Time Varying Taylor Rule Estimation For Turkey with Flexible Least Square Method

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Abstract

In this study, we estimate a time-varying Taylor rule for evaluating the policy reaction function of the Central Bank of the Republic of Turkey. Even though the Turkish economy has constantly been evolving in the last 15 years, previous studies that analyze the monetary policy rule of the CBRT mainly use time-invariant monetary policy functions. We propose a flexible two-stage least square regression to deal with both instability and endogeneity problems in monetary policy functions. By analyzing the period between 2004 and 2019, we clearly show that the monetary policy function of the Central Bank of the Republic of Turkey changes over time and using a time-invariant monetary policy rule model would yield incorrect results.

Keywords: Taylor Rule; Monetary Policy; Time-Varying Parameter; Turkey
JEL: E52; E58; C32

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1 Introduction

After Turkey suffered from years of high inflation and frequent economic recessions in the 90s, the Central Bank of the Republic of Turkey (CBRT) adopted implicit inflation targeting between 2002 and 2005 to combat with inflation. During this period, the CBRT reduced inflation from 70 percent to single-digit numbers using a high real interest rate. When technical conditions for the full-fledged inflation-targeting regime is fulfilled at the end of 2005, the CBRT switched to the explicit inflation-targeting regime in 2006. During most of the explicit inflation-targeting regime, the CBRT managed to stabilize inflation around 8 percent while reducing the real interest rate. However since 2017, inflation is drifting away from the official inflation target. After the sharp depreciation of Turkish Lira in the third quarter of 2018, inflation in October 2018 reached 25 percent, which is 20 percentage points higher than the official inflation target. Fortunately since November 2018, inflation is declining and below 20 percent once again due to the tight monetary policy followed by the CBRT and the contraction of the Turkish economy. As mentioned very briefly above, the structure of the Turkish economy and the monetary policy stance of the CBRT have undergone several phases in the last 15 years. In this study, we aim to evaluate the CBRT's monetary policy function during the inflation targeting regime using a model that allows for coefficients of the monetary policy function to change over time.

There are already quite a few studies that analyze the policy reaction function of the CBRT using so-called Taylor (1993) rule equations since the implementation of the implicit inflation-targeting regime. Most of these studies disregard the possibility of parameter changes in monetary policy function of the CBRT (e.g. Aklan and Nargeleçekenler, 2008; Demirbaş and Kaya, 2012; Yapraklı, 2011; Yazgan and Yilmazkuday, 2007; Zortuk, 2007). However, the monetary policy function of central banks usually changes over time (Yüksel et al., 2013). Therefore, it is important to model the time-varying nature of the policy function. In one of the notable studies, Kayhan et al. (2013) use a two-state Markov switching model following the approach of King et al. (1996) to investigate the monetary policy function of the CBRT between 2002M02 and 2011M02. However, a simple two state Markov switching model is not flexible enough to capture the complete evaluation of the monetary policy conducted by the CBRT as Turkey faces many different economic phases during the last 15 years. In another notable study, Soybilgen et al. (2019) use two-stage least squares (2SLS) with structural breaks that takes account of the endogeneity problem of the forward-looking monetary policy rules and the possibility of parameter changes of these rules. Soybilgen et al. (2019), which use the inflation gap, the output gap, and the first lag of the real rate as explanatory variables, find that there are four different monetary policy periods in Turkey: 2002M03–2004M08, 2004M09–2008M11, 2008M12–2011M10, and 2011M11–2018M08. In their study, Soybilgen et al. (2019) clearly show that each period has different characteristics. Additionally, the authors claim that studies that do not take into account the parameter instability would yield incorrect results.

In this study, we extend the framework outlined by Soybilgen et al. (2019) in two major ways. First, we adopt a 2SLS with flexible least squares (FLS) instead of a 2SLS with ordinary least squares and structural breaks, as the former procedure provides a more flexible and smooth evaluation of coefficients over time. Secondly, we add the real effective exchange rate (REER) gap into our policy function in addition to the inflation gap, the output gap and the smoothing term, the first lag of the real rate, as Mohanty and Klau (2005) show that many central banks in emerging countries respond strongly to the exchange rate. Our results show that the CBRT puts increasingly more emphasis on the inflation gap over time. Furthermore, the CBRT usually follows a counter-cyclical monetary policy function, but in some periods the CBRT decreases (increases) the policy rate when economy accelerates (decelerates) instead of the other way around. Finally, the CBRT did not much take into account of the changes in the REER until recently, but in the last two years, the CBRT tries to prevent the depreciation of Turkish Lira. We also estimate a regular time-invariant Taylor rule equation and show that without considering parameter instability, fully comprehending the monetary policy of the CBRT is not possible.

The rest of the study is organized as follows: In Section 2, we introduce our flexible 2SLS model. In section 3, we present our data. In Section 4, we present our empirical results, and we conclude in Section 5.

2 Estimation Model

2.1 A Two Stage Regression Framework

In this paper, we consider a monetary policy response function which is augmented with the real exchange rate dynamics and time-varying coefficients. We represent this function with the following linear Taylor rule equation,

$$r_t = \alpha_t + \rho_t r_{t-1} + \beta_{1,t}\tilde{\pi}_{t+k} + \beta_{2,t}x_t + \beta_{3,t}ex_t + u_t \quad \forall t = 1, \dots, T, \tag{1}$$

where T is the sample size, r_t is the real rate target which is the difference between the nominal policy rate and the inflation target of the CBRT, and $\tilde{\pi}_{t+k}$ is the inflation gap which is defined as the deviation of the inflation target from 12 months ahead inflation expectations. x_t and ex_t are defined as the output and the REER gaps which are the cyclical components of the industrial production index (IPI) and the REER, respectively. Finally, ρ_t is the smoothing parameter.

As the literature shows that the Equation (1) is subject to the endogeneity problem, estimating the equation (1) using an ordinary or a nonlinear least square procedure is not possible (e.g. Carvalho and Nechio, 2014; Clarida et al., 1998; Kim and Nelson, 2006). Therefore, we use a 2SLS procedure to estimate Equation (1) by taking into account the endogeneity problem. Our 2SLS procedure can be summarized as follows:

1. We regress each of $\tilde{\pi}_{t+k}$, x_t and ex_t on the lagged values of these variables by using the equations in (2)-(4):

$$\tilde{\pi}_{t+k} = \beta_{0,\tilde{\pi}} + \sum_{j\in S}\beta_{j,\tilde{\pi}}\tilde{\pi}_{t+k-j} + \sum_{j\in S}\theta_{j,\tilde{\pi}}\tilde{x}_{t-j} + \sum_{j\in S}\beta_{j,\tilde{\pi}}ex_{t-j} + \sum_{j\in S/\{1\}}\beta_{j,\tilde{\pi}}r_{t-j} + e_{t,\tilde{\pi}}; \tag{2}$$

$$x_t = \beta_{0,x} + \sum_{j\in S}\beta_{j,x}\tilde{\pi}_{t+k-j} + \sum_{j\in S}\theta_{j,x}\tilde{x}_{t-j} + \sum_{j\in S}\phi_{j,x}ex_{t-j} + \sum_{j\in S/\{1\}}\beta_{j,x}r_{t-j} + e_{t,x}; \tag{3}$$

$$ex_t = \beta_{0,ex} + \sum_{j\in S}\beta_{j,ex}\tilde{\pi}_{t+k-j} + \sum_{j\in S}\theta_{j,ex}\tilde{x}_{t-j} + \sum_{j\in S}\phi_{j,ex}ex_{t-j} + \sum_{j\in S/\{1\}}\beta_{j,ex}r_{t-j} + e_{t,ex}, \tag{4}$$

where S is a set of integers and we set $S = \{1, \dots, 6, 9, 12\}$ as in Clarida et al. (1998). Note that for each equation in (2)-(4), we need to estimate 33 parameters including the intercept term. Considering the degrees of freedom in each equation, we decide to use a more parsimonious model. To achieve this goal, we adopt a penalized regression framework which consists of two steps. In the first step, we employ the conventional Lasso estimation for each equation to determine non-zero coefficients in Equations (2)-(4). After dropping the variables that have zero coefficients in the first stage, we estimate Equations (2)-(4) using OLS in the second stage. A similar method is also proposed by Belloni et al. (2013).

2. From the first stage of the 2SLS procedure, we obtain the fitted values of $\tilde{\pi}_{t+k}$, x_t and ex_t and denote them as $\hat{\tilde{\pi}}_{t+k}$, $\hat{x}_t$ and $\widehat{ex}_t$. Then, we plug these values into the Equation (1) as follows:

$$r_t = \alpha_t + \rho_t r_{t-1} + \beta_{t,1}\hat{\tilde{\pi}}_{t+k} + \beta_{2,t}\hat{x}_t + \beta_{3,t}\widehat{ex}_t + u_t, \tag{5}$$

   where we can estimate this regression model with Flexible Least Square (FLS) method of Kalaba and Tesfatsion (1988).

This method can be considered as a time-varying parameter 2SLS model. Time variation in the policy and smoothing parameters allows us to achieve a flexible policy analysis.

2.2 Flexible Least Squares

We devote this section to discuss the details of the FLS algorithm, which follows Kalaba and Tesfatsion (1988). According to Kalaba and Tesfatsion (1988), FLS method relies on the prior specifications on the measurement equation and the coefficient stability. These specifications can be customized for our analysis as follows:

$$\text{Prior measurement specification}: \quad r_t - Z_t^\top \beta_t = error_{M,t} \approx 0, \quad \forall t = 1, \ldots, T; \tag{6}$$

$$\text{Prior dynamic specification}: \quad \beta_{t+1} - \beta_t = error_{C,t} \approx 0, \quad \forall t = 1, \ldots, T, \tag{7}$$

where $Z_t = [1, r_{t-1}, \hat{\tilde{\pi}}_{t+k}, \hat{x}_t, \widehat{ex}_t]$ is the vector of the regressors in the second stage and $\beta_{t+1} = [\alpha_t, \rho_t, \beta_{1,t}, \beta_{2,t}, \beta_{3,t}]$ is the vector of the coefficients in Equation (5).

In this model, there are two types of error. The first one is the measurement error, $error_{M,t}$, that appears in Equation (6). The second error observed in Equation (7), $error_{C,t}$, is associated with coefficient stability. We can calculate the sum of squared errors for both measurement and coefficient stability errors by using the following equations:

$$SSR_M(\beta;T) = \sum_{t=1}^{T}(r_t - Z_t^\top \beta_t)^2,$$
$$SSR_C(\beta;T) = \sum_{t=1}^{T}(\beta_{t+1} - \beta_t)^\top(\beta_{t+1} - \beta_t),$$

where $\beta = (\beta_1, \ldots, \beta_T)$ and "$\top''$ denotes the vector transpose. To obtain the FLS estimator, we can write the objective function as follows:

$$\begin{aligned} C\left(\beta;T,\mu\right) &= SSR_M(\beta;T) + \mu SSR_C(\beta;T) \\ &= \sum_{t=1}^{T}(r_t - Z_t^\top \beta_t)^2 + \mu \sum_{t=1}^{T}(\beta_{t+1} - \beta_t)^\top(\beta_{t+1} - \beta_t). \end{aligned}$$

This cost function is a linear combination of the sum of squared errors from measurement and coefficient equations. Here, the crucial parameter, $\mu \geq 0$, is used to determine the trade-off between a smooth coefficient or a better model fit. Note that if $\mu = \infty$, FLS collapse to the classical least square problem. Additionally, if $\mu = 0$, then measurement error goes to zero, thus the model perfectly fits the dependent variables. These two conditions indicates that the solution of FLS algorithm depends on the choice of μ. In this study, we use three different μ values which are 1, 10 and 100.

We can compute the solution for β by using a recursive algorithm summarized below:

1. Set μ as a positive real number;
2. Define $Z(T) = [Z_1^\top, \ldots, Z_T^\top]^\top$ as a $T \times 5$ matrix, $\beta(T) = [\beta_t^\top, \ldots \beta_T^\top]$ as a $5T \times 1$ vector and $r(T) = (r_1, \ldots, r_T)^\top$ as a $T \times 1$ vector;
3. The cost function for estimation of the vector $\beta(T)$, $C(\beta(T);T,\mu)$ can be written in matrix notation as:

   $$C\left(\beta(T);T,\mu\right) = \beta(T)^\top A(\mu,T)\beta(T) - 2\beta(T)^\top G(T)r(T) + r(T)^\top r(T),$$

where

$$G(T) = \begin{bmatrix} Z_1 & & 0 \\ & \ddots & \\ 0 & & Z_T \end{bmatrix};$$

$$A(\mu, T) = \begin{bmatrix} A_1(\mu) & -\mu I & 0 & \dots & \dots & 0 \\ -\mu I & A_2(\mu) & -\mu I & & & \cdot \\ 0 & -\mu I & \cdot & & & \cdot \\ \cdot & & & \cdot & & 0 \\ \cdot & & & & \cdot & -\mu I \\ 0 & \dots & \dots & 0 & -\mu I & A_T(\mu) \end{bmatrix}; \quad A_t(\mu) = \begin{cases} Z_1 Z_1^\top + \mu I & if \quad t = 1; \\ Z_t Z_t^\top + 2\mu I & if \quad t \neq 1, T; \\ Z_T Z_T^\top + \mu I & if \quad t = T. \end{cases}$$

4. Minimizing $C(\beta(T); T, \mu)$ with respect to $\beta(T)$, we get the FLS estimator as $\beta^{FLS}(\mu; T) = A(\mu, T)^{-1} G(T) r(T)$. Notice that $\beta(T)$ can be unstacked to obtain time varying coefficients for each regressors.

Further details of the procedure can be found in (Kalaba and Tesfatsion, 1988), thus we skip them for brevity.

3 Data

As the inflation gap, we use the difference between annual inflation and 12 months ahead inflation expectations retrieved from the CBRT's survey of expectation. For the real rate target, we use the difference between the policy rate of the CBRT and the inflation target of the CBRT. Since the start of the inflation targeting, the CBRT uses various policy rates. Between 2002M02 and 2010M05, the CBRT employs the overnight interest rate on borrowing as the policy rate. On 18.05.2010, the CBRT declared that 1-week repo rate is the new policy rate, but shortly after this decision, the CBRT adopts a heterodox monetary policy in 2011 and used the weighted average funding rate as the effective policy rate. Therefore for the policy rate, we use the overnight interest rate on borrowing between 2002M02 and 2010M05, then the 1-week policy rate between 2002M06 and 2010M12, and finally we use the weighted average funding rate after 2011. We obtain data for policy rates from the Turkish Data Manager. For the inflation target, we need to obtain 12 months ahead inflation target of the CBRT. However, the CBRT only releases fixed year-end inflation targets. By following

Yazgan and Yilmazkuday (2007), we construct the variable inflation targets for each month from the fixed inflation targets. For the output gap, we detrended the seasonally adjusted industrial production index, which is obtained from the Turkish Statistical Institute by the Hodrick-Prescott (HP) filter. Finally, we detrended the CPI-based effective real interest rate derived by the CBRT by the HP filter for the REER gap.

4 Empirical Results

In this section, we present the first stage results of our 2SLS methodology and evolution of the Taylor rule equation's coefficients estimated with the flexible 2SLS methodology. We also test whether the instruments used in the two stage procedure are valid. Our estimation covers the period between 2004M03 and 2019M03. We use three different μ in the estimation of our flexible 2SLS methodology. As a baseline model, we also present the coefficients of the regular 2SLS regression without time-varying coefficients.

First, we employ the over-identification restrictions test by following the seminal articles of Sargan (1958) and Hansen (1982). This test simply checks whether the instruments used in the two stage procedure are valid. The validity criterion is satisfied if the instruments are independent of the residuals of the second stage regression. This test requires an additional regression, which has the residuals of the second stage as dependent variable and the instruments as explanatory variables. The test statistic for Sargan-Hansen test can be calculated as $T \times R^2$ where R^2 is the goodness of fit measure if this additional regression. Under the null hypothesis of the overidentification restrictions on the instruments are valid, the test statistic is asymptotically $\chi^2(m - k_z)$ distributed, where m is the number of endogenous regressors and k_z is the included instruments in the first stage. In our case, $m - k_z = 18$ and the null hypothesis can be rejected if the test statistic is larger than %95 quantile of $\chi^2(m - k_z)$. We present the test results in Table 1. According to these results, we can claim that the instruments used in the first stage of our estimation procedure are independent of the residuals of the second stage and thus are valid instruments. This conclusion is apparent for all values of the smoothing parameter μ. Notice that, the critical value of thetest statistic is the same for all μ, since we utilize the same instruments from the firsts stage regression.

Table 2 presents OLS results of the first stage regressions after the Lasso estimation for the inflation, output, and REER gaps. Without utilizing a Lasso regression, we need to estimate 33 parameters for each equation. Thanks to the Lasso regression, we only need to estimate seven parameters for the output gap, fourteen parameters for the inflation gap, and fifteen parameters for the REER gap equations. This procedure simply removes the redundant regressors and decrease the estimation complexity.

Next, we present the second stage results of our flexible 2SLS procedure. Figure 1 shows the evaluation of the Taylor rule equation's coefficients. We demonstrate in Figure 1 that the evaluation of coefficients is much smoother when using $\mu = 100$ instead of $\mu = 10$ or $\mu = 1$. However, using various μ parameters does not change the general trend of coefficients.

To complete our analysis,

The coefficient of the smoothing parameter fluctuates around 1 until 2008. Then, it declines until 2012 and afterwards it slowly increases to 0.8. It seems that the CBRT places a great emphasis on the previous period's real target rate at the start of the inflation targeting regime, then the importance of the smoothing term declines when inflation stabilizes in the single digits. However, the smoothing parameter again is gaining importance in the CBRT's policy function. This situation may be related to the surge of inflation in the last few years.

Except for the period between 2004 and 2006, the coefficient of the inflation gap is always positive. It means that whenever inflation deviates from the target, the CBRT increases the interest rate. According to $\mu = 100$, the importance of the inflation gap in the monetary policy function of the CBRT is increasing steadily. However, for $\mu = 1$ and $\mu = 10$, we see a peak around 2012M05. This date is the period where the coefficient of the smoothing term bottoms out. It seems that the coefficient of the inflation gap and the smoothing term is negatively correlated in the CBRT's policy function.

The coefficient of the output gap is usually positive, which indicates that the CBRT follows a counter-cyclical monetary policy. When the Turkish economy accelerates (slows down), the CBRT increases (decreases) the policy rate. However, there are two periods where the CBRT follows a mild pro-cyclical monetary policy: the period of 2004-2005 and the period of 2009-2011. We see this pro-cyclical effect, especially when we set $\mu = 1$. There are also other periods such as 2014M09 and 2016M10, where the coefficient of the output gap becomes zero. Soybilgen et al. (2019) also present a similar finding for 2009-2011 and argue that this pro-cyclical monetary policy may explain the very high growth rates that occurred in 2010 and 2011.

Finally, we analyze the coefficient of the REER gap. Until 2017, the coefficient of the REER gap is generally either close to zero or have a small negative coefficient. However for the last two years, the CBRT systematically tries to prevent the depreciation of Turkish Lira by increasing the policy rate. We can conclude that the sensitivity of the CBRT's policy function to the fluctuations in the REER increases significantly in the last period.

We also present the results of a time-invariant Taylor rule model in Figure 1. As can be seen in Figure 1, we would miss all changes in the monetary policy function of the CBRT without relying on a time-varying Taylor model. According to the regular 2SLS methodology, the coefficient of the smoothing term is 0.96, the coefficient of the output gap is 0.09, the coefficient of the inflation gap is 0.13, and the coefficient of the REER gap is -0.06. These coefficients only tell us that the CBRT follows a mild counter-cyclical monetary policy with a string smoother parameter and can not capture changes in the monetary policy function of the CBRT.

5 Conclusion

Many studies analyze the monetary policy function of the CBRT. However, none of them uses a time-varying endogenous model to estimate the Taylor rule equation of the CBRT, even though the Turkish economy has undergone various structural transformations in the last 15 years. In this study, we propose a novel 2SLS methodology using Lasso estimation in the first stage and the FLS estimation in the second stage. FLS extimation takes into account of both the endogeneity problem and time-varying nature of the monetary policy function of the CBRT.

Our results show that the CBRT usually follows a counter-cycle monetary policy which increases (decreases) the policy rate whenever the economy accelerates (decelerates). However, in some periods such as the period of 2009-2011, the CBRT seems to follow a pro-cycle monetary policy which causes the Turkish economy to overheat in 2010 and 2011.

Our time-varying 2SLS procedure also indicates that the CBRT usually does not react or reacts very mildly to the depreciation of the Turkish Lira until 2017. However for the last two years, the CBRT tries to offset the depreciation of the Turkish Lira more strongly.

Furthermore, we show that the CBRT did not put too much emphasis on the inflation gap until 2008 and mostly focused on smoothing the monetary policy function by considering the last period's real target rate. However since 2008, the inflation gap becomes increasingly crucial for the CBRT.

By comparing our time-varying Taylor equation to a time-invariant Taylor equation, we clearly show that ignoring time-variant nature of monetary policy equations would yield incorrect results. Therefore, future studies should pay attention to parameter changes in Taylor rules.

References

Aklan, N. A. A. and M. Nargeleçekenler (2008). Taylor kuralı: Türkiye üzerine bir değerlendirme. *Ankara Üniversitesi SBF Dergisi 63*(02), 21–41.

Belloni, A., V. Chernozhukov, et al. (2013). Least squares after model selection in high-dimensional sparse models. *Bernoulli 19*(2), 521–547.

Carvalho, C. and F. Nechio (2014). Do people understand monetary policy? *Journal of Monetary Economics 66*, 108–123.

Clarida, R., J. Galı, and M. Gertler (1998). Monetary policy rules in practice: Some international evidence. *European Economic Review 42*(6), 1033–1067.

Demirbaş, E. and M. V. Kaya (2012). Testing the validity of Taylor principle for Turkey from a different perspective. *Abant İzzet Baysal Üniversitesi Sosyal Bilimler Enstitüsü Dergisi 12*, 81–110.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the Econometric Society*, 1029–1054.

Kalaba, R. and L. Tesfatsion (1988). The flexible least squares approach to time-varying linear regression. *Journal of Economic Dynamics and Control 12*(1), 43–48.

Kayhan, S., T. Bayat, and A. Koçyiğit (2013). Enflasyon hedeflemesi rejiminde öğrenme süreci ve asimetri: Markov switching yaklaşımı. *Eskişehir Osmangazi Üniversitesi İktisadi ve İdari Bilimler Dergisi 8*(1), 191–212.

Kim, C.-J. and C. R. Nelson (2006). Estimation of a forward-looking monetary policy rule: A time-varying parameter model using ex post data. *Journal of Monetary Economics 53*(8), 1949–1966.

King, M. et al. (1996). How should central banks reduce inflation? Conceptual issues. *Economic Review-Federal Reserve Bank of Kansas City 81*, 25–52.

Mohanty, M. S. and M. Klau (2005). Monetary policy rules in emerging market economies: Issues and evidence. In R. J. Langhammer and L. V. de Souza (Eds.), *Monetary Policy and Macroeconomic Stabilization in Latin America*, pp. 205–245. Berlin, Heidelberg: Springer.

Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. *Econometrica: Journal of the Econometric Society*, 393–415.

Soybilgen, B., B. A. Eroğlu, and H. Yener (2019). Taylor rule for Turkey under multiple structural breaks. In Ç. Yurtseven and M. Tekce (Eds.), *Current Issues in Turkish Economy: Problems and Policy Suggestions*, pp. 11–24. Bern, Switzerland: Peter Lang.

Taylor, J. B. (1993). Discretion versus policy rules in practice. In *Carnegie-Rochester conference series on public policy*, Volume 39, pp. 195–214. Elsevier.

Yapraklı, S. (2011). Türkiye'de açık ekonomi para politikası kuralının geçerliliği: Sınır testi yaklaşımı. *The Journal of Industrial Relations and Human Resources 13*(1), 127–142.

Yazgan, E. and H. Yilmazkuday (2007). Monetary policy rules in practice: Evidence from Turkey and Israel. *Applied Financial Economics 17*(1), 1–8.

Yüksel, E., K. Metin-Ozcan, and O. Hatipoglu (2013). A survey on time-varying parameter Taylor rule: A model modified with interest rate pass-through. *Economic Systems 37*(1), 122–134.

Zortuk, A. G. D. M. (2007). Koşulluluk aracı olma bağlamında kısa vadeli faiz oranlarının hedeflenen enflasyondan sapmada kullanımı: Bounds test yaklaşımı (Türkiye örneği). *Ekonometri ve İstatistik e-Dergisi* (6), 41–68.

Table 1: The Results of the Over-identification Restrictions Test

μ	Test Statistic	Critical Value($\chi^2(18)$)	p-value
1	8.8527		0.9631
10	11.93385	28.8693	0.8506
100	9.8179		0.9376

Table 2: OLS Results of the First Stage Regressions after Lasso Estimation

Variables	x_t Coefficient	$\tilde{\pi}_t$ Coefficients	ex_t Coefficients
Intercept	-0.010	0.086	0
r_{t-2}	0	0	0
r_{t-3}	0	0	0
r_{t-4}	0	0	0
r_{t-5}	0	0	0
r_{t-6}	0	-0.011	0
r_{t-9}	0	0	0.023
r_{t-12}	0	0	0
x_{t-1}	0.584	0.018	0.037
$\tilde{\pi}_{t-1}$	0	1.087	0.214
ex_{t-1}	0.043	-0.033	0.947
x_{t-2}	0.190	0	0
$\tilde{\pi}_{t-2}$	0	0	0
ex_{t-2}	0	0.005	-0.361
x_{t-3}	0	0.005	0
$\tilde{\pi}_{t-3}$	0	-0.075	0
ex_{t-3}	0	0.017	0.167
x_{t-4}	0	0	0
$\tilde{\pi}_{t-4}$	0	0	0
ex_{t-4}	0	0	-0.102
x_{t-5}	0	-0.007	0
$\tilde{\pi}_{t-5}$	0	0	0
ex_{t-5}	0	0	0
x_{t-6}	0	0	0.014
$\tilde{\pi}_{t-6}$	0	0	0
ex_{t-6}	0	0	0.032
x_{t-9}	0	0	-0.128
$\tilde{\pi}_{t-9}$	0	-0.042	0
ex_{t-9}	0.019	-0.001	-0.070
x_{t-12}	-0.059	0	0
$\tilde{\pi}_{t-12}$	0	0.041	-0.221
ex_{t-12}	0	0	-0.158

Figure 1: Evaluation of the Flexible 2SLS Coefficients According to Several μ parameters and Coefficients from Time Invariant (Fixed) 2SLS Estimation