



## **Do Financial Conditions have a Predictive Power on Inflation in Turkey?**

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### **ABSTRACT**

This paper aims at examining the causal relationships between financial conditions and inflation in Turkey by employing quarterly data from 2005:Q1 to 2015:Q3. To this end, the paper, first, constructs a financial conditions index (FCI) in Turkey and observes that the FCI can considerably capture the developments in Turkey and in the world. Then, the paper follows unit root tests. Finally, the paper conducts the asymmetric causality test. The asymmetric causality test explores that the FCI and inflation have a predictive power on each other and thus presents valuable information to the Central Bank of the Republic of Turkey (CBRT). Eventually, upon its findings, the paper asserts that the FCI: (i) Should be updated periodically, (ii) should be extended with new financial variables, if necessary, and (iii) should be monitored carefully by the CBRT in order to achieve inflation targets.

**Keywords:** The Central Bank of the Republic of Turkey, Financial Conditions Index, Inflation, Asymmetric Causality Test

**JEL Classifications:** C32, C43, E52, G17

### **1. INTRODUCTION**

Financial conditions, in a general sense, are current values of financial variables that can affect behaviors of economic actors and thus the situation of an economy in the future (Hatzius et al., 2010). From this point of view, a financial conditions index (FCI) is a tool to obtain some information in current values of financial variables in order to forecast the future position of an economy (Hatzius et al., 2010; Osario et al., 2011; Vonen, 2011; Kara et al., 2012). More clearly, an FCI, as an indicator of the stance of monetary policy and of aggregate demand conditions, includes information about developments in financial markets along with future economic activities and inflationary pressures (Castro, 2011). For this reason, the variables that will be used to build up an FCI are expected to affect future output and inflation through monetary transmission mechanisms (Mayes and Virén, 2001; Chow, 2012). An FCI is more comprehensive than a monetary conditions index that consists of the weighted averages of short-term interest rates and exchange rates (Goodhart and Hofmann, 2001; Thompson et al., 2015) and is developed using more variables. Some of the variables that are used to construct an FCI are interest

rates (indicating the cost of capital usage and reflecting the trade-off between consumption today and consumption in the future), exchange rates (working through trade channel), total credits, stock and house prices (affecting assets, expectations and expenditures of households and firms) (Chow, 2012). FCIs can be employed to identify periods when financial conditions worsen, to evaluate credit constraints, and to forecast economic developments (Koop and Korobilis, 2014).

The global financial crisis beginning in 2007-2008 exhibit the negative effects of the developments in financial conditions on economies and demonstrate that watching and assessing financial conditions is essential for policy makers in order to implement stable and strong macroeconomic policies (Chow, 2012; Kara et al., 2012; Koop and Korobilis, 2014; Thompson et al., 2015). For this reason, although FCIs have long been utilized to evaluate the current state of financial conditions (Matheson, 2012), many papers have been conducted to produce an FCI especially since the global financial crisis. In other respects, as Kara et al. (2012; 2015) remark, the Central Bank of the Republic of Turkey (CBRT) has adopted a new monetary policy framework to achieve price stability along with financial stability since the last quarter of

2010<sup>1</sup>. As the CBRT uses short-term interest rates and credit and liquidity policies, the need for developing a comprehensive benchmark has increased to measure and to evaluate the degree of tightness and looseness of the policies. Instead of dealing with financial variables one by one, to establish an FCI using the regarded variables, to follow this index, and to consider the index while conducting monetary policy can increase the efficiency of monetary policy in Turkey.

To the best of my knowledge, there are two papers that build up an FCI for Turkey using a variety of financial variables (Kara et al., 2012; 2015). Therefore, one may argue that there is a research gap about the financial conditions in Turkey. Additionally, these papers do not examine whether there is a relationship between the FCI and inflation and/or economic growth. From this point of view, this paper aims at constructing an FCI for Turkey and examining whether this FCI has a predictive power on inflation in Turkey by using quarterly data covering the period 2005:Q1-2015:Q3. In other words, this paper constructs an FCI for Turkey and examines the performance of this FCI in forecasting inflation.

How this paper contributes to the literature on FCIs lies in the following three points: (i) While there is an extending literature on FCIs (Diclemente et al., 2008; Guichard and Turner, 2008; Rosenberg, 2009; Castro, 2011; Osario et al., 2011; Chow, 2012; Milas and Naraidoo, 2012; Gumata et al., 2012; Matheson, 2012; Ho and Lu, 2013; Angelopoulou et al., 2014; Zheng and Yu, 2014; Koop and Korobilis, 2014; Thompson et al., 2015), there are only two papers that construct an FCI for Turkey as denoted above. Hence this paper studies a relatively new subject in Turkey, (ii) this paper not only builds up an FCI but also examines the relationship between the FCI and inflation. Thereby this paper provides researchers and policy makers with empirical evidence about the predictive power of the FCI on inflation, (iii) this paper employs the asymmetric causality test developed by Hatemi (2012) to obtain more reliable findings since the asymmetric causality test presents not only the direction of causality but also the sign of causality.

The rest of the paper is organized as follows: Section 2 produces an FCI for Turkey. Section 3 reveals data and estimation methodology. Estimation results are reported in section 4. Section 5 concludes the paper with a summary of the findings and some policy proposals.

## 2. PRODUCTION OF THE FCI FOR TURKEY

As Koop and Korobilis (2014) remark, the construction and the use of an FCI contains three issues: (i) The selection of the financial variables to build up the FCI, (ii) the weights of these variables in the index, and (iii) the relationship between the FCI and the macroeconomy.

When one examines the literature on FCIs, he/she will observe that some papers employ a plenty of variables to produce an FCI (Brave and Butters, 2012; Matheson, 2012; Angelopoulou et al.,

2014; Koop and Korobilis, 2014) while others employ relatively fewer variables (Diclemente et al., 2008; Guichard and Turner, 2008; Castro, 2011; Osario et al., 2011; Chow, 2012; Kara et al., 2012; Milas and Naraidoo, 2012; Zheng and Yu, 2014; Kara et al., 2015). In this paper, I employ six financial variables to produce an FCI for the Turkish economy since: (i) Data for some variables have been available since only a few years in Turkey<sup>2</sup>, (ii) some financial variables have strong impacts on other financial variables in the data set<sup>3</sup>, and (iii) an FCI produced through relatively few variables can be updated and monitored more easily in the future. Additionally, in today's world, domestic financial indicators depend on global factors in a small open economy like Turkey (Kara et al., 2012), and so external factors should be included in the index, too.

Table 1 presents the variables used to construct the FCI for Turkey.

As shown in Table 1, the first five variables are domestic financial indicators and all of them can affect future output and inflation through monetary transmission mechanisms. As depicted in the Table 1, I detrend real domestic credits, real effective exchange rate, and real stock market index through the HP filter just as Castro (2011) and Milas and Naraidoo (2012) do. In this way, I observe how much these variables deviate from their trends. I add real commercial loan rate along with real short-term interest rate to the index. Because, the credit channel has gained importance together with financial deepening with regard to financial conditions in recent years (Kara et al., 2015) and the CBRT has especially emphasized the importance of real credits to achieve financial stability (e.g., Başıç and Kara, 2011; Bulut, 2015). Besides, real loan rates give valuable information about credit conditions in Turkey. The last variable is the real shadow rate in the US and identifies external financial factors. Some recent papers use the shadow rate as the stance of monetary policy in the US (Bullard, 2012; Krippner, 2013; Wu and Xia, 2014), and this paper follows them. The federal funds rate has been at the zero lower bound since late 2008, and the Federal Open Market Committee launched three large-scale asset purchase programmes (quantitative easing programmes) to boost the US economy further during December 2008-October 2014. In such an environment, the federal funds rate cannot capture the developments in the monetary policy in the US since the federal funds rate has been pegged near zero since late 2008. However, the shadow rate, that has been negative since the third quarter of 2009, describes the stance of monetary policy in the US<sup>4</sup>. Quarterly data covering the period 2005:Q1-2015:Q3 are used in the paper to construct an FCI for Turkey. In order to obtain real domestic credits gap, real effective exchange rate gap, and real stock market index gap, I employ data for real domestic credits, real effective exchange rate, and real stock market index for the period 2003:Q1-2015:Q3, respectively.

The weights of the regarded variables in the FCI depend on the methodology. This paper adopts principal components analysis (PCA) by following Osario et al. (2011), Ho and Lu (2013), Zheng

2 For instance, real house price index has been announced since 2010.

3 For instance, net capital inflows are not used to produce the FCI since net capital inflows are expected to have strong effects on real effective exchange rates and credits.

4 See Wu and Xia (2014) for further explanations about the shadow rate.

1 Başıç and Kara (2011) and Ozatay (2011) for details about the new monetary policy framework of the CBRT.

**Table 1: Variables that are used to construct the FCI**

Variable	Calculation	Source
Real domestic credits gap	To obtain real domestic credits, first, the effects of exchange rates on nominal credits are removed, and second, credits are divided by the CPI. Thus real domestic credits are obtained. Real domestic credits gap is calculated through Hodrick and Prescott (1997, hereafter HP) filter	Banking Regulation and Supervision Agency and CBRT
Real effective exchange rate gap	Real effective exchange rate gap is calculated through HP filter	CBRT
Real stock market index gap	Nominal stock market index (Borsa Istanbul 100 Index, 1986=1) is divided by the CPI and real stock market index is obtained. Real stock market index gap is calculated through HP filter	CBRT
Real short-term interest rate	Annual inflation expectation is subtracted from nominal short-term interest rate <sup>6</sup>	CBRT and Banks Association of Turkey
Real commercial loan rate	Annual inflation expectation is subtracted from nominal annual commercial loan rate	CBRT
Real shadow rate	Annual inflation expectation is subtracted from nominal shadow rate	Wu and Xia (2014) and Thomson Reuters/University of Michigan (2015)

CPI: Consumer price index

**Table 2: Results of the PCA**

Variables and variance	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
Real domestic credits gap	0.251	0.170	0.912	-0.017	-0.159	0.221
Real effective exchange rate gap	0.097	0.662	-0.173	0.706	-0.139	0.053
Real stock market index gap	0.157	0.673	-0.085	-0.586	0.400	-0.102
Real short-term interest rate	0.574	-0.119	0.043	0.085	-0.094	-0.798
Real commercial loan rate	0.535	-0.254	-0.067	0.253	0.667	0.367
Real shadow rate	0.535	-0.015	-0.351	-0.291	-0.583	0.405
Share of total variance explained (%)	46.47	28.05	15.37	6.86	1.92	1.33

PCA: Principal components analysis

and Yu (2014), Thompson et al. (2015) whereas some papers employ vector autoregressive (VAR) approach (Diclemente et al., 2008; Guichard and Turner, 2008; Chow, 2012; Kara et al., 2012; 2015). Because, PCA does not involve any estimations and is derived through a linear transformation of the series (Angelopoulou et al., 2014) whereas VAR analysis involves some estimations and depends on time-series properties of the data. Besides, this paper constructs an alternative FCI to the FCIs produced by Kara et al. (2012; 2015) since VAR analysis is employed to construct the FCI in these papers<sup>5</sup>.

PCA is a method that transforms some interrelated variables into a new variable by utilizing covariances of these variables (Everitt and Skrondal, 2002) and is widely used for index generation (Thompson et al., 2015). The new variable is the linear function of these variables (Angelopoulou et al., 2014; Thompson et al., 2015). As Angelopoulou et al. (2014) point out, the principal components of the variables are acquired by computing the eigenvalue decomposition of the observed variance matrix, and each principal component is an optimal linear combination of the observed variables. When the variables have different units of measurement, variables must be standardized in order to obtain more consistent findings. Therefore, the variables are standardized in this paper.

Table 2 presents the principal components in the data set along with the share of total variance that is explained by each component. While

one decides which principal component can be used to construct the FCI, the threshold for the share of total variance explained can be set at 70% (Angelopoulou et al., 2014). Therefore, one can argue that either first or second principal component can be utilized for the construction of the FCI. When these principal components are examined, it is seen that the coefficients of the regarded variables differ with regard to the principal components. Accordingly, while coefficients of all variables are positive in the first principal component, the first three variables' coefficients are positive and other variables' coefficients are negative in the second component. Therefore, one can argue that the second principal component corresponds to expectations. Because, an increase in the FCI implies a loosening in financial conditions while a decrease in the FCI implies a tightening in financial conditions. Accordingly, an increase in real domestic credits gap, in real effective exchange rate gap, and in real stock market index gap induces looser financial conditions while an increase in real short-term interest rate, in real commercial loan rate, and in real shadow rate induces tighter financial conditions.

Figure 1 shows the FCI obtained through the second principal component for Turkey. An upward movement indicates a loosening in financial conditions while a downward movement indicates a tightening in financial conditions. Accordingly, the FCI hit rock bottom in the first quarter of 2009 because of the global crisis,

<sup>5</sup> In addition to PCA, I employ VAR models to construct an FCI for Turkey. However, the coefficients obtained through VAR models do not correspond to expectations. I do not present this FCI here, but it is available upon request.

<sup>6</sup> Nominal short-term interest rate is TRLibor in this paper. It is expected to be a positive and high correlation between TRLibor and Borsa Istanbul overnight repo interest rate. Hence the correlation between them is 0.98 over the period 2012-2014.

and then the FCI rose quickly accompanied by the decreases in the effects of the global crisis. During the period December 2008-mid 2010, the FED implemented the first quantitative easing programme, and one might argue that this policy contributed to the increase in the index. Another characteristic of the regarded period is that domestic credits rose rapidly in Turkey. In the last quarter of 2010, the CBRT designed a new monetary policy framework to achieve financial stability. As a result of this new policy mix along with the debt crisis in the Euro Area, financial conditions began to tighten throughout 2011 despite of the FED's second quantitative easing programme between November 2010 and July 2011. As Kara et al. (2015) remark, the CBRT loosened the liquidity policy and the global risk appetite increased in 2012. Hence the acceleration of the capital inflows towards the Turkish economy and increases in real domestic credits and in real stock market index enabled financial conditions to loosen in 2012. One might argue that the third quantitative easing programme, beginning in September 2012, contributed to the loosening in financial conditions. In September 2012, the FED began to purchase assets that were worth 85 billion USD from financial institutions month by month. The depreciation of the Turkish Lira, decreases in stock market index, and increases in real short term interest rates and in real commercial loan rates accompanied by the decreases in the asset purchases of the FED caused financial conditions to tighten beginning from the second half of 2013. Asset purchases of the FED decreased by 10 billion USD in December 2013 (from 85 billion USD to 75 billion USD) and in February 2014 (from 75 billion USD to 65 billion USD). Despite of the continuing decreases in asset purchases during 2014, the financial conditions in Turkey loosened in Turkey during the year 2014. Because, real domestic credits, real effective exchange rate, and real stock market index increased while short-term real interest rates and real commercial loan rates decreased in the regarded period. In the last quarter of 2014, the FED finished asset purchases from the financial institutions and the expectations that the FED would increase the interest rates in the forthcoming periods became prevalent in the US. Real effective exchange rate and real stock market index decreased while real commercial loan rate increased in Turkey beginning from the last quarter of 2014. As a result of these developments, the financial conditions began to tighten in Turkey during 2015 even though the European Central Bank announced that it would implement an asset purchase program for the following 18 months in January 2015.

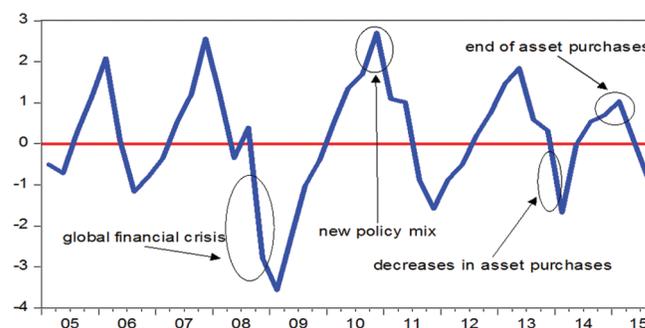
As seen, the evolution of the FCI constructed in this paper reflects both internal and external factors and the FCI can substantially capture the developments in the Turkish economy and in the world.

### 3. DATA, METHODOLOGY AND FINDINGS

#### 3.1. Data

This paper follows time series analysis for Turkey. The data are quarterly and cover the period 2005:Q1-2015:Q3. The variables are FCI and inflation rate. The construction of the FCI and data for FCI are demonstrated above. Inflation rate is calculated as the annual percent change of CPI and is obtained from the CBRT. While FCI represent the FCI, INF represents inflation rate.

**Figure 1:** The financial conditions index for Turkey (2005:Q1-2015:Q3)



**Table 3: Descriptive statistics and correlation matrix for INF and FCI, 2005:Q1-2015:Q3**

Descriptive statistics and correlation matrix	INF	FCI
Descriptive statistics		
Mean	8.29	0.11
Median	8.37	0.28
Maximum	11.65	2.70
Minimum	4.35	-3.56
Standard deviation	1.60	1.34
Observations	43	43
Correlation matrix		
INF		-0.19
FCI	-0.19	

FCI: Financial conditions index, INF: Inflation

Descriptive statistics and correlation matrix are presented in Table 3. One notes that all descriptive statistics of INF are greater than those of FCI. One may notice, as well, that there is a negative correlation between INF and FCI. Descriptive statistics are of course to provide one with some initial and/or preliminary inspection between INF and FCI. However, beyond table observations, one may need to consider, as well, some statistical methodologies to obtain unbiased and efficient output.

#### 3.2. Methodology and Findings

##### 3.2.1. Unit root tests

Specifying the order of integration of variables is the first step in time series analyses since one may experience spurious regression problem when regarding analyses employ conventional ordinary least squares estimations.

Unit root tests developed by augmented Dickey and Fuller (1981, hereafter ADF) and Phillips and Perron (1988, hereafter PP) are commonly utilized in the econometrics literature. The main shortcoming of these tests is that they do not take into account possible structural breaks in series. However, it should be considered that series may have structural breaks before a relationship between variables is investigated.

Lee and Strazicich (2003) suggest an endogenous two-break Lagrange multiplier (LM) unit root test (hereafter LS) allowing for breaks and assert that their methodology is extended from the LM unit root test produced by Schmidt and Phillips (1992).

The methodology of the LS unit root test can be summarized herein below:

$$y_t = \delta'Z_t + e_t, e_t = \beta e_{t-1} + \varepsilon_t \quad (1)$$

Where,  $Z_t$  is a vector of exogenous variables and  $\varepsilon_t \sim iid N(0, \sigma^2)$ . Two structural breaks are considered as follows. Model A allows for two shifts in level and is described by  $Z_t = [1, t, D_{1t}, D_{2t}]'$ , where  $D_{jt} = 1$  for  $t \geq T_{Bj} + 1, j = 1, 2$ , and 0 otherwise.  $T_{Bj}$  denotes the time period when a break occurs. Model C includes two changes in level and trend and is described by  $Z_t = [1, t, D_{1t}, D_{2t}, DT_{1t}, DT_{2t}]'$ , where,  $DT_{jt} = t - T_{Bj}$  for  $t \geq T_{Bj} + 1, j = 1, 2$ , and 0 otherwise. This process considers breaks both under the null hypothesis ( $\beta = 0$ ) and the alternative hypothesis ( $\beta < 1$ ). In Model A (a similar argument can be developed for Model C), depending on  $\beta$ , the hypotheses are pointed as:

$$\text{Null: } y_t = \mu_0 + d_1 B_{1t} + d_2 B_{2t} + y_{t-1} + v_{1t} \quad (2)$$

$$\text{Alternative: } y_t = \mu_1 + \gamma_t + d_1 D_{1t} + d_2 D_{2t} + v_{2t} \quad (3)$$

Where,  $v_{1t}$  and  $v_{2t}$  are stationary error terms.  $B_{it} = 1$  for  $t = T_{Bj} + 1, j = 1, 2$ , and 0 otherwise, and  $d = (d_1, d_2)'$ . In Model C,  $D_{jt}$  terms are added to Equation (2) and  $DT_{jt}$  terms are added to Equation (3), respectively. The Equation (2), indicating the null hypothesis, includes dummy variables  $B_{jt}$ .

The LS unit root test statistic is obtained as the following (Strazicich et al., 2004):

$$\Delta y_t = \delta' \Delta Z_t + \phi \tilde{S}_{t-1} + \sum \gamma_i \Delta \tilde{S}_{t-i} + u_t \quad (4)$$

Where,  $\tilde{S}_t = y_t - \tilde{\psi}_x - Z_t \tilde{\delta}, t = 2, \dots, T$ .  $\tilde{\delta}$  is a vector of coefficients in the regression of  $\Delta y_t$  on  $\Delta Z_t$ ,  $\tilde{\psi}_x = y_1 - Z_1 \tilde{\delta}$ , and  $y_1$  and  $Z_1$  show the first observations of  $y_t$  and  $Z_t$ , respectively.  $\Delta$  is the difference operator.  $u_t$  is contemporaneous error term and is assumed independent and identically distributed with zero mean and finite variance.  $\Delta \tilde{S}_{t-i}, i = 1, \dots, k$ , terms are included to correct for serial correlation.  $Z_t$  is the vector of exogenous variables defined by the data generating process. The null hypothesis is described by  $\phi = 0$ , and the LM test statistic is characterized as  $\tilde{\tau}$ .

To endogenously determine the location of two breaks ( $\lambda_j = T_{Bj}/T, j = 1, 2$ ), the LS unit root test uses a grid search as follows (Strazicich et al., 2004):

$$LM_\tau = \inf_\lambda \tilde{\tau}(\lambda) \quad (5)$$

The breakpoints are determined to be where the test statistic is minimized. Critical values for Model C depend on the location of the breaks. If LM test statistics are greater than critical values in Lee and Strazicich (2003), the null hypothesis is rejected, and the rejection of the null hypothesis indicates a stationary process.

Table 4 depicts the results of ADF and PP unit root tests. As shown from the Table 4, these unit root tests present mixed results. Accordingly, INF is stationary with regard to the intercept form

**Table 4: ADF and PP unit root tests**

Variable <sup>a</sup>	ADF test statistic		PP test statistic	
	Intercept	Intercept and trend	Intercept	Intercept and trend
INF	-1.70	-2.08	-2.66 <sup>d</sup>	-2.63
FCI	-4.71 <sup>b</sup>	-4.66 <sup>b</sup>	-3.11 <sup>c</sup>	-3.06
$\Delta$ INF	-8.27 <sup>b</sup>	-8.15 <sup>b</sup>	-6.36 <sup>b</sup>	-6.13 <sup>b</sup>
$\Delta$ FCI	-5.51 <sup>b</sup>	-5.46 <sup>b</sup>	-5.51 <sup>b</sup>	-5.46 <sup>b</sup>
Critical values				
1%	-3.61	-4.22	-3.60	-4.19
5%	-2.94	-3.53	-2.93	-3.52
10%	-2.61	-3.20	-2.60	-3.19

<sup>a</sup> $\Delta$  is the first difference operator, <sup>b</sup>Illustrates 1% statistical significance, <sup>c</sup>Illustrates 5% statistical significance, <sup>d</sup>Illustrates 10% statistical significance. FCI: Financial conditions index, ADF: Augmented Dickey and Fuller, PP: Phillips and Perron, INF: Inflation

PP test while it is stationary at first difference with regard to intercept and trend form of PP test and both forms of ADF test. Additionally, FCI is stationary at first difference with regard to intercept and trend form of PP test while it is stationary with regard to intercept form of PP and both forms of ADF test. Therefore, to obtain more reliable findings, the results of the LS unit root test are presented in Table 5.

As seen in Table 5, the null hypothesis of a unit root can be rejected for both variables. In other words, both variables are stationary with regard to both models of the LS unit root test. Besides, the breaking periods of the LS unit root test indicate considerable periods for the Turkish economy. Accordingly, the global financial crisis on the Turkish economy may account for the breaks detected in 2008 and 2009. The loosening in the liquidity policy of the CBRT and the increase in the global risk appetite may account for the breaks detected in 2012. Besides, the third quarter of 2010 and the first quarter of 2011 correspond to the periods when financial conditions were loose and when financial conditions began to tighten in Turkey, respectively.

**3.2.2. Asymmetric causality test**

Since the seminal paper of Granger (1969) on causality, to test whether or not a variable causes another variable has increasingly drawn attention in empirical research. In his original paper, Granger (1969) defines causality as “We say that  $Y_t$  is causing  $X_t$  if we are better able to predict  $X_t$  using all available information than if the information apart from  $Y_t$  had been used.” Hatemi (2012) remarks that it is assumed that positive and negative shocks have same impacts in previously published papers on causality. In other words, these papers assume that the causal impact of a positive shock is the same as the causal impact of a negative shock. Hatemi (2012) asserts that positive and negative shocks may have different causal impacts and thus develops an asymmetric causality test. Assume that one aims at investigating the causal relationship between two integrated variables  $y_{1t}$  and  $y_{2t}$  defined like the following random walk processes<sup>7</sup>:

$$y_{it} = y_{i,t-1} + \varepsilon_{it} = y_{i0} + \sum_{i=1}^t \varepsilon_{it} \quad (6)$$

7 Hatemi-J (2012) denotes that the asymmetric causality test can also be employed for stationary variables. In that case, positive or negative changes can be used instead of cumulative sums.

**Table 5: LS unit root test**

Variable <sup>a</sup>	Model	Test statistic	Break dates	λ values	Critical values <sup>a</sup>		
					1%	5%	10%
INF	A	-7.15 <sup>b</sup>	2008:4, 2012:2	λ <sub>1,2</sub> =(0.4, 0.8)	-4.54	-3.84	-3.50
	C	-8.23 <sup>b</sup>	2009:1, 2012:4		-6.42	-5.65	-5.32
FCI	A	-5.61 <sup>b</sup>	2010:3, 2011:1	λ <sub>1,2</sub> =(0.2, 0.4)	-4.54	-3.84	-3.50
	C	-7.13 <sup>b</sup>	2008:2, 2009:4		-6.16	-5.59	-5.27

<sup>a</sup>Critical values are obtained from Table 2 in Lee and Strazicich (2003), <sup>b</sup>Illustrates 1% statistical significance, FCI: Financial conditions index, INF: Inflation

$$y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{20} + \sum_{i=1}^t \varepsilon_{2i} \quad (7)$$

Where,  $t = 1, 2, \dots, T$ , the constants  $y_{10}$  and  $y_{20}$  are the initial values, and  $\varepsilon_{1t}$  and  $\varepsilon_{2t}$  indicate white noise disturbance terms. The subsequent notation is used to identify positive and negative shocks:  $\varepsilon_{1t}^+ = \max(\varepsilon_{1t}, 0)$ ,  $\varepsilon_{2t}^+ = \max(\varepsilon_{2t}, 0)$ ,  $\varepsilon_{1t}^- = \min(\varepsilon_{1t}, 0)$ ,  $\varepsilon_{2t}^- = \min(\varepsilon_{2t}, 0)$ , respectively. Then, one can state  $\varepsilon_{1t} = \varepsilon_{1t}^+ + \varepsilon_{1t}^-$ , and  $\varepsilon_{2t} = \varepsilon_{2t}^+ + \varepsilon_{2t}^-$ . It follows that:

$$y_{1t} = y_{1t-1} + \varepsilon_{1t} = y_{10} + \sum_{i=1}^t \varepsilon_{1i}^+ + \sum_{i=1}^t \varepsilon_{1i}^- \quad (8)$$

$$y_{2t} = y_{2t-1} + \varepsilon_{2t} = y_{20} + \sum_{i=1}^t \varepsilon_{2i}^+ + \sum_{i=1}^t \varepsilon_{2i}^- \quad (9)$$

Finally, the positive and negative shocks of each variable can be defined in a cumulative form as  $y_{1t}^+ = \sum_{i=1}^t \varepsilon_{1i}^+$ ,  $y_{1t}^- = \sum_{i=1}^t \varepsilon_{1i}^-$ ,  $y_{2t}^+ = \sum_{i=1}^t \varepsilon_{2i}^+$ ,  $y_{2t}^- = \sum_{i=1}^t \varepsilon_{2i}^-$ . Each positive together with negative shock has a permanent impact on the underlying variable. The next step is to test for the causal relationship between these components by using these cumulative sums. Here we focus on the case of testing for causal relationship between positive cumulative shocks<sup>8</sup>. On the assumption that  $y_t^+ = (y_{1t}^+, y_{2t}^+)$ , the test for causality can be implemented by employing the following VAR model of order p, VAR (p):

$$y_t^+ = v + A_1 y_{t-1}^+ + \dots + A_p y_{t-p}^+ + u_t^+ \quad (10)$$

Where,  $y_t^+$  is the  $2 \times 1$  vector of variables,  $v$  is the  $2 \times 1$  vector of intercepts, and  $u_t^+$  is a  $2 \times 1$  vector of error terms. The matrix  $A_r$  represents a  $2 \times 2$  matrix of parameters for lag order  $r$  ( $r = 1, \dots, p$ ). The optimal lag order can be determined using either conventional information criteria such as the Schwarz Bayesian criterion and the Akaike information criterion or the information criterion suggested by Hatemi (2003; 2008). This information criterion is defined as follows:

$$HJC = \ln \left( \left| \hat{\Omega}_j \right| \right) + j2^{-1} T^{-1} \left( n^2 \ln T + 2n^2 \ln(\ln T) \right), \quad j = 0, \dots, p \quad (11)$$

Where,  $\ln \left( \left| \hat{\Omega}_j \right| \right)$  denotes the determinant of the estimated variance-covariance matrix of the error terms in the VAR model

<sup>8</sup> To carry out tests for causality between negative cumulative shocks, the vector  $y_t^- = (y_{1t}^-, y_{2t}^-)$  is utilized. Other combinations are possible.

using lag order  $j$ ,  $n$  is the number of equations in the VAR model, and  $T$  is the number of observations. After determining the optimal lag order, the null hypothesis that  $k^{\text{th}}$  element of  $y_t^+$  does not Granger cause the  $\omega^{\text{th}}$  element of  $y_t^+$  is tested. This null hypothesis is defined as:

$$H_0: \text{The row } \omega, \text{ column } k \text{ element in } A_r \text{ is equal to zero for } r = 1, \dots, p \quad (12)$$

Some denotations are used to define a Wald test:

$$Y := (y_1^+, \dots, y_T^+) \quad (n \times T) \text{ matrix,}$$

$$D := (v, A_1, \dots, A_p) \quad (n \times (1 + np)) \text{ matrix,}$$

$$Z_t := \begin{bmatrix} 1 \\ y_t^+ \\ y_{t-1}^+ \\ \vdots \\ y_{t-p+1}^+ \end{bmatrix} \quad ((1 + np) \times 1) \text{ matrix, for } t = 1, \dots, T,$$

$$Z := (Z_0, \dots, Z_{T-1}) \quad ((1 + np) \times T) \text{ matrix, and,}$$

$$\delta := (u_1^+, \dots, u_T^+) \quad (n \times T) \text{ matrix.}$$

Now, the VAR (p) model can be defined more compactly as follows:

$$Y = DZ + \delta \quad (13)$$

The following Wald test statistic can be utilized in order to test the null hypothesis of non-Granger causality defined as

$$H_0 : C \hat{\beta} = 0 :$$

$$\text{Wald} = (C\hat{\beta})' \left[ C \left( (Z'Z)^{-1} \otimes S_U \right) C' \right]^{-1} (C\hat{\beta}) \quad (14)$$

Where,  $\beta = \text{vec}(D)$  and  $\text{vec}$  indicates the column-stacking operator,  $\otimes$  refers to the Kronecker product, and  $C$  represents a  $p \times n(1 + np)$  indicator matrix with elements ones for restricted parameters and zeros for the rest of the parameters.  $S_U$  is the estimated variance-covariance matrix of the unrestricted VAR model that is estimated as  $S_U = \frac{\hat{\delta}_U' \hat{\delta}_U}{T - q}$ , where  $q$  is the number of parameters in each equation of the VAR model. When the assumption of normality is held, the Wald test statistic in Equation (14) has an asymptotic

**Table 6: Hatemi-J (2012) asymmetric causality test<sup>a</sup>**

Null hypothesis	Test statistic	Critical values <sup>b</sup>		
		1%	5%	10%
FCI <sup>+</sup> does not Granger cause INF <sup>+</sup>	37.65 <sup>c</sup>	31.61	19.77	15.78
FCI <sup>-</sup> does not Granger cause INF <sup>-</sup>	33.21 <sup>d</sup>	66.69	26.40	17.40
FCI <sup>+</sup> does not Granger cause INF <sup>-</sup>	17.48	75.23	33.13	21.56
FCI <sup>-</sup> does not Granger cause INF <sup>+</sup>	8.04	101.27	41.18	26.90
INF <sup>+</sup> does not Granger cause FCI <sup>+</sup>	19.53 <sup>d</sup>	20.34	10.85	7.93
INF <sup>-</sup> does not Granger cause FCI <sup>+</sup>	64.53 <sup>d</sup>	76.60	32.85	21.77
INF <sup>+</sup> does not Granger cause FCI <sup>-</sup>	24.68	99.52	41.51	27.43
INF <sup>-</sup> does not Granger cause FCI <sup>-</sup>	22.84	90.95	37.60	24.79

<sup>a</sup>Maximum lag length is 5, and the HJC is used to determine the optimal lag length.

<sup>b</sup>Critical values are obtained through 10,000 bootstrap replications, <sup>c</sup>Illustrates 1% statistical significance, <sup>d</sup>Illustrates 5% statistical significance. FCI: Financial conditions index, INF: Inflation

$\chi^2$  distribution with the number of degrees of freedom that is equal to the number of restrictions to be tested (in this case it is equal to  $p$ ). Some data may not be distributed normally and there may be autoregressive conditional heteroscedasticity effects for some data. To fix these problems, the bootstrap simulation technique can be made use of. If the calculated Wald statistic is greater than the bootstrap critical values, the null hypothesis of non-Granger causality is rejected (Hatemi, 2012) for the details of the bootstrap simulation technique).

Table 6 presents the results of Hatemi (2012) asymmetric causality test. Accordingly, the null hypothesis that a positive shock in FCI does not Granger cause a positive shock in inflation can be rejected at 1% significance level, and the null hypothesis that a negative shock in FCI does not Granger cause a negative shock in inflation can be rejected at 5% significance level. In addition, the null hypothesis that a positive shock in inflation does not Granger cause a positive shock in FCI can be rejected at 5% significance level, and the null hypothesis that a negative shock in inflation does not Granger cause a negative shock in FCI can be rejected at 5% significance level.

The estimation results reveal that a positive shock in one variable causes a positive shock in another variable while a negative shock in one variable causes a negative shock in another variable. In other words, FCI and inflation have a predictive power on each other. Accordingly, if financial conditions become looser, inflation will increase in Turkey, and *viz.* Besides, if inflation increases, financial conditions will become looser in Turkey, and *viz.*

#### 4. CONCLUSION AND POLICY IMPLICATIONS

This paper investigates the causal relationships between financial conditions and inflation by utilizing quarterly data from 2005:Q1

to 2015:Q3 for the Turkish economy. In order to examine the relationships between financial conditions and inflation, the paper, first, constructs a FCI for Turkey and observes that the FCI can considerably capture the developments in the Turkish economy and in the world. Second, the paper conducts ADF, PP, and LS unit root tests to investigate the order of integration of variables. Finally, the paper employs the asymmetric causality test developed by Hatemi (2012). According to the empirical findings, a positive shock in FCI Granger causes a positive shock in inflation while a negative shock in FCI Granger causes a negative shock in inflation. Besides, a positive shock in inflation Granger causes a positive shock in financial conditions while a negative shock in inflation Granger causes a negative shock in inflation. That is to say, FCI and inflation have a predictive power on each other. Accordingly, the paper explores two considerable findings for Turkey. First, if financial conditions become looser, inflation will increase in Turkey, and *viz.* Second, if inflation increases, financial conditions will become looser in Turkey, and *viz.*

As known, the CBRT has been adopting inflation targeting strategy since 2006 and realized inflation rates exceeded inflation targets except for 2009 and 2010 in Turkey. Based on the empirical findings of this paper, one may argue that the CBRT should monitor the financial conditions more carefully in Turkey in order to achieve inflation targets. Monitoring the financial conditions more carefully can help the CBRT not only guard financial stability but also achieve price stability. Hence the findings of the paper imply that the FCI constructed in the paper may present valuable information to the CBRT about the evolution of the financial conditions and the relationships between financial conditions and inflation in Turkey. Hence the paper argues that the FCI in this paper should be updated periodically, should be extended with new financial variables, if necessary, and should be monitored carefully by the CBRT in order to achieve inflation targets.

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