2010; Gürkaynak et al., 2015). The Banks Association of Turkey (TBB) established the TRlibor market to build a reference interest rate among the banks and their clients.[31] We use the end of month observations of weekly TRlibor ask rates to obtain monthly rates.

[31] The TRLIBOR (ask) rate is calculated by the Banks Association of Turkey with a random selection of quotations entered by the participating banks by five times for O/N, weekly, monthly quotations and taking arithmetical average of the entered values excluding highest and lowest values. The same applies for the bid rates (Akçelik and Talaslı, 2020).

Figure 6.3 gives the impulse response functions of selected variables to a positive shock to the TRlibor rate.[32] In the first glance, it arises that both policy rate and TRlibor rate reveal very similar response patterns for almost all series. One exception is that following a shock to the TRlibor rate, the fall in the real sector confidence becomes more consistent. Besides, the transmission of a TRlibor rate shock to credit interest rates occurs with a delays opposing to the policy rate shock. That the policy rate and TRlibor rate generate parallel responses on the selected economic indicators can be attributed to the fact that the participating banks bear considerably in minds the existing and expected policy rates while setting their quotation rates. Besides, the existence of a close co- movement between these two rates is appreciated by the literature (see Alp et al., 2010).[33]

[32] Figure D.3 in Appendix D gives the impulse response functions to TRlibor shock with 10% significance bands.
[33] For the sample period we observe significantly high comovement (69%) between two rates.

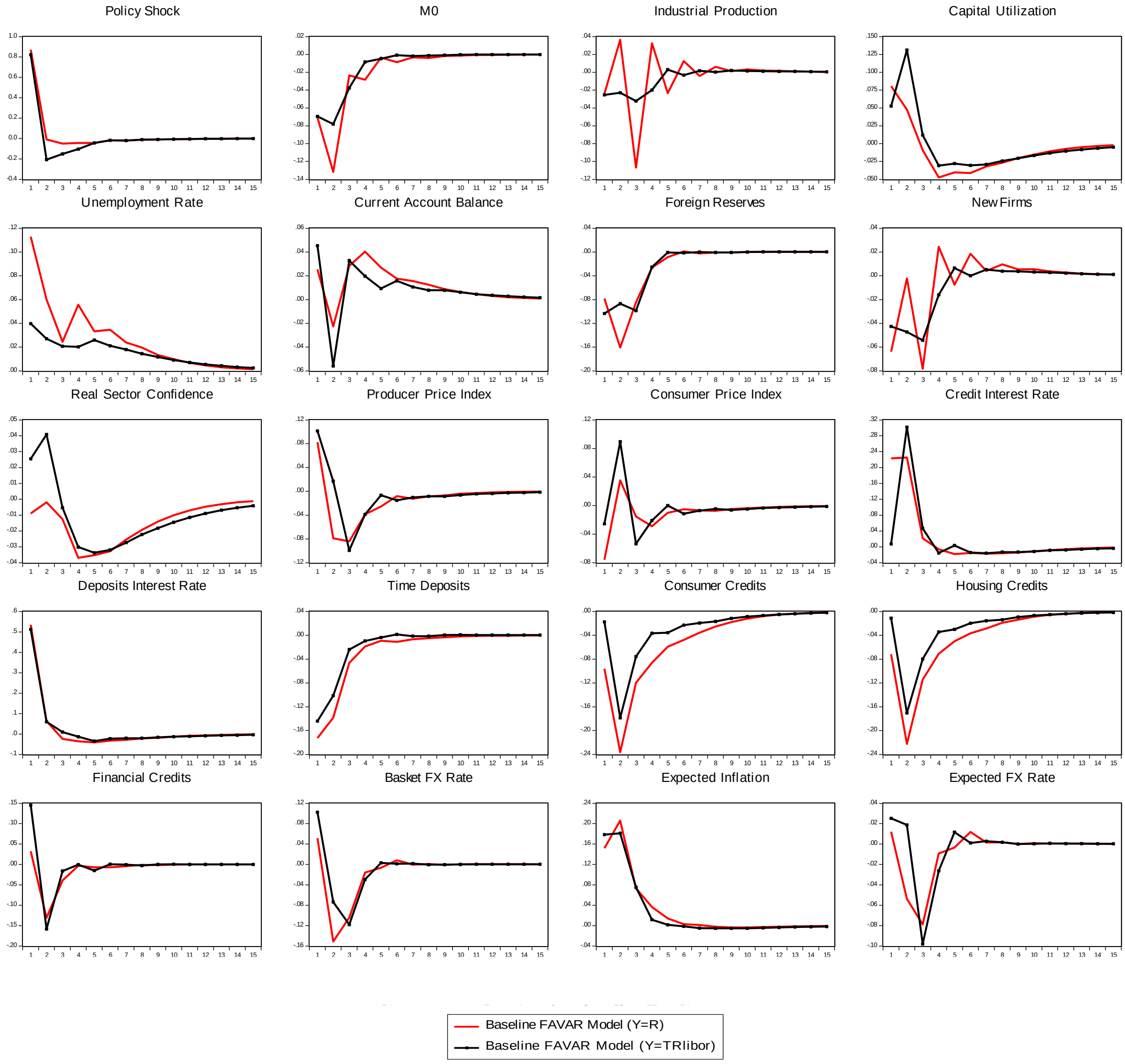

Figure 6.3: Impulse Response Functions to a Shock to the Policy Rate and TRlibor Rate under Baseline Model

Next, we provide the impulse responses of selected variables assuming for a disturbance to money beside to responses following a shock to the policy rate under the baseline model (Figure 6.4). We aim to see if money innovations improve the strength of the transmission of the monetary policy to the economic indicators. Broadly defined Divisia type monetary aggregates are taken as the observable variable (Y = Divisia M2) and stand for the money supply[34]. As in other policy tools, one-standard deviation is used to define the money shock. As introduced in Chapter 1, the Divisia monetary aggregates intrinsically include the interest rates prevailing in the market via the user costs and are advocated as a robust indicator compared to the policy rates in the conduct of monetary policy (Belongia and Ireland, 2018).

Following a negative disturbance to money, the responses of the real activity variables feature expected patterns. Notice firstly that the responses of real activity variables are more short-winded compared to the responses of model under the policy rate. Besides, the response of the unemployment is negative following a contractionary money supply shock. Besides, a money supply shock results in more robust and instantaneous decline in the responses of the basket exchange rate compared to a policy rate shock. Besides, replacing the policy rate disturbances with money supply disturbances provides consistent estimates with respect to response of the prices. That is, the monetary contraction through the monetary aggregates is significantly deflationary. Indeterminacy in the response of aggregate price index following a shock to the policy rate, thus, disappears in this setting. Note also that the PPI inflation is still more responsive to the money supply shock compared to the CPI inflation. Following a money disturbance, true to type, both M0 and time deposits are negatively and significantly affected. With regard to the responses of the credit market variables it arises, however, that the shocks to (Divisia type) monetary aggregates do not transmit effectively to credit market compared to shocks to the policy rate. Firstly, both credit and deposit rates do not respond properly to the money disturbances. Also, while loans market (consumer, housing and financial loans) responds negatively and instantaneously to a money shock, the related impact is short-winded and becomes slightly positive after the first quarter. Following a negative money disturbance, agents' expectations on both inflation and exchange rates are negatively and robustly affected which is not observed in the case of policy rate shock.

[34] We choose the Divisia M2 that includes the assets held in deposits and participation banks to stand for the money supply. We do not use the officially announced monetary aggregates since i) the results obtained in Chapter 1 reveal a (slightly) better predictive power of Divisia M2 relative to simple-sum aggregates and ii) Divisia M2 has the highest performance in predicting for the variance of selected 20 variables compared to its simple-sum counterparts. It is used the logarithmic change of the money stock in estimation.

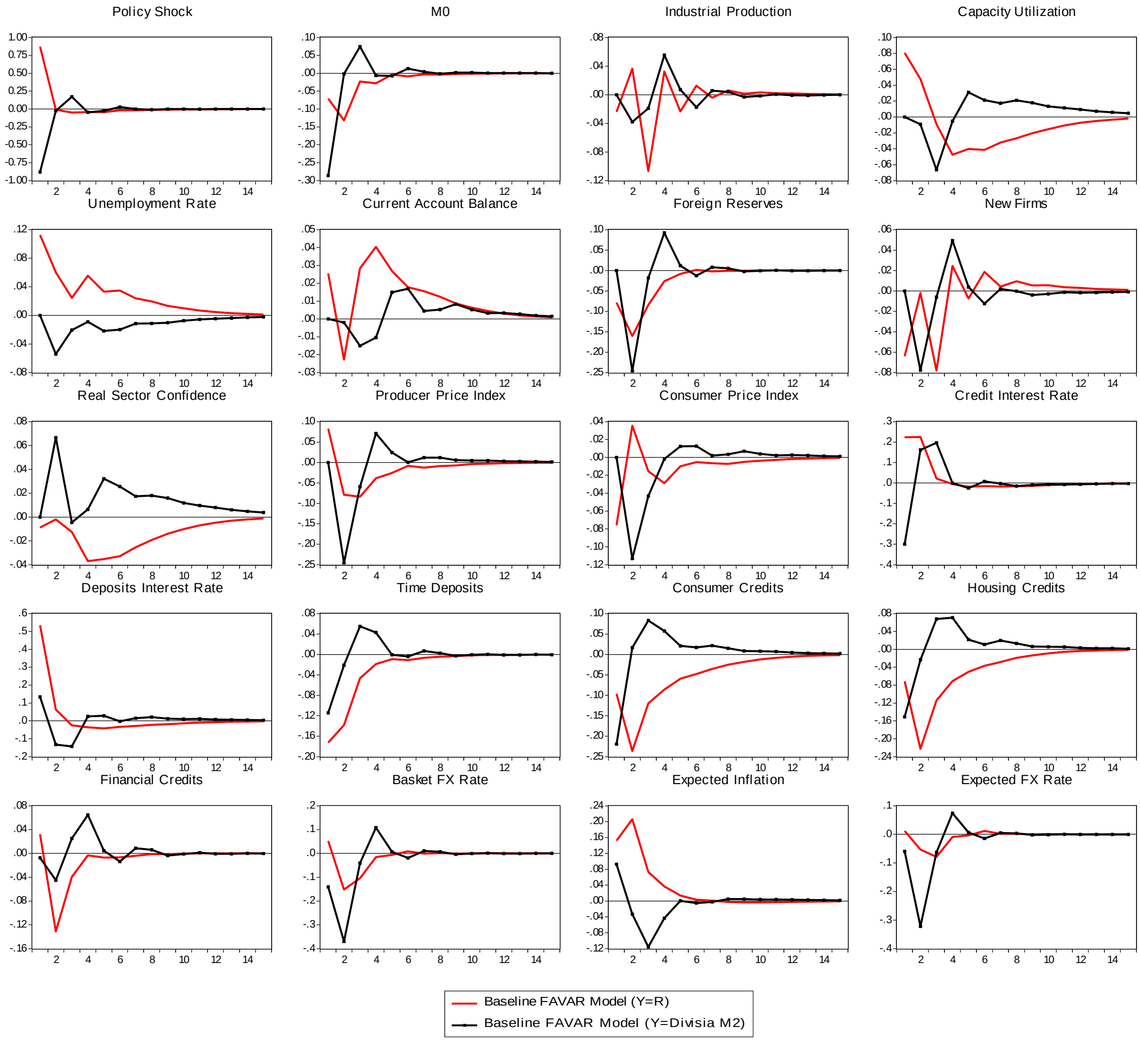

Figure 6.4: Impulse Response Functions to Shocks to the Policy Rate and Divisia M2 under Baseline Model

6.3 Comparison with the VAR Model

In this part we compare estimation results of the FAVAR models under different specifications with that of an unrestricted monetary VAR model to see whether inclusion of factors improves the estimation and resolves anomalies, if there exists any. Following the related literature (among others, Kelly, et al., 2011) our VAR model includes the industrial production index, the consumer price index, narrowly defined money, nominal exchange rate (vis-á-vis U.S. dollar and Euro) and the policy rate. Regarding the lag-order of the VAR model, the standard test statistics give the number of lags as order two.

The exchange rate is ordered before the policy rate, so that the short-term interest rate responds contemporaneously to the changes in exchange rate.[35]

Figures 6.5 and 6.6 display the impulse response functions of the VAR model as well as different specifications of FAVAR model following a contractionary policy shock. We select the baseline model with the policy rate, extended model and the baseline model with Divisia M2 for comparison.[36] The impulse responses are reported in standard deviation units. We examine the responses of the industrial production index – standing for an aggregate the economic activity measure –, an aggregate price index (CPI) and basket exchange rate – in comparison of the models.

Under alternative model specifications we do not confront with any different pronounced impact of contractionary policy shocks on the industrial production. Even though defining the policy shocks via money supply (Divisia M2) generates a negative effect on the industrial production at the first glance, the resulting effect is insignificant. Including factors into the model, hereby, does not reveal any worth-mentioning difference with respect to the response pattern of the industrial production. This result contributes to the empirical evidence that the transmission of the monetary policy innovations to the industrial production in Turkey is low (Varlık and Berument, 2017). The main argument held by Sims (1992) is that the VAR models lead to price puzzles as they mis-specify the information sets that central banks have and, thus, unable to capture dynamics on the leading indicators of the inflation. Here, inclusion of all the relevant information using factors is argued to solve the puzzling behaviors in prices (Bernanke et al., 2005; Boivin, 2009). With regard to response of the aggregate price index, the VAR model and the FAVAR model with the policy rate represent the different patterns: following the disturbance, the CPI inflation increases but insignificantly under the VAR setting signaling a puzzling behavior. The response of the CPI inflation in the FAVAR model with the policy rate, however, is negative following an initial positive response. Also, inclusion of the monetary policy factors generates negative responses of the CPI inflation

[35]In alternative specification of the VAR setting, the exchange rate is ordered last to provide the policy rate affect the exchange rate immediately, but not vice versa. Following the policy shock, accordingly, the resulting impact on the exchange rate gets higher, but is not significantly different from the baseline scenario.

[36]The impulse response functions of the VAR model with confidence bands are displayed in Figure D.2 in Appendix D. The none of the response variables reveals statistically significant reactions.

with a delay (Figure 6.5). Replacing the policy rate with the Divisia M2, however, generates significant and negative impacts on aggregate price index where the most pronounced impact on CPI inflation occurs at the second period (Figure 6.6). Figures also show that all of the model specifications, except for the extended model, do not pave the way for a puzzling response for the exchange rate following a monetary disturbance: a contractionary policy shock negatively and significantly influence the basket exchange rate and the resulting impact dies within two quarters. Even if the policy shocks are well-transmitted to the exchange rate, the most prominent impact arises under the FAVAR model with the Divisia M2. In the case of the extended model, however, when the multiple-policy environment is taken into account, the aforementioned negative impact of shock to the policy rate vanishes away: it results a positive and insignificant impact on the exchange rates. Besides, under all FAVAR specifications, being consistent with the related literature (Uhlig, 2005; Belviso and Milani, 2006; Bağzıbağlı, 2014) following a contractionary jumping behavior that lasts for two to three months, the selected monetary policy instruments respond adversely to their own shocks. This response pattern is, however, lacking under the VAR model.

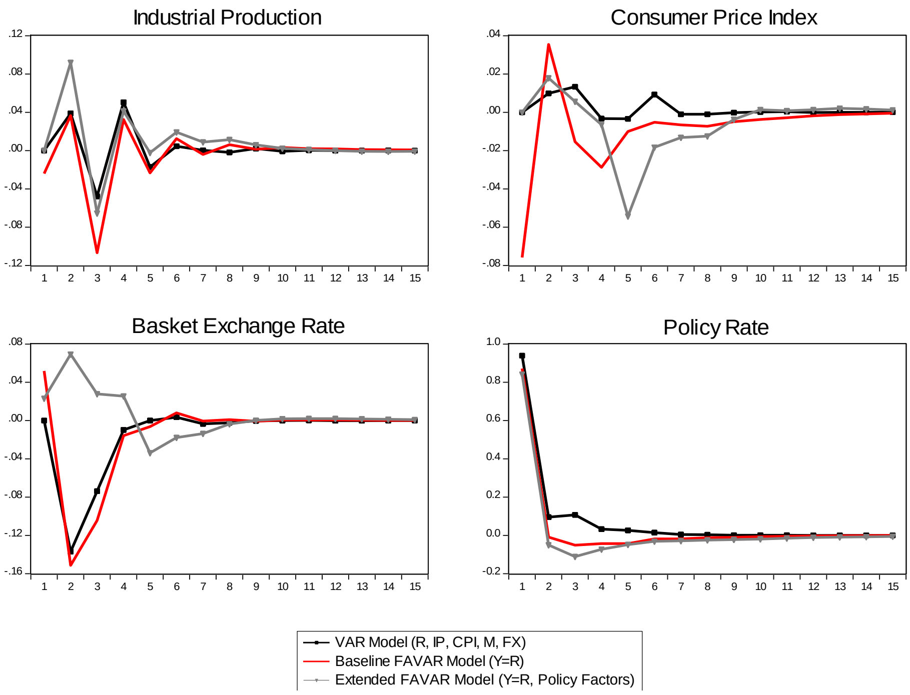

Figure 6.5: Comparison with the VAR Model (Baseline and Extended FAVAR Models)

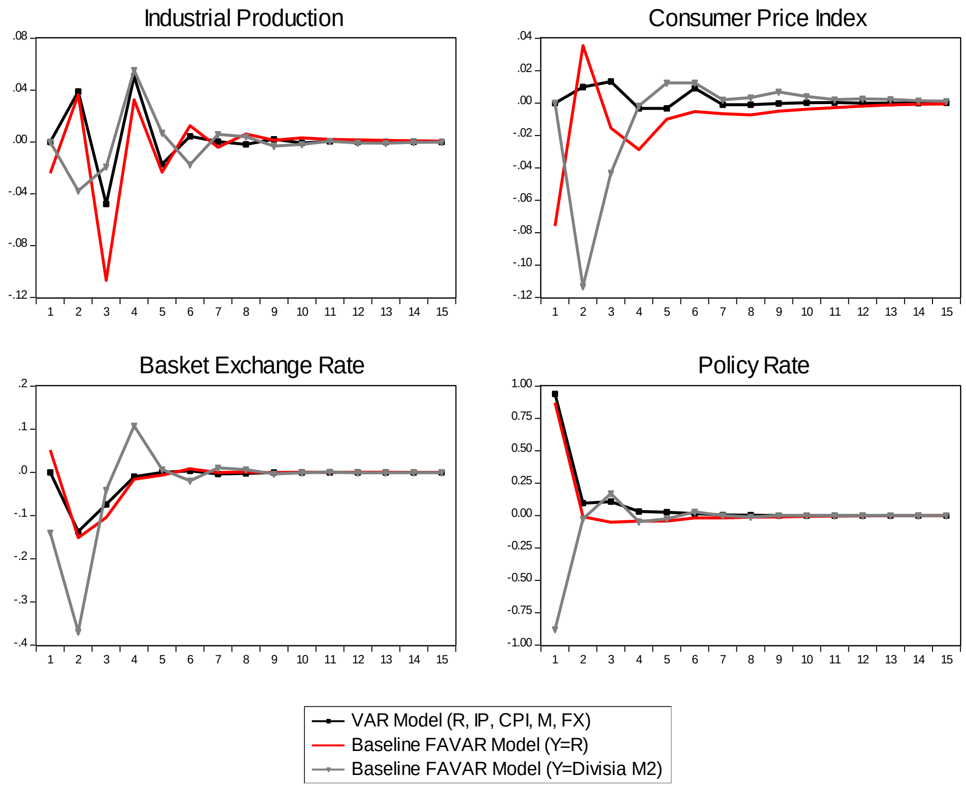

Figure 6.6: Comparison with the VAR Model (Baseline Model (Y=R) and Baseline Model (Y=Divisia M2))

6.4 Variance Decomposition and R^2

We continue with the forecast error variance decomposition (FEVD) and R^2 analyses reported in Table 6.1 for the variables used in the previous figures to better shed light on the performance of the policy shocks under different specifications (the baseline model with $Y = R$, the extended model with $Y = R$, Policy Factors, the baseline model with $Y = \text{TRlibor}$ and the baseline model with $Y = \text{Divisia M2}$) and of common factors in estimation. The FEVD reports the fraction of the variance of the forecast error of each variable explained by the policy shock. Let $\hat{X}_{t+h|t}$ be the h-horizon ahead forecast of X_{t+h} at t and the forecast error be $X_{t+h} - \hat{X}_{t+h|t}$. Hence, the part of the variance of the forecast error due to monetary policy disturbances, ε_t^r, can be given as

$$\frac{\operatorname{var}(X_{t+h} - \hat{X}_{t+h|t} | \varepsilon_t^r)}{\operatorname{var}(X_{t+h} - \hat{X}_{t+h|t})}. \tag{13}$$

Besides, being intrinsic to the FAVAR models, R^2 reports the explanatory power of the common components for the variance of each variable.[37] A high value of R^2 denotes that the information contained in the selected variable is well summarized by the common factors while a low R^2 implies for less confidence in the impulse response functions (Soares, 2013).

At the first glance, apart from the credit and deposit interest rates, the contribution of the policy rate shock varies from 0.2 to 9.3 under the baseline model, from 0.4 to 7.3 in the extended model, from 0.3 to 4.7 in the baseline model with the TRlibor rate and from 0.1 to 14.7 in the baseline model with Divisia M2. The commonly held argument of the low contribution of policy shocks to the volatility of variables of output (Christiano et al., 1999; Bernanke et al; 2005 and Soares, 2013) is also valid in our model: the contribution of the policy shocks under different models is less than 3% for the real activity variables. Table 6.1 also reveals that the policy shocks under alternative models explain relatively a larger fraction of the forecast error of PPI inflation compared to the CPI inflation being in line with differences in impulse responses of PPI and CPI and that money supply shocks leads to higher volatility of the aggregate price indexes than shocks to the policy rate. The money supply shocks, however, contribute prominently to the exchange rate variance compared to the shocks to the policy rate. Further, we observe that the forecast error of financial loans is less responsive to the policy shocks relative to that of consumer loans. Besides, shocks to the TRlibor rate increase the model fit for only the credit market compared to a policy rate shock while for the remaining group of indicators the former does not provide any improvement.

Regarding the R^2 decomposition analysis, Table 6.1 displays firstly that the common components perform well in explaining the variance of the selected variables with certain exceptions. The explanatory power of the common components is particularly high for the industrial production, real sector confidence, consumer loans and exchange rates while for unemployment rate, current account balance, time deposits and financial loans the performance of the common components are not equivalently

[37] It corresponds to the regression of each variable on the common components $\hat{C}(F_t, Y_t)$ i.e., the part of the variance of each variable explained by $\hat{F}_t$ and Y_t in the observation equation (2.2) in estimation part.

satisfying. For the latter variables, thus, we need to be less convenient in interpreting the impulse responses and the FEVDs. Also, while defining policy shocks under alternative models do not alter dramatically the R^2 (which promotes the arguments for modest place of the unsystematic component of the monetary policy in affecting state variables), the shocks to the policy rate under the extended model provides the highest explanatory power for the Turkish case.

Table 6.1: Forecast Error Variance Decomposition and R^2 for Selected Variables

	Baseline (Y=R)		Extended (Y=R, Policy Factors)		Baseline (Y=TRlibor)		Baseline (Y=Divisia M2)	
Variables	FEVD*	R^2	FEVD*	R^2	FEVD*	R^2	FEVD*	R^2
M0	2.2	14.9	2.1	18.6	1	15.4	8.2	17.5
Industrial Prod.	1.3	91.6	1.2	92.9	0.3	91.4	0.3	91.4
Capacity Utilization	1.9	57.9	1.7	59.5	2.6	58	0.9	58.7
Unemployment Rate	2.3	33.7	2.1	35.3	0.6	33.4	0.5	33.7
CA Balance	0.3	26.3	0.4	28	0.9	26.3	0.1	26.4
Foreign Reserves	3.7	41.7	3.3	43.3	2.6	44.3	6.4	42.5
New Firms	1	49	0.9	50.3	0.7	48.9	0.6	48.8
Real Sector Confidence	0.2	72.3	0.4	75.6	0.8	72.3	0.4	72.3
Producer Price Index	2.2	56.9	2.1	59.6	2.5	57	6.7	56.3
Consumer Price Index	0.7	39.4	0.6	42.7	1.3	38.7	1.4	38.9
Credit Interest Rate	10.6	63.9	8.3	65.1	9.6	66.4	16.3	63.8
Deposit Interest Rate	35.3	75.9	32	77.7	31	77.2	7.4	65.6
Time Deposits	4.9	23	3.1	25.7	2.3	24.6	1.6	22.1
Consumer Credits	9.3	78.8	7.3	79.8	4.7	78.7	6.4	78.7
Housing Credits	7.7	62	5.8	63.1	4.6	62.6	3.1	62.4
Financial Credits	1.8	30.1	0.5	32.1	4.4	30.7	0.3	32.6
Basket FX rate	3.4	92.4	3.1	93.7	2.8	92.4	14.7	93
Expected Inflation	6.8	46.1	5.5	47.4	6	44.9	2.3	47.3
Expected FX Rate	0.8	73.1	0.9	74.3	1	73	10.1	73.2

*The numbers are expressed in the percentage. The analysis is provided for 15-month horizon.

6.5 Robustness Control

6.5.1 The New Monetary Policy Period

We proceed with analyzing the effectiveness of the policy rate in the stance of monetary policy for the period between 2011:1 – 2018:4 that witnesses a vigorous and simultaneous use of multiple instruments by the CBRT. The central bank designed a new monetary policy framework in the late of 2010 incorporating the financial stability as a secondary objective beside to the price stability to smooth the volatilities in the financial markets e.g., to prevent the adverse impacts of the high volatility of capital flows on the financial markets (Kara, 2013). During this period the CBRT called on a more of cluttered policy stance and allowed the interest rates prevailing in the market to diverge from the officially announced rate and made the latter to be determined within a wide interest rate corridor (Özdemir, 2015).

In this regard, acknowledging the arguments that favor the effective rates compared to the policy rate in the policy making and in transmission of the policy shocks to the economy during this period of time (Binici et al., 2018; Çatık and Akdeniz, 2019) we report the impulse responses of the selected variables to both officially announced interest rate (one-week repo rate) and effective rate (BIST overnight repo rate). Note that the latter is determined indirectly by the interaction of the officially announced rates with central bank funding decisions (Binici et al., 2018). We also report impulse responses to the money supply shock using Divisia M2 controlling the multiple policy framework.

In comparing the official interest rate with the effective interest rate we do not include the observations belonging conventional monetary policy episode into the analysis as the central bank passed on to the new monetary policy state with the end of 2010 (Küçük et al., 2016) during which the central bank allowed the policy rate and the market rates to diverge (Binici et al., 2018). This divergence enables us, thus, to use a rich variation in the corresponding series which is lacking in the previous episode. Also, as the CBRT is net lender to the banks during this period, it deserves an inquiry to investigate the liquidity effects of changes in the lending rates set directly or indirectly by the CBRT on e.g., funding needs of agents.

We use the BIST overnight interbank repo rate to represent the effective rate given the findings that interbank rates matter more than officially announced rates for the monetary transmission in the cases under which the two rates are consistently different (Binici et al., 2018). Under the asymmetric interest corridor band, when the central bank meets the liquidity needs of the banking system partly with the one-week repo auctions and requires the banks to use costlier over-night lending rates (marginal funding) for their remaining needs, it leads interbank rate (or effective rate) to increase and results in another equilibrium different from the officially announced unique interest rate system i.e., it generates different rates of one-week repo rate, over-night borrowing or lending rates. In such a case, since the officially announced policy rate, the interbank rate and the average funding rate become different from each other, the selected unique policy rate *per se* may not stand sufficiently for the stance of the monetary policy.

The figure 6.7 reports the impulse responses of the selected series to contractionary policy shocks (to the one-week repo rate, BIST interbank repo rate and Divisia M2) while the Tables 6.2 gives the corresponding variance decomposition and R^2 analysis.[38] We estimate the extended FAVAR model as it enables us to control for the multiple policy framework.[39]

Firstly, we observe limited impact of policy disturbances on the real activity variables as found in the previous sections. At the first glance, neither the interbank rate nor the Divisia M2 pave the way for significant and different response patterns on real activity compared to the one-week rate. One exception is that even though R^2 is quite high, the shock to the interbank rate leads to small impact on the industrial production compared to the official rate. Besides, it arises anomalies in responses of unemployment rate and capacity utilization to a positive disturbance to the interbank rate. Model fits for these two variables are not convincingly high.

Table 6.2 displays that the estimated factors and all of the policy instruments explain convincingly high the variables of industrial production, new firms, producer and consumer price indexes, credit and deposit rates, consumer and financial credits, basket exchange rate and expected exchange rates. Note that, when the policy tool is defined as the interbank rate, credit and deposit rates fluctuate more compared to other tools while when the policy tool is defined as the money supply, we observe more profound negative impacts on the impulse response of industrial production, producer price index, credit

[38]The Figure D.4 and D.5 in the Appendix D display the impulse responses of selected variables to shocks to the interbank rate and Divisia M2 under the extended model along with the confidence intervals at 10%, respectively.

[39]The panel of information criteria gives the number of factors for the state variables as five. Also, we observe that the estimated residuals are stable. When the interbank rate is used as the policy instrument, we consider the one-week repo rate among the series that are used to extract the policy factors. We determine the number of monetary policy factors and lag–length as two.

market and exchange rates grounded on the FEVD and R^2. Besides, FEVD analysis provides that a policy shock to the Divisia M2 explains 20% of the volatility of the exchange rate being quite effective relative to other two tools.

With respect to the responses of aggregate price indexes for the period that encapsulates a vigorous use of multiple policy tools, we observe that the policy rate becomes more passive in coping with the CPI inflation compared to the whole sample results. That is, the volatility of the inflation is less affected by a shock to the policy rate under the new policy episode (Table 6.2). This result confirms with the multiple-policy environment that de-potentiates the policy rate in coping with a trade-off that might occasionally realize between different objectives (Kara, 2013). Replacing the policy rate with effective rate and money supply and assuming contractionary disturbances, however, result in both PPI inflation and CPI inflation to be negatively and significantly affected. In this regard, we do not come across with an indeterminacy state when the policy shock is given to effective rate determined by the central bank's funding policy or the Divisia M2 that includes intrinsically market interest rates.

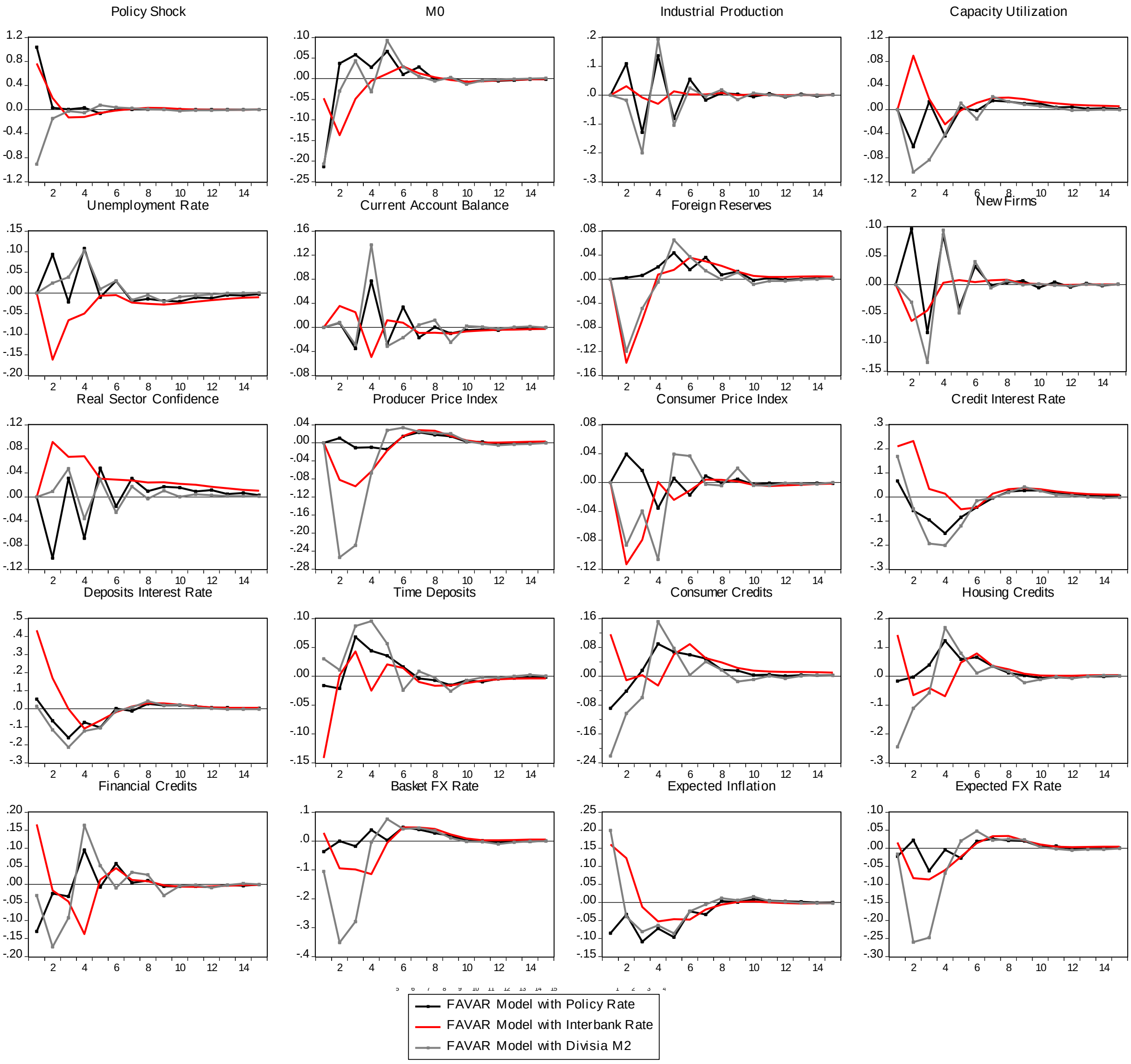

Figure 6.7: Impulse Response Functions to Shocks to the Policy Rate, Interbank Rate and Divisia M2 under Extended Model

Credit and deposit rates are relatively more responsive to policy disturbances to the interbank rates confirming the findings in Binici et al. (2018). Besides, the response of the deposit rate to shocks to the policy rate and money supply is surprisingly negative. Following a contractionary shock to the policy rate, the negative impact on the financial and consumer credits is short-winded and insignificant. Besides, replacing the policy rate with the interbank rate does not result in any meaningful improvement in its impact on the loans market. The overall impact on the loans market is most pronounced when the policy innovation is defined over the money supply. The negative and significant response of the financial and consumer loans to a contractionary shock to the Divisia M2 persists for one quarter and vanishes away in the subsequent periods. Besides, the transmission of the policy rate shocks to the exchange market and expectations on FX rates is not robust in the new monetary policy period while the shocks to effective rate as well as money result in negative and significant effects on the exchange rates and expectations where the most pronounced effect is due to shocks to Divisia M2.

Table 6.2: Forecast Error Variance Decomposition and R^2 for the Selected Variables: The New Monetary Policy Period

	Policy Rate		**Interbank Rate**		**Divisia M2**	
Variables	**FEVD***	**R^2**	**FEVD***	**R^2**	**FEVD***	**R^2**
M0	3.2	24	2.5	28.5	4	27.3
Industrial Prod.	1.9	94.6	0.2	95.2	4.5	94.9
Capacity Utilization	0.3	22.5	0.1	36.2	3.1	29.5
Unemployment Rate	0.9	37.8	3.9	37.3	0.5	36.6
CA Balance	0.8	30.9	0.6	32.7	0.5	32.8
Foreign Reserves	3.1	41.2	6	44.2	3.3	44.4
New Firms	0.7	51.2	0.5	52.9	1.8	52.0
Real Sector Confidence	1	40	1.2	41.7	0.6	41.4
Producer Price Index	1.6	64.7	3	64.8	12.1	64.8
Consumer Price Index	0.8	41.5	2	45.1	1.6	45.9
Credit Interest Rate	10.3	69.5	13	69.6	9.2	70.4
Deposit Interest Rate	20.6	66.8	26.8	74.2	7.3	70.6
Time Deposits	1.4	28.1	2.2	33.3	1	29.9
Consumer Credits	3.4	71.5	1.7	75.8	6.4	72.1
Housing Credits	3.2	54.5	2.8	60.6	7.6	54.3
Financial Credits	1.7	54.6	2.8	55.4	4.3	56.7
Basket FX rate	1.2	91.3	3.4	91.7	20.4	92.9
Expected Inflation	3.7	48.3	4.2	50.7	4.7	50.2
Expected FX Rate	1.4	77	2.1	77	11.9	77.8

*denotes the percentage. The analysis is provided for 15-month horizon.

6.5.2 Number of Factors

We proceed by controlling whether our results are robust to changes in factors which are determined using varieties of information criteria and scree plot analysis. The Figure 6.8 displays the impulse responses of the selected variables to the policy rate shock under the baseline model with respect to different number of factors ($k = 3, 5, 7, 9$). In this regard, we observe that increasing the number of estimated factors does not alter dramatically the response patterns of the variables. Considering a relatively small number of the factor $(k = 3)$ however, results in qualitatively different patterns. The credit market variables are among the series that feature divergence in impulse responses. That is, the robust pass through to the credit market (consumer, housing and financial loans) becomes weak with $k = 3$.

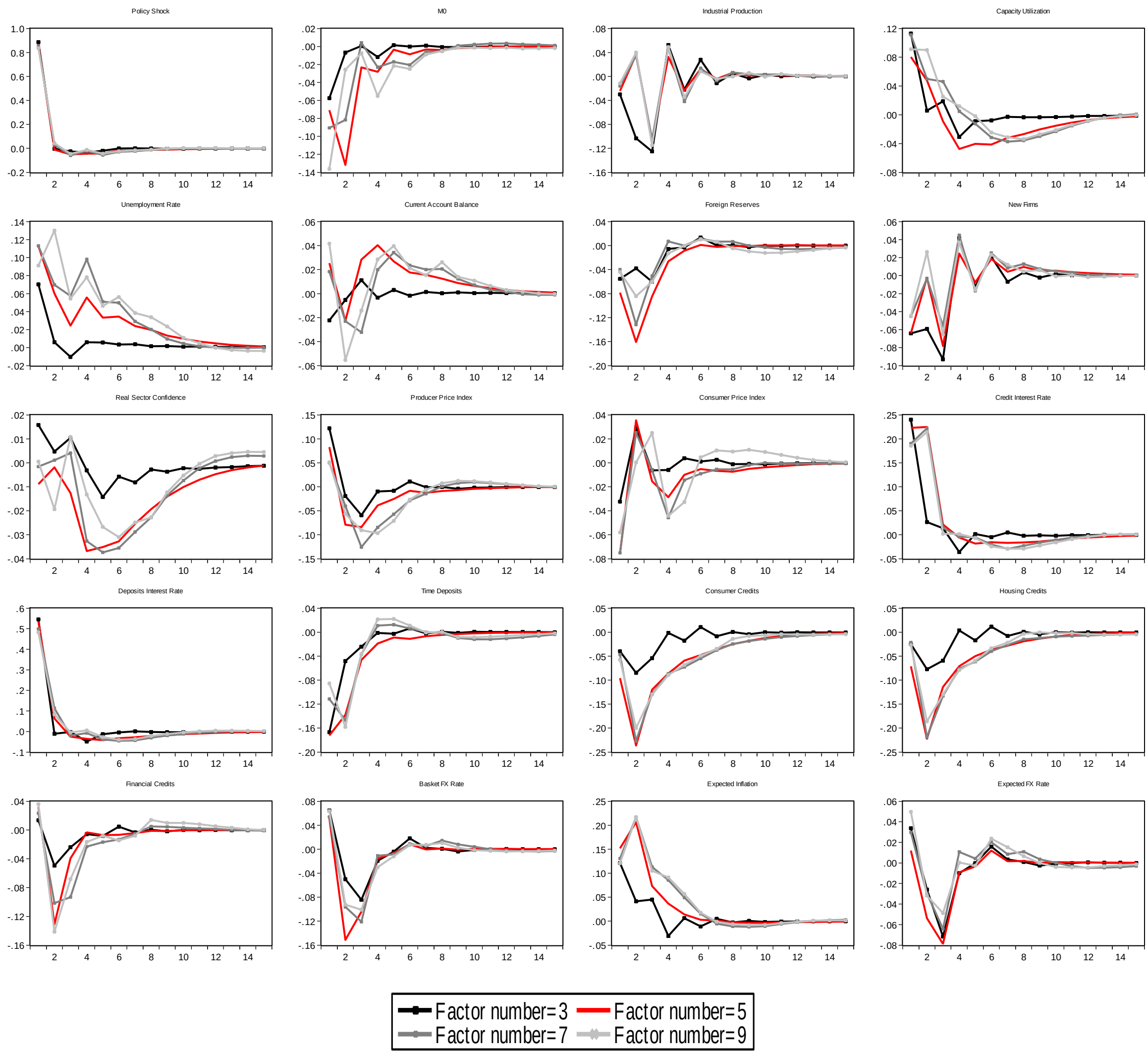

Figure 6.8: Impulse Response Functions to a Shock to the Policy Rate with Different Number of Factors

Beside to the impulse response functions reported above, we evaluate the performance of common factors in estimation using the R^2 analysis. Table 6.3 reveals that increasing the number of estimated factors leads the goodness-of-fit of almost all the variables to considerably rise. The variables related to exchange rates, among others, arise as exceptions. Besides, increasing the number of factors from five to seven or nine does not improve pronouncedly the performance of the factor model except for the variables of money supply, time deposits and unemployment rate.

Table 6.3: Forecast Error Variance Decomposition and R^2 for the Selected Variables: Different Number of Factors

	$k = 3$	$k = 5$	$k = 7$	$k = 9$
	R^2	R^2	R^2	R^2
M0	5.6	14.9	39.4	52.8
Industrial Prod.	76	91.6	92.3	92.4
Capacity Utilization	51	57.9	68.7	73.1
Unemployment Rate	19	33.7	40.1	74.8
CA Balance	6	26.3	38	39.1
Foreign Reserves	35.5	41.7	46.3	52.7
New Firms	45.9	49	51	51.8
Real Sector Confidence	63.8	72.3	74.1	82.5
Producer Price Index	52.1	56.9	73.1	77.8
Consumer Price Index	26	39.4	40	57.7
Credit Interest Rate	31	63.9	65.7	69.7
Deposit Interest Rate	69	75.9	78.5	80.9
Time Deposits	18.6	23	41.6	44.1
Consumer Credits	57.3	78.8	81.4	90.2
Housing Credits	44.3	62	68.2	78.9
Financial Credits	18.7	30.1	34.7	38
Basket FX rate	85.8	92.4	93.4	94.1
Expected Inflation	17.2	46.1	52.6	52.9
Expected FX Rate	73	73.1	75.7	76.9

7. CONCLUSION

This study materializes an analysis on the effectiveness of the pass-through in the stance of monetary policy of Turkey. More specifically, we investigate to what extent changes in the policy rate that the monetary authority periodically announces to operate the markets, aggregate demand and expectations, penetrate into the targeted variables. That the tools basket of the central bank has become heavier and the arguments favoring the effective rates compared to the policy rates in transmission to the economy have articulated on the one side, and that the central bank clamorously announces its loyalty to the policy rate, on the other side, motivate us in such an inquiry. In doing so, we benefit from the dynamic factor model setting to avoid the drawbacks of the small-scale VAR models as well as to incorporate the disaggregated series into the estimation. Using the FAVAR model enables us to reveal the strength of transmission mechanism to all series included in the data set rather than only to aggregate economic indicators. Also, as the sample period includes both the conventional and the new monetary policy episodes, instead of working on any potential impact of time variation on estimation results, we prefer to control for the observations belonging to the latter episode in the name of robustness. In this way, we are able to examine more efficiently the pass through of the policy rate which is determined within a wide and asymmetric interest rate corridor and compare it with effective interest rate indirectly determined by funding policy of the CBRT.

In broad strokes, the performance of estimated factors along with the policy tools are found to be well in explaining the variance of selected variables. The explanatory power of the common components is particularly satisfying for the industrial production, real sector confidence, consumer loans and exchange rates while it is not equivalently well in explaining unemployment rate, current account balance, time deposits and financial loans. We reach also that defining policy disturbances to different policy instruments and under alternative specifications does not alter dramatically the model fit which may promote the arguments for a modest place for the unsystematic components of the monetary policy in passing through the markets. Moreover, the extended model that takes the multiple policy framework into consideration displays the highest explanatory power for all the variables.

Prevailing under different model formations, a monetary tightening via unexpected policy rate changes leads largely to a small but expected decline in the real activity indicators, an appreciation of the domestic currency implying no exchange rate puzzles, no liquidity anomalies guaranteed by a fall in the monetary aggregates or credits and indeterminacy in responses of aggregate price indexes. Moreover, we observe that the policy rate becomes consistently weaker in affecting the variables of interest controlling the multiple policy framework being in line with the empirical evidence that regards the policy rate as a poor indicator of the policy stance in Turkey operating vigorously a variety of instruments. Considering the impact on liquidity conditions, among others, the disturbance to the policy rate passes less effectively through loan/deposit rates and credit market under extended model. In comparison of the policy rate with a hypothetical formation of money stock, it is revealed that the shocks to the policy rate pass more properly through the credit market variables while those to the Divisia M2 have more consistent but short-winded effects on the aggregate price indexes, solving the indeterminacy state observed under policy rate changes. In addition, we evaluate the effectiveness of the officially announced interest rate for the new monetary policy episode through which the CBRT is net lender to the banks and allows a notable divergence between the policy rates and effective rates. In this regard, the impulse response functions and variance decomposition analysis provide that the performance of one-week repo rates is significantly poorer compared to the BIST interbank repo rates evaluated under the unconventional conduct of monetary policy. More specifically, the policy rate becomes more passive in coping with the CPI inflation during this period and the indeterminacy state in response of CPI inflation vanishes away when the policy innovation is defined by interbank rate or the Divisia M2 that includes intrinsically market interest rates via the user costs.

REFERENCES

Ahn, S. and A. Horenstein (2013). Eigenvalue Ratio Test for the Number of Factors. Econometrica. 81.3, 1203–1227.

Akçelik, F. and A. Talaslı. (2020). Market-Based Monetary Policy Expectations for Turkey, Central Bank Review Volume. 20.1, 9-19.

Alp, H., R. Gürkaynak, H. Kara, G. Keleş and M. Orak. (2010). Türkiye'de Piyasa Göstergelerinden Para Politikası Beklentilerinin Ölçülmesi. İktisat İşletme ve Finans. 25.295, 21-45.

Aysan, A. F., S. Fendoğlu and M. Kılınç. (2014). Managing Short Term Capital Flows in New Central Banking: Unconventional Monetary Policy Framework in Turkey. *Working Paper*.14/03. CBRT.

Bai, J. and S. Ng. (2002). Determining the Factors in Approximate Factor Models. *Econometrica*. 70.1, 191-221.

Bai, J. and S. Ng. (2007). Determining the Number of Primitive Shocks in Factor Models. *Journal of Business and Economic Statistics*. 25, 52–60.

Bağzıbağlı, K. (2014). Monetary Transmission Mechanism and Time Variation in the Euro Area. *Empirical Economics*. 47.3, 781-823.

Barhoumi, K., O. Darn, and L. Ferrara. (2010). Are Disaggregate Data Useful for Factor Analysis in Forecasting French GDP? *Journal of Forecasting*. 29.1-2, 132–144.

Belaygorod, A. and M. Dueker. (2007). Timing Transitions Between Determinate and Indeterminate Equilibria in DSGE Models: Benefits and Implications. *Working Paper* 2007-025, Federal Reserve Bank of St. Louis.

Belongia, M. T. and P. N. Ireland. (2018). Targeting Constant Money Growth at the Zero Lower Bound. *International Journal of Central Banking*. 14, 159–204.

Belviso, F and F. Milani. (2006). Structural Factor-augmented VARs (SFAVARs) and the Effects of Monetary Policy. *Topics in Macroeconomics*. 6.3, 1–46.

Benkovskis, K., A. Bessonovs, M. Feldkircher and J. Wörz. (2011). The Transmission of Euro Area Monetary Shocks to the Czech Republic, Poland and Hungary: Evidence from a FAVAR Model. *Focus on the European Economic Integration*. 8–36.

Bernanke, B.S., J. Bovian and P. Eliasz (2005). Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach. *Quarterly Journal of Economics*. 120, 387-422.

Binici, M., H. Kara and P. Özlü. (2018). Monetary Transmission with Multiple Policy Rates: Evidence from Turkey. *Applied Economics*. 1–25.

Breitung, J. and S. Eickmeier. (2011). Testing for Structural Breaks in Dynamic Factor Models. *Journal of Econometrics*. 163.1, 71–84.

Boivin, J., M. Giannoni and I. Mihov. (2009). Sticky Prices and Monetary Policy: Evidence from Disaggregated U.S. Data. *American Economic Review*. 99.1, 350- 384.

Castelnuovo, E. and P. Surico. (2010). Monetary Policy, Inflation Expectations and the Price Puzzle. *The Economic Journal*. 120.549, 1262–1283.

Central Bank of the Republic of Turkey. (2011). Annual Report 2010.

Central Bank of the Republic of Turkey. (2015). Annual Report 2014.

Central Bank of the Republic of Turkey. (2019). Annual Report 2018.

Christiano, L. J., M. Eichenbaum and C. L. Evans. (1999). Monetary Policy Shocks: What Have We Learned and to What End? J. B. Taylor and M. Woodford. (Ed.). In *Handbook of Macroeconomics*. 1A. Amsterdam. Elsevier.

Çatık, A. N. and C. Martin. (2012). Macroeconomic Transitions and the Transmission Mechanism: Evidence from Turkey. *Economic Modelling*. 29.4, 1440-1449.

Çatık, A. N. and C. Akdeniz. (2019). The Evolution of the Monetary Transmission Channels in Turkey: Evidence from a TVP-VAR Model. Applied Economics Letters. 26.13, 1072-1079.

Eickmeier, S., W. Lemke and M. Marcellino. (2015). Classical Time-Varying FAVAR Models—Estimation, Forecasting and Structural Analysis. *Journal of Royal Statistical Society* 178.3, 493–533.

Erdoğan, S. and D. Ç. Yıldırım. (2010). Is There an Interest Rate Channel for Monetary Policy in Turkey? *METU Studies in Development*, 37.3, 247-266.

Favero, C. (2001). *Applied Macroeconomics*. Oxford Univ. Press.

Fernald, J. G., M. M. Spiegel and E. T. Swanson. (2014). Monetary Policy Effectiveness in China: Evidence from a FAVAR Model. *Journal of International Money and Finance*. 49a, 83-103.

Gupta, R., M. Jurgilas and A. Kabundi (2010). The Effect of Monetary Policy on Real House Price Growth in South Africa: A Factor-Augmented Vector Autoregression (FAVAR) Approach. Economic Modelling. 27.1, 315-323.

Gürkaynak, T., Z. Kantur, M. A. Taş and S. Yıldırım. (2015). Monetary Policy in Turkey After Central Bank Independence. *CFS Working Paper Series.* 520, Center for Financial Studies.

Holguín, J. S., and J. M. Uribe. (2019). The Credit Supply Channel of Monetary Policy: Evidence from A FAVAR Model with Sign Restrictions. *Empirical Economics*. doi:10.1007/s00181-019-01759-5.

Kara, A. (2013). Monetary Policy after the Global Crisis, *Atlantic Economic Journal*. Springer; *International Atlantic Economic Society*. 41.1, 51-74.

Kelly, L., W. Barnett and J. Keating. (2011). Rethinking the Liquidity Puzzle: Application of a New Measure of the Economic Money Stock. *Journal of Banking and Finance*. 35.4, 768–774.

Küçük, H., P. Özlü, A. Talaslı, D. Ünalmış and C. Yüksel. (2016). Interest Rate Corridor, Liquidity Management and the Overnight Spread. *Contemporary Economic Policy*. 34.4, 746–761.

Küçükefe, B. and D. M. Demiröz, (2018). Türkiye Ekonomisi Fiyat Katılıklarının FAVAR Modeli ile Analizi. Hacettepe Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi. 36.4, 75-94.

Onatski, A. (2010). Determining the Number of Factors from Empirical Distribution of Eigenvalues. *The Review of Economics and Statistics*. 92.4, 1004–1016.

Özdemir, K. A. (2015). Interest Rate surprises and transmission Mechanism in Turkey: Evidence from Impulse Response Analysis. *Working Paper*. Central Bank of the Republic of Turkey No:15/04.

Sims, C. (1980). Macroeconomics and Reality. *Econometrica*. 48.1, 1- 48.

Sims, C. (1992). Interpreting the Macroeconomic Time Series Facts: The Effects of Monetary Policy. *European Economic Review.* 36.5, 975-1000.

Soares, R. 2013. Assessing Monetary Policy in the Euro Area: A Factor-Augmented VAR Approach. *Applied Economics.* 45.19, 2724–2744.

Stock, J. and M. Watson. (1998), Diffusion Indexes. *Working Paper.* 6702, August, NBER.

Stock, J. and M. Watson. (2002a). Forecasting using Principal Components from a Large Number of Predictors. *Journal of the American Statistical Association*. 97, 1167-1179.

Stock, J. and M. Watson. (2002b). Macroeconomic Forecasting using Diffusion Indexes. *Journal of Business and Economic Statistics*. 20.2, 147-162.

Stock, J. and M. Watson. (2005). Implications of Dynamic Factor Models for VAR Analysis. *Working Paper*. 11467, June, NBER.

Stock, J. and M. Watson. (2016). Chapter 8 - Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics. J. B. Taylor and H. Uhlig. (Ed.). In *Handbook of Macroeconomics*. Elsevier, 2: 415-525,

Şahin, S. and Çiçek, S. (2018). Interest Rate Pass-Through in Turkey During the Period of Unconventional Interest Rate Corridor. *Quantitative Finance and Economics*. 2, 837-859.

Uhlig, H. (2005). What are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure. *Journal of Monetary Economics*. 52.2, 381-419.

Uysal, M. (2017). Financial Stability and Macroprudential Policy in Turkey. *Macroprudential Policy Frameworks, Implementation and Relationships with Other Policies*. Bank for International Settlements. 94, 349-364

Varlık, S., and M. H. Berument. (2017). Multiple Policy Interest Rates and Economic Performance in a Multiple Monetary-Policy-Tool Environment. *International Review of Economics & Finance*. 52, 107–126.

APPENDIX A

Bootstrapping Confidence Bands

Each variable included in X and each factor in F are standardized. The unobserved factors in F are extracted using PCA. Loadings Λ and VAR residuals $\phi(L)$ are obtained with the OLS. The estimation of the orthogonal invertible matrix A is made by taking the inverse of Cholesky decomposition. To obtain the confidence bands for the IRFs, bootstrap procedure is employed by re-sampling the factors grounded on the observation equation (2) and, conditional on the rotated factors, by bootstrapping the VAR coefficients in the transition equation (1).

The related bootstrapping procedure is based on the recursive-design residual bootstrap algorithm and can be summarized in the following steps:

Step 1: To extract F from X, perform the PCA and standardize F to have zero mean and one standard deviation.

Step 2: Estimate model parameters Λ and $\phi(L)$ with the standardized X and standardized F from the VAR model. Generate residuals e and v of reduced form equations (2) and (1), respectively. Then generate IRFs.

Step 3: Determine the number of replications R and the level of significance α.

Step 4: Generate v^* by uniformly sampling columns belonging v with replacement. Next, generate recursively pseudo common forces F^* (see equation (1)) using v^*, $\phi(L)$ and randomly selected initial values of F. Next, make F^* standardized and name it as $\hat{F}^*$. Generate e^* by uniformly sampling columns belonging e with replacement. Next, generate pseudo observed endogenous time series X^* (see equation (2)) using e^*, Λ and $\hat{F}^*$. Next, make X^* standardized and name it as $\hat{X}^*$. Estimate Λ^* and $\phi(L)^*$ using $\hat{X}^*$, $\hat{F}^*$ and A^* which is recalculated with $\hat{F}^*$(see equation (6)). Next, generate impulse responses with the bootstrapped estimates and data.

Step 5: Repeat Step 4 for R times ($r = 2,3 \ldots, R$).

Step 6: Produce bootstrapped confidence bands for the impulse responses generated in Step 2 based on the bootstrap distributions in Steps 4 and 5.

APPENDIX B

Table B.1: Description of the Data

#	Acronym	Description	S/F	Tr.	Source
		Domestic Series			
1	IP	Industrial Production Index (IP) (2010=100) (SA)	S	5	TUIK
2	IPINT	IP - Intermediate Goods (SA)	S	5	TUIK
3	IPDUR	IP - Durable Consumption Goods (SA)	S	5	TUIK
4	IPNONDUR	IP - Nondurable Consumption Goods (SA)	S	5	TUIK
5	IPENERG	IP - Energy (SA)	S	5	TUIK
6	IPCAP	IP - Capital Goods (SA)	S	5	TUIK
7	VEHICLE	Number of Registered Motor Vehicles (SA)	S	5	TUIK
8	CAP	Capacity Utilization Rate	S	2	CBRT
9	UNEMP	Unemployment Rate (SA)	S	4	TUIK
10	UNEMPEXCL	Unemployment Rate - Excluding Agriculture (SA)	S	4	TUIK
11	CA	Current Account Balance (Million Turkish Lira - TL)	S	5	CBRT
12	CAPF*	Capital + Financial Account Balance (Million TL)	S	5	CBRT
13	ERR*	Net Errors and Emissions (Million TL)	S	5	CBRT
14	RESERV*	Reserve Assets (Million TL)	S	5	CBRT
15	GOLDNK*	Net Exports (NX) - Gold (Million TL)	S	5	CBRT
16	ENERNX	Net Exports - Energy (Million TL)	S	5	CBRT
17	FXRESERV	Foreign Currency Reserves (Million TL)	S	5	CBRT
18	GOLDRESERV	Gold Reserves (Million TL)	S	5	CBRT
19	BANKRESERV	Banks Correspondence Accounts (Million TL)	S	5	CBRT
20	STDEBT	Short-term External Debt (Million TL)	S	5	TUIK
21	LTDEBT	Long-term External Debt (Million TL)	S	5	TUIK
22	CONNX	NX - Consumption Goods (Million TL)	S	5	TUIK
23	INTNX	NX - Intermediate Goods (Million TL)	S	5	TUIK
24	CAPNX	NX - Capital Goods (Million TL)	S	5	TUIK
25	GOVTEXP	Budget Expenditures Excluding Interest Payments (Million TL) (SA)	S	5	MTF
26	GOVTEXPINT	Interest Payments (Million TL) (SA)	S	2	MTF
27	BUILDING	Number of New Residential Buildings	S	2	TUIK
28	NEWFIRM	Number of New Firms	S	5	TUIK
29	CCI	Consumer Confidence Index (2003=100)	S	2	TUIK

30	RSCI	Real Sector Confidence Index (2005=100) (SA)	S	2	TUIK
31	PPI	Producer Price Index (PPI) (2003=100)	S	5	TUIK
32	PPIMINING	PPI - Mining and Quarrying	S	5	TUIK
33	PPIMAN	PPI - Manufacturing	S	5	TUIK
34	PPIELECT*	PPI - Electricity Production and Distribution	S	5	TUIK
35	CPI	Consumer Price Index (CPI) - (2003=100)	S	5	TUIK
36	CPIFOOD	CPI - Food and Soft Drinks	S	5	TUIK
37	CPIALC	CPI - Alcoholic and Tobacco	S	5	TUIK
38	CPICLOTH	CPI - Cloth and Shoe (SA)	S	5	TUIK
39	CPIHOUSE	CPI - Housing, Water, Electricity, Gas and Fuels	S	5	TUIK
40	CPIFURN	CPI - Furniture	S	5	TUIK
41	CPIHEALTH*	CPI - Health	S	5	TUIK
42	CPITRANSP	CPI - Transportation	S	5	TUIK
43	CPICOMM	CPI - Communication	S	5	TUIK
44	CPIEDUC*	CPI - Education (SA)	S	5	TUIK
45	CPIREST	CPI - Restaurants and Hotels	S	5	TUIK
46	CPIAGR*	CPI - Agricultural Products	S	5	TUIK
47	LIVING	General Living Index - Wage Earners (2005=100)	S	5	TUIK
48	M0	Currency	F	5	CBRT
49	M1*	M1	F	5	CBRT
50	M2*	M2	F	5	CBRT
51	DM1	M1 (Divisia)	F	5	CBRT + Author's calculation
52	DM2	M2 (Divisia)	F	5	CBRT + Author's calculation
53	M1PARTC	M1 including Participation Banks	F	5	CBRT
54	M2PARTC	M2 including Participation Banks	F	5	CBRT
55	DM1PARTC	M1 including Participation Banks (Divisia)	F	5	CBRT + Author's calculation
56	DM2PARTC	M2 including Participation Banks (Divisia)$^{+}$	F	5	CBRT + Author's calculation
57	SIGHTD	Sight Deposits	F	5	CBRT
58	TIMED	Time Deposits	F	5	CBRT
59	FXDEP	Time Deposits - Foreign Currency	F	5	CBRT
60	CREDITCOMP	Credits (Non-financial Companies) (Million TL)	F	5	CBRT
61	CREDITSMALLCOMP	Credits (Small Companies) (Million TL)	F	5	CBRT
62	CREDITCONS	Credits (Consumers) (Million TL)	F	5	CBRT
63	CREDITHOUSE	Credits (Housing) (Million TL)	F	5	CBRT
64	CREDITCAR	Credits (Cars) (Million TL)	F	5	CBRT
65	CREDITNEED	Credits (Need) (Million TL)	F	5	CBRT
66	CREDITCARD	Credits (Over Credit Cards) (Million TL)	F	5	CBRT
67	CREDITFINANC	Credits (Financial Companies) (Million TL)	F	5	CBRT
68	CDS	5 Year CDS premium	F	5	Bloomberg
69	REER	Real Effective Exchange Rate (CPI Based) - (2003=100)	F	5	CBRT
70	USFX	Exchange Rate (U.S. Dollar)	F	5	CBRT

71	EURFX	Exchange Rate (Euro)	F	5	CBRT
72	BSKTFX	Exchange Rate (Basket Rate)	F	5	CBRT
73	BIST100	BIST 100 - Stock Market Index (1986=1)	F	5	Bloomberg
74	GOLD	Gold Selling Price	F	5	Bloomberg
75	EXPINF	CPI -Expectation - End of the Year	F	2	CBRT
76	EXPUSFX	Exchange Rate - Expectation (U.S. Dollar) - End of the Year	F	5	CBRT
77	EXPCA	Current Account - Expectation - End of the Year	F	5	CBRT
78	EXGDP*	GDP growth - Expectation - End of the Year	F	4	CBRT
79	INTCONS	Interest Rate on Credits (Needs)	F	4	CBRT
80	INTCAR	Interest Rate on Credits (Cars)	F	4	CBRT
81	INTHOUSE	Interest Rate on Credits (Housing)	F	4	CBRT
82	INTCOMM	Interest Rate on Credits (Commercial)	F	4	CBRT
83	INTGOVTBOND	Interest Rate - 1 Year Government Bond	F	4	CBRT
84	INT1MHTL	Interest Rate on Deposits - 1 month	F	4	CBRT
85	INT3MTL*	Interest Rate on Deposits - 3 month	F	4	CBRT
86	INT6MTL*	Interest Rate on Deposits - 6 month	F	4	CBRT
87	INT1YTL	Interest Rate on Deposits - 1 year	F	4	CBRT
88	INT1MFX	Interest Rate on Deposits (Foreign Currency) - 1 month	F	4	CBRT
89	INT3MFX	Interest Rate on Deposits (Foreign Currency) - 3 month	F	4	CBRT
90	INT6MFX	Interest Rate on Deposits (Foreign Currency) - 6 month	F	4	CBRT
91	INT1YFX	Interest Rate on Deposits (Foreign Currency) - 1 Year	F	4	CBRT
		External Series			
92	VIX	CBOE volatility Index (Foreign Series)	F	2	FRED
93	VSTOXX	STOXX 50 Volatility Index (Foreign Series)	F	2	Reuters
94	EURUSD	Euro/Dollar Parity (Foreign Series)	F	5	ECB
95	FEDFUND	Federal Funds Rate (Foreign Series)	F	4	FRED
96	PE	S&P 500 PE Ratio (Foreign Series)	F	2	Bloomberg
97	LIBOR	3-Month London Interbank Offered Rate (Foreign Series)	F	4	FRED
98	OILEUR	Europe Brent Spot Price (Foreign Series)	F	5	FRED
		Monetary Policy Instruments			
99	DISCOUNT	Rediscount Rate	F	4	CBRT
100	ADVANCE	Advance Interest Rate	F	4	CBRT
101	BORROWING	Overnight Borrowing Rate	F	4	CBRT
102	LENDING	Overnight Lending Rate	F	4	CBRT
103	LATEBORROWING	Late Liquidity Window Borrowing Rate	F	4	CBRT
104	LATELENDING	Late Liquidity Window Lending Rate	F	4	CBRT
105	ONEWEEK	One Week Repo Auctions Rate[++]	F	4	CBRT
106	FUNDING	Weighted Average of Cost of Funding[+++]	F	4	CBRT
107	OMO	Ratio of Open Market Operations to Total Assets of CBRT	F	4	CBRT
108	RRTL	Required Reserve Ratio - TL	F	4	CBRT

109	RRFX	Required Reserve Ratio - Foreign Currency	F	4	CBRT
110	BASE	BASE MONEY (Currency + Required Reserves of Banking Sector+Free Deposits) (Million TL)	F	5	CBRT
111	INTBANKBIST	BIST Overnight Interbank Rate++++	F	4	CBRT, FRED
112	TRLIBOR	The Turkish Lira Interbank Offered Rate	f	4	TBB
113	POLICY	Policy Rate	F	4	CBRT

Note: CBRT – Central Bank of the Republic of Turkey; TUIK - Turkish Statistical Institute; MTF - Ministry of Treasury and Finance of the Republic of Turkey; FRED – Federal Reserve Bank of St. Louis; TBB – the Banks Association of Turkey. S/F shows whether the variable is treated as "slow-moving" (S) or "fast-moving" (F) in the first-stage of the estimation. Tr. shows how the variable is transformed to have approximate stationarity: 2 means the variables in logarithm, 4 means the first difference and 5 means logarithmic-difference. (SA) shows the series that are seasonally adjusted. +The monetary aggregates calculated using the Divisia Index (DM1PARTC and DM2PARTC) are not used in calculation of the factors and are controlled as the alternative policy instruments. ++Since the one-week repo rates are not available until 2010:5 we use the lending rate accordingly for the missing observations. +++Observations for the average funding cost is available starting from 2011:1. ++++To set the interbank rate, we use the CBRT overnight interbank repo rate until 2010:12 and the BIST overnight interbank repo rate, thereafter. *shows the time series which are corrected for their outliers using the technique in Stock and Watson (2005).

APPENDIX C

Factors and the Correlation with Macroeconomic Series

We add below the dynamics of the first five factors with the selected macroeconomic variables for the sample period (see Figures C.1 through C.5) and the corresponding Pearson correlation coefficients with some subset of variables (see Table C.1) to provide a tentative interpretation of the factors. Note firstly that using the non-parametric methods the static factors are estimated directly without having any model specification for these factors or assuming any form of distributions for the disturbance terms (Stock and Watson, 2016). Relevantly, as the FAVAR model lacks any structural identification scheme that relates each factor to some subset of macroeconomic series[40] and as the orthogonality across static factors implies estimating a space spanned by factors instead of the factors themselves (Soares, 2013), the estimated factors may not fully capture the true dynamics of the economy. Hence, the interpretation of the factors here is more of an informal analysis but still elucidative in revealing the potential matching across our rotated factors and macroeconomic series, otherwise lacking in the analysis.

Table C.1 gives the highest five Pearson's correlation coefficients among the estimated factors and some of the macroeconomic series based on the permutation test with the statistical significance level at 1%. Notice that except for the case of factor 1, the

[40] See Belviso and Milani (2006) for a structurally identified FAVAR setting.

correlation coefficients are not quite high which makes us to be more elaborate in making the interpretation of those coefficients. From the table, it arises firstly that the first factor captures the dynamics of the exchange rate and foreign debts markets with higher than 80% coefficient of correlation. The Figure C.1 visualizes this relation using factor 1 and basket exchange rate which is selected as it has the highest correlation with the estimated factor.[41] The figure illustrates notably similar paths of factor 1 and the basket exchange rate. Besides, for the second factor 2, it seems to capture the dynamics of credit conditions as displayed by its relatively high correlation with credits on consumer loan, cars and housing. In the corresponding figure (Figure C.2), factor 2 and the consumer credits move noticeably together. Third and fourth factors are essentially correlated with the aggregate industrial production index, industrial production index of intermediate goods, industrial production index of consumption goods, number of new firms and registered motor vehicles which leads us to take these factors as real activity factor. The Figures C.3 and C.4 give the plot of comovement of these factors with the industrial production. The fifth factor seems to capture with consumer confidence as provided by its negative correlation with the consumer confidence index variable. The corresponding plot is given in Figure C.5. Notice, however, that the correlation coefficients for the Factors 4 and 5 are not convincingly high to draw more credible conclusions.

[41] The same procedure applies for the remaining figures as well.

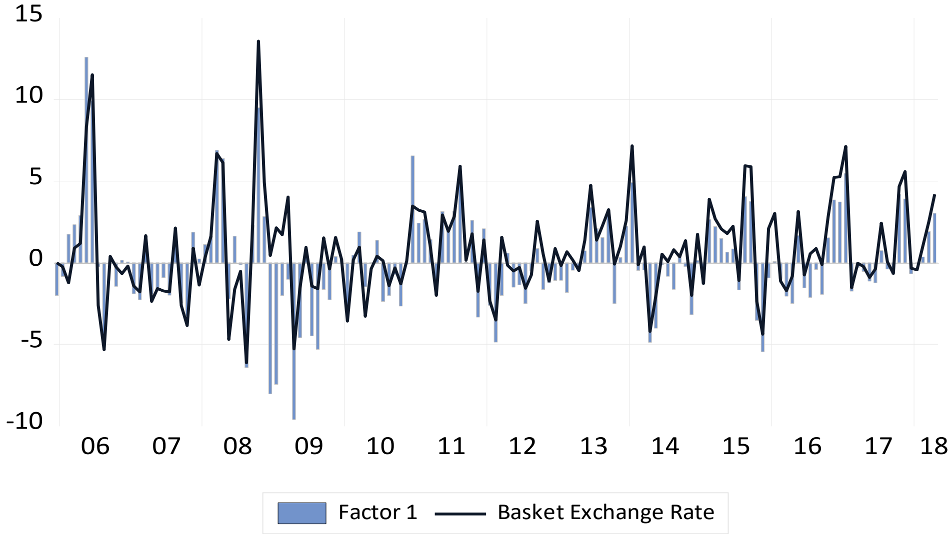

Figure C.1: Factor 1 and Basket FX Rate

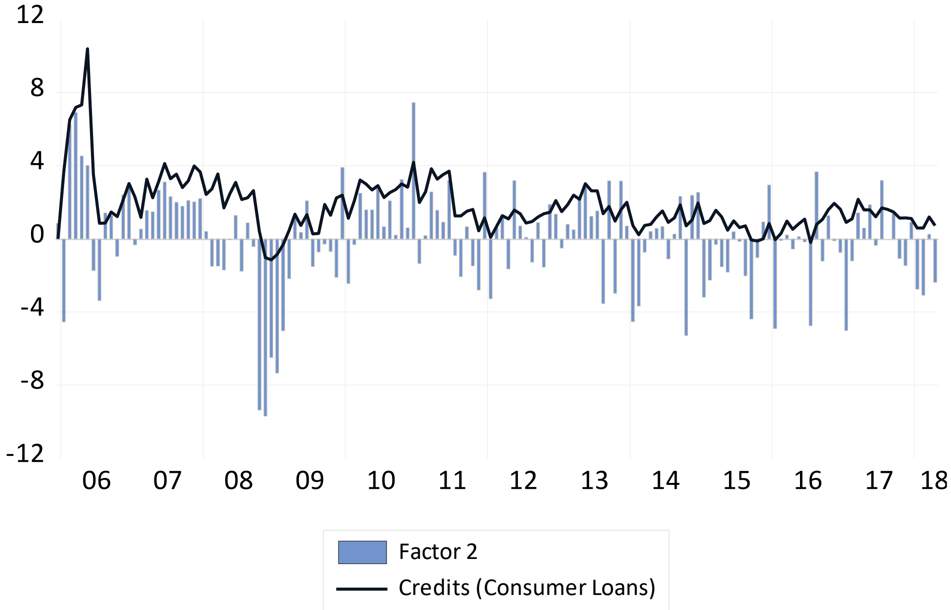

Figure C.2: Factor 2 and Consumption Loans

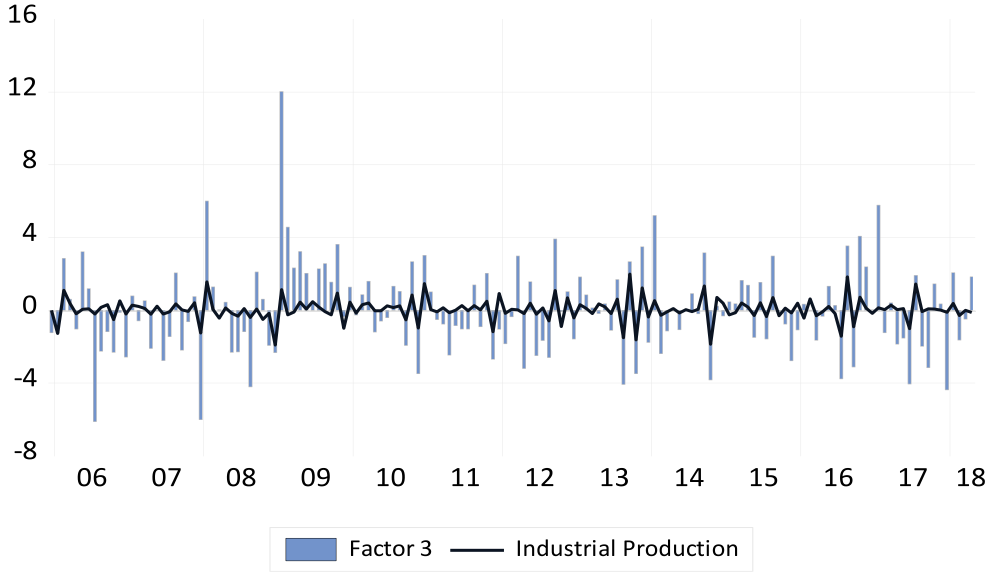

Figure C.3: Factor 3 and Industrial Production Index

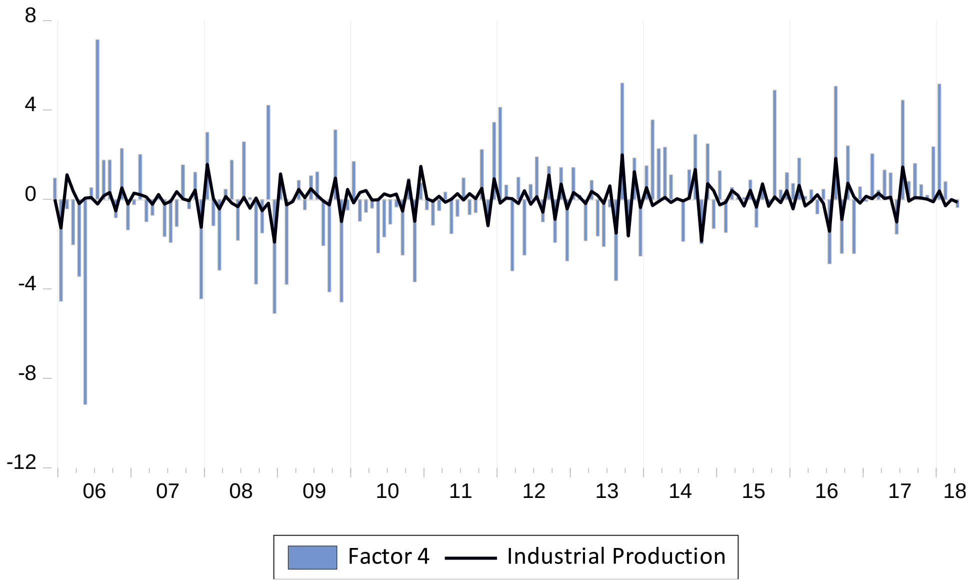

Figure C.4: Factor 4 and Industrial Production Index

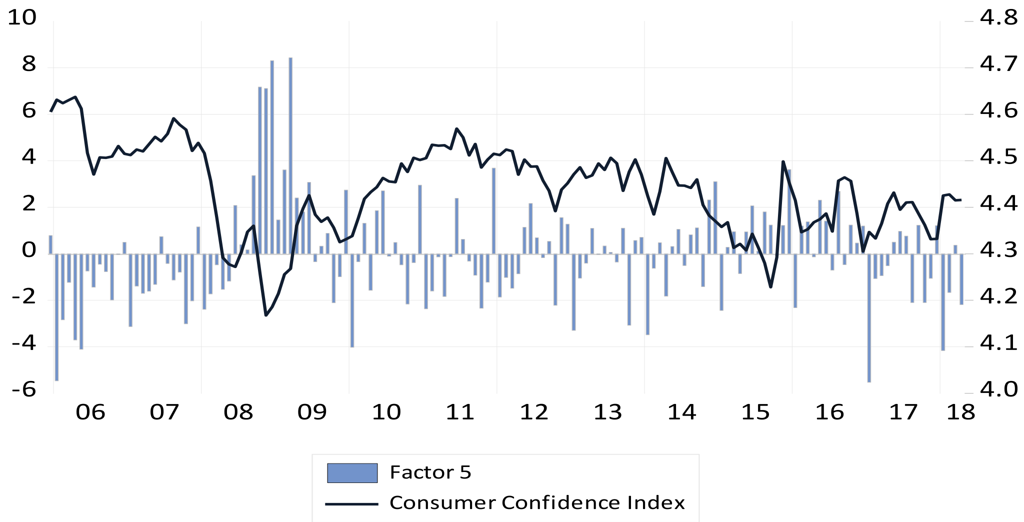

Figure C.5: Factor 5 and Consumer Confidence Index

Note: Factor 5 is scaled in the left-side whereas the consumer confidence index variable is scaled in the right-side.

Table C.1: Correlations Between Factors and Macroeconomic Variables

	Coefficients of Correlation	
Factor 1	Exchange Rate (Basket Rate)	0.838***
	Long-term External Debt	0.826***
	Current Account - Expectation - End of the Year	0.679***
	Short-term External Debt	0.651***
	Producer Price Index	0.625***
Factor 2	Credits (Consumer Loans)	0.625***
	Credits (Cars)	0.562***
	Consumer Confidence Index	0.555***
	Credits (Housing)	0.545***
	Industrial Production Index (Capital Goods)	0.542***
Factor 3	Industrial Production Index	0.661***
	Industrial Production Index (Intermediate Goods)	0.646***
	Industrial Production Index (Nondurable Consumption Goods)	0.626***
	Number of New Firms	0.592***
	Number of Registered Motor Vehicles	0.583***
Factor 4	Industrial Production Index	0.550***
	Industrial Production Index (Intermediate Goods)	0.544***
	M2	-0.545***
	Interest Rate on Credits (Cars)	0.487***

	Industrial Production Index (Energy)	0.483***
	Consumer Confidence Index	-0.559***
	Current Account Balance	0.463***
Factor 5	Consumer Price Index	-0.448***
	NX - Capital Goods	0.378***
	Unemployment Rate	0.371***

**** show the statistical significance levels for Pearson coefficients at 1%.

APPENDIX D

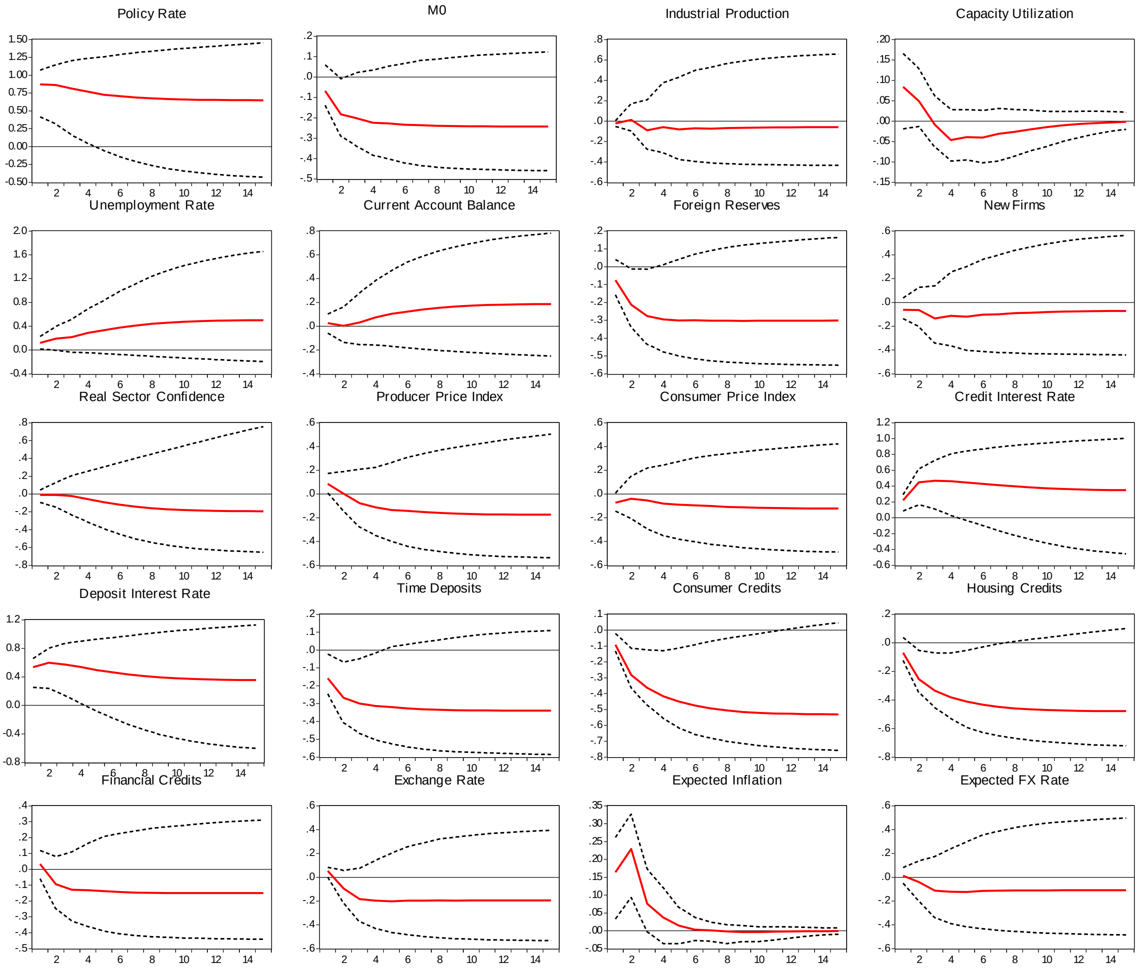

Figure D.1: Cumulative Response Functions to a Shock to the Policy Rate under Baseline Model

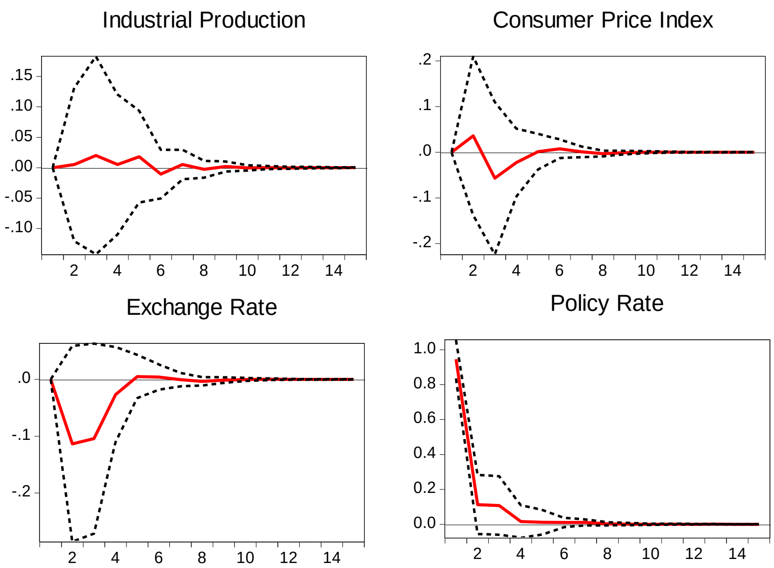

Figure D.2: Impulse Response Functions to a Shock to the Policy Rate under VAR Model

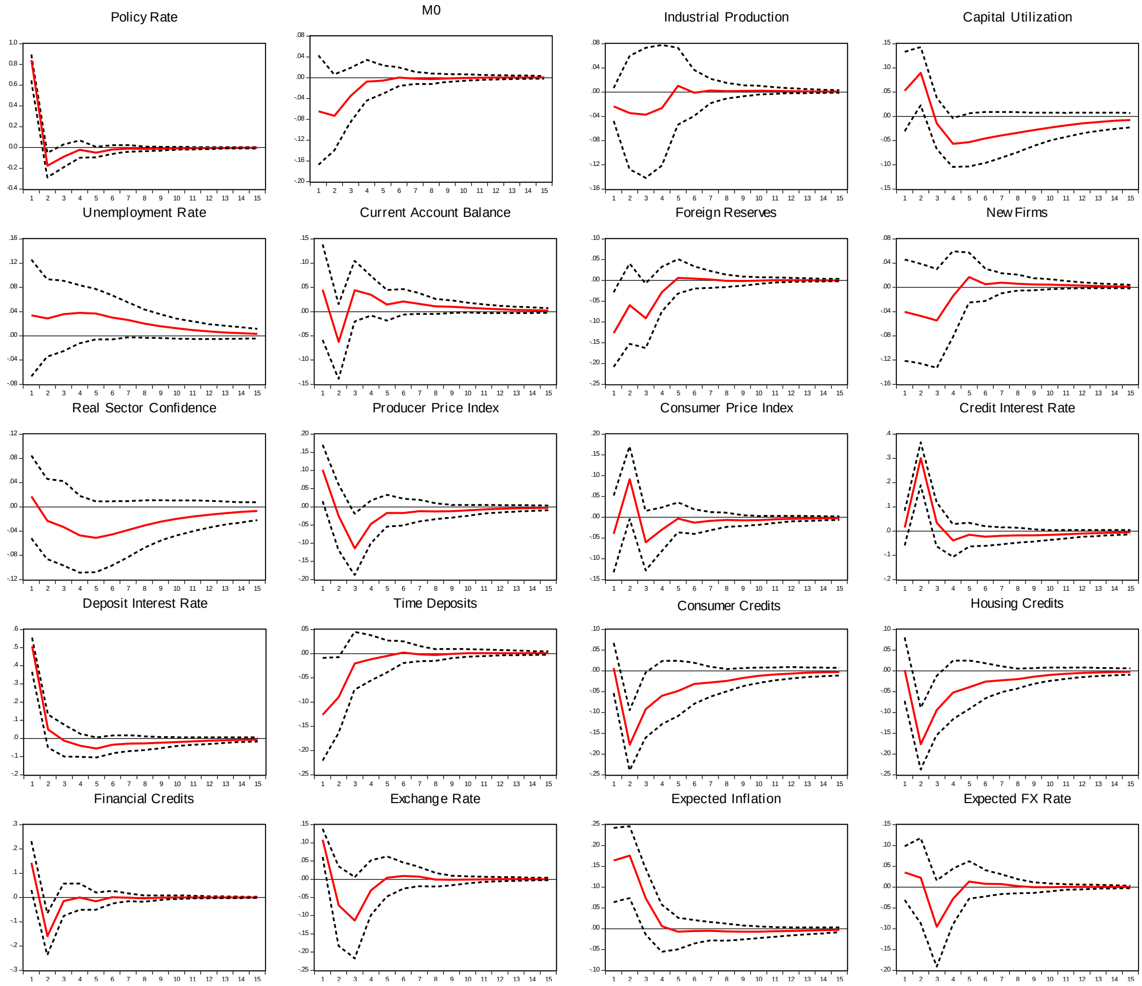

Figure D.3: Impulse Response Functions to a Shock to the TRlibor Rate under the Baseline Model

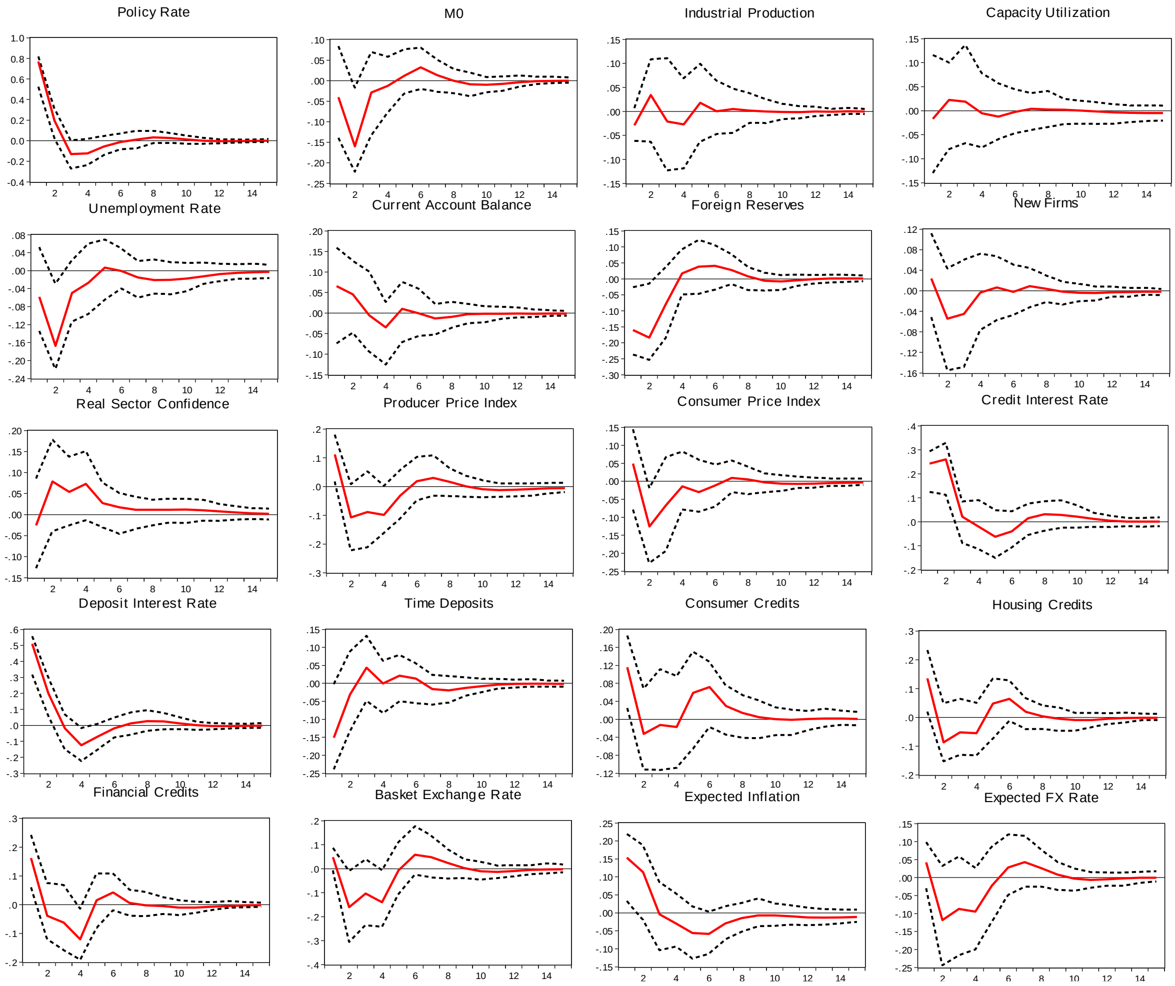

Figure D.4: Impulse Response Functions to a Shock to the Interbank Rate under the Extended Model (the New monetary policy Area)

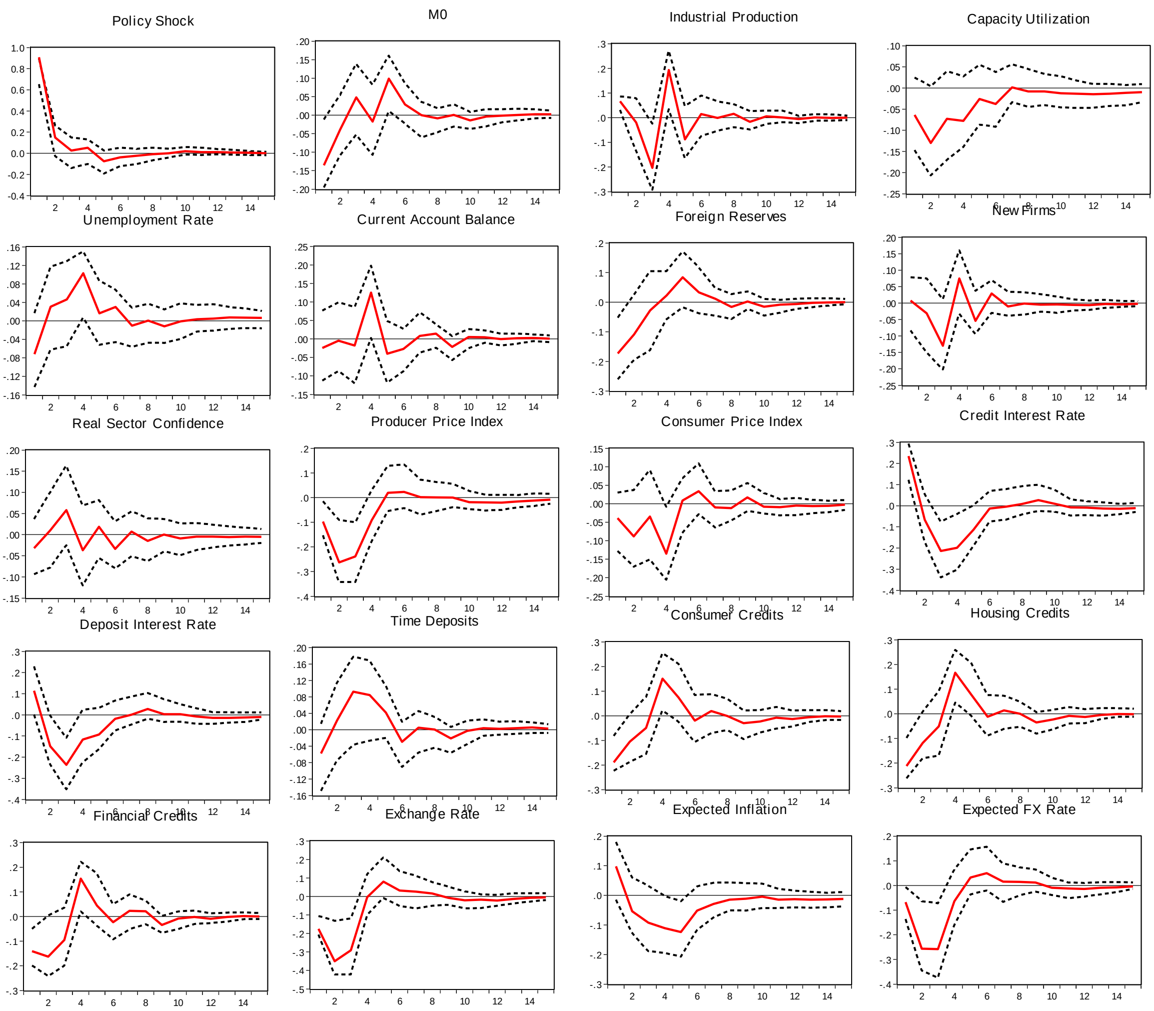

Figure D.5: Impulse Response Functions to a Shock to the Divisia M2 under the Extended Model (the New monetary policy Area)

CHAPTER 3

ECONOMIC SOURCES OF EXCHANGE RATE VOLATILITY: EVIDENCE FROM A GARCH-MIDAS MODEL

1. INTRODUCTION

Most financial time series feature relative tranquil episodes followed by phases of high volatility. The exchange rates are not exceptions to this case. Even though it is a fact that they largely behave as random-walk process in the short term periods (Enders, 2014), exchange rate volatilities may exhibit clustering pattern in the long-term periods. Grounded largely on volatility models this clustering behavior is related and explained by a wide range of factors including economic activity, industrialization levels of countries, nominal prices, policy innovations, speculative behaviors, external innovations and persistence pattern of the volatility (see Hausmann et al., 2006; Ganguly and Breuer, 2010; Giannellis and Papadopoulos, 2011; Cevik et al., 2015, among others). In better depicting the clustering dynamics of the financial volatility and determining economic sources of it, Engle et al., (2009; 2013) recently contributed to the analysis of volatility based on the component models. Introducing short- and long-term components to the volatility formation they relate directly the low-frequency macroeconomic data with the high-frequency financial data with the mixed data sampling (MIDAS). In this study, we follow these recent contribution's lead and analyze determinants of exchange rate volatility which are sampled at lower frequencies for Turkish economy.

The exchange rate market in Turkish economy features high fluctuations in exchange rates along with a long-lasting depreciation of its domestic currency. The high volatility of exchange rates that intertwines highly fragile structure of Turkish economy amplifies the vulnerability to external shocks and financial instability of the economy and leads to vital consequences on economy. While the devastating effects of exchange rate volatility on Turkish economy are quite tangible (see Demir, 2010) it is not equally well-studied to what extent the exchange rates fluctuate beyond absorbing the shocks to the domestic macroeconomic factors. Besides, there is a large gap in examining the dynamics of the long-term exchange rate volatility for Turkish data under the floating regime. In this context, this study aims to contribute the understanding of secular exchange rate volatility for Turkey grounded on component models and represent the degree to which changes in economic fundamentals stands for the long-term component of volatility. Herein it would be beneficial to track at least chronologically the fundamentals of the exchange rate policy of Turkey under the floating exchange regime and analyze the Turkish literature that investigates the impacts of this particular way of the exchange rate policy on the economy.

Following a range of economic and financial crisis of Turkish economy, last of which fatefully occurred in February 2001, the crawling peg exchange rate regime was replaced by the floating regime (Uygur, 2010). In the initial years of transition to the floating regime the CBRT implemented discretionary foreign exchange interventions and auctions as major tools of its exchange rate policy that helped to improve its reserve position for the sake of consolidating as a buffer against potential economic and financial turmoil. This position towards consolidation in the foreign exchange reserves had also continued thereafter but moderately declined after 2013 along with persistent depreciation of the domestic currency (CBRT, 2019). To back up preventing the contagion of external shocks with the onset of the global financial crisis and improving the liquidity conditions of banking sector, the foreign exchange buying auctions were suspended in the late of 2008. Besides, by increasing foreign currency transaction limits of banks, foreign currency required reserve ratios, improving the export rediscount credit conditions and reducing the overnight lending rates the CBRT provided additional liquidity to the markets and aimed at consolidating the financial depth (CBRT, 2008; 2009). As the capital flows turned towards emerging economies with the end of 2009 the central bank took many steps to the manage the liquidity glut e.g., it re-started to apply foreign exchange buying auctions among others. Thereafter, the CBRT designed a new monetary policy stance in the late of 2010 that determined the financial stability as a supplementary objective beside to the price stability and adopted, accordingly, new instruments to smooth the fluctuations in the financial markets e.g., to control better capital flows or mitigate exchange rate volatilities (Kara, 2016). Further, at the end of 2010, it conducted substantial policy changes in regulations on foreign currency reserves, required reserve ratios and liquidity managements (CBRT, 2011). Starting from the end of 2011 the CBRT implemented reserve option mechanism (ROM) as a new instrument that allows banks to hold part of their reserves in foreign currency to ease the adverse effects of volatile capital flows and external shocks on financial and macroeconomic stability e.g., excessive exchange rate volatility and credit growth (Aslaner et al., 2015). Along with the ROM the CBRT actively used the upper bound of the asymmetric interest rate corridor to make further monetary tightening. With these tools it was intended to limit the pressures on Turkish lira and give signals to the public on its earnestness against preventing high volatility of exchange rate market (Değerli and Fendoğlu, 2013). Applying actively these tools, the monetary authority called a halt to foreign exchange buying auctions and direct foreign exchange buying interventions while had preferred to use selling auctions and direct selling interventions until 2017 to cope with excessive volatility and risky price formations arising from the speculative behavior (CBRT, 2016).

The excessive volatility in the exchange rate market led by the political crisis of August 2018 resulted in the CBRT to implement a set of financial stability-oriented instruments. Following the sudden depreciation of the Turkish lira the CBRT reduced the upper limit of the foreign exchange maintenance facilities of the ROM, lowered the reserve requirement ratios, regulated the collateral conditions of the banks and launched Turkish lira currency swap market (CBRT, 2018) and in response to cost-push shocks and deteriorations in the inflation outlook caused by the exchange rate volatility the CBRT sharply contracted its monetary policy. In the following-up periods the central bank attempted to build up the market mechanism deteriorated dramatically by the foreign exchange rate shocks and meet the funding needs of economy.

When the Turkish literature on the determinants of volatility in the exchange rate market is analyzed it is observed a limited number of studies and that the existing contributions largely build upon particular aspects of the economy in affecting the exchange rate and its volatility. Among these studies, Özlü and Ünalmış (2012) find evidence that exchange rates are more responsive to surprises to the current account balance and policy rates while those to inflation and output do not lead to significant responses on exchange rates. With regard to the transmission of the shocks to the interest rates to the foreign exchange volatility Tuna (2011) finds that overnight interest rate differentials are effectively used to mitigate the volatility while in Aysoy and Küçükkocaoğlu (2016) it is argued that the exchange rate volatility is augmented by rises in policy rates. Besides, the ROM is proposed under the multiple-policy framework of the CBRT in effectively reducing the exchange rate volatility (Oduncu et al., 2013). Regarding the resulting impacts of the foreign exchange controls of the central bank the literature does not reach a consensus. Although Herrera and Özbay (2005) and Tuna (2011) argue that central bank intervention operations in Turkey through direct interventions or auctions actually lead to higher, not lower, volatility in Akgül and Sayyan (2008) and Aysoy and Küçükkocaoğlu (2016) it is found the inability of foreign exchange interventions in affecting the exchange rate volatility.

Next to the literature that discloses the economic sources of the exchange rate volatility based on some aspects of the economy we explore the economic sources of volatility for Turkish economy using wide number of potentially related macroeconomic series with an intrinsic assumption that the exchange rate and its volatility are endogenous to macroeconomic fundamentals. We adopt specifically the GARCH-MIDAS model building upon MIDAS to link directly the macroeconomic factors and exchange rates sampled at different frequencies and, while doing so, to avoid any loss of potentially useful information in explaining the volatility process. The model combines a GARCH (1,1) model with mean reversion and MIDAS polynomial with low frequency data. Besides, as the model is grounded on a parsimoniously fix number of parameters compared to alternative models with computational complexities, inclusion of different number of lags in estimation does not pave the way for any parameter proliferation and it becomes appropriate to compare the estimates under different periods of time and for different regressors.

For the rest of the chapter, in Section 2 we introduce the methodology of the GARCH-MIDAS model and the data set. In Section 3 we firstly control for the model fit by estimating GARCH-MIDAS model, drawing Beta weights and distribution of errors for both full-sample and subsamples which enables in turn us to see parameter consistency and whether any identification issue arises. Then, we estimate the model with selected macroeconomic variables replacing the realized volatility by exogenous regressors. Lastly, for robustness we estimate an ARDL model and employ bounds test at the monthly frequency. Section 4 concludes.

2. THE METHODOLOGY AND DATA SET

2.1 Methodology

In explaining the underlying methodology, we follow Engle and Rangel (2008) and Engle et al., (2009, 2013) that have contributed to articulation of GARCH-MIDAS as the new class of component models. Before introducing the GARCH-MIDAS model it would be beneficial to define a $\mathrm{GARCH}(1,1)$ model for convenience. Assume that r_t is the logarithmic change of exchange rate returns at period t. Then, the $\mathrm{GARCH}(1,1)$ model can be defined as follows:

$$r_t = E_{t-1}(r_t) + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \sqrt{\sigma_t^2 \chi_t} \tag{2}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{3}$$

where $E_{t-1}(r_t)$ is the conditional expectation, χ_t is the innovation process, ε_t is the residual, σ_t^2 is the conditional variance and ω, α and β are the model parameters.

GARCH-MIDAS model builds upon the GARCH(1,1) model and can be taken as an extension to spline-GARCH model[1] introduced by Engle and Rangel (2008). The GARCH-MIDAS model proposed by Engle et al. (2009; 2013) relates directly the long-term volatility driven by the exogenous regressors with daily financial data. It is achieved by combining the GARCH component with the MIDAS component. The model holds a fixed and parsimonious number of parameters, which in turn enables us to compare different GARCH-MIDAS models belonging different time periods and number of lags.[2] Below we explain the underlying of the model setting.

Assume that r_{it} is the logarithmic change of exchange rate returns on day i during the month t having the following process:

$$r_{it} = E_{i-1,t}(r_{it}) + \sqrt{\tau_t g_{it} \chi_t}, \quad \forall i = 1, \dots, N_t, \tag{4}$$

where $E_{i-1,t}(r_{it})$ is the conditional expectation given information $\varepsilon_{it}|\Phi_{i-1,t} \sim N(0,1)$ set up to day $(i-1)$ and N_t is the number of trading days in each month. Notice that subtracting conditional expectations from the daily returns i.e., $r_{it} - E_{i-1,t}(r_{it})$, gives the unexpected part of the returns $\left(\varepsilon_t = \sqrt{\tau_t g_{it} \chi_t}\right)$. That is, $\sqrt{\sigma_t^2} = \sqrt{\tau_t g_{it}}$.

Hereby, the term $\sqrt{\tau_t g_{it} \chi_t}$ stands for the volatility with two components: g_{it} which represents the short-run component corresponding to daily fluctuations and τ_t represents the long-run (secular) component. Note that under different specifications the τ component can be held as constant throughout the month, quarter or semi-annually periods or assumed to vary daily. Underlying idea of the equation (1) is that different events may have different impacts on financial markets, depending on whether they have consequences over short or long horizons (Engle et al., 2013). The g component is assumed to be related to short-lived factors of daily liquidity conditions, speculative or external shocks while the τ component has to do with macroeconomic conditions where the past values of those conditions are assumed to be informative in depicting the

[1] In the spline-GARCH model, it is assumed for a two-step estimation. In the first step, the daily equity volatility is assumed to be a function of a slowly varying component and a mean reverting unit GARCH. In the second step, the slowly varying component is regressed on the economic activity series of interest.
[2] The recent literature appreciates the GARCH-MIDAS modeling as being capturing the exchange rate volatility (see Zhou et al., 2019; You and Liu, 2020).

volatility in the exchange rate market and contribute to the long memory of the volatility a la Baillie et al. (1996).

Equation (4) is rewritten as follows:

$$r_{it} = \mu + \sqrt{\tau_t g_{it} \chi_t}, \quad \forall i = 1, \ldots, N_t, \tag{5}$$

given that for high-frequency there is so low degree of feedback or predictability in returns, $E_{i-1,t}(r_{it})$ is taken as equal to μ.

The g_{it} component is assumed to follow a daily GARCH(1,1) process:

$$g_{it} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} \beta g_{i-1,t}. \tag{6}$$

In measuring the long-run volatility it can be defined the realized volatility, RV_t, over a month in our case, to feature the long-term component (τ_t) of the volatility. The model with the realized volatility can be taken as a benchmark case "against which we will measure the success of empirical specifications involving macroeconomic variables" (Engle et al., 2013, p. 777).

The τ_t component can be specified by smoothing RV_t and utilizing a rolling-window MIDAS filter[3] as follows:

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, RV_{t-k}, \tag{7}$$

where m and θ stand for intercept and slope coefficient of the filter, respectively; K is the number of periods over which the smoothed volatilities are obtained and RV_{t-k} is the realized volatilities at a lag k, so that

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 \tag{8}$$

[3] Engle et al. (2013) argue that using realized volatilities instead of long-term components arises as noisy measures of volatility and results in mistakes in causal patterns and propose the MIDAS filtering in the equation (7) to stand for the realized volatility.

Accordingly, when $N = 22$, the fixed window RV_t is obtained at monthly basis. Under fixed time span τ_t is assumed to be the same throughout the month.

To close the model, we define below the weighting polynomial $\varphi_k(\omega)$ that provides us to specify the long-run component of volatility. Notice that the choice of weights is of critical importance and arises as leading ingredient of specification of the GARCH MIDAS model setting (Colacito et al., 2011) as it contributes to the inclusion of the data sets defined in different frequencies and enables us to include the lagging behavior of the long-term component without any parameter proliferation.

The weighting functions can be defined in alternative forms; still it is desirable to achieve both parsimony as well as flexibility in the number of parameters (Armesto et al., 2010). Ghysels et al. (2004, 2005 and 2006) suggest some finite functional forms under MIDAS formation that serve as candidates to fulfill both features and, in all forms suggested, once the functional form is determined, the lag length is purely driven by the data (Ghysels et al., 2007).

One candidate is the Beta weighting scheme suggested Ghysels et al. (2004, 2005):[4]

$$\varphi_k(\omega) = \frac{(k/K)^{\omega_1 - 1}(1 - k/K)^{\omega_2 - 1}}{\sum_{j=1}^{K} (j/K)^{\omega_1 - 1}(1 - j/K)^{\omega_2 - 1}} \tag{9}$$

where weighting parameters are ω_1 and ω_2. Those weights represent the impact of the past information on the volatility. The higher degree of weights corresponds to higher explanatory power and the parameterized weights can decrease at different rates as the number of lags increases. Among others, the simple averaging of the high frequency data is reached with $\omega_1 = \omega_2 = 1$ (Armesto et al., 2010). A declining pattern is guaranteed when $\omega_2 > 1$.

[4] We introduce the weighting schemas following the formation used by Engle et al. (2013).

Besides, one other candidate is the Exponential Almon Polynomial weighting scheme due to Ghysels (2007). It builds upon the conventional Almon modeling in estimation of the distributed lags and can be defined as

$$\varphi_k(\omega) = \frac{\omega_2}{\sum_{j=1}^{K}(\omega^j)} \tag{10}$$

where the simple averaging of the high frequency data is reached with $\omega_1 = \omega_2 = 0$ (Armesto et al., 2010). A declining pattern is guaranteed when $\omega_2 \leq 0$.

Note that both *Beta* and Exponential lag polynomial functions are suitable for accommodating various lag structures and that with different parametrizations of (ω_1, ω_2) they can provide monotonically decreasing or hump-shaped weighting schemes and shape the rate of decay and, thus, determine the number of lags to be included in the model (Ghysels et al., 2007). We select the Beta polynomial as the weighting scheme for its high flexibility for generating various shapes with a parsimonious number of parameters.[5] For instance, setting $\omega_1 = 1$ and letting $\omega_2 = \omega$ leads to a slowly declining functional form (Ghysels et al., 2006). In this case, $\varphi_k(\omega)$ becomes:

$$\varphi_k(\omega) = \frac{(1-k/K)^{\omega-1}}{\sum_{j=1}^{K}(1-j/K)^{\omega-1}}. \tag{11}$$

Hereby, equations (5) through (9) generate a GARCH-MIDAS model for time-varying conditional volatility with fixed time span and parameter space $\Theta = \{\mu, \alpha, \beta, m, \theta, \omega_1, \omega_2\}$.

Considering a rolling window specification for the MIDAS filter, the restriction that τ_t is fixed for month t is removed, which makes both g and τ vary at the daily frequency. To do this, it is introduced the rolling window RV rather than the fixed-span RV specification. Hereby, the rolling window RV can be defined as

$$RV_i^{(rw)} = \sum_{j=1}^{N'} r_{i-j}^2 \tag{12}$$

[5] Still, in examining the model fit we observe that exponentially weighted Almon polynomial performs equivalently well.

where r_{i-j} indicates that we restore the days across various periods t. When $N' = 22$, we can call it as a monthly rolling window RV. Then, the MIDAS filter can be redefined as

$$\tau_i^{(rw)} = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, RV_{i-k}^{(rw)}. \tag{13}$$

Now, Equations (5), (6) and (9) along with Equations (12) and (13) generate a GARCH-MIDAS model with rolling window RV.

The GARCH-MIDAS model structure introduced so far is grounded on a MIDAS filter involving only the RVs. Beside to this, the GARCH-MIDAS model can be grounded on the MIDAS filter that involves past macroeconomic variables replacing the realized volatilities. It requires the long term component to slightly change in formation. That is,

$$\log\tau_t = m_l + \theta \sum_{k=1}^{K_l} \varphi_k\left(\omega_{1,l}, \omega_{2,l}\right) X_{t-k} \tag{14}$$

where the long-term component is expressed in the log-form to opt for the macroeconomic series and each of the macroeconomic variables is represented by the term X_{t-k}. Note that the model formation allows only one regressor to enter the model setting. The parameters θ and φ_k are of primary importance in drawing the very abstract of the link between the macroeconomic variables and exchange rate volatility. Equations (5), (6), (8) and (9) along with Equation (14) generate a GARCH-MIDAS model with exogenous regressor and under fixed span.

2.2 Data

The sample period is between 2001:3 and 2020:2 to cover the floating exchange rate regime period in Turkey that begun to be implemented from the year of 2001. We use two different groups of data differing in terms of sampling frequency: one is the exchange rate series with daily data (five-days data) and the other belongs to the macroeconomic series with monthly data.[6] To stand for the exchange rate we use the daily

[6] We do not prefer to express the long-term component with the quarterly data to avoid deterioration of the model fit that we encounter by using the latter and prevent a substantial reduction in the number of observations.

nominal exchange rate of Turkish lira against U.S. Dollar. The exchange rate series are collected for the period between 03/01/2001 and 02/28/2020 and used in estimation in the percentage change form to serve as a proxy for daily returns.[7]

Since the GARCH-MIDAS model by formation is a reduced-form model and allows only one regressor in estimation we utilize a variety of economic activity variables to capture exhaustively the idiosyncratic features of the Turkish economy and draw implications in the policy making. We use, accordingly, potential drivers of exchange rate volatility i.e., total foreign currency reserves, foreign currency interventions, external debts, net exports and net capital flows beside to the indicators of industrial production, inflation, money stock and interest rate. Even though these series capture different aspects of the economic activity, we need to acknowledge many other variables excluded which could potentially lead the exchange rate volatility. Due to data limitations we cannot analyze the effects of e.g., investors' and consumers' expectations on exchange rates and prices, confidence indexes and political risk indicators. Table 2.1 gives the list of macroeconomic series used in estimation. All series except the one for the interest rate is expressed as month-over-month percentage changes which induces stationarity for these series. For the interest rate series, we take TL Libor rate as the reference interest rate and use the difference of the series. Besides, it is only the series of foreign currency auctions expressed in levels but featuring stationarity.

[7] The logarithmic change of the nominal exchange rates $r_t = log\left(\frac{e_t}{e_{t-1}}\right)$ gives similar parameter estimates.

Table 2.1: List of the Exogenous Regressors

Exogenous Regressors	Source
Industrial Production Index[1]	TUIK
CPI Index[2]	TUIK
Money Supply[3]	CBRT
Interest Rate[4]	TBB
Foreign Currency Reserves[5]	CBRT
Foreign Currency Debt Stock[6]	CBRT
Net Export[7]	TUIK
Capital Inflows[8]	CBRT
Foreign Currency Buying/Selling Auctions[9]	CBRT

Note:[1]Seasonally and calendar adjusted (2005:100); [2] (2003:100); [3] Broadly defined money stock, M2, for the observations before 2005:12 M2Y is taken; [4] TRLibor Rate, due to data availability it covers the period 2002:8 through 2020:2; [5] Official foreign currency reserve assets that includes cash, deposit accounts, securities and financial derivatives, million$; [6] Short-term foreign currency debt stock, million$; [7] Total net export volume, seasonally adjusted, million$, [8] Sum of FDI and portfolio investment liabilities, million$. [9] Monthly sum of selling or buying auctions made by the CBRT. The series are used in their logarithms, million$

3. RESULTS

3.1 Model Fit and Estimation with RV

To estimate the parameter space $\Theta = \{\mu, \alpha, \beta, m, \theta, \omega_1, \omega_2\}$ of GARCH-MIDAS model we use the maximization of the following log-likelihood function (LLF):[8]

$$LLF = -\frac{1}{2}\sum_{t=1}^{T} \text{x}\left[\log(2\pi) + \log g_t(\Phi)\tau_t(\Phi) + \frac{(r_t-\mu)^2}{g_t(\Phi)\tau_t(\Phi)}\right] \quad (15)$$

Firstly, for controlling the extent to which Turkish exchange rate market fits the GARCH-MIDAS model and if any identification problem arises we estimate the Beta

[8]The GARCH-MIDAS codes for estimation are taken from Hang Qian (2020) who provides MIDAS Matlab Toolbox in MATLAB Central File Exchange (https://www.mathworks.com/matlabcentral/fileexchange/45150-midas-matlab-toolbox). Retrieved April 16, 2020.

weighting functions for both full-sample and two subsamples, examine the distribution of estimation errors and control parameter consistency across different periods.

As previously stated, the sample period covers the floating exchange rate regime period i.e., from 2001:3 through 2020:2. In capturing if there exists any identification problem resulting from the model fit we choose two different sub-periods: i. 2001:3 – 2008:9 and 2008:10 – 2020:2 and ii. 2001:3 – 2010:9 and 2010:10 – 2020:2.[9] For the former choice (i.e., 2001:3 – 2008:9 and 2008:10 – 2020:2), the sub-samples are determined with an attempt to distinguish potential differences between the pre-crisis and post-crisis episodes for Turkish economy. In this way, we firstly aim at capturing the transition dynamics to the floating exchange regime in which the adjustment process had generated relatively higher volatilities of exchange rates (see e.g., Figure 3.6). Besides, we plan to evaluate the post-crisis episode that possesses its own dynamics in the policy making side. The date of 2008:9 is determined as the contagion of the global financial crisis to Turkey had become more prominent with the beginning of the last quarter of 2008 (Rodrik, 2012). More specifically, following this date, the Turkish economy confronted with a sudden tumble in its industrial production and employment rate, fall in export volume, sizable net capital outflows and depreciation of its domestic currency (Uygur, 2010).

For the latter choice (2001:3 – 2010:9 and 2010:10 – 2020:2), the sub-samples are determined to account for a policy shift in the monetary policy stance that targeted more on the financial variables in the aftermath of the crisis. That is, the monetary authority designed a new monetary policy conduct in the late of 2010 considering the financial stability as a secondary objective beside to the price stability and adopted new instruments under a multiple-policy framework to smooth the fluctuations in the financial markets e.g., to control better capital flows or mitigate volatility of the exchange rates (Kara, 2016). Also, at the end of 2010, the CBRT conducted vital policy changes in regulations on foreign currency reserves, required reserve ratios and liquidity managements (CBRT, 2011). For controlling existence of any structural break in

[9] Another group of sub-samples could be determined looking at the central bank's recent attempts on simplification of its monetary policy at the beginning of 2016 (Akçelik and Talaslı, 2020). As these attempts towards simplification are newly emerging we do not consider the post-2016 as an idiosyncratic sub-period.

exchange rate series (r_{it}) across full-sample and considered sub-samples, we follow Engle et al. (2013) and apply also a likelihood ratio test to LLF values belonging fixed and rolling window RV as well as macroeconomic series. Applying the likelihood ratio test statistic (LR) we examine the difference in goodness-of-fit of two nested models (of full-sample and sum of sub-samples). That is,

$$LR = -2\left[LLF_{fullsample} - \left(LLF_{subsample1} + LLF_{subsample2}\right)\right] \sim \chi^2 \text{ with } df \qquad (16)$$

The number of restrictions (df) is set as $\text{the number of parameters} * (\text{the number of subsamples} - 1)$. We compare the LLF of the full-sample with the sum of sub-samples of RV as well as different economic variables. The results are provided in Table A.1 in Appendix A. LR indicates the existence of structural break under all long-run components and for both group of sub-samples. The results also provide that the model fit deteriorates when it is used the macroeconomic series instead of realized volatility.

Before drawing the Beta weighting functions and estimating the model we determine the number of MIDAS lags (K). Note that in the model setting of GARCH-MIDAS, the number of lags does not influence the number of the model parametrization while the penalty for over-selecting K is equal to sacrificing a higher number of observations for the initialization (Ghysels, 2017). With regard to the lag selection of the MIDAS filter, the guide book is to choose "the smallest number of MIDAS lags after which the log-likelihoods of the volatilities seem to reach their plateau" (Colacito et al., 2011: 50). In this regard, we use firstly the LLF to shoot for an optimal number of lags (see Figure A.2 in Appendix A). We also exploit Beta weights polynomials to control if the determined MIDAS lags suffice to obtain all relevant information provided by the previous values.

A monthly time span t for the MIDAS lags (k) is used in order to provide sufficient number of in-sample forecasts. Accordingly, for the fixed span RV τ_t is fixed throughout the month while for the rolling window RV it is assumed a daily change in τ component. In determining the MIDAS lag length, the likelihood values using the BIC do not result in any plateau with increases in the lag-lengths. The MIDAS weighting function, however, approaches to zero around 8th months (which is particularly the case after 2008). Given a relatively short observation number of series, to avoid sacrificing observations further for initialization we determine the lag number as eight.[10] Hence, the history of eight months' realized volatility will be averaged by the MIDAS weights to determine the long-run conditional variance (Ghysels, 2017). It costs 176 observations for the sake of initialization.

Next, to control for homogeneity of MIDAS weighting parameter across different time periods we draw MIDAS weighting functions for the full-sample as well as above-mentioned sub-samples. Note that to obtain a decaying pattern of the Beta weighting functions for the sake of giving higher weights to recent past, the optimal ω_1 is set equal to one, so that it is allowed only for ω_2 to change.[11] Figures 3.1 to 3.5 reveal the Beta weights. We firstly reach that for the full-sample ω_2 is close to 1 implying almost equal weights across the lagged values. Contrarily, for the sub-samples (except for the period between 2001:3 – 2010:9), we observe that the Beta polynomials feature monotonically decreasing patterns, so that the more recent observations the more contribution they provide for the long-term component volatility. Also, the rapidly decreasing patterns of weights imply larger values of ω_2. It arises, thus, different lagged effects of the long-term component across different time periods. In this regard, we estimate the model parameters for both the full-sample and sub-samples which enables us to control if different Beta weights generate different impacts on the volatility. Beside to the Beta weights we also draw distribution of error terms in Figures 3.1 to 3.5. In computing the log-likelihood functions it is assumed for normally distributed disturbance term. The figures reveal that the distribution of errors fits normal distribution under different periods featuring symmetric distributions and low number of outliers. One exception is the sub-sample of 2001:3 – 2008:9 that features skewness and relatively high number of outliers which may be attributed to initial years of floating exchange regime that passed with adjustment.[12]

---

[10] We also reach that the estimation results are robust to choice of higher lag numbers.

[11] Setting $\omega_1 > 1$ generates hump-shaped patterns which are not in line with the volatility literature.

[12] To control if the initial adjustment process to floating regime alters the estimation results we take the full-sample period as 2002:1 – 2020:2. We reveal similar parameter estimates while the distribution of error terms improves (see Table A.2 and Figure A.2 in Appendix A).

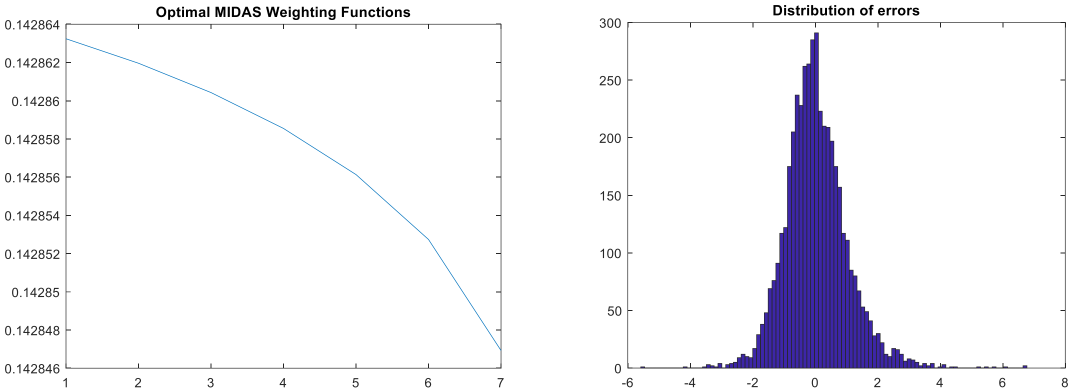

Figure 3.1: MIDAS Weighting Functions and Distribution of Errors for the Full-Sample

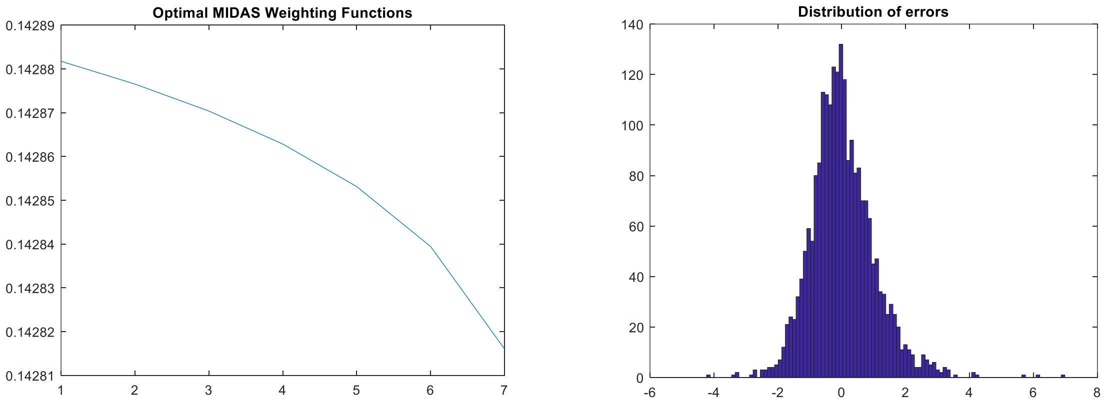

Figure 3.2: MIDAS Weighting Functions and Distribution of Errors for the Sample between 2001:3–2010:9

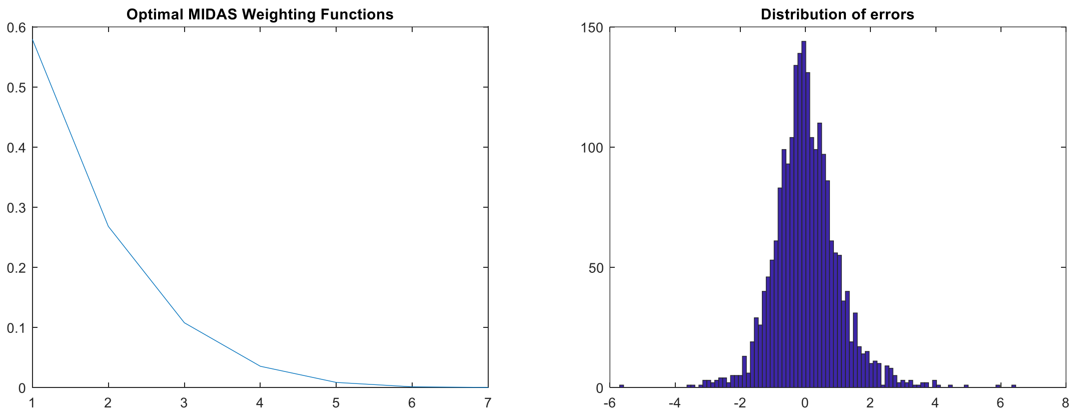

Figure 3.3: MIDAS Weighting Functions and Distribution of Errors for the Sample between 2010:10–2020:2

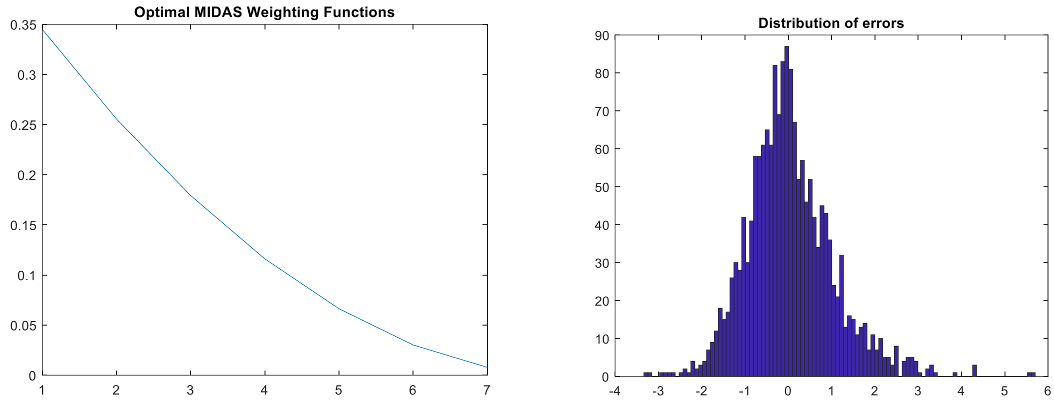

Figure 3.4: MIDAS Weighting Functions and Distribution of Errors for the Sample between 2001:3 – 2008:9

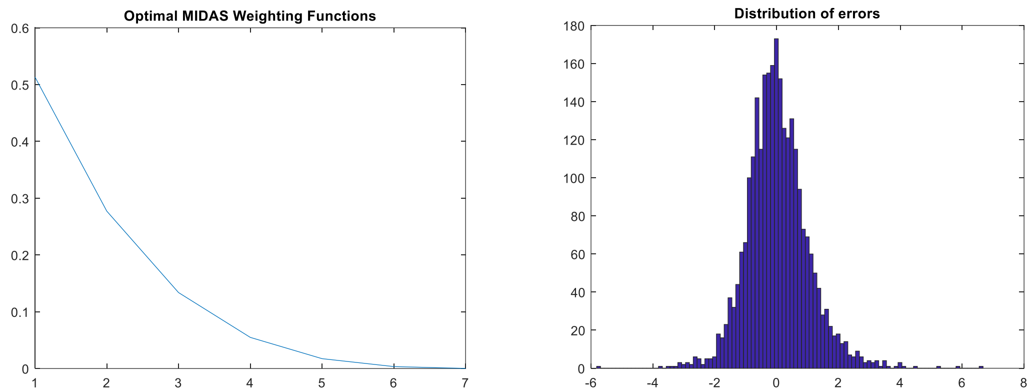

Figure 3.5: MIDAS Weighting Functions and Distribution of Errors for the Sample between 2008:10 – 2020:2

Figures 3.6 and 3.7 display the total volatility of the exchange rates along with its long-term component calculated at monthly base with fixed span RV and rolling window RV, respectively. Since τ is calculated at daily frequencies, true to form, the long-term volatility under rolling window RV (Figure 3.7) is smoother. The figures displays firstly that the exchange rate series feature volatility at a higher degree in the pre-crisis episode. Also, we observe a dramatic rise in the volatility during two periods of time: during the 2008 – 2009 financial crisis period and the political crisis of August 2018 justifying the counter-cyclical pattern of exchange volatility during the financial turmoil. Besides, even though the secular component follows note-worthily the total volatility for the full-sample, it is during more turbulent periods that the volatility expands dramatically to the long-run.

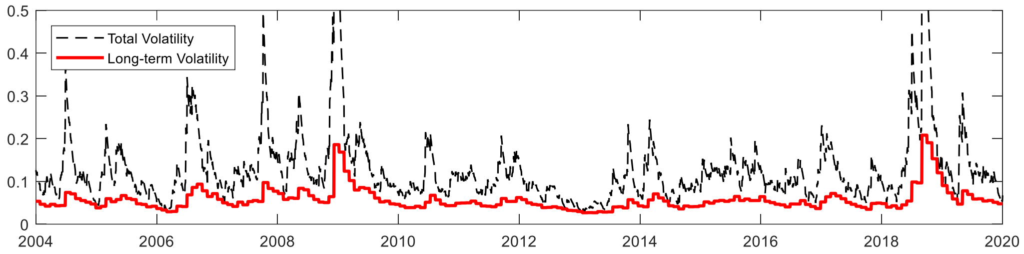

Figure 3.6: Total Volatility of Exchange Rate and its Long-term Component (Fixed Window)

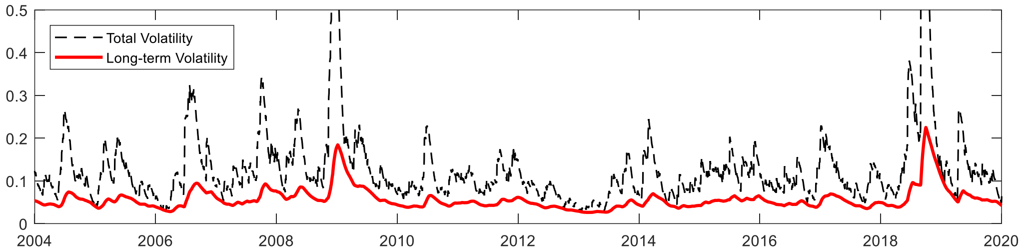

Figure 3.7: Total Volatility of Exchange Rate and its Long-term Component (Rolling window)

Table 3.1 gives the parameter estimates with RV under fixed window and rolling window for the full-sample, estimates for sub-samples and GARCH(1,1) model. The Table provides that both windows yield nearly the same parameter and log-likelihood (LLF) values under the full-sample This indicates that there exists no appreciable difference between holding the long-term τ constant throughout the month or allowing it to vary every day during the month for the likelihood of the data. Estimates are reported with standard errors in parenthesis. The parameter μ is the sample average of observations, α and β stand for coefficients for the short-term component, θ for the long-term component, ω for the Beta weighting parameter and m for the location parameter of the long-term component.

We observe that parameter estimates under different samples are significant which promotes the goodness of the model fit. Besides, under all specifications, θ is strongly significant and positive implying a worth-mentioning information content of the realized volatility of last eight months in explaining the long-term volatility. The value of the parameter θ changes and the corresponding impact gets more robust when estimation is upheld under sub-samples and the realized volatility clustering becomes highest for the period between 2010:10 – 2020:2. For the full-sample, the sums of α and β are 0.9900 and 0.9899 for the fixed span and rolling window span, respectively, being so close to 1. The sub-sample periods also feature similar values for the sums of α and β. It implies for the $\text{GARCH}(1,1)$ part a stationary solution and mean-reversion. Still, the parameter β reveals high degree of persistence for the short-term volatility. We also estimate and report the volatility of exchange rate with a $\text{GARCH}(1,1)$ process which assumes intrinsically $\theta = 0$. It gives similar coefficients with those of the short-term component of GARCH-MIDAS model but with a smaller likelihood value.

Table 3.1: Parameter Estimates for GARCH-MIDAS with Realized Volatility

Time Period	μ	α	β	θ	ω	m	LLF
Full Sample-Fixed RV	0.0002***	0.0696***	0.9204***	0.0887***	1.0001***	0.0013***	16594.8
	(0.0094)	(0.0002)	(0.0002)	(0.0173)	(0.1392)	(0.0000)	
Full Sample-Rolling RV	0.0002***	0.0697***	0.9202***	0.0893***	1.0002***	0.0012***	16613.4
	(0.0087)	(0.0002)	(0.0002)	(0.0001)	(0.5427)	(0.0008)	
2001:1 – 2010:9+	-0.003**	0.1351***	0.8120***	0.12793***	1.0450*	0.0073***	7990.53
	(0.0001)	(0.0112)	(0.0292)	(0.0295)	(0.6746)	(0.0011)	
2010:10-2020:2+	0.0003***	0.1490***	0.8276***	0.1787***	6.0002**	0.0006***	8197.67
	(0.0092)	(0.0000)	(0.0000)	(0.0000)	(0.0420)	(0.0000)	
2001:3 – 2008:9+	-0.0003**	0.1999***	0.7367***	0.1434***	2.9458*	0.0006***	6253
	(0.0165)	(0.0185)	(0.0204)	(0.0194)	(1.0177)	(0.0000)	
2008:10 – 2020:2+	0.0003***	0.0690***	0.9309***	0.09000***	4.9963***	0.0013***	9996.86
	(0.0001)	(0.0032)	(0.0029)	(0.0180)	(0.7256)	(0.0000)	
$\mathbf{GARCH(1,1)}$ Model	0.0001***	0.0979***	0.8979***	-	-	-	11502.6
	(0.0002)	(0.0059)	(0.0049)				

Note: + The estimation is made under the Rolling Window. ***, **, * represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis.

3.2 Model Estimation with Macroeconomic Series

After introducing the components of the exchange rate volatility, in this section, we replace the realized volatility by the macroeconomic variables to understand extent to which the latter is successful in explaining the long-term volatility. Such an attempt requires equation (14) in estimation. That is, using exogenous regressors X_{t-k} with k lags we explain the long-term volatility τ_t. In determining the Beta weighting functions, as in the case of RV, we use restricted Beta function by taking $\omega_1 = 1$ and reporting only ω_2 to prevent inconsistent shapes of weighting scheme. Also, the Beta weights are drawn using the past eight months of the selected macroeconomic variables.

We utilize a variety of economic activity variables to represent exhaustively the idiosyncratic features of the Turkish economy and draw policy implications. We use, accordingly, potential drivers of exchange rate volatility i.e., total foreign currency reserves, foreign currency interventions, external debts, net exports and net capital flows beside to the indicators of industrial production, inflation, money stock and interest rate. The model estimation with exogenous regressors is upheld using monthly data since at the lower frequencies the model fit is found to deteriorate. Besides, we estimate the model using sub-samples beside to the full-sample to see whether the impacts of macroeconomic variables changes with respect to different policy states.

Figure 3.8 to 3.15 display the time series paths of total volatility of exchange rates, $g \times \tau$ and the long-term component represented by each of exogenous regressors, τ. It arises that the parameter θ becomes smoother when the selected macroeconomic variables are used. That is, the macroeconomic variables follow the total volatility to a lesser extent compared to the RV. It can be attributed to prima facie a dominance of the intrinsic dynamics of the foreign exchange market e.g., speculative formation or external factors in influencing the exchange rates. Still, we elaborate below how substantial the economic sources of the exchange rate volatility are using the significance and the magnitude of the related parameters.

Regarding the time series path of each of the series along with the total volatility we observe that even though some of the variables (i.e., CPI inflation and net export changes) fail to track the exchange rate volatility even in the turbulent periods the other variables (i.e., industrial production growth, money growth, interest rate changes, reserves, debts and capital inflows) persistently follow the exchange rate ups-and-downs.

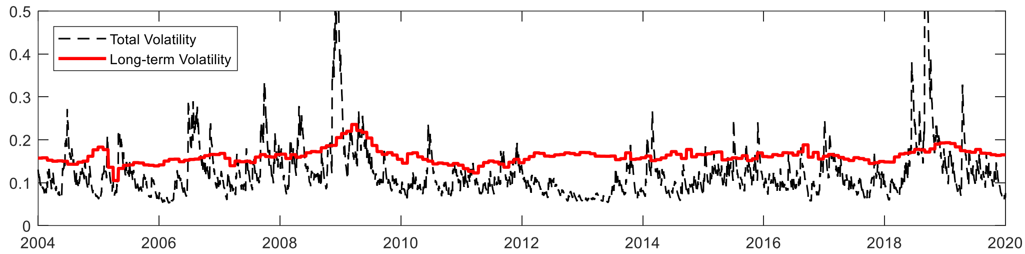

Figure 3.8: Total Volatility of Exchange Rate and the Industrial Production Growth

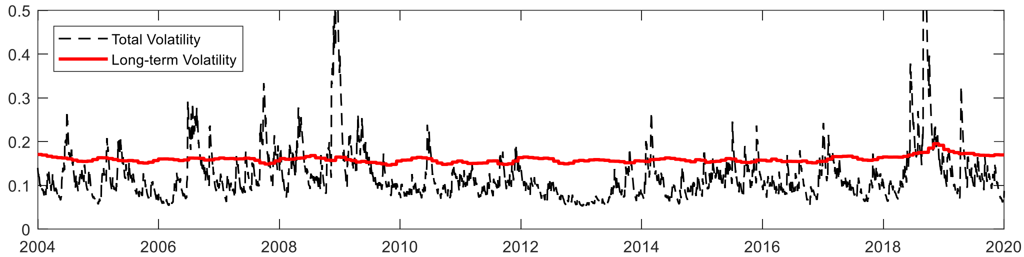

Figure 3.9: Total Volatility of Exchange Rate and the CPI Inflation

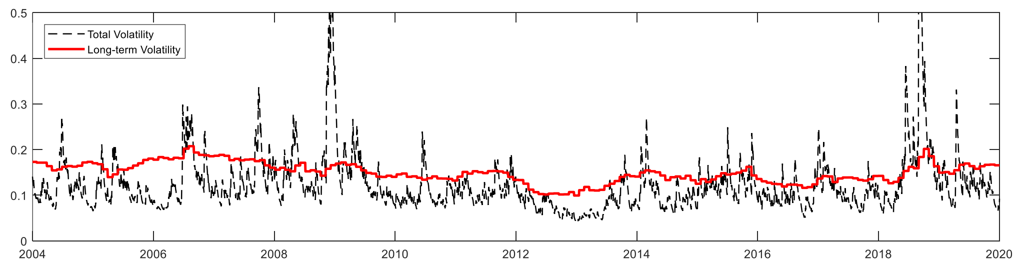

Figure 3.10: Total Volatility of Exchange Rate and the Money Growth

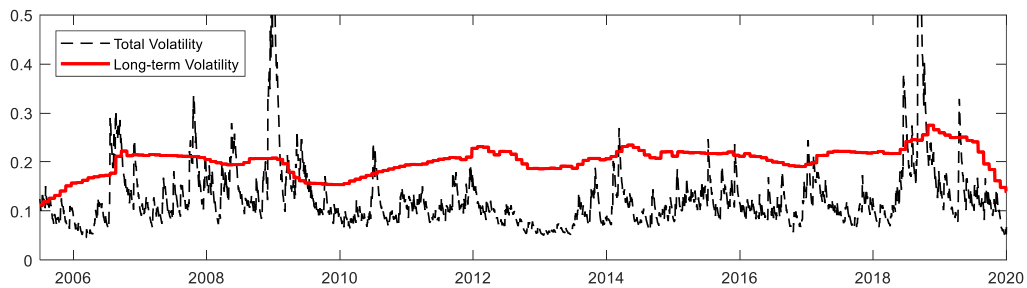

Figure 3.11: Total Volatility of Exchange Rate and the Interest Rate Changes

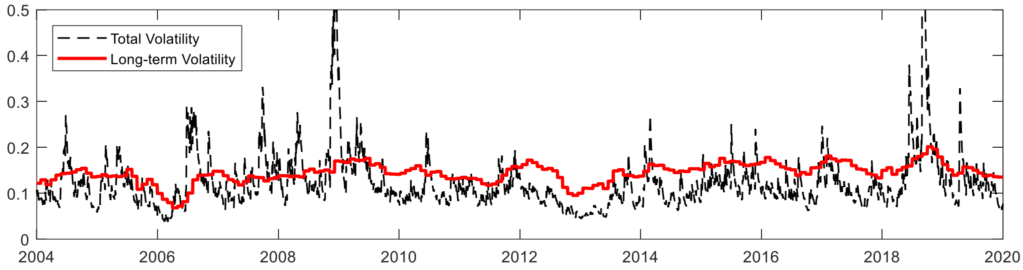

Figure 3.12: Total Volatility of Exchange Rate and the Change in Foreign Currency Reserves

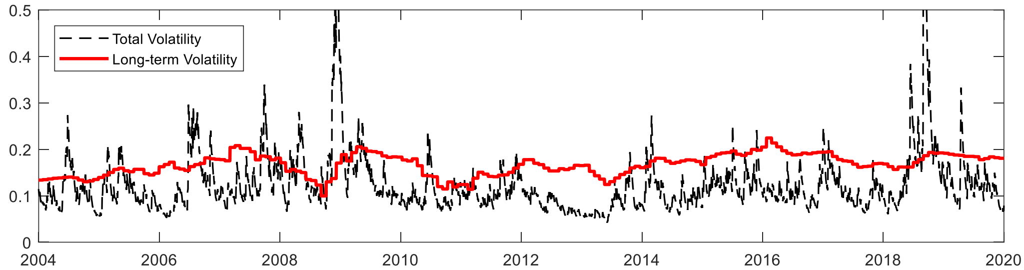

Figure 3.13: Total Volatility of Exchange Rate and the Change in Foreign Currency Debt Stock

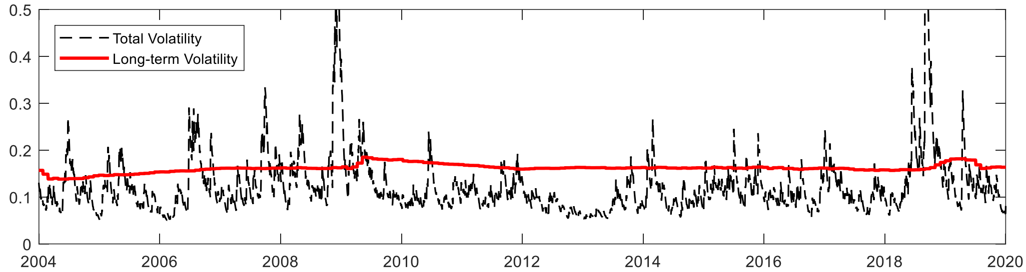

Figure 3.14: Total Volatility of Exchange Rate and the Net Export Changes

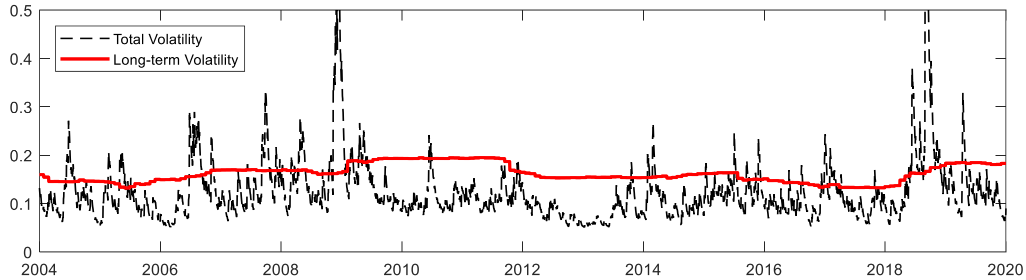

Figure 3.15: Total Volatility of Exchange Rate and the Change in Capital Inflow

Next we report the parameter estimates of GARCH-MIDAS model with each of macroeconomic variables in Tables 3.2 to 3.9. As in the model with RV, we make the estimation under two different specifications of sub-samples along with the full-sample. By this way, we test the parameter significance and, thus, the model fit across different samples. We also explore the degree to which the impact of economic forces on the exchange rate market changes in between i. pre- and post- crisis periods and ii. during the period in which the financial stability is officially targeted by the monetary authority. The exogenous regressors are determined also to match the series that are largely in control of the policy makers, have potential to lead the exchange rates and facilitate to draw policy implications. In this regard, beside to other variables, to serve as proxy for the degree of liquidity management, overall risk level and indebtness we include the foreign currency reserves, debt stock and net capital flows in our analysis.

From the tables it arises that the parameters μ and m significantly locate around zero in almost all cases. The parameters of α and β are also significant and close to one in all the cases denoting low degree of clustering patterns of short-term volatility. Notice that the parameters θ and ω are particularly of importance in depicting the link between the economic sources and the volatility and in distinguishing between the relative impacts of macroeconomic variables on the long-term volatility. In the first instance, it arises that even though the parameter θ is largely significant for the selected variables and promotes the counter cyclical pattern of exchange rate volatility, still it differs in significance and with respect to the direction of the link across full-sample and subsamples making the analysis with sum-samples more suggestive.

In addition to using the information the parameter θ *per se* provides, following Engle et al. (2013), we use the formula $\left(\hat{\tau} = e^{\theta * \varphi_k(\omega)} - 1\right)$ to capture the magnitude of the particular impact of each variable on the exchange rate volatility. It is assumed a positive shock to the selected macroeconomic variable and the model does not postulate any asymmetry between negative and positive shocks which can be taken as a downside of the setting. Notice that the term $\varphi_k(\omega)$ corresponds to the Beta weights defined in equation 10 for the k^{th} lag. We report the calculated impacts, $\hat{\tau}$, for all the series and under all the periods at Table 3.11.

When the industrial production growth at $t-1$ stands for the exogenous regressor in explaining the long-term volatility at t it arises that the parameter θ significantly and negatively leads the exchange rate volatility for the time episode before 2010 while it affects pronouncedly positive thereafter. Regarding the magnitude of the impacts, the estimated parameters for the full-sample are $\theta = -0.0035$ and $\omega = 1.1284$. The latter puts the 0.1563 on the first lag. Thus, a 1% increase in industrial production growth during the current month leads to a $e^{-0.0035*1.1563} - 1 \approx -0.05\%$ fall in the exchange rate volatility in the next month. This negligible impact improves for the subsample of 2001:3 – 2010:9 and materializes as a -0.27% fall in the volatility.

In the case of CPI inflation, even though the inflation does not lead to the exchange rate volatility when the estimation is upheld under the full-sample, the estimation under sub-samples features different patterns. For the sub-sample of 2001:3 – 2008:9 witnessing a transition from two-digit inflation period to one-digit one for Turkish economy the CPI inflation results in a negative impact on volatility and generate -0.44% fall in volatility while for the period of 2010:10 – 2020:2 the rise in CPI inflation leads to a higher volatility (0.32%) in exchange rates. Inclusion of the 2008-2009 crisis years' observations, thus, seems to blur the corresponding link. The money growth creates a similar impact on volatility with the CPI inflation under the sub-samples. As in the case of CPI inflation the money growth contributes negatively to the exchange rate volatility in the pre-crisis episode (with the coefficient of -0.26%) while the corresponding impact turns out to be significantly positive thereafter (with the coefficient of 0.36%).

Grounded on the TRlibor rate standing as a leading reference rate in the policy making (see Gürkaynak et al., 2015) we reach a consistently positive impact of the short-term rates on exchange rate volatility for both full-sample and different sub-samples. Besides, the term $\hat{\tau}$ displays that the mentioned link becomes more pronounced in the post-crisis episode being in line with the financial stability objective of the monetary authority practiced during this period. In this regard, a 1% increase in the interest rates during the current month leads to a 0.36% rise in the exchange rate volatility in the subsequent month.

To control if the degree of the liquidity management of the CBRT matters for the exchange rate volatility we consider the total official foreign currency reserves as another exogenous regressor. The official foreign currency reserves of the CBRT can also be taken as a buffer against windy days. We observe that the parameters θ and $\hat{\tau}$ reveal consistently a negative link between reserves held in foreign currency and volatility under all estimation periods. This finding, in turn, promotes the functioning of augmenting reserves for the sake of controlling exchange rate movements. The corresponding impact is still far from resulting a proportional change in exchange rate volatility. Within its foreign exchange reserve policy framework, the CBRT adopted also an active attitude toward using the foreign exchange interventions to support the market mechanism and provide financial consolidation. In this regard, we decide to evaluate the foreign exchange interventions as a spot-on instrument within its reserve policy. Even though the CBRT ended to use foreign exchange interventions and auctions with the year of 2017, foreign exchange controls had been frequently applied in preceding years. We examine the central bank's intervention to the foreign exchange market using the foreign exchange buying and selling auctions.[13] As the sample period covers less number of observations i.e., from 2001:3 through 2016:4 and it is used the series in their levels with missing observations we single out the foreign exchange interventions from other variables and report the estimation results in Appendix A. We display the time series path of the exchange rate interventions in standing for the long term component of volatility in Figure A.3. Besides, the estimation results and the calculated magnitudes of the impacts belonging full-sample and subsamples are given in Tables A.3 and A.4, respectively. At first glance, we observe a smooth time path of the long-term volatility when the realized volatility is represented by the foreign exchange auctions. Also, opposed to what the CBRT intended, the estimation results reveal significant and positive impacts of central bank's foreign exchange interventions under sub-samples being in line with the previous findings (Herrera and Ozbay, 2005; Tuna, 2011). The corresponding impact in magnitude, however, is quite subordinate.

[13] We collected both buying and selling auctions held by the CBRT together as the central bank decided to use either buying or selling auctions for certain period of time. We did not consider the direct foreign exchange interventions with rare utilization of buying and selling interventions.

Considering the potential impact of the external debt stock changes on the volatility in the exchange rate market we reach surprisingly a negative link under all samples such that a 1% rise in the foreign currency debt stock leads to a mild but significant fall in exchange rate volatility (with a coefficient of around 0.10%). Besides, considering a potential relationship between the trade structure of Turkish economy and the dynamics of the exchange rates we reach that the changes in the net export lead pronouncedly and negatively for only the more recent period i.e., 2010:10 – 2020:2. Hence, a 1% rise in net export of Turkey in the current month results in a -0.37% decline in the volatility in the next month. Lastly, we also control the potential impact of capital inflows on exchange rate volatility given the former's highly-voiced reputation in influencing idiosyncratic dynamics of Turkish economy and financial stability. The capital inflow changes can be taken as rough proxy of the degree of openness along with net export changes. We consider changes in the net capital inflows as the sum of the net portfolio investments and the foreign direct investments to Turkey to stand for the exogenous regressor in the model. The parameters θ and $\hat{\tau}$ demonstrate that a rise in net investment to Turkey which could partly be taken as a rise in its liabilities leads to a decline in exchange rate volatility in all cases except for the period 2001:3 – 2008:9.[14]

Overall we observe a smoother long-term component of exchange rate volatility when the realized volatility is replaced by potential exogenous regressors. The estimation results still reveal that the selected variables largely lead to the volatility in the exchange market and that the effects may change in accordance with the specification of sample-periods. Further, the changes in the exogenous regressors remain limited in regard to the magnitude of the impacts and do not create proportional changes in the exchange rate volatility.

We controlled for the effects of the exogenous regressors defined so far in their first moments by considering the change in the corresponding variables e.g., we consider the growth of industrial production. Subsequent to the levels of variables, we also include the second moments into the analysis using the volatility of the macroeconomic variables

[14] As the foreign direct investments differ from portfolio investments by formation we also control both variables separately and reach that even though they feature significant and mitigating impacts on the volatility the former dominates in magnitude.

to see the degree to which the volatility in the economic activity matters for exchange rate volatility. From a theoretical point of view, the macroeconomic variables may be volatile "if their actual rates deviate from their long-run (sustainable) values [...and] the exchange rate will be at equilibrium levels if the macroeconomic fundamentals are at their sustainable levels" (Giannellis and Papadopoulos, 2011, 41). Notice that this theoretical argument is too strong as it excludes many other factors that could lead the exchange rate volatility even if the macroeconomic fundamentals do not deviate their long run levels. Still it would be elucidative to see degree to which volatility of macroeconomic factors affects exchange rate volatility. We estimate a GARCH(1,1) model for each of the series and take monthly GARCH variance series to account monthly macroeconomic volatility.[15] The corresponding volatility patterns of the series are given in Figure B.1 in Appendix B. Table 3.10 gives the GARCH-MIDAS model results with volatilities of exogenous regressors. The estimation results are reported under the full-sample period for convenience.

Table 3.2: Parameter Estimates for GARCH-MIDAS with Industrial Production Growth

Time Period	μ	α	β	θ	ω	m	*LLF*
Full Sample-Rolling Window	0.0001***	0.1242***	0.8639***	-0.0035**	1.1284***	0.0001***	15019.6
	(0.0000)	(0.0000)	(0.0000)	(0.0014)	(0.0006)	(0.0000)	
2001:3-2010:9	-0.0003*	0.1290***	0.8460***	-0.0053**	4.2397***	0.0001***	6201.94
	(0.0000)	(0.0099)	(0.0094)	(0.0017)	(1.2443)	(0.0000)	
2010:10 – 2020:2	0.0004***	0.1659***	0.7947***	0.0062**	1.0599***	0.0001***	6123.52
	(0.0000)	(0.0000)	(0.0000)	(0.0014)	(0.6746)	(0.0000)	
2001:3-2008:9	-0.0003**	0.1675***	0.7953***	-0.0106*	2.1298*	0.0001***	4452
	(0.0000)	(0.0187)	(0.0199)	(0.0057)	(1.1363)	(0.0000)	
2008:10 – 2020:2	0.0004***	0.1187***	0.8731***	-0.0002	33.323	0.0001***	8196.86
	(0.0000)	(0.0059)	(0.0064)	(0.0000)	(140.25)	(0.0003)	

Note: ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis.

[15] Alternatively, one can estimate an AR model following Schwert (1989). Engle et al. (2013) point that estimation under GARCH or AR models reveal similar results.

Table 3.3: Parameter Estimates for GARCH-MIDAS with CPI Inflation

Time Period	μ	α	β	θ	ω	m	LLF
Full Sample-	0.0001	0.1224***	0.8659***	0.0038	4.5273	0.0000***	15016.5
Rolling Window	(0.0000)	(0.0049)	(0.0042)	(0.027)	(3.6557)	(0.0000)	
2001:3-2010:9	-0.0002*	0.1216***	0.8592***	-0.0050	13.421	0.0001***	6196.55
	(0.0001)	(0.0009)	(0.0083)	(0.0031)	(8.3207)	(0.0000)	
2010:10 – 2020:2	0.0004***	0.2298***	0.6508***	0.0033***	28.024***	0.0001***	6126.22
	(0.0000)	(0.0016)	(0.0271)	(0.0007)	(8.1737)	(0.0000)	
2001:3-2008:9	-0.0004**	0.1741***	0.7858***	-0.0047**	20.9222*	0.0001***	4449
	(0.0001)	(0.0200)	(0.0212)	(0.0022)	(11.627)	(0.0000)	
2008:10 – 2020:2	0.0003***	0.1259***	0.8948***	0.0089*	2.945	0.0001***	8159.47
	(0.0001)	(0.0066)	(0.0069)	(0.0049)	(2.1387)	(0.0003)	

Note: ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis.

Table 3.4: Parameter Estimates for GARCH-MIDAS with Money Growth

Time Period	μ	α	β	θ	ω	m	LLF
Full Sample-	0.0000	0.1275***	0.8546***	0.0096***	1.9773***	0.0000**	15024
Rolling Window	(0.0000)	(0.0001)	(0.0054)	(0.0021)	(0.4238)	(0.0000)	
2001:3-2010:9	-0.0002*	0.1267***	0.8571***	0.0057	2.5508	0.0001	6194.82
	(0.0001)	(0.0107)	(0.0102)	(0.0040)	(1.5835)	(0.0000)	
2010:10 – 2020:2	0.0003**	0.2363***	0.6140***	0.0035***	8.0164***	0.0001*	6127.46
	(0.0001)	(0.0169)	(0.0301)	(0.0007)	(1.6204)	(0.0000)	
2001:3-2008:9	-0.0004**	0.1803***	0.7789***	-0.0037**	8.639*	0.0001***	4452.79
	(0.0001)	(0.0203)	(0.0203)	(0.0020)	(4.5436)	(0.0000)	
2008:10 – 2020:2	0.0002**	0.1488***	0.8018***	0.0179***	1.5895***	-0.0001***	8174.22
	(0.0001)	(0.0084)	(0.0118)	(0.0024)	(0.1743)	(0.0003)	

Note: ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis.

Table 3.5: Parameter Estimates for GARCH-MIDAS with Interest Rate Change

Time Period	μ	α	β	θ	ω	m	LLF
Full Sample-	0.0001*	0.1222***	0.8704***	0.01339**	2.9473***	0.0001***	13708.1
Rolling Window	(0.0000)	(0.0051)	(0.0046)	(0.0059)	(0.4888)	(0.0000)	
2001:3-2010:9	-0.0001	0.1252***	0.8499***	0.01159***	1.0319***	0.0001***	4886.33
	(0.0001)	(0.0107)	(0.0105)	(0.0029)	(0.0586)	(0.0000)	
2010:10 – 2020:2	0.0004***	0.2112***	0.6639***	0.0129***	1.4393***	0.0000*	6137.38
	(0.0001)	(0.0152)	(0.0271)	(0.0021)	(0.1460)	(0.0000)	
2001:3-2008:9	-0.0002	0.1688***	0.7800***	0.0100***	1.012***	0.0001***	3135.65
	(0.0002)	(0.0220)	(0.0260)	(0.0024)	(0.0349)	(0.0000)	
2008:10 – 2020:2	0.0003***	0.1373***	0.8285***	0.0218***	1.251***	0.0001***	8168.71
	(0.0001)	(0.0076)	(0.0098)	(0.0023)	(0.0212)	(0.000)	

Note: ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis.

Table 3.6: Parameter Estimates for GARCH-MIDAS with Change in Foreign Currency Reserves

Time Period	μ	α	β	θ	ω	m	*LLF*
Full Sample-	0.0001	0.1259***	0.8527***	-0.0016***	8.0416***	0.0001***	15031.4
Rolling Window	(0.0000)	(0.0052)	(0.0047)	(0.0002)	(2.1552)	(0.0000)	
2001:3-2010:9	-0.0002*	0.1243***	0.8517***	-0.0012***	10.619*	0.0001***	6196.68
	(0.0001)	(0.0094)	(0.0081)	(0.0004)	(5.8863)	(0.0000)	
2010:10 – 2020:2	0.0004***	0.2125***	0.6623***	-0.0025***	6.8644***	0.0001*	6138.21
	(0.0001)	(0.0157)	(0.0277)	(0.0003)	(0.8223)	(0.0000)	
2001:3-2008:9	-0.0003**	0.1703***	0.7771***	-0.0011***	20.719***	0.0002***	4453.61
	(0.0001)	(0.0191)	(0.0219)	(0.0001)	(6.6553)	(0.0001)	
2008:10 – 2020:2	0.0002***	0.1434***	0.8021***	-0.0021***	5.0609***	0.0001***	8184.91
	(0.0001)	(0.0080)	(0.0113)	(0.0004)	(0.7149)	(0.000)	

Note: ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis.

Table 3.7: Parameter Estimates for GARCH-MIDAS with Change in Foreign Currency Debt Stock

Time Period	μ	α	β	θ	ω	m	*LLF*
Full Sample-	0.0001	0.1277***	0.8611***	-0.0019***	7.4654***	0.0001***	15021.7
Rolling Window	(0.0000)	(0.0053)	(0.0048)	(0.0006)	(2.594)	(0.0000)	
2001:3-2010:9	-0.0003*	0.1260***	0.8582***	-0.0014*	7.2481*	0.0000***	6196.06
	(0.0001)	(0.0096)	(0.0076)	(0.0007)	(4.0236)	(0.0000)	
2010:10 – 2020:2	0.0004***	0.0713***	0.8983***	-0.0004	5.2409	0.0001***	6107.43
	(0.0001)	(0.0040)	(0.0074)	(0.0002)	(7.0615)	(0.0000)	
2001:3-2008:9	-0.0004**	0.1853***	0.7717***	-0.0040**	1.5983***	0.0001***	4456.75
	(0.0001)	(0.0210)	(0.0207)	(0.0012)	(0.2728)	(0.0001)	
2008:10 – 2020:2	0.0002**	0.1395***	0.8474***	-0.0033**	5.1117***	0.0001***	8186.39
	(0.0001)	(0.0075)	(0.0012)	(0.0012)	(1.8815)	(0.000)	

Note: ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis.

Table 3.8: Parameter Estimates for GARCH-MIDAS with Net Export Change

Time Period	μ	α	β	θ	ω	m	*LLF*
Full Sample-	0.0001	0.1224***	0.8663***	-0.0089	1.6898	0.0001***	15016.8
Rolling Window	(0.0000)	(0.0049)	(0.0045)	(0.0059)	(1.1617)	(0.0000)	
2001:3-2010:9	-0.0002*	0.1251***	0.8582***	-0.0035	4.3495	0.0001***	6194.53
	(0.0001)	(0.0091)	(0.0072)	(0.051)	(7.6491)	(0.0000)	
2010:10 – 2020:2	0.0004***	0.1695***	0.7767***	-0.0092**	3.6971**	0.0002***	6127.82
	(0.0001)	(0.0096)	(0.0122)	(0.0045)	(1.7277)	(0.0000)	
2001:3-2008:9	-0.0004**	0.1735***	0.7954***	0.0030	21.361	0.0000***	4447.52
	(0.0001)	(0.0187)	(0.0189)	(0.0043)	(43.2)	(0.0001)	
2008:10 – 2020:2	0.0003***	0.1151***	0.8781***	0.0044	25.689	0.0001***	8160.74
	(0.0001)	(0.0059)	(0.0061)	(0.0031)	(22.781)	(0.0000)	

Note: ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis.

Table 3.9: Parameter Estimates for GARCH-MIDAS with Change in Capital Inflow

Time Period	μ	α	β	θ	ω	m	*LLF*
Full Sample-	0.0001	0.1239***	0.8645***	-0.0031**	1.0083***	0.0001***	15019.9
Rolling Window	(0.0000)	(0.0049)	(0.0044)	(0.0010)	(0.0280)	(0.0000)	
2001:3-2010:9	-0.0002*	0.1237***	0.8578***	-0.0024*	1.0145***	0.0001***	6195.98
	(0.0001)	(0.0089)	(0.0068)	(0.0012)	(0.0495)	(0.0000)	
2010:10 – 2020:2	0.0004***	0.1683***	0.7790***	-0.0014***	5.5282***	0.0000***	6126.78
	(0.0001)	(0.0101)	(0.0132)	(0.0003)	(1.9939)	(0.0000)	
2001:3-2008:9	-0.0004**	0.1710***	0.7938***	0.0019**	12.768	0.0001***	4452.22
	(0.0001)	(0.0185)	(0.0182)	(0.0009)	(7.8049)	(0.0000)	
2008:10 – 2020:2	0.0003***	0.1211***	0.8691***	-0.0021**	2.6081*	0.0001***	8161.65
	(0.0001)	(0.0064)	(0.0068)	(0.0011)	(1.4669)	(0.0000)	

Note: ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis.

Replacing the level of the series with the corresponding volatilities results in a loss of significance for the location parameter μ. As in the case of levels of the series, the persistence parameters of α and β is close to but less than one. Beta weighting parameter ω becomes significant only for industrial production growth, change in the foreign currency debt stock and change in capital inflows. The parameter θ is significant except for CPI inflation and interest rate changes and becomes smoother in effect compared to the levels of the series. To evaluate the overall magnitude of the impacts we take into account only the series for which the parameters of ω and θ are both significant i.e., industrial production growth, change in the debt stock and change in the capital inflows (Table 3.11). In this regard, the volatility of the industrial production growth generates surprisingly negative but mild effect (0.03%) the exchange rate volatility. The impact of the volatility of changes in foreign currency debt stock and capital flows, however, provides positive and more notable impacts on exchange rate volatility. A 1% rise in the volatilities of external debt stock changes and change in net investment generates 0.13% and 0.14% rise in the volatility of exchange rates, respectively.

Table 3.10: Parameter Estimates for GARCH-MIDAS with Volatilities of Macroeconomic Series

Regressor	μ	α	β	θ	ω	m	*LLF*
Industrial Production Growth	0.0001	0.1223***	0.8662***	-0.0014**	2.2553**	0.0001***	15018.5
	(0.0001)	(0.0049)	(0.0044)	(0.0006)	(0.9083)	(0.0000)	
CPI Inflation	0.0001	0.1205***	0.8691***	0.0001	7.3886	0.00011***	15015.9
	(0.0001)	(0.0048)	(0.0042)	(0.0001)	(31.17)	(0.0000)	
Money Growth	0.0001	0.1248***	0.8623***	0.0055***	12.663	0.0000***	15018
	(0.0001)	(0.0051)	(0.0045)	(0.0019)	(11.763)	(0.0000)	
Interest Rate Change	0.0001*	0.1158***	0.8769***	0.0012	13.496	0.0001***	13699.8
	(0.0000)	(0.0047)	(0.0042)	(0.0009)	(24.301)	(0.0001)	
Change in Foreign Currency Reserves	0.0001	0.1213***	0.8708***	-0.0010**	44.19	0.0002***	15018.4
	(0.0002)	(0.0048)	(0.0042)	(0.0004)	(65.25)	(0.0003)	
Change in Foreign Currency debt Stock	0.0001	0.1233***	0.8625***	0.0015***	17.536*	0.00011**	15025
	(0.0001)	(0.0049)	(0.0048)	(0.0003)	(9.9141)	(0.0000)	
Net Export Change	0.0001	0.1215***	0.8703***	-0.0019***	1.0601	0.0000***	15018.6
	(0.0001)	(0.0049)	(0.0043)	(0.0007)	(0.1521)	(0.0000)	
Change in Net Capital Inflow	0.0001	0.1245***	0.8659***	0.0098**	1.0517***	0.0002	15023.1
	(0.0002)	(0.0051)	(0.0046)	(0.0046)	(0.2660)	(0.0003)	

Note: ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis.

Table 3.11: The impact of Macroeconomic Series on the Long-term Volatility of Exchange Rate

Industrial Production Growth	$\boldsymbol{\theta}$	$\varphi_k(\omega)$	$\hat{\tau}$	CPI Inflation	$\boldsymbol{\theta}$	$\varphi_k(\omega)$	$\hat{\tau}$
Full Sample	-0.0035	0.1563	-0.0547*	**Full Sample**	0.0038	0.4789	0.1821
2001:3-2010:9	-0.0053	0.4567	-0.2417*	**2001:3-2010:9**	-0.005	0.8596	-0.4288
2010:10-2020:2	0.0062	0.1491	0.0924*	**2010:10-2020:2**	0.0033	0.9851	0.3255*
2001:3-2008:9	-0.0106	0.2636	-0.279*	**2001:3-2008:9**	-0.0047	0.9553	-0.4479*
2008:10-2020:2	-0.0002	0.9963	-0.0199*	**2008:10-2020:2**	0.0089	0.3448	0.3073
Full Sample-volatility	-0.0014	0.2766	-0.0387*	**Full Sample-volatility**	0.00001	0.6567	0.0006

Money Growth	$\boldsymbol{\theta}$	$\varphi_k(\omega)$	$\hat{\tau}$	Interest Rate Changes	$\boldsymbol{\theta}$	$\varphi_k(\omega)$	$\hat{\tau}$
Full Sample	0.0096	0.2476	0.2379*	**Full Sample**	0.01339	0.3450	0.4629*
2001:3-2010:9	0.0057	0.3066	0.1748	**2001:3-2010:9**	0.01159	0.1461	0.1694*
2010:10-2020:2	0.0035	0.6869	0.2406*	**2010:10-2020:2**	0.0129	0.1897	0.2449*
2001:3-2008:9	-0.0037	0.7142	-0.2638*	**2001:3-2008:9**	0.01	0.1441	0.1441*
2008:10-2020:2	0.0179	0.2060	0.3693*	**2008:10-2020:2**	0.0218	0.1694	0.3699*
Full Sample-volatility	0.0055	0.8427	0.4645	**Full Sample-volatility**	0.0012	0.8611	0.1033

Change in Foreign Currency Reserves	$\boldsymbol{\theta}$	$\varphi_k(\omega)$	$\hat{\tau}$	Change in Foreign Currency Debt Stock	$\boldsymbol{\theta}$	$\varphi_k(\omega)$	$\hat{\tau}$
Full Sample	-0.0016	0.6891	-0.1101*	**Full Sample**	-0.0019	0.6605	-0.1254*
2001:3-2010:9	-0.0012	0.7868	-0.0943*	**2001:3-2010:9**	-0.0014	0.6495	-0.0908*
2010:10-2020:2	-0.0025	0.6292	-0.1571*	**2010:10-2020:2**	-0.0004	0.5302	-0.0212
2001:3-2008:9	-0.0011	0.9542	-0.1049*	**2001:3-2008:9**	-0.004	0.2059	-0.0823*
2008:10-2020:2	-0.0021	0.5177	-0.1086*	**2008:10-2020:2**	-0.0033	0.5213	-0.1718*
Full Sample-volatility	-0.0010	1.0428	-0.1042	**Full Sample-volatility**	0.0015	0.9244	0.13874*

Net Export Changes	$\boldsymbol{\theta}$	$\varphi_k(\omega)$	$\hat{\tau}$	Change in Capital Inflows	$\boldsymbol{\theta}$	$\varphi_k(\omega)$	$\hat{\tau}$
Full Sample	-0.0089	0.366	-0.3251	**Full Sample**	-0.0031	0.1437	-0.0445*
2001:3-2010:9	-0.0035	0.4653	-0.1627	**2001:3-2010:9**	-0.0024	0.1443	-0.0346*
2010:10-2020:2	-0.0092	0.4123	-0.3785*	**2010:10-2020:2**	-0.0014	0.5495	-0.0768*
2001:3-2008:9	0.0030	0.9586	0.2879	**2001:3-2008:9**	0.0019	0.8452	0.1607
2008:10-2020:2	0.0044	0.9789	0.4316	**2008:10-2020:2**	-0.0021	0.3122	-0.0655*
Full Sample-volatility	-0.0019	0.1491	-0.0283	**Full Sample-volatility**	0.0098	0.1482	0.14532*

Note: *denotes the cases where both parameters of θ and ω are significant at least 10% level. $\hat{\tau}$ denotes the impact of a 1% change in X_{t-1} on the long-term volatility.

3.3 Robustness Control: ARDL model and Bounds test

For robustness we control if there exists any long-term relation between the long-term exchange rate volatility and selected exogenous regressors when sampled at the same frequency. In the first stage, we transform the daily long-term component of the volatility into the realized volatility at monthly frequency. The transformation is upheld using the end of month data. The time period covers 2001:10 through 2020:2 as the observations belonging first eight months are used for initialization.[16] The Figure 3.16 displays the monthly realized volatility calculated in both fixed and rolling windows. Both forms of RV feature very similar patterns of volatility, so that it does not make any difference in using either fixed span or rolling window in drawing the long-term relation with macroeconomic series.

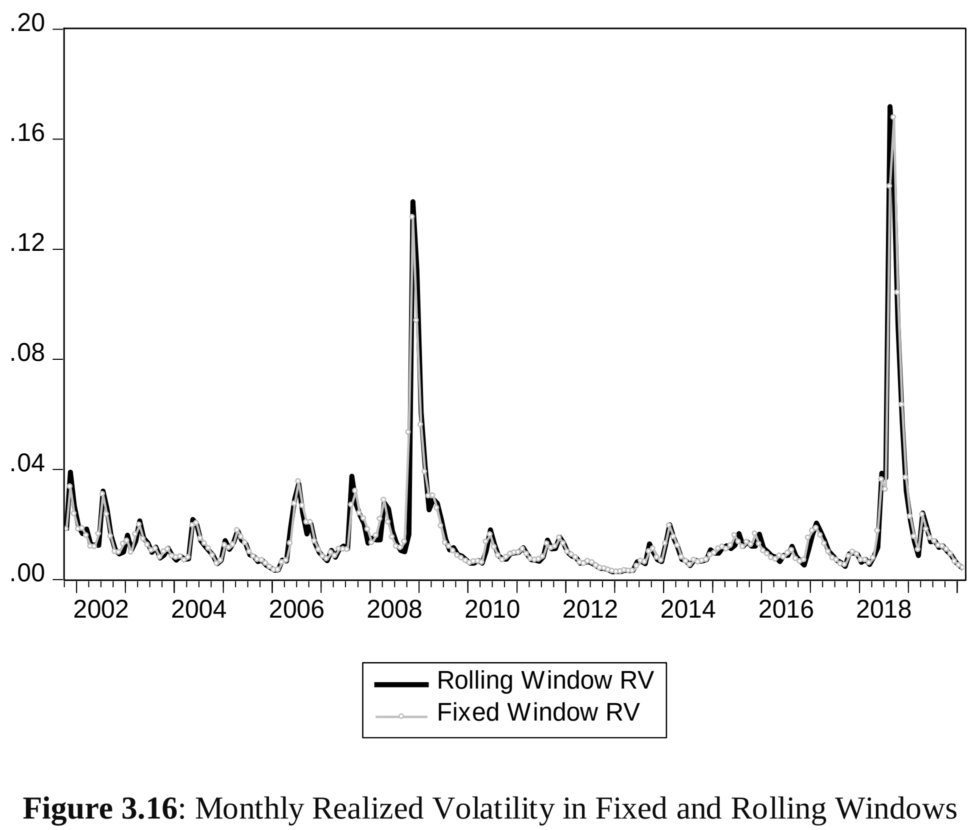

Figure 3.16: Monthly Realized Volatility in Fixed and Rolling Windows

[16] As the TRLibor rate series is from 2002:8 through 2020:2 we arrange the realized volatility observations to match this sample period when the interest rate is used as the regressor.

We estimate the following autoregressive distributed lag model (ARDL) to uphold the estimation of the intertemporal dynamics and employ the Pesaran et al. (2001) bounds test to see if any long-run relation arises at levels of the series.

$$RV_t = a_0 + \sum_{i=1}^{p} \psi_i RV_{t-i} + \sum_{j=1}^{k} \sum_{l_j=1}^{q_j} \gamma_{j,l_j} X_{j,t-l_j} + \epsilon_t \qquad (17)$$

where RV_t stands for the long-term volatility component at time t with maximum lag number of p, X_j for the exogenous regressors with maximum lag number of q_j, ϵ_t for the residual term, the term a_0 for the constant term as the only deterministic term. The exogenous regressors are expressed in their levels among which only the series of interest rate, logarithm of the foreign currency reserves, net exports and capital inflows are found to be stationary and none of the remaining series are $\mathrm{I}(2)$. Besides, the money stock, foreign currency reserves and debt stocks are used in logarithmic terms. The terms ψ_i and γ_{j,l_j} are the estimated coefficients of lagged values. The selection of the optimal lag length for both RV_t and $X_{j,t-1}$ is made among 20 candidates i.e., $p * (q + 1)^k$.

To be compatible with the GARCH-MIDAS model setting, firstly, we estimate the ARDL model and bounds test considering only one regressor beside to the dependent variable, RV_t. Besides, we relate the lagged values of X_j to the current exchange rate volatility as in the GARCH-MIDAS model.[17] The constant parameter is restricted to enter to equation as the realized volatility does not center around zero while it is not assumed for any linear trend.

Table 3.12 gives the estimation results. We control for the serial correlation using autocorrelation and partial – autocorrelation patterns of error terms, Ljung and Box Q-statistic and Breusch and Godfrey LM tests and do not confront with serial correlation in the

[17] We also relate the exogenous regressors to the realized volatility at the same period i.e., RV_t and $X_{j,t}$, and reach largely insignificance of the current values of macroeconomic series in affecting the exchange rate volatility. Still, the long-run relationship at level holds among macroeconomic series and volatility.

estimated errors. Grounded on the Breusch, Pagan and Godfrey test we control for the existence of heteroscedasticity in the estimated errors and observe heteroscedasticity for the series of CPI index and net export. Robust standard errors are obtained using Newey and West (HAC) standard errors. The estimated models are found to be dynamically stable using the CUSUM test. For the realized volatility it is detected two lags to enter the equation while the exogenous regressors feature different number of lags ranging from zero to three. In all model specifications, the past two values of long-term volatility arise as significant in which RV_{t-1} positively (and with a coefficient of around 0.8) while RV_{t-2} negatively (and with a coefficient of around -0.17) affect the current realized volatility. It implies for the existence of a high persistence in long-term volatility of exchange rates calculated using the GARCH-MIDAS model.

Table 3.12: ARDL Model: Estimation Results

	Industrial Production Index	CPI Index⁺	Money Supply	Interest Rate	Foreign Currency Reserves	Foreign Currency Debt Stock	Net Export⁺	Capital Inflows
Model Selection $(\mathbf{p}, \mathbf{q})$	(2,0)	(2,0)	(2,1)	(2,1)	(2,3)	(2,3)	(2,2)	(2,3)
$\boldsymbol{RV_{t-1}}$	0.8540***	0.8538***	0.8056***	0.8466***	0.7868***	0.8186****	0.8607***	0.8052***
	0.0667	(0.0205)	(0.0686)	(0.0690)	(0.0708)	(0.0688)	(0.0296)	(0.0711)
$\boldsymbol{RV_{t-2}}$	-0.1706**	-0.174***	-0.111	-0.177***	-0.1713**	-0.1414**	-0.1901***	-0.1715**
	0.0067	(0.0299)	(0.0701)	(0.0687)	(0.0681)	(0.0685)	(0.0414)	(0.0714)
$\boldsymbol{X_{t-1}}$	0.0001	0.0001	0.1191**	0.0012	-0.0631**	-0.085***	0.0001	0.0000
	0.0002	(0.0001)	(0.0467)	(0.0007)	(0.0280)	(0.0316)	(0.0000)	(0.0000)
$\boldsymbol{X_{t-2}}$			-0.1186**	-0.0011	0.0116	0.0835*	0.0000	0.0000
			(0.0462)	(0.0008)	(0.0383)	(0.459)	(0.0000)	(0.0000)
$\boldsymbol{X_{t-3}}$					0.0114	0.0226	0.0000	0.0000
					(0.0372)	(0.0458)	(0.0000)	(0.0000)
$\boldsymbol{X_{t-4}}$					0.0381	0.1050**		0.0000
					(0.0272)	(0.0423)		(0.0000)
$\boldsymbol{c}$	0.0027	0.0034	-0.0087	0.0036*	0.0286		0.0393**	0.0069***
	0.0042	(0.0024)	(0.0206)	(0.0019)	(0.0222)		(0.0018)	(0.0020)
$\mathbf{Adj.\ R^2}$	0.5444	0.5445	0.5555	0.5502	0.5562	0.5613	0.5510	0.5585
SSR	0.0396	0.0396	0.0385	0.0386	0.0380	0.0374	0.0386	0.0378
LLF	632.8679	632.9059	636.0771	601.7047	630.6715	629.0543	632.2680	631.2358
$\mathbf{F-statistic}$	87.8228	87.8781	69.1017	64.6189	46.1150	40.2986	54.2622	46.5380
$\mathbf{Prob(F-statistic)}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
AIC	-5.7431	-5.7434	-5.7633	-5.7101	-5.7481	-5.7505	-5.7456	-5.7533

Note:⁺ denotes the models for which Newey – West (HAC) standard errors are used to correct for the heteroscedasticity. ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis. SSR denotes the values of the sum of squared residuals, LLF denotes the log-likelihood value and AIC denotes the value of Akaike information criterion.

The Table also reveals that individual impacts of the exogenous regressors on the long-term exchange volatility are limited in both magnitude and significance which promotes the findings in the GARCH-MIDAS model. Among them, only the past values of the series of money supply, the foreign currency reserves and debt stock arise as significant in affecting the current realized volatility. Their corresponding impacts in magnitude and direction are in line with previous findings in GARCH-MIDAS model. Also, the forceful impact of the effective interest rate on the exchange rate volatility that we encounter in the volatility model, does not come into sight under ARDL setting which may be attributed to the additional information provided by the MIDAS functions with the inclusion of observations belonging to the daily frequency. We also report the values of Adj. R^2, sum of squares of residuals, log-likelihood function, F-statistic and Akaike criteria to inform about the model fit. It arises essentially that none of the regressors leads a dramatic improvement in the model fit.

Next, we use the bounds test to control for the joint significance of lagged values of RV_t and X_{t-1}. We decide on the bounds test in controlling the linear long run relation as it allows for different integration orders at the same level. In our case, among exogenous regressors, the series of interest rate, net export, reserves and capital inflows are found to be $\mathrm{I}(0)$ while the rest of the series are $\mathrm{I}(1)$. Re-arranging the equation (20) we obtain

$$\Delta RV_t = a_0 + \sum_{i=1}^{p} \psi_i \Delta RV_{t-i} + \sum_{j=1}^{k} \sum_{l_j=1}^{q_j} \gamma_{j,l_j} \Delta X_{j,t-l_j} + \theta_0 RV_{t-1} + \theta_1 X_{t-2} + e_t \qquad (18)$$

to perform a F-statistic of the null hypothesis $H_0\colon \theta_0 = \theta_1 = 0$ against the alternative $H_1\colon \theta_0 = \theta_1 \neq 0$. Table 3.13 displays the estimation results of the bounds test for each of the regressors with one regressor $(k = 1)$ and corresponding asymptotic critical values of lower $\mathrm{I}(0)$ and upper bounds $\mathrm{I}(1)$ for the F-statistics provided by Pesaran et al. (2001).[18] The lower bound (the upper bound) is grounded on the assumption that the variables are $\mathrm{I}(0)$

[18] See Table CI(ii) in Pesaran et al. (2001) that determines the critical values of bounds test with restricted constant term and no linear trend.

(I(1)). Note that the distribution of F-statistic depends on whether the variables in the ARDL model are I(0) or I(1); the number of explanatory variables; whether it is made any restriction on constant term and/or linear trend and size of the sample (Narayan, 2005). For the case that the calculated F-statistic is higher than the I(1) the null hypothesis of no long-run relation between two series is rejected. In other cases where the calculated F-statistic lies between I(0) and I(1) it becomes inconclusive to comment on co-integration and the calculated F-statistic is lower than I(0) the null hypothesis cannot be rejected.

The Table reveals that under all the cases, the resulting F-statistic is higher than asymptotic critical values at 1%, 5% and 10% significance levels.[19] Thus, it arises existence of a long-run relationship between the long-term exchange rate volatility and *each* of domestic macroeconomic variables. Moreover, we also report the error correction terms in Table 3.14 to draw the long-term coefficients of X_{t-1} along with the constant term. The error correction model (ECM) can simply be defined grounded on equation (18), so that the error correction term (Z_{t-1}) is equal to ($RV_t - \theta_1 X_{t-1} - a_0$). Even though the bounds test promotes the existence of a long run relationship among macroeconomic series and the exchange rate volatility, the long-run level equations report quite negligible coefficients of the macroeconomic sources. Still, the direction of the coefficients largely conforms with the GARCH-MIDAS model estimates.

Table 3.13: Bounds Test: Estimation Results

Regressors	F-statistic Value	Significance Levels	Bounds	
Industrial Production Index	13.9604		I(0)	I(1)
CPI Index	13.9901		Asymptotic: n=1000	
Money Supply	14.4662	10%	3.02	3.51
Interest Rate	13.8092	5%	3.62	4.16
Foreign Currency Reserves	16.302	1%	4.94	5.58
Foreign Currency Debt Stock	12.863			
Net Export	14.5451			
Capital Inflows	15.6139			

[19] As our sample size is sufficiently large i.e., n=219, we do not use adjusted critical values for small samples i.e., $n < 80$ (see Narayan, 2005).

Table 3.14: Long-run Level Equation: Estimation Results

$\mathbf{X_{t-1}}$	**Level Equation**
Industrial Production Index	$\mathrm{EC_t} = \mathrm{RV_t} - (0.0001 * X^{*}_{t-1} + 0.0088)$
CPI Index	$\mathrm{EC_t} = \mathrm{RV_t} - (0.0000 * \mathrm{X_{t-1}} + 0.0107)$
Money Supply	$\mathrm{EC_t} = \mathrm{RV_t} - (0.0019 * X^{*}_{t-1} + 0.0107)$
Interest Rate	$\mathrm{EC_t} = \mathrm{RV_t} - (0.0003 * X^{*}_{t-1} + 0.0107)$
Foreign Currency Reserves	$\mathrm{EC_t} = \mathrm{RV_t} - (-0.005 * X^{*}_{t-1} + 0.0744)$
Foreign Currency Debt Stock	$\mathrm{EC_t} = \mathrm{RV_t} - (-0.0008 * X^{*}_{t-1} + 0.0251)$
Net Export	$\mathrm{EC_t} = \mathrm{RV_t} - (-0.0000 * \mathrm{X_{t-1}} + 0.0119)$
Capital Inflows	$\mathrm{EC_t} = \mathrm{RV_t} - (0.0001 * X^{*}_{t-1} + 0.0190)$

Note: *denotes significant long-run coefficient of exogenous regressor at 10%. $\mathrm{EC_t}$ denotes the error correction term.

Grounded on the path of the realized volatility in Figure 3.16 we may also consider relatively higher volatilities during the two crisis periods i.e., 2008:10 – 2008:11 and 2018:08 – 2018:10, as outliers and assign dummies, accordingly. In this case we intrinsically assume that the exchange rate volatility features a conditional heteroscedasticity as there are points in which the variance gets relatively higher while the unconditional variance i.e., long-run variance, is close to a constant (Enders, 2014). We report the estimation results in Appendix B (Tables B.1 to B.3). We observe firstly that estimation results of ARDL model with dummies do not feature the high persistence pattern of the volatility opposed to the ARDL model without dummies. Moreover, it arises serial correlations in the residuals and, thus, biased estimates for some series, namely foreign currency reserves, debt stock and capital inflows which could not be tackled easily with over-parametrization as suggested by Pesaran et al. (2001). The bounds test gives quite high F-statistic values and reveal long-run relation in levels. Besides, as in the above-mentioned results on the ARDL model the long run level equation with dummies gives low coefficients of macroeconomic series.

4. CONCLUSION

We tack the exchange rate and macroeconomic series together sampled at different frequencies using the GARCH-MIDAS model which prevents a potential veiling of the volatility patterns resulting from a temporal aggregation of the former. Grounded on the mixed data sampling we aim to disclose the extent to which the economic sources are responsible for the long-term exchange rate volatility in Turkish economy. Thus, in visualizing the economic determinants of the exchange rate volatility in an exhaustive manner and as the model setting allows only one regressor in estimation by formation we control each of potentially relevant series that represents different aspects of the economy i.e., economic activity, monetary policy stance and foreign exchange and liquidity conditions. Also, as the GARCH-MIDAS model setting enables us to differentiate between short- and long-term components of the volatility we explore the degree to which the realized volatility is captured by the economic determinants.

In the first glance to control if the Turkish exchange rate data fits the GARCH-MIDAS model and if any identification problem arises we draw the Beta weighting functions, examine the distribution of errors and control parameter consistency across different periods. We decide on two different sub-periods: one is determined to distinguish potential differences across the pre-crisis and post-crisis episodes for Turkish economy and the other is set to account for the policy shift in the monetary policy stance in the late of 2010 towards the financial stability objective and compare the full-sample with sub-samples, accordingly.

Consistency of parameter estimates and distribution of estimation errors across different samples give promoting evidence for the goodness of model fit. Further, controlling for the homogeneity of MIDAS weighting schemas across different time periods it is obtained different lagged effects of the long-term components which prompts us to provide model estimates and examine the transition of economic shocks to the exchange rate volatility under different samples. Considering the model with realized volatility, estimation results reveal an outstanding information content of the past months in explaining the long-term volatility. Besides, it is estimated a high degree of persistence for the short-term component of exchange rate volatility. Next, we replace the realized volatility by each of selected macroeconomic series to see to what extent the latter covers the information content of the long-term volatility and is responsible for the long-term volatility in Turkish economy. We observe a smoother long-term component of exchange rate volatility when the realized volatility is replaced by exogenous regressors. We still reach that economic fundamentals are relevant in explaining the long term component of the volatility. The resulting change of macroeconomic variables generates, however, less than a proportional change in the volatility in magnitude. The ARDL model estimates with calculated monthly realized volatility also confirm the estimation results of GARCH-MIDAS model with exogenous regressors and point out limited effects of economic determinants. More specifically, a rise in industrial production growth, official foreign exchange reserves, short-term debt stock and capital inflows is found to lead a decline in long-term exchange rate volatility being consistent with different sample periods. The improvement in the export structure mitigates the long-term volatility but only during the new monetary policy period. An increase in the TRlibor rate and foreign exchange controls via auctions cause the long-term volatility to rise where the latter brings quite negligible effects in magnitude. Besides, with increases in money growth and CPI inflation the exchange rate volatility increases but only during the post-crisis episode.

In the policy making both the narrative of floating regime period of last two decades and empirical evidence provide the fact the CBRT gives signals for taking the excess volatility in the exchange rate market seriously (Değerli and Fendoğlu, 2013). This study also promotes this fact by pointing out the pertinent transmission of money supply, interest rate and official foreign exchange reserve changes directly designated by the monetary authority towards the long-term exchange rate volatility. The foreign exchange interventions, however, increase but slightly the volatility being contrary to intention of the CBRT. Overall, along with the findings that the long-term volatility of exchange rates features high degree of persistence pattern it arises that corresponding fluctuations are largely due to shocks to exchange rate market itself rather than occurring to absorb shocks to monetary policy indicators or economic factors.

REFERENCES

Akçelik, F. and A. Talaslı. (2020). Market-Based Monetary Policy Expectations for Turkey. *Central Bank Review Volume.* 20.1, 9-19.

Akgül, I. and H. Sayyan. (2008). Modelling and Forecasting Long Memory in Exchange Rate Volatility vs. Stable and Integrated GARCH Models. *Applied Financial Economics*. 18.6, 463-483.

Armesto, M. T., K. M. Engemann and M. T. Owyang, (2010), Forecasting with Mixed Frequencies. *Federal Reserve Bank of St. Louis Review*. 92, 521–536.

Aslaner O., U. Çıplak, H. Kara, and D. Küçüksaraç. (2015). Reserve Options Mechanism: Does it Work as an Automatic Stabilizer? *Central Bank Review*. 15.1, 1-18.

Aysoy, D and G. Küçükkocaoğlu. (2016). Döviz Müdahalelerinin Kur Üzerindeki Etkisi. *Bankacılık Düzenleme ve Denetleme Kurumu Bankacılık ve Finansal Piyasalar Dergisi*. 10.1, 65-94.

Baillie, R. T., T. Bollerslev and H. O. Mikkelsen. (1996). Fractionally Integrated Generalized Autoregressive Conditional Heteroscedasticity. *Journal of Econometrics*. 74, 3–30.

Central Bank of Republic of Turkey. (2008). Monetary and Exchange Rate Policy 2009.

Central Bank of Republic of Turkey. (2009). Monetary and Exchange Rate Policy 2010.

Central Bank of Republic of Turkey. (2011). Annual Report 2010.

Central Bank of Republic of Turkey. (2016). Monetary and Exchange Rate Policy 2017.

Central Bank of Republic of Turkey. (2018). Monetary and Exchange Rate Policy 2019.

Central Bank of Republic of Turkey. (2019). Monetary and Exchange Rate Policy 2020.

Cevik, S., R. Harris and F. Yilmaz. (2015). Soft Power and Exchange Rate Volatility. *IMF Working Paper*. 1-34.

Colacito, R., R. F. Engle and E. Ghysels. (2011). A Component Model for Dynamic Correlations. *Journal of Econometrics*, 164.1, 45–59.

Değerli, A. and S. Fendoğlu. (2013). Döviz Kuru Beklentileri ve TCMB Para Politikası. *TCMB Ekonomi Notları*. 02, 1-13.

Demir, F. (2010). Exchange Rate Volatility and Employment Growth in Developing Countries: Evidence from Turkey. *World Development*. 38.8, 1127–1140.

Enders, W. (2014). *Applied Econometric Time Series*. John Wiley High Education. Fourth edition.

Engle, R. F., E. Ghysels and B. Sohn. (2009). On the Economic Sources of Stock Market Volatility. *Working paper*. New York University.

Engle, R. F., E. Ghysels and B. Sohn. (2013). Stock Market Volatility and Macroeconomic Fundamentals. *Review of Economics and Statistics*. 95, 776–797.

Engle, R. F., and J. G. Rangel. (2008). The Spline-GARCH Model for Low-Frequency Volatility and Its Global Macroeconomic Causes. *Review of Financial Studies*. 21, 1187–1222.

Ganguly, S. and J. B. Breuer. (2010). Nominal Exchange Rate Volatility, Relative Price Volatility, and the Real Exchange Rate. *Journal of International Money and Finance*. 29, 840–856.

Ghysels, E. P. Santa-Clara and R. Valkanov. (2004). The MIDAS Touch: Mixed Data Sampling Regression Models. *Working paper*. June 2004. http://docentes.fe.unl.pt/~psc/MIDAS.pdf.

Ghysels, E. P. Santa-Clara and R. Valkanov. (2005). There Is a Risk-Return Trade-off After All. *Journal of Financial Economics*, June 2005, 76.3, 509-48.

Ghysels, E. P. Santa-Clara and R. Valkanov. (2006). Predicting Volatility: Getting the Most Out of Return Data Sampled at Different Frequencies. *Journal of Econometrics*, March/April 2006, 131.1/2, 59-95.

Ghysels, E. P. Santa-Clara and R. Valkanov. (2007). MIDAS Regressions: Further Results and New Directions. *Econometric Reviews*. 26.1, 53-90.

Ghysels, E. (2017). MATLAB Toolbox for Mixed Sampling Frequency Data Analysis Using MIDAS Regression Models. *Available on MATLAB Central at* https://www.mathworks.com/matlabcentral/fileexchange/45150-midas-matlab-toolbox.

Giannellis, N. and A. P. Papadopoulos. (2011). What Causes Exchange Rate Volatility? Evidence from Selected EMU Members and Candidates for EMU Membership Countries. *Journal of International Money and Finance*. 30, 39–61.

Gürkaynak, T., Z. Kantur, M. A. Taş and S. Yıldırım. (2015). Monetary policy in Turkey after Central Bank independence. *CFS Working Paper Series*. 520, Center for Financial Studies.

Hausmann, R., U. Panizza and R. Rigobon. (2006). The Long-Run Volatility Puzzle of The Real Exchange Rate. *Journal of International Money and Finance*. 25, 93-124.

Herrera, A. M. and P. Özbay. (2005). A Dynamic Model of Central Bank Intervention: Evidence from Turkey. *Working Paper*. 05/01. Central Bank of the Republic of Turkey.

Kara, H. (2016). Turkey's Experience with Macroprudential Policy. *BIS Papers*. 86. Bank for International Settlements.

Narayan, P. K. (2005). The Saving and Investment Nexus For China: Evidence From Cointegration Tests, *Applied Economics*, 37.17, 1979-1990,

Pesaran, M. H., Y. Shin and R. J. Smith. (2001). Bounds Testing Approaches to the Analysis of Level Relationships. Journal of Applied Econometrics. 16.3, 289-326.

Rodrik, D. (2012). The Turkish Economy after the Crisis. *Ekonomi-tek*. 1, 41–61.

Oduncu, A., E. Ermişoğlu and Y. Akçelik. (2013). Merkez Bankasının Yeni Enstrümanı Rezerv Opsiyonu Mekanizması ve Kur Oynaklığı. *Bankacılar Dergisi*. 86, 43-52.

Özlü, P. and D. Ünalmış (2012). Makroekonomik Gostergelerin Doviz Kurlari Uzerine Etkisi. *CBT Research Notes in Economics* 1221, Research and Monetary Policy Department, Central Bank of the Republic of Turkey.

Schwert, G. W. (1989). Why Does Stock Market Volatility Change Over Time? *Journal of Finance*. 44, 1115-1153.

Tuna, G. (2011). The Effectiveness of Central Bank Intervention: Evidence from Turkey. *Applied Economics*. 43.14, 1801-1815.

Uygur, E. (2010). The Global Crisis and the Turkish Economy. *TWN Global Economy Series.* 21.

Qian, H. (2020). MIDAS MATLAB Toolbox. (https://www.mathworks.com/matlabcentral/fileexchange/45150-midas-matlab-toolbox). MATLAB Central File Exchange. Retrieved April 16, 2020.

You, Y. and X. Liu. (2020). Forecasting Short-Run Exchange Rate Volatility with Monetary Fundamentals: A GARCH-MIDAS Approach. *Journal of Banking & Finance*. 116, 105849.

Zhou Z. B., Z. Y. Fu and Y. Jiang. (2019). Can Economic Policy Uncertainty Predict Exchange Rate Volatility? New Evidence from the GARCH-MIDAS model. *Finance Research Letters*. 34, 101258.

APPENDIX A

Table A.1: Results of Likelihood Ratio Test Statistic

		Full-sample and sub-samples: 2001:1-2010:9 2010:10-2020:2		Full-sample and sub-samples: 2001:1-2008:9 2008:10-2020:2	
Long-term Component	**df**	**LR value**	**P-value- χ^2**	**LR value**	**P-value- χ^2**
Fixed Window RV	6	808	0%	726	0%
Rolling Window RV	6	856	0%	724	0%
Industrial Production Growth	7	5388	0%	4742	0%
CPI Inflation	7	5387	0%	4815	0%
Money Growth	7	5403	0%	4794	0%
Interest Rate changes	7	5437	0%	4796	0%
Change in the FX Reserves	7	5393	0%	4785	0%
Change in the FX Debt Stock	7	5436	0%	4757	0%
Net Export Changes	7	5388	0%	4817	0%
Change in the Capital Inflow	7	5395	0%	4812	0%

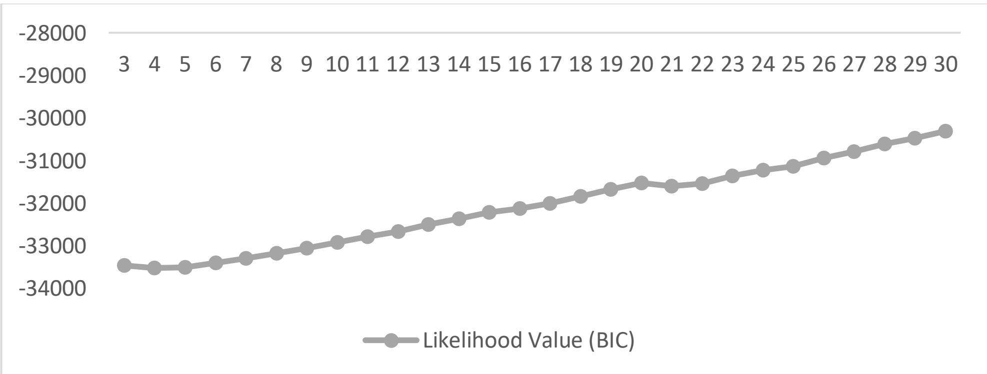

Figure A.1: Likelihood Value at Different Lag Numbers

Table A.2: Parameter Estimates for GARCH-MIDAS with Realized Volatility

Regressors	μ	α	β	θ	ω	m	*LLF*
2001:3-2020:2	0.0002***	0.0697***	0.9302***	0.0893***	1.0002***	0.0012***	16613.4
	(0.0087)	(0.0002)	(0.0002)	(0.0001)	(0.5427)	(0.0008)	
2002:1 – 2020:2	0.0002	0.0695***	0.9304***	0.0903***	1.4852***	0.0012***	15900.5
	(0.0021)	(0.0002)	(0.0021)	(0.0087)	(0.2508)	(0.0002)	

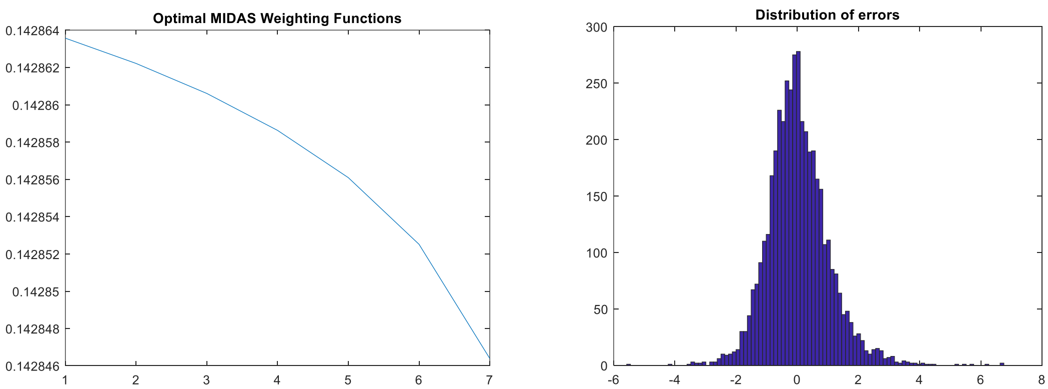

Figure A.2: MIDAS Weighting Functions and Distribution of Errors for the sample 2002:1 – 2020:2

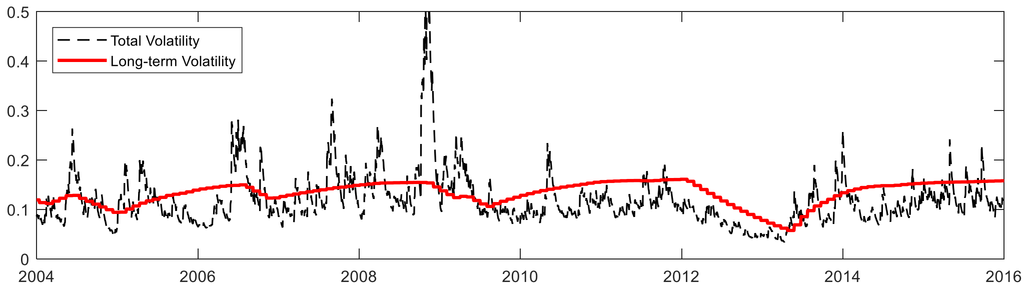

Figure A.3: Total Volatility of Exchange Rate and Foreign Currency Buying/Selling Auctions

Table A.3: Parameter Estimates for GARCH-MIDAS with Foreign Currency Buying/Selling Auctions

Time Period	μ	α	β	θ	ω	m	LLF
Full Sample-	0.0001	0.1146***	0.8633***	0.0013***	3.5382	0.0000	11594.4
Rolling Window	(0.0000)	(0.0074)	(0.0067)	(0.0003)	(0.8530)	(0.0001)	
2001:3-2010:9	-0.0003*	0.1296***	0.8476***	0.0026***	1.6846**	-0.0001	6199.34
	(0.0001)	(0.0103)	(0.0090)	(0.0008)	(0.7748)	(0.0001)	
2010:10 – 2016:4	0.0003*	0.1604***	0.6406***	0.0008***	1.2523***	0.0000	2687.13
	(0.0002)	(0.0273)	(0.0712)	(0.0002)	(0.3345)	(0.0000)	
2001:3-2008:9	-0.0004**	0.1786***	0.7830***	0.0023***	1.0049***	-0.0001***	4451.11
	(0.0001)	(0.0204)	(0.0217)	(0.0008)	(0.0658)	(0.0002)	
2008:10 – 2016:4	0.0002	0.0994***	0.8247***	0.0006***	9.1295	0.0001***	4742.31
	(0.0001)	(0.0169)	(0.0287)	(0.0000)	(2.4846)	(0.0000)	

***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis. Full-sample period covers the period 2001:3 – 2016:4.

Table A.4: Foreign Currency Buying/Selling Auctions

	θ	$\varphi_k(\omega)$	$\hat{\tau}$
Full Sample	0.0013	0.5555	0.0722
2001:3-2010:9	0.0026	0.2353	0.0611*
2010:10-2020:2	0.0008	0.1741	0.0139*
2001:3-2008:9	0.0023	0.1424	0.0327*
2008:10-2020:2	0.0006	2.1589	0.1296

*denotes the cases where both parameters of θ and ω are significant at least 10% level. $\hat{\tau}$ denotes the impact of a 1% change in X_{t-1} on the long-term volatility

APPENDIX B

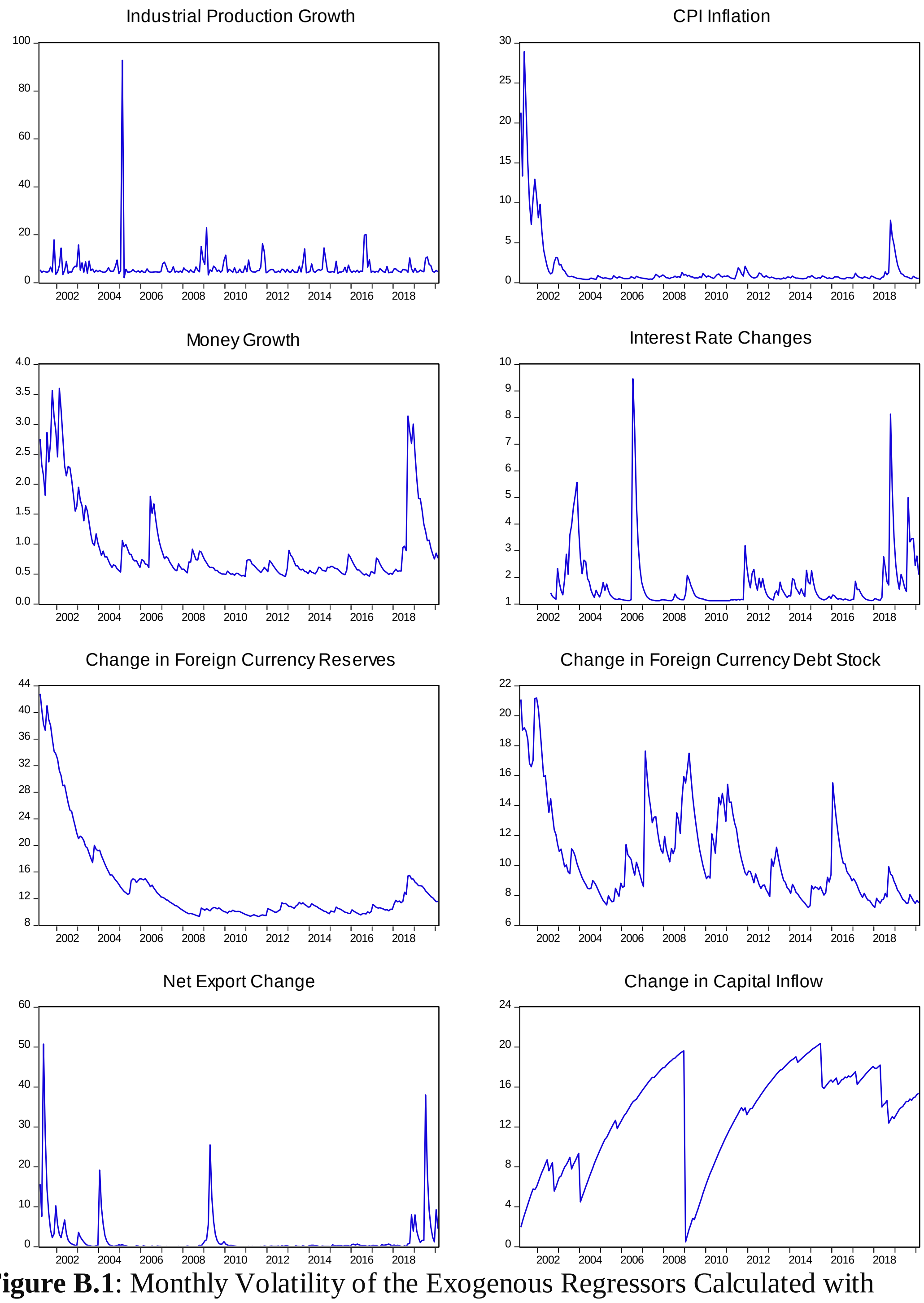

Figure B.1: Monthly Volatility of the Exogenous Regressors Calculated with $GARCH(1,1)$ Model

Table B.1: ARDL Model with Outliers: Estimation Results

	Industrial Production Index	CPI Index	Money Supply	Interest Rate	Foreign Currency Reserves†	Foreign Currency Debt Stock†	Net Export	Capital Inflows†
Model selection (p,q)	(1,0)	(4,1)	(4,1)	(1,0)	(4,3)	(1,1)	(1,1)	(4,3)
RV_{t-1}	0.3147***	0.28889*	0.2253	0.3064***	0.2574*	0.3001***	0.3198***	0.2436
	0.0911	(0.1667)	(0.1592)	(0.0933)	(0.1540)	(0.0901)	(0.0865)	(0.1591)
RV_{t-2}		0.0980	0.1293		0.0486			0.0632
		(0.1468)	(0.1745)		(0.1886)			(0.1790)
RV_{t-3}		-0.1671	0.1283		-0.1481			-0.1610
		(0.1172)	(0.0804)		(0.0986)			(0.1147)
RV_{t-4}		0.0957	0.1074		0.1228			0.1416
		(0.0669)	(0.0804)		(0.0888)			(0.1088)
X_{t-1}	-0.0002*	-0.0011	0.1444**	0.0001*	-0.0432	-0.0342**	0.0000	0.0000
	0.0001	(0.0010)	(0.0668)	(0.0000)	(0.0281)	(0.0147)	(0.0000)	(0.0000)
X_{t-2}		0.0011	-0.145**		0.0259	0.0324**	0.0000	0.0000
		(0.0010)	(0.0664)		(0.0411)	(0.0144)	(0.0000)	(0.0000)
X_{t-3}					-0.0323			0.0000
					(0.0300)			(0.0000)
X_{t-4}					0.0466			
					(0.0285)			
D_1	0.0918***	0.0953***	0.095***	0.0932***	0.0934***	0.0905***	0.0932***	0.093***
	0.0125	(0.0148)	(0.0127)	(0.0127)	(0.0130)	(0.0122)	(0.0123)	(0.0129)
D_2	0.0633***	0.0742***	0.066***	0.0624***	0.0638***	0.0635***	0.0629***	0.063***
	0.0179	(0.0203)	(0.0174)	(0.0180)	(0.0175)	-0.0178	(0.0181)	(0.0171)
c	0.0116***	0.0098***	0.0253**	0.0069**	0.043***	0.0289***	0.0088***	0.009***
	0.0025	(0.0019)	(0.0114)	(0.0013)	(0.0110)	(0.0078)	(0.0017)	(0.0014)
$\mathbf{Adj.\,R^2}$	0.7535	0.7718	0.7790	0.7627	0.7669	0.7614	0.7594	0.7711
SSR	0.0215	0.0193	0.0187	0.0204	0.0196	0.0206	0.0207	0.0191
Log − likelihood	703.6407	703.8743	707.3685	672.1907	702.6208	704.7075	703.8264	701.4210
F − statistic	168.3611	92.3086	96.1807	168.8987	72.0602	140.1055	138.6413	66.8538
Prob(F − statistic)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
AIC	-6.3513	-6.4044	-6.4366	-6.3542	-6.3744	-6.3809	-6.3728	-6.3835

[+] denotes the models for which Newey – West (HAC) standard errors are used to correct for the heteroscedasticity. ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis. SSR denotes the values of the sum of squared residuals, LLF denotes the log-likelihood value and AIC denotes the value of Akaike information criterion. † denotes the existence of serial correlations in the residual of estimation. All the series feature heteroscedasticity.

Table B.2: Bounds Test: Estimation Results

Regressors	F-statistic Value	Significance Levels	Bounds	
Industrial Production Index	72.1915		**I(0)**	**I(1)**
CPI Index	64.4332		Asymptotic: n=1000	
Money Supply	69.9098	10%	3.02	3.51
Interest Rate	73.3132	5%	3.62	4.16
Foreign Currency Reserves	65.2272	1%	4.94	5.58
Foreign Currency Debt Stock	76.3005			
Net Export	71.7791			
Capital Inflows	624638			

Table B.3: Long-run Level Equation: Estimation Results

$\mathbf{X_{t-1}}$	**Level Equation**
Industrial Production Index	$\mathrm{EC_t} = \mathrm{RV_t} - (-0.0001 * X_{t-1}^{*} + 0.0170)$
CPI Index	$\mathrm{EC_t} = \mathrm{RV_t} - (0.0000 * \mathrm{X_{t-1}} + 0.0144)$
Money Supply	$\mathrm{EC_t} = \mathrm{RV_t} - (-0.0015 * X_{t-1}^{*} + 0.0381)$
Interest Rate	$\mathrm{EC_t} = \mathrm{RV_t} - (0.0001 * X_{t-1}^{*} + 0.0100)$
Foreign Currency Reserves	$\mathrm{EC_t} = \mathrm{RV_t} - (-0.0042 * X_{t-1}^{***} + 0.0599)$
Foreign Currency Debt Stock	$\mathrm{EC_t} = \mathrm{RV_t} - (-0.0026 * X_{t-1}^{***} + 0.0414)$
Net Export	$\mathrm{EC_t} = \mathrm{RV_t} - (0.0000 * \mathrm{X_{t-1}} + 0.0130)$
Capital Inflows	$\mathrm{EC_t} = \mathrm{RV_t} - (-0.0001 * X_{t-1}^{***} + 0.0135)$

*,***denotes significant long-run coefficient of exogenous regressor at 10% and 1%, respectively. $\mathrm{EC_t}$ denotes the error correction term.