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An Assessment of Turkish Inflation Dynamics Based on Phillips Curve Variants With Import Price Index

Türkiye Enflasyon Dinamiklerinin İthalat Fiyat Endeksli Phillips Eğrisi Varyantlarına Dayalı Bir Değerlendirmesi

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ABSTRACT

This study aims to present an assessment on Phillips curve models based on import price index in order to account for inflation dynamics in Turkey over the period 2002Q1:2021Q1 by employing state-space approach in potential output computations. In order to deal with the expectation terms in estimating equations and to avoid the associated endogeneity issue, the Generalized Method of Moments (GMM) technique has been used, and two distinct measures of output gap based on Hodrick-Prescott filter and Kalman Filter algorithm have been performed. First, the time varying slope coefficients regarding traditional hybrid Phillips curve (PC) have been estimated through rolling window approach for Turkey. Then, two variants of the hybrid PCs have been formulated by including import price index regressor to all of them and the forecasting performances of the models have been evaluated.

Keywords: Inflation, output gap, GMM, kalman filter algorithm, rolling window.

ÖZ

Bu çalışma, potansiyel çıktı hesaplamalarında durum uzayı yaklaşımını kullanarak 2002Q1:2021Q1 dönemi boyunca Türkiye'deki enflasyon dinamiklerini açıklamak için ithalat fiyat endeksine dayalı Phillips eğrisi modelleri üzerine bir değerlendirme sunmayı amaçlamaktadır. Denklemlerin tahmininde beklenti terimlerini ele almak ve ilgili içsellik sorundan kaçınmak için Genelleştirilmiş Momentler Yöntemi (GMM) tekniği kullanılmış, ve Hodrick-Prescott filtresi ile Kalman Filtresi algoritmasına dayalı iki farklı çıktı açığı ölçümü yapılmıştır. İlk olarak, geleneksel hibrit Phillips eğrisine (PC) ilişkin zamanla değişen eğim katsayıları, Türkiye için yuvarlanan pencere yaklaşımıyla tahmin edilmiştir. Daha sonra hibrit PC'lerin iki varyantı, hepsine ithalat fiyat endeksi regresörü dahil edilerek formüle edilmiş ve modellerin tahmin performansları değerlendirilmiştir.

Anahtar Kelimeler: Enflasyon, çıktı açığı, GMM, kalman filtresi algoritması, yuvarlanan pencere.

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1. INTRODUCTION

The way for a good governance of inflation expectations, realization of the targets concerning inflation and not diving into a chronic high inflation trap go through a grasp on inflation dynamics. Particularly, Hybrid New Keynesian Phillips Curve (NKPC) is a prominent path in the researches to build suitable models that account for inflation (Narayan et al., 2023) represented as the extension of the baseline NKPC with Calvo-type adjustment to prices: $p_t = \phi p_{t-1} + (1-\phi) p_t{*}$ where p_t shows the aggregate price level, ϕ shows the ratio of the firms who hold their prices constant in any given time period (thus, $1-\phi$ denotes a fixed probability that firms should optimally adjust their prices each period) and $p_t{*}$ shows the optimal reset price. The well-known representation of NKPC is $\pi_t = \beta E_t(\pi_{t+1}) + \delta x_t$ where $\pi_t = p_t - p_{t-1}$ represents the inflation rate, $E_t(\pi_{t+1})$ represents the expected inflation and x represents either a measure of real marginal cost or output gap. However, NKPC has brought some limitations together; and capturing inflation persistence has been one of the effectual motivations in the transition to hybrid version of NKPC that is improved by Gali and Gertler (1999) with the addition of lagged inflation term: $\pi_t = \gamma_f E_t(\pi_{t+1}) + \gamma_b \pi_{t-1} + \delta x_t$ with the parameters γ_f and γ_b that belong to the forward- and backward-looking components respectively (Gali and Gertler, 1999; Sümer, 2020).

How the NKPC models are constructed is a driving impulse in understanding the tendency of central banks over against the real life occurrences during the situation of adherence to inflation targets on the one hand (Nason and Smith, 2005). Motivated by the quest for a good model to take inflation dynamics into account, there exist a vast amount of studies in the literature: Du Plessis and Burger (2006) examine whether the NKPC is valid for the period 1975Q1-2003Q4 in the South African economy. In the study in which the GMM method is applied the variables of consumer price index, inflation, output gap, import prices, remuneration per worker, the open economy version of real marginal cost, yield spread have been discussed. In conclusion, it is reported that the NKPC is valid and the structural model can be estimated with GMM without suffering from weak instrument problem. Dupuis (2004) handles three structural models of US inflation and reports that the new Keynesian hybrid Phillips curve including the output gap as an explanatory variable operates in a better manner compared to the other models to a little extent. Korkmaz (2010) estimates the New Phillips Curve that was created in hybrid form - including the model variables such as import price index, money supply, oil prices and wage index, interest rate, exchange rate etc.- in order to determine whether the forward-looking or backward-looking approach is more effective in determining inflation in Turkey using two-stage least squares method for the time period 1997Q3-2006Q4, and reveals that inflation is mostly determined according to inflation expectations, that is, firms' pricing behavior is forward-looking. Eruygur (2011) discusses the inflation dynamics within the framework of NKPC model reporting the iterated GMM and Continuous Updating GMM estimation results and reveal that the open economy NKPC can be associated with Turkish economy in the empirical manner. In their study, Baser et al. (2013) focus on Bayesian estimates of the hybrid NKPC to account for the consumer price inflation dynamics for Turkish economy, and they report that the baseline model including the output gap provides a better job in explaining the consumer price inflation in relative to other specifications that contain the unit labor cost. Bari and Şıklar (2021) cover the inflation phenomenon under the inflation targeting regime with the floating exchange rate regime for the period 2002M1-2020M7 through the estimation of the open economy Hybrid NKPC. In the study, output gap calculations to measure the domestic markup are presented based on the HP filter and Kalman filter methods. In conclusion, it is reported that the domestic output gap has no significant impact on inflation for all models, the model with the Kalman Filter's output gap shows better estimation performance, and forward-looking inflation expectations are effective on current inflation level.

Considering the importance of Phillips curves, this study aims to detect whether a suitable model exists or not for shedding light on Turkish inflation dynamics within the framework of import price index series which is considered to be a remarkable component of open economy framework, by augmenting the hybrid NKPC.

2. ESTIMATION METHODOLOGY

2.1. Generalized Method of Moments (GMM) Procedure

Under the assumption of rational expectations hypothesis (REH) implying “model-consistent” expectations discussed by Hansen and Sargent (1980) who made pivotal contributions to the estimation of rational expectations models, economic agents formalize their expectations by utilizing from the efficient usage of current and past information set. Thus, the expectational error term in order to forecast future inflation term π_{t+1} is uncorrelated with the information set $\mathbf{z}_t$ (D'Amato and Garegnani, 2009) given in the following basic reduced-form moment condition for the baseline NKPC model:

$$E_t\left\{(\pi_t - \alpha\pi_{t+1} - \gamma x_t)\mathbf{z}_t\right\} = 0 \tag{1}$$

where π_t is the inflation rate at time t, x_t is a measure of marginal costs, α is the discount factor and $\mathbf{z}_t$ represents a vector of instruments dated in period t and before (therefore, being orthogonal to the inflation surprise in period $t+1$). A more explicit form of Eq. (1) can be stated in a way that will include the structural parameter θ -which denotes the frequency of price adjustment and is related with γ according to $\gamma = \theta^{-1}(1-\theta)(1-\alpha\theta)$ - and take two distinct normalizations of orthogonality conditions into consideration:

$$E_t\left\{(\theta\pi_t - \theta\alpha\pi_{t+1} - (1-\theta)(1-\alpha\theta)x_t)\mathbf{z}_t\right\} = 0 \tag{2}$$

$$E_t\left\{(\pi_t - \alpha\pi_{t+1} - \theta^{-1}(1-\theta)(1-\alpha\theta)x_t)\mathbf{z}_t\right\} = 0 \tag{3}$$

by forming a basis for the generalized method of moments (GMM) procedure. While the nonlinearity cases are reduced as much as possible in Eq. (2), in Eq. (3) inflation coefficient is normalized to unity. On the other hand, the corresponding orthogonality conditions with two type of normalizations in the case of Hybrid NKPC model in which all variables are defined as deviations from steady state as in $\pi_t = \lambda_b\pi_{t-1} + \lambda_f E_t\pi_{t+1} + \gamma x_t + \varepsilon_t$ -where $\lambda_b = \dfrac{w}{\varphi}$, $\lambda_f = \dfrac{\alpha\theta}{\varphi}$, $\gamma = \dfrac{(1-w)(1-\theta)(1-\alpha\theta)}{\varphi}$ with $\varphi = \theta + w[1-\theta(1-\alpha)]$ and ε_t is the error term- are given by

$$E_t\left\{(\varphi\pi_t - w\pi_{t-1} - \alpha\theta\pi_{t+1} - (1-w)(1-\theta)(1-\alpha\theta)x_t)\mathbf{z}_t\right\} = 0$$

(4)
and

$$E_t\left\{(\pi_t - \varphi^{-1}w\pi_{t-1} - \varphi^{-1}\alpha\theta\pi_{t+1} - \varphi^{-1}(1-w)(1-\theta)(1-\alpha\theta)x_t)\mathbf{z}_t\right\} = 0 \tag{5}$$

respectively (Gali and Gertler, 1999). Since (rationally) expected inflation term on which Phillips curve models have been grounded is unobservable, GMM procedure has a large-scale usage with respect to tackling with this problem in most empirical macroeconomic analyses by replacing $E_t\pi_{t+1}$ with the realized inflation (Jondeau and Le Bihan, 2005).

In their analysis, Gali and Gertler (1999) consider a standard two-step GMM estimator proposed by Hansen (1982). For a concise description of the method, consider the simple linear regression model:

$$y = X\alpha + \varepsilon \tag{6}$$

where X is an $(n \times k)$ matrix with n and k indicating the number of observations and the number of explanatory variables respectively; ε has a distribution with mean zero and variance σ^2 and we suspect about the ε being correlated with some endogenous regressor variables, i.e. X_i, that is, $E(X_i'\varepsilon_i) \neq 0$. In the instrumental variables manner, an appropriate suggestion would be to detect instrumental variables $\mathbf{z}$ being correlated with X_i but uncorrelated with ε; in other saying, the orthogonality condition takes the form of $E(\mathbf{z}'\varepsilon) = 0$ where α represents the vector of unknown parameters. More specifically, let us define $f(\mathbf{z}, \alpha) = \mathbf{z}_i'\varepsilon_i = \mathbf{z}_i'(y_i - X_i\alpha)$ for $\alpha = \alpha_0$ where α_0 denotes the true value of the parameter. Thus, the moment condition as an indicator of the exogeneity of instruments becomes $E\left[f(\mathbf{z}, \alpha)\right] = 0$. In this situation, the sample counterpart in accordance with the moment condition for the population is written as

$$\frac{1}{n}\sum_{i=1}^{n} f(\mathbf{z}, \hat{\alpha}) = \frac{1}{n}\sum_{i=1}^{n} \mathbf{z}_i'(y_i - X_i\hat{\alpha}) = \frac{1}{n}\mathbf{z}'\hat{\varepsilon} \tag{7}$$

and taking $E\left[f(\mathbf{z}, \alpha)\right] = 0$ into account, the optimal two-step GMM estimator based on Hansen (1982) that minimizes Eq. (7) with respect to $\hat{\alpha}$ yields

$$\hat{\alpha}_{2_{\mathbf{GMM}}} = \arg\min_{\hat{\alpha}} \left(\frac{1}{n}\sum_{t=1}^{n} f(\mathbf{z}, \alpha)'\hat{\Omega}(\hat{\alpha}_1)^{-1} \frac{1}{n}\sum_{t=1}^{n} f(\mathbf{z}, \alpha) \right) \tag{8}$$

Using Eq. (7), Eq. (8) can also be expressed as

$$\hat{\alpha}_{2_{\mathbf{GMM}}} = \min_{\hat{\alpha}} \left(\frac{1}{n}[\mathbf{z}'(y - X\hat{\alpha})]' \cdot \hat{\Omega}^{-1} \cdot \frac{1}{n}[\mathbf{z}'(y - X\hat{\alpha})] \right) \tag{9}$$

where $\hat{\alpha}_1$ is a first step consistent estimator for α_0 that is usually obtained through the identity matrix as an optimal weighting matrix, and $\hat{\Omega}^{-1}$ is a consistent estimator of the inverse of the asymptotic variance-covariance matrix (i.e. $\left(\mathrm{var}\left[(1/n)(\mathbf{z}'\varepsilon)\right]\right)^{-1}$) as related to the moment condition in interest (Guay and Pelgrin, 2004). In the case of homoscedasticity and serially-independency, the optimal estimator in Eq. (9) will be equivalent to two-stage least squares (2SLS) estimator as a special case of GMM procedure. Moving from the first-order conditions with respect to $\hat{\alpha}$ given as follows:

$$\hat{\alpha}_{\mathbf{GMM}} = \left(X'\mathbf{z}\,\hat{\Omega}^{-1}\mathbf{z}'X \right)^{-1} \left(X'\mathbf{z} \right)\hat{\Omega}^{-1}\mathbf{z}'y \tag{10}$$

Under the assumption that it is possible to find an estimate of $\hat{\sigma}^2$, 2SLS estimator could be obtained by reformulating Eq. (10) as

$$\hat{\alpha} = \left[X'\mathbf{z}\left(\mathbf{z}'\mathbf{z}\right)^{-1}\mathbf{z}'X \right]^{-1} \left[X'\mathbf{z}\left(\mathbf{z}'\mathbf{z}\right)^{-1}\mathbf{z}'y \right] \tag{11}$$

(Johnston and Dinardo, 1997).

Let L represent the number of moment or orthogonality conditions. Given that K is the number of parameters to be estimated; in the case of $L = K$, the model is called exactly identified while $L > K$ implies an over-identified equation (Baum et al., 2003) and carrying out GMM procedure necessitates at least as many orthogonality conditions as there are parameters to be estimated (Faff and Gray, 2006). For over-identifying restrictions, GMM method utilizes from the J -statistic which is suggested by Hansen (1982), takes the deviations of all average moments from 0 as the basis and follows a chi-squared distribution with degrees of freedom being equal to the number of over-identifying restrictions, $L-K$ (Imbens, 2002).

2.2. State-Space Approach

In this study, two measures of output gap obtained through both Hodrick–Prescott (HP) filter and Kalman filter (KF) algorithm approach have been used. For the Kalman-filtered case, potential output has been estimated based on the state space model which is expressed as (Harvey, 1985; Clark, 1987):

$$\begin{aligned} y_t &= \tau_t + c_t \\ \tau_t &= \tau_{t-1} + d_{t-1} + \varepsilon_{1t} \\ d_t &= d_{t-1} + \varepsilon_{2t} \\ c_t &= \alpha_1 c_{t-1} + \alpha_2 c_{t-2} + \varepsilon_{3t} \end{aligned} \tag{12}$$

where y_t represents the actual output, τ_t represents the potential output which follows a random walk, c_t represents the cyclical output which exhibits a stationary AR(2) process, d_t represents the drift term, ε_t 's represent white noise error terms (Furuoka et al., 2021).

3. DATA AND EMPIRICAL RESULTS

Inferences on Turkish inflation dynamics have been captured through an extension of Gali and Gertler (1999)'s approach. More specifically, in this study, it has been aimed to analyze that to which extent inflation dynamics in Turkey can be described through a hybrid version of the New Keynesian Phillips curve, hereafter HNKPC, based on the basis of so-called "Triangle model" of inflation proposed by Gordon which is a three-cornered approach taking demand-pull & cost-push inflation types and inertia of price setting in inflation behavior into consideration. As a departure from the Calvo's baseline model, the new hybrid model has an advantage with respect to combining forward-looking and backward-looking price setting firms together by including the inflation inertia in the matter.

As for the variables performed in the research, they have been compiled based on quarterly data over the period 2002Q1:2021Q1. In this study, we aim to determine the best model for explaining Turkish inflation dynamics in the best way. To this end, Table 1 presents the models covered in the analyses of the research. According to this, we employed labor share of income as the proxy of real marginal cost and output gap as driving variables for the first two models -being augmented with import price index- respectively. Additionally, we proposed a third model based on New Keynesian Dynamic IS Equation and investigated its contribution to the forecasting of Turkish inflation dynamics.

Table 1. Models Covered in the Analysis

1) Hybrid NKPC with real marginal cost (augmented with import price index):
$$\pi_t = \lambda_b \pi_{t-1} + \lambda_f E_t \pi_{t+1} + \gamma_1 x_t + \gamma_2 import_t + \varepsilon_t$$

2) Hybrid NKPC with output gap (augmented with import price index):
$$\pi_t = \lambda_b \pi_{t-1} + \lambda_f E_t \pi_{t+1} + \gamma_1 \tilde{y}_t + \gamma_2 import_t + \varepsilon_t$$

Note. π_t denotes actual inflation, x_t denotes labor income share, $\tilde{y}_t$ denotes output gap, *import* denotes import price index.

Variables of the study with their descriptions and sources have been listed in Table 2. All variables have been incorporated into the study as seasonally adjusted.

Table 2. Data Description and Sources

Variable	Definition	Source
inf	Quarter-on-quarter inflation rate	Obtained using consumer price index (CPI) [Source of CPI: Central Bank of the Republic of Turkey (CBRT)]
lnmc	Labor income share (logarithmic) as a proxy for real marginal cost	OECD
imp	Import price index	CBRT
exch	Nominal effective exchange rate	Federal Reserve Economic Data (FRED)
GDP	Gross domestic product	CBRT
outgap	Output gap	Obtained using Hodrick–Prescott (HP) filter on quarterly real gdp series
kalman	Output gap	Obtained using Kalman filter (KF) algorithm

Note. In covered models defined in Table 1, “imp” has been defined as the deviation from their HP-filtered trend. For “imp” series, deviation of its logarithmic form has been used.

As described in Table 2, we employ two measures of the output gap which reflects the real economic activity by defining the difference between actual and potential GDP:

"outgap" as Hodrick-Prescott filtered (log) real GDP [i.e. as the log deviation of output from its potential level] (with penalty parameter λ = 1600) and "kalman" as the (Kalman-filtered) output gap measure where potential output was estimated depending on the-state space model as expressed in Harvey (1985) and Clark (1987).

In the analyses, Generalized Method of Moments (GMM) estimation procedure has been implemented. As well known, it has a flexible usage in order to avoid the heteroskedasticity and autocorrelation issues and GMM estimates are quite sensitive to the instrument variable choice. To this end, this study follows the procedure proposed by Nason and Smith (2008) in the instrument specification for GMM estimation. In accordance with the specified procedure, subsequent to the vector univariate autoregressions from order 1 through a maximum lag 6 evaluated with the AIC (Akaike Information Criterion) and the SIC (Schwarz Information Criterion), we made a pre-test of the null hypothesis that inflation series does not Granger-cause real marginal cost and the other independent variables covered in our models. The results have shown that in

Table 3. Unit Root Test Results

Variables	LEVEL			
	ADF	**PP**	**KPSS**	**ADF-SB**
inf	-3.238***	-2.393	0.092	-7.151*
	(1)	(1)	(3)	[2018Q2]
lnmc	-2.065	-6.666*	0.500*	-3.577
	(4)	(26)	(36)	[2015Q3]
outgap	-5.280*	-5.229*	0.066	-5.790*
	(0)	(4)	(4)	[2018Q3]
kalman	-5.673*	-66.677*	0.500*	-7.741*
	(4)	(36)	(36)	[2020Q2]
imp	-5.492*	-5.495*	0.051	-5.660*
	(0)	(1)	(0)	[2018Q3]
exch	-1.503	-1.344	0.218*	-3.255
	(0)	(4)	(4)	[2018Q2]
Variables	**FIRST DIFFERENCE**			
	ADF	**PP**	**KPSS**	**ADF-SB**
dlnmc	-3.832**		0.140***	-4.608***
	(5)		(10)	[2020Q2]
dexch	-5.521*	-6.002*	0.125***	-7.188*
	(4)	(10)	(10)	[2018Q2]

Note. *, ** and *** represent 1%, 5% and 10% significance levels respectively. Optimal lag lengths that are determined based on SIC for ADF test and bandwidths that are determined based on Newey West method using Bartlett kernel for PP and KPSS tests are given in parantheses. Breakpoint values for ADF-SB test are given in brackets. "dlnmc" and "dexch" represent first-differenced (logarithmic) labor income share and exchange rate variables respectively. ADF and PP test statistics have been compared with MacKinnon (1996) critical values.

Asymptotic critical values for the KPSS test are available at Kwiatkowski et al. (1992). In addition, For ADF-SB test, critical values could be obtained from Furuoka (2017; Table 3). According to Table 3 findings, “inf” series is stationary for all tests excluding PP test. “lnmc” series was found to be non-stationary for all tests excluding PP test. Although “outgap” and “imp” are stationary for all tests, “kalman” and “gov” are stationary for all tests excluding KPSS test. Besides, “exch” series was detected to be non-stationary under all test procedures. As for ADF-SB test, only “lnmc” and “exch” variables were detected to include unit roots. These results confirm that we should use the first-differenced forms of “lnmc” and “exch” series, and level forms of the other remaining variables for stationarity.

cases where only the lags of the variables in the main model are used as instrumental variables, either the regression outputs give meaningless results or the coefficient signs do not match the expectations. For our study, adding an extra variable other than the variables included in the main regression (here, exchange rate) to the model provided a better estimation of the three variants of Hybrid PCs with respect to obtaining the findings in line with the expectations. Throughout the paper, the general set of instruments for covered three variants of Hybrid PC models contain some combinations of a constant (otherwise stated), maximum 12 lagged values of inflation, real marginal cost, output gap (either Kalman or HP-filtered), import price index, exchange rate, government expenditures, real interest rate gap and wage inflation.

GMM technique requires the variables in question to be stationary. For this reason, before starting the analyses, we checked out the stationarity situations of all series under the study using ADF, PP, KPSS and ADF with structural break (ADF–SB) test (Perron and Vogelsang, 1992). Unit root test results have been given in Table 3.

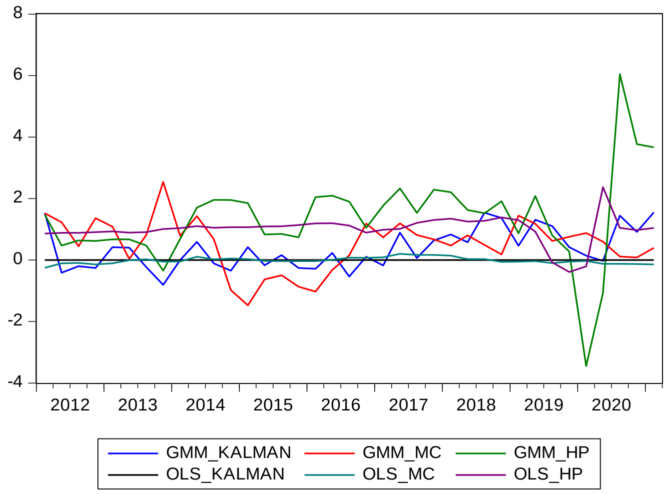

Figure 1. Time varying slope coefficients for the traditional hybrid PC

Before starting the analyses of the research with the three variants of Phillips Curve (PC) given in Table 1, we tried to examine the time varying slope coefficients of the traditional hybrid PC which includes only prospective and retrospective inflation terms with the proxies of real marginal cost. We estimated time varying coefficients through the rolling-window method and the size of the method was considered as 40.

Table 4. GMM Estimation Results of the Model I

Sets	inf(1)	inf(-1)	dlnmc	imp	J-Stat	Adjusted R^2	Weight Updating	Kernel
1	0.590388*	0.410577*	0.444755*	0.362772*	11.73801	0.874207	N=1	Bartlett
	(2.23E-13)	(2.04E-13)	(1.05E-11)	(4.57E-11)	[0.466943]			
F-stat: 1.17E+23 [0.0000]; Jarque-Bera: 0.990145 [0.609527]								
1	0.601564*	0.400494*	0.610617*	0.585332*	14.27056	0.872065	N=1	Parzen
	(4.79E-12)	(4.11E-12)	(1.84E-10)	(1.51E-09)	[0.283766]			
F-stat: 1.32E+22 [0.0000]; Jarque-Bera: 1.113343 [0.573114]								
2	0.590446*	0.409747*	0.297802*	2.905768*	12.34053	0.864974	N=1	Bartlett
	(5.77E-10)	(4.61E-10)	(2.89E-09)	(2.93E-08)	[0.418733]			
F-stat: 1.04E+19 [0.0000]; Jarque-Bera: 1.180366 [0.554226]								
2	0.617711*	0.384644*	0.505942*	1.299323*	15.01823	0.866664	N=1	Parzen
	(3.09E-13)	(2.74E-13)	(2.28E-12)	(2.13E-11)	[0.240441]			
F-stat: 1.83E+23 [0.0000]; Jarque-Bera: 1.289898 [0.524689]								
3	0.493977*	0.509876*	0.245582**	3.040958**	10.27355	0.878679	N=1	Bartlett
	(0.001094)	(0.003200)	(0.103794)	(1.349909)	[0.505962]			
F-stat: 60.70630 [0.0000]; Jarque-Bera: 0.925971 [0.629402]								
4	0.574002*	0.422375*	0.189196*	0.614811*	10.25456	0.875039	N=1	Bartlett
	(1.49E-12)	(1.80E-12)	(6.97E-11)	(3.85E-11)	[0.593639]			
F-stat: 2.26E+21 [0.0000]; Jarque-Bera: 0.812205 [0.666242]								
4	0.562395*	0.435233*	0.298755*	1.035506*	12.14849	0.875341	N=1	Parzen
	(3.55E-13)	(4.28E-13)	(2.83E-11)	(6.74E-11)	[0.433829]			
F-stat: 3.06E+22 [0.0000]; Jarque-Bera: 0.827683 [0.661106]								
5	0.470622*	0.533679*	0.253367*	5.831241*	12.19533	0.871234	N=1	Parzen
	(0.011443)	(0.012745)	(0.017812)	(1.338624)	[0.349141]			
F-stat: 7.241397 [0.0071]; Jarque-Bera: 1.073091 [0.584765]								
6	0.567957*	0.429987*	0.250916*	4.207956*	12.22288	0.866706	N=3	Bartlett
	(0.003377)	(0.002393)	(0.005546)	(0.229248)	[0.427950]			
F-stat: 607.0788 [0.0000]; Jarque-Bera: 0.986419 [0.610663]								
6	0.576371*	0.421377*	0.317377*	4.570880*	12.19796	0.863816	N=4	Bartlett
	(0.002856)	(0.000812)	(0.081097)	(0.218825)	[0.429915]			
F-stat: 1896.069 [0.0000]; Jarque-Bera: 1.107395 [0.574820]								
6	0.582274*	0.414975*	0.369884*	4.997754*	12.21590	0.860726	N=5	Bartlett
	(0.001669)	(0.000530)	(0.091673)	(0.125449)	[0.428500]			

F-stat: 22887.58 [0.0000]; Jarque-Bera 1.203008 [0.547987]

Table 4 (*Continued*)

Set	inf(1)	inf(-1)	dlnmc	imp	J-Stat	Adjusted R^2	Weight Updating	Kernel
6	0.590002*	0.408674*	0.155122*	5.758280*	15.19411	0.854747	N=3	
	(0.000921)	(0.000508)	(0.050272)	(0.030560)	[0.230993]			Parzen
F-stat: 204434.3 [0.0000]; Jarque-Bera: 1.299791 [0.522100]								
6	0.602419*	0.396158*	0.447119*	6.356279*	15.38279	0.848870	N=4	Parzen
	(0.001370)	(0.002623)	(0.098503)	(0.030606)	[0.221167]			
F-stat: 2832.129 [0.0000]; Jarque-Bera: 1.557863 [0.458896]								
6	0.610139*	0.388353*	0.742996*	6.825949*	15.62155	0.844253	N=5	Parzen
	(0.007141)	(0.009087)	(0.085204)	(0.310204)	[0.209191]			
F-stat: 198.2687 [0.0000]; Jarque-Bera: 1.757916 [0.415215]								
7	0.561744*	0.438188*	0.531883**	1.322029*	13.98845	0.878309	N=1	Parzen
	(0.001331)	(0.001268)	(0.213562)	(0.421540)	[0.301446]			
F-stat: 2399.534 [0.0000]; Jarque-Bera: 0.829993 [0.660343]								
8	0.525137*	0.469431*	0.482626***	11.17720*	10.12383	0.830962	N=1	Parzen
	(0.025989)	(0.025564)	(0.258916)	(1.535511)	[0.429697]			
F-stat: 1.242107 [0.2692]; Jarque-Bera: 1.101311 [0.576572]								
9	0.582727*	0.413269*	0.649582***	7.304639**	10.35403	0.847588	N=1	Parzen
	(0.035959)	(0.032605)	(0.351390)	(3.019962)	[0.322592]			
F-stat: 6.498722 [0.0132]; Jarque-Bera: 1.428064 [0.489666]								
10	0.567182*	0.428962*	0.560640***	4.129113*	9.571339	0.867487	N=1	Bartlett
	(0.017087)	(0.017271)	(0.334423)	(1.480246)	[0.478870]			
F-stat: 17.32464 [0.0001]; Jarque-Bera: 1.014736 [0.602078]								
10	0.576407*	0.420794*	0.722545***	4.281263**	10.96155	0.865550	N=1	Parzen
	(0.026375)	(0.025762)	(0.402817)	(1.987857)	[0.360522]			
F-stat: 9.504961 [0.0030]; Jarque-Bera: 1.182913 [0.553520]								

Note: Standard errors in parantheses; prob values in brackets; *, ** and *** represent 1%, 5% and 10% significance levels respectively. Newey-West estimates of the covariance matrix (using HAC weighting matrix) with fixed bandwidth value of 4 have been performed. Sample period is 2002Q1-2021Q1. J-stat represents Hansen (1982)'s J-statistic which tests the given model's over-identifying restrictions. Jarque-Bera (JB) represents the normality test statistics. F-stat represents F-statistics for the null hypothesis that $\gamma_b = \gamma_f$.

Figure 1 shows the plots of time varying slope coefficients for the hybrid PC by using both ordinary least squares (OLS) and GMM procedure, and including two measures of the output gap (based on HP-filter and Kalman-filter algorithm) and labor income share as a proxy for real marginal cost (MC). As inferred from Figure 1, when tried to be modelled with the traditional PC model, Turkish inflation dynamics tend to be represented by a flattened PC. However, it may seem very unrealistic, as inflation increases its sensitivity to changing economic conditions to high levels. Thus, the usage of a traditional model does not seem to reflect the reality of the inflation dynamics and results appear as not consistent with the intrinsic nature of PC. To this end, instead of the traditional Hybrid PC, moving from this justification, we decided about formulating distinct PC models in order to handle the Turkish inflation dynamics in a more comprehensive way.

Table 4 presents GMM estimation findings of various specifications for the Model I which is one of the models mentioned in Table 1 (see Table A1 in the Appendix A for performed instrumental variables list). Some of the poor estimation results obtained by not including exchange rate variable as an instrument are presented in Table A2 for the Model I with different instrument sets and Table A3 gives information about the sets of instrumental variables used in Table A2 (see the Appendix A). Table A2 indirectly helps imply the importance of adding the exchange rate variable as an instrument in the Model 1 by showing the results where only the lags of the variables in the main model are used as instrumental variables. Such that although all specifications confirm the validity of overidentifying restrictions, we mostly observe the unexpected negative signs with insignificant coefficient estimates for import price index and real marginal cost.

Amongst numerous model trials, only 19 of them are reported in Table 4 for the sake of saving space. As a prior benchmark for the study, all specifications with different instrument sets seem to satisfy the normality conditions (Jarque-Bera statistic) and overidentifying restrictions (J-stat) for 5% significance level with probability values (well) above 0.05. Overall estimation outcomes are as expected in terms of the variable dlnmc in which coefficients fall below 1 with a positive sign and are significant. Apart from this, forward price-setting behavior -represented by a coefficient magnitude being greater than 0.52- describes the dynamics of inflation more heavily than the backward-looking rule of thumb for all instrument sets excluding set 3 and set 5. For only 1 of the 19 specifications, i.e. the one containing the set 8, the hypothesis that backward and forward behaviors do not differ in magnitude could not be rejected with an F-statistic of 1.242107 [p-value: 0.2692], thus implying the divergent effects that backward- and forward looking behavior components exhibit for the majority of specifications. Without imposing any restriction that the sum of backward and forward coefficients is unity, this appears to have been achieved to a large extent. On the other hand, the coefficient on (logarithmic) real marginal cost lies in the interval 0.155-0.742. Although that interval indicates a wide dispersion within itself, it is seen that the volatility of the import coefficients, considering all model specifications, is more noteworthy. Unreported findings suggest that N-step iterative weight updating procedure renders better findings than iterative to convergence method for instrument sets 1 and 2. Depending on the options except for the iterative to convergence method and Parzen kernel, the results have been in line with expectations for set 3. More specifically, the coefficient on real marginal cost has become insignificant when Parzen kernel is chosen. Although GMM estimation outcomes with the instrument set 4 present significant findings in case HP-filtered output gap takes place as one of the instruments in the set for the Bartlett kernel, however, “imp” tends to take a negative sign and this emerges as a justification for using kalman-filtered output gap as an instrument in Table 4. Additionally, among distinct weight updating procedures, N-step iterative method is the best one for the specifications with the set 6 and the findings obtained especially after 3 iterations seem to conform to the theory of the model.

Dynamic in-sample forecasting performances for the models given in Table 4 are reported in Table 5. Only N-step iterative weight updating procedure results have been given place. According to this, regression outputs have been numarized from 1 to 10. With the aim to determine a sound specification for forecasting, some forecast accuracy measures as well as Theil inequality coefficient are summarized for 19 models and the forecast error has been splitted into three proportions as BIAS, VAR and COV.

Table 5. Evaluation of Dynamic In-Sample Forecasting Performances for Model I

Output	Instr.	Kernel	Weight	RMSE	MAE	MAPE	BIAS	VAR	COV	Theil
1	1	Bartlett	1-step	1.691321	1.211076	11.08354	0.007709	0.048905	0.943386	0.074712
2	1	Parzen	1-step	1.734134	1.235049	11.37743	0.013048	0.037542	0.949410	0.076405
3	2	Bartlett	1-step	1.819534	1.317339	12.08753	0.009250	0.017383	0.973368	0.080139
4	2	Parzen	1-step	1.827437	1.298142	11.95721	0.016063	0.021466	0.962471	0.080328
5	3	Bartlett	1-step	**1.588186**	1.224642	11.41025	0.025961	0.049893	0.924145	**0.069823**
6	4	Bartlett	1-step	1.666821	1.199445	**10.73707**	**0.000135**	0.066502	0.933363	0.074210
7	4	Parzen	1-step	1.646633	**1.193952**	10.77507	0.000204	0.064275	0.935521	0.073166
8	5	Parzen	1-step	2.848001	1.776645	15.53961	0.131755	0.397246	0.470999	0.098479
9	6	Bartlett	3-step	1.813558	1.325903	12.11204	0.003503	0.015067	0.981430	0.080083
10	6	Bartlett	4-step	1.861203	1.359556	12.40090	0.003813	0.010469	0.985718	0.082124
11	6	Bartlett	5-step	1.905926	1.390483	12.65654	0.003410	0.007162	0.989428	0.084075
12	6	Parzen	3-step	2.068547	1.571758	15.15513	0.004498	0.021143	0.974359	0.075676
13	6	Parzen	4-step	2.129984	1.603505	15.64355	0.001962	0.007962	0.990076	0.078202
14	6	Parzen	5-step	2.180801	1.627525	15.99723	0.000970	**0.003194**	**0.995837**	0.080240
15	7	Parzen	1-step	1.648976	1.205509	11.02544	0.004675	0.054146	0.941179	0.072961
16	8	Parzen	1-step	2.447800	1.816689	16.87543	0.015734	0.170693	0.813573	0.087821
17	9	Parzen	1-step	2.149718	1.629962	15.68621	0.001285	0.024882	0.973834	0.078733

18	10	Bartlett	1-step	1.933536	1.464761	13.82794	0.003075	0.046630	0.950296	0.070638
19	10	Parzen	1-step	1.945247	1.475633	14.05570	0.003523	0.032316	0.964160	0.071146

Note. RMSE: Root Mean Squared Error; MAE: Mean Absolute Error; MAPE: Mean Absolute Percentage Error; BIAS: Bias; VAR: Variance; COV: Covariance; Theil: Theil Inequality Coefficient.

Bold values imply the lowest metrics for forecasting evaluation, except for the COV -in which the greatest proportion- is given based on the justification that we would like to get values for BIAS and VAR as close as possible to zero and thus for COV to one.

In Table 5, output 5 is seen to have the smallest Theil inequality coefficient which always takes values between zero and one, therefore, it displays a good fit. However, this should not be taken as a sharp-cut indicator; since all estimations are almost close to zero implying that the given models perform in a similar manner with respect to that metric. Despite this general result, it would be more sensible to choose a model that considers a minimum bias for forecasting and output 6 performing the set 4 records a small systematic bias of 0.0135%. The 4th instrument set also produces the desirable forecast outcomes when MAE and MAPE metrics are taken into account. On the other hand, although the forecasting performance of the output 6 is better with the minimum bias when compared to others; two proportions of Theil inequality, variance and covariance, indicate that the best forecasting performance among 19 models belongs to the one having the instrument set 6, more clearly 14th output [VAR: 0.003194, COV: 0.995837], and moreover with a bias of 0.097% that is close to zero. The poor performance is represented by the model with the instrument set 5 that generates the largest bias (13.2%) and variability (39.7%), thus the smallest covariance proportion (47.1%). In brief, the usage of maximum 6 lags in the instrument set that does not include any output gap variable provides a reliable forecasting for Model I. According to the GMM estimation results for the 14th output, ceteris paribus, a 1% increase in imports will give rise to approximately an increase of 6.8% in inflation and forward-looking price-setting behaviors has become predominant with a coefficient value of 0.610139 on the one-quarter ahead expected inflation. Figure 2 presents the actual and dynamic in-sample inflation forecast values based on the output 14 for Model I and it can be said that the forecasts are largely close to the actual observed values.

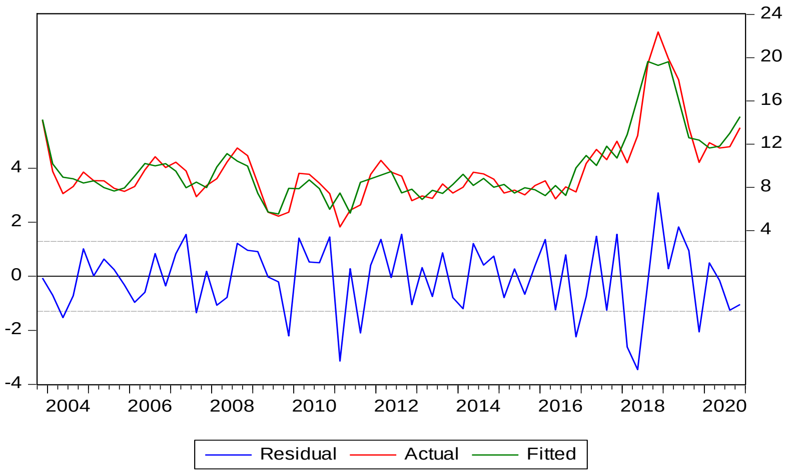

Figure 2. Observed versus dynamic in-sample inflation forecast values for Model I

Table 6. GMM Estimation Results of the Model II

Set	inf(1)	inf(-1)	outgap	imp	J-Stat	Adjusted R^2	Weight Updating	Kernel
1	0.597598*	0.403551*	0.788680*	0.803480*	12.12156	0.869965	N=1	Bartlett
	(7.45E-13)	(8.70E-13)	(5.85E-11)	(7.51E-11)	[0.435967]			
F-stat: 1.17E+20 [0.0000]; Jarque-Bera: 1.009887 [0.603540]								
1	0.617768*	0.384680*	1.398132*	0.294385*	14.36188	0.867100	N=1	Parzen
	(3.55E-12)	(3.43E-12)	(1.04E-11)	(1.07E-10)	[0.278199]			
F-stat: 6.73E+20 [0.0000]; Jarque-Bera: 1.088660 [0.580231]								
2	0.582957*	0.417362*	0.482408*	1.714600*	11.83228	0.869579	N=1	Bartlett
	(9.84E-13)	(9.20E-13)	(1.42E-11)	(5.44E-11)	[0.459242]			
F-stat: 8.05E+21 [0.0000]; Jarque-Bera: 0.991661 [0.609065]								
2	0.599684*	0.401583*	0.828650*	1.554274*	14.06201	0.866892	N=1	Parzen
	(8.45E-13)	(7.56E-13)	(1.49E-11)	(1.16E-10)	[0.296766]			
F-stat: 1.64E+22 [0.0000]; Jarque-Bera: 1.084973 [0.581301]								
3	0.605432*	0.395856*	1.625843*	2.079553*	14.20377	0.862262	N=1	Parzen
	(9.80E-13)	(1.28E-12)	(1.54E-10)	(2.83E-10)	[0.287886]			
F-stat: 9.37E+21 [0.0000]; Jarque-Bera: 1.143061 [0.564661]								
3	0.581450*	0.418329*	0.865252*	2.999175*	12.01490	0.864189	N=1	Bartlett
	(1.90E-12)	(1.57E-12)	(2.46E-10)	(4.63E-10)	[0.444484]			
F-stat: 1.25E+22 [0.0000]; Jarque-Bera: 1.043363 [0.593522]								
4	0.447521*	0.550003*	0.512245*	3.697129*	11.01356	0.870191	Iterative to Conv.	Parzen
	(4.24E-13)	(4.57E-13)	(5.77E-11)	(2.94E-11)	[0.527757]			

F-stat: 1.44E+22 [0.0000]; Jarque-Bera: 0.203789 [0.903125]								
4	0.553693*	0.445297*	-0.576788*	0.514401*	9.843506	0.877588	N=1	Bartlett
	(5.61E-11)	(4.85E-11)	(1.83E-08)	(1.94E-09)	[0.629688]			
F-stat: 1.14E+18 [0.0000]; Jarque-Bera: 0.809568 [0.667121]								
4	0.546872*	0.453483*	-0.901228*	0.215533*	11.65111	0.878921	N=1	Parzen
	(7.71E-12)	(1.03E-11)	(2.03E-09)	(1.39E-09)	[0.474091]			
F-stat: 2.86E+19 [0.0000]; Jarque-Bera: 0.823521 [0.662483]								
5	0.587672*	0.412423*	0.938474	-3.444791	11.73649	0.883180	N=1	Bartlett
	(0.023092)	(0.057877)	(4.387916)	(10.54024)	[0.467068]			
F-stat: 4.972880 [0.0292]; Jarque-Bera: 0.565251 [0.753802]								
5	0.596188*	0.404964*	1.494354	-3.534839	13.17013	0.881888	N=1	Parzen
	(0.026092)	(0.004225)	(2.891298)	(5.030039)	[0.356797]			
F-stat: 42.23296 [0.0000]; Jarque-Bera: 0.600726 [0.740549]								
5	0.551234*	0.434605*	23.80205*	2.134142*	10.33147	0.775341	Iterative	Parzen
	(0.010794)	(0.002628)	(5.788394)	(0.298753)	[0.586905]		to Conv.	
F-stat: 80.15373 [0.0000]; Jarque-Bera: 0.253833 [0.880807]								

Table 6 (*Continued*)

Set	inf(1)	inf(-1)	outgap	imp	J-Stat	Adjusted R^2	Weight Updating	Kernel
6	0.232472*	0.762480*	8.675557*	22.85093*	5.397557	0.692166	Iterative	Bartlett
	(0.021617)	(0.023627)	(3.265142)	(2.496331)	[0.863090]		to Conv.	
F-stat: 147.1290 [0.0000]; Jarque-Bera: 4:768889 [0.092140]								
6	0.278352*	0.716120*	7.453213*	22.29887*	5.705472	0.710629	Iterative	Parzen
	(0.021412)	(0.024572)	(2.508141)	(2.693145)	[0.839371]		to Conv.	
F-stat: 98.24273 [0.0000]; Jarque-Bera: 3.415116 [0.181308]								
6	0.502872*	0.489261*	5.813833	9.172467*	8.017750	0.834065	N=1	Bartlett
	(0.018392)	(0.017163)	(3.691192)	(1.503686)	[0.627103]			
F-stat: 0.156143 [0.6940]; Jarque-Bera: 0.431944 [0.805758]								
6	0.505166*	0.487140*	6.266432	9.234706*	9.308298	0.831966	N=1	Parzen
	(0.023974)	(0.022874)	(3.984108)	(1.669836)	[0.503116]			
F-stat: 0.157661 [0.6926]; Jarque-Bera: 0.426570 [0.807926]								
7	0.534378*	0.453812*	8.249317***	7.983268**	8.053373	0.828766	N=2	Bartlett
	(0.025074)	(0.022124)	(4.504250)	(3.934379)	[0.528777]			
F-stat: 3.098625 [0.0831]; Jarque-Bera: 0.416077 [0.812176]								
8	0.538553*	0.453908*	7.578377**	4.139790**	8.509633	0.852941	N=1	Bartlett
	(0.022762)	(0.015672)	(3.759658)	(1.683044)	[0.579185]			
F-stat: 5.201154 [0.0259]; Jarque-Bera: 0.398032 [0.819537]								
8	0.538521*	0.454183*	8.174800**	4.254451	9.767305	0.850469	N=1	Parzen
	(0.036358)	(0.028560)	(4.043987)	(2.595400)	[0.461140]			

F-stat: 1.797852 [0.1846]; Jarque-Bera: 0.385040 [0.824878]								
9	0.474594*	0.524123*	7.299835*	5.452538*	9.811860	0.871725	N=1	Bartlett
	(0.010219)	(0.009785)	(1.746164)	(1.999815)	[0.547386]			
F-stat: 7.049175 [0.0099]; Jarque-Bera: 0.276568 [0.870851]								
9	0.461952*	0.537406*	8.245246*	6.162597	11.67307	0.866778	N=1	Parzen
	(0.017920)	(0.011796)	(2.951218)	(4.206107)	[0.388712]			
F-stat: 7.165147 [0.0094]; Jarque-Bera: 0.218985 [0.896289]								
9	0.344970*	0.658743*	11.35134*	8.563019*	8.771908	0.840434	Iterative to Conv.	Bartlett
	(0.013959)	(0.011873)	(2.892913)	(1.847567)	[0.642937]			
F-stat: 162.3317 [0.0000]; Jarque-Bera: 0.419030 [0.810977]								
9	0.343187*	0.658726*	9.093076**	14.00998*	9.329152	0.817915	Iterative to Conv.	Parzen
	(0.029216)	(0.018101)	(4.236780)	(4.394995)	[0.591539]			
F-stat: 47.25735 [0.0000]; Jarque-Bera: 1.288179 [0.525140]								
9	0.423954*	0.575546*	10.94853*	7.034777***	10.72556	0.855749	N=2	Parzen
	(0.020659)	(0.012150)	(3.588154)	(4.192035)	[0.466533]			
F-stat: 23.44507 [0.0000]; Jarque-Bera: 0.069678 [0.965761]								

Table 6 (*Continued*)

Sets	inf(1)	inf(-1)	kalman	imp	J-Stat	Adjusted R^2	Weight Updating	Kernel
$2^{\#}$	0.613425*	0.388842*	-4.41E-09*	-2.232544*	11.32565	0.878942	N=1	Bartlett
	(1.23E-11)	(1.24E-11)	(5.10E-19)	(6.35E-10)	[0.501236]			
F-stat: 2.06E+20 [0.0000]; Jarque-Bera: 0.849615 [0.653896]								
$2^{\#}$	0.627412*	0.376412*	-4.25E-09*	-2.520072*	13.56461	0.877359	N=1	Parzen
	(3.02E-11)	(2.99E-11)	(2.70E-19)	(5.94E-10)	[0.329371]			
F-stat: 1.64E+19 [0.0000]; Jarque-Bera: 0.935489 [0.626413]								
$2^{\#}$	0.840646*	0.154496*	-8.40E-10*	-9.980633*	8.496914	0.825975	Iterative to Conv.	Bartlett
	(3.99E-12)	(3.64E-12)	(1.36E-19)	(2.03E-10)	[0.745193]			
F-stat: 5.74E+23 [0.0000]; Jarque-Bera: 6.716367 [0.034798]								
$2^{\#}$	0.875550*	0.115470*	-2.29E-09*	-12.76815*	10.28154	0.812151	Iterative to Conv.	Parzen
	(2.71E-11)	(2.50E-11)	(3.21E-19)	(9.55E-10)	[0.591276]			
F-stat: 3.16E+20 [0.0000]; Jarque-Bera: 8.108405 [0.017349]								
$4^{\#}$	0.413451*	0.582422*	1.30E-09*	13.78077*	10.22084	0.819945	Iterative to Conv.	Parzen
	(4.03E-12)	(3.86E-12)	(4.24E-19)	(2.73E-10)	[0.596593]			
F-stat: 4.88E+20 [0.0000]; Jarque-Bera: 1.618484 [0.445195]								
$4^{\#}$	0.574007*	0.424222*	-6.40E-09*	-0.607587*	10.66566	0.880863	N=1	Bartlett
	(1.49E-11)	(4.87E-11)	(1.18E-16)	(1.52E-09)	[0.557768]			
F-stat: 2.09E+19 [0.0000]; Jarque-Bera: 0.805902 [0.668345]								
$4^{\#}$	0.560756*	0.439475*	-4.14E-09*	0.197925*	12.86969	0.879735	N=1	Parzen
	(2.03E-13)	(5.97E-13)	(1.09E-18)	(2.71E-10)	[0.378583]			

	F-stat: 7.06E+22 [0.0000]; Jarque-Bera: 0.806214 [0.668240]							
7#	0.590518*	0.405870*	4.37E-11	4.554199	9.255473	0.860701	N=1	Bartlett
	(0.055634)	(0.038186)	(1.09E-08)	(14.00748)	[0.414034]			
	F-stat: 9.504961 [0.0030]; Jarque-Bera: 1.182913 [0.553520]							
7#	0.590550*	0.406078*	2.02E-10	5.564090	10.76991	0.855215	N=1	Parzen
	(0.089288)	(0.067190)	(1.07E-08)	(14.79654)	[0.291811]			
	F-stat: 1.478254 [0.2284]; Jarque-Bera: 1.211872 [0.545564]							
8#	0.578971*	0.417783*	-1.38E-09	1.495809	9.216665	0.876229	N=1	Bartlett
	(0.078792)	(0.054628)	(5.59E-09)	(12.23058)	[0.511672]			
	F-stat: 1.551324 [0.2174]; Jarque-Bera: 0.836324 [0.658255]							
8#	0.578136*	0.419064*	-1.23E-09	2.318308	10.82980	0.873439	N=1	Parzen
	(0.136329)	(0.093668)	(2.39E-09)	(17.96145)	[0.370931]			
	F-stat: 0.508060 [0.4785]; Jarque-Bera: 0.891729 [0.640271]							
9#	0.515411*	0.487211*	-2.71E-09	3.555768*	10.06751	0.891173	N=1	Bartlett
	(0.006587)	(0.006883)	(2.42E-09)	(1.164770)	[0.524325]			
	F-stat: 0.083898 [0.7730]; Jarque-Bera: 0.621468 [0.732909]							

Table 6 (*Continued*)

9#	0.505521*	0.498592*	-2.55E-09	3.493151*	11.53479	0.891027	N=1	Parzen
	(0.007357)	(0.006399)	(2.51E-09)	(1.131808)	[0.399606]			
	F-stat: 0.348981 [0.5567]; Jarque-Bera: 0.639238 [0.726426]							

Note: Standard errors in parantheses; prob values in brackets; *, ** and *** represent 1%, 5% and 10% significance levels respectively. Newey-West estimates of the covariance matrix (using HAC weighting matrix) with fixed bandwidth value of 4 have been performed. Sample period is 2002Q1-2021Q1. J-stat represents Hansen (1982)'s J-statistic which tests the given model's over-identifying restrictions. Jarque-Bera (JB) represents the normality test statistics. F-stat represents F-statistics for the null hypothesis that $\gamma_b = \gamma_f$. Instrument sets including the notation # represent the sets where "kalman" series takes place as an instrument instead of "outgap". "Iterative to Conv." denotes iterative to convergence weight updating procedure.

Table 6 presents GMM estimation results of various specifications for the Model II (see Table A4 in the Appendix A for instrumental variables list). The difference of Model 2 from Model 1 is that the output gap is used instead of the labor income share as a proxy for real marginal cost. Two measures of the output gap that are based on both HP-filter and KF algorithm have been used in the analysis.

Figure 3 reveals a comparison of actual output (GDP) and potential output (GDP_POTF) for the given time period. The potential output presented in the state-space model (12) has been estimated by using KF algorithm. Although it represents an increasing trend, potential output experienced obvious large fluctuations after the 1st quarter of 2020. Especially, amid uncertainties surrounding the epidemic time, increased credit-driven momentum also contributed to soaring economic activity in the 3rd quarter of 2020 by far exceeding the full-capacity output which crashes to the bottom. This created a huge divergence in output gap resulting in positive levels and then the output gap switched over the negative territory in the late 2020. This negativity in turn reversed with upswings recorded towards the 1st quarter of 2021 and subsequently again positive output gap was experienced.

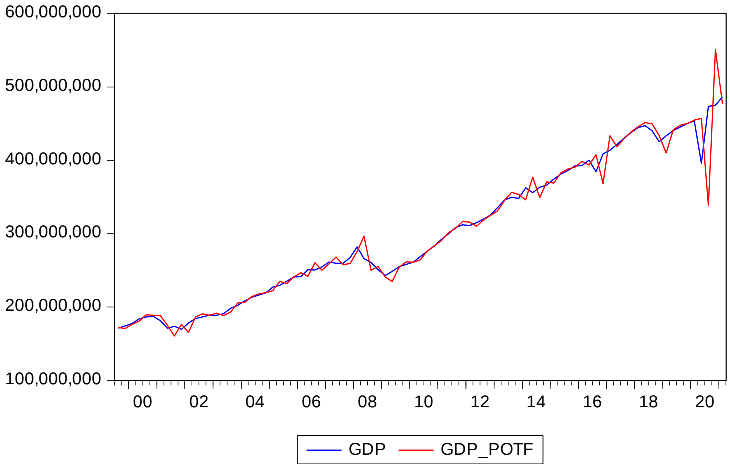

Figure 3. GDP and potential GDP based on Kalman filter (KF)

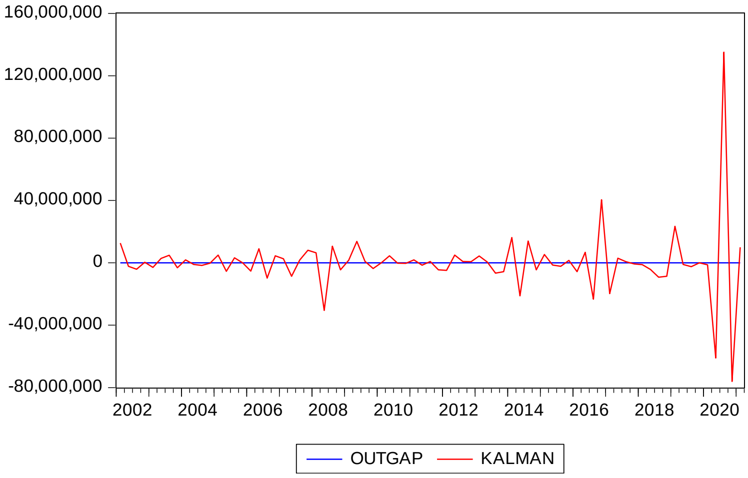

Figure 4. Output gap indicators

Figure 4, shows the comparison of output gap indicators based on both HP (OUTGAP) and KF (KALMAN) filters. An output gap is desirable as being around the zero, implying a sound picture of the economy and two indicators for output gap seem to satisfy their zero means on average as a crucial characteristic of a steady-state economy.

As for Table 6 findings, Hansen (1982)'s over-identifying restrictions based on Hansen (1982)'s test are valid for all specifications. Regression results have been reported using two measures of output gap. “kalman” regressor was used for totally 13 specifications, the coefficient sign of import price index variable is minus for 5 specifications. When the output gap is calculated using the kalman filter, although the coefficient magnitude is close to zero in most cases, it cannot be interpreted due to its meaningless, and the coefficient sign is also negative, which is not in line with the expectations. We cannot reject the hypothesis that backward and forward behaviors do not differ in magnitude for the 5% significance level in those certain cases related with only 3 out of totally 9 sets: More specifically, they are set 6 (1-step iterative procedure + Bartlett & Parzen kernels), set 7 and set 8 (1-step iterative procedure + Parzen kernel). Thus, considering the remaining 6 instrument sets, it is concluded that backward and forward-looking behaviors differ significantly in terms of magnitude in Model 2 predominantly. In 16 of the 24 specifications in which the HP-filtered output gap variable is included as a regressor, all coefficients have been found to be significant and in line with expectations in terms of signs (i.e. coefficients are greater than zero for "imp" and "outgap" regressors). Of these 16 models in which all coefficients are significant, forward pricing behaviour is predominant in 9 and backward pricing behaviour in 7. Retrospective dominant behaviour has been mostly detected when iterative to convergence weight updating procedure is used. Considering the 5% significance level, the null hypothesis of $\gamma_b = \gamma_f$ has been rejected in all but 1 of these 16 regression specifications, and the significant difference in the magnitude of the coefficients regarding the pricing behaviors for set 7 has been valid at the 10% significance level. The "outgap" coefficient has been found to be less than 1 for 5 specifications belonging to only 4 instrument variable sets (set1: 0.789, set2: 0.482 [Bartlett], set2: 0.829 [Parzen], set3: 0.865, set4: 0.512), and the backward behavior becomes dominant for only set 4 where iterative to convergence weight procedure is used. The common feature of the 5 outputs where the outgap coefficient is less than 1 in magnitude is that, unlike the other regression outputs, higher order lags such as the 7th and 8th lags of inflation are incorporated into the instrument set. That is, we obtain outgap coefficient values as less than 1 only by using high lags of inflation as instrumental variables. In addition, we can say that the N-step weight updating method is more preferable than the iterative to convergence method as it gives more consistent results. As a matter of fact, as a result of using the iterative to convergence method for set5, the coefficient of HP-filtered output gap has taken a rather large value (23.80205), contrary to the general findings of the other specifications.

Table 7. Evaluation of Dynamic In-Sample Forecasting Performances for Model II

Output	Inst	Kernel	Weight	RMSE	MAE	MAPE	BIAS	VAR	COV	Theil
1	**1**	**Bartlett**	**1-step**	**1.805524**	**1.355234**	**13.10388**	0.006952	0.009258	0.983790	**0.066197**
2	**1**	**Parzen**	**1-step**	1.833669	1.356233	13.29585	0.004161	**0.000001**	**0.995838**	0.067524
3	**2**	**Bartlett**	**1-step**	1.835522	1.385087	13.22497	0.010294	0.029825	0.959882	0.067031
4	**2**	**Parzen**	**1-step**	1.849474	1.388055	13.43304	0.007075	0.008613	0.984311	0.067800
5	**3**	**Bartlett**	**1-step**	1.910858	1.445744	13.77027	0.009353	0.032918	0.957730	0.069744

6	**3**	**Parzen**	**1-step**	1.908061	1.428219	13.87723	0.005335	0.004559	0.990106	0.070042
7	**4**	**Parzen**	**Conv.**	2.855402	1.767514	14.75683	0.078181	0.431070	0.490748	0.099223
8	**4#**	**Parzen**	**Conv.**	3.624454	2.220769	19.04983	0.092423	0.489697	0.417880	0.123195
9	**6**	**Bartlett**	**Conv.**	8.550535	5.139262	43.48746	0.200751	0.514898	0.284351	0.252823
10	**6**	**Parzen**	**Conv.**	6.822097	4.115346	34.74005	0.165817	0.549139	0.285045	0.211102
11	**7**	**Bartlett**	**2-step**	2.421036	1.860415	17.60366	**0.000574**	0.086241	0.913185	0.088355
12	**8**	**Bartlett**	**1-step**	2.169504	1.630519	15.16509	0.000816	0.092801	0.906384	0.078973
13	**9**	**Bartlett**	**1-step**	2.685387	1.793146	15.99338	0.068517	0.351427	0.580056	0.094116
14	**9**	**Parzen**	**2-step**	3.500369	2.295121	20.34291	0.104259	0.454682	0.441059	0.119323
15	**9**	**Bartlett**	**Conv.**	5.364605	3.312119	27.64715	0.181054	0.506367	0.312579	0.172263
16	**9**	**Parzen**	**Conv.**	5.367068	3.286688	27.61187	0.176917	0.524600	0.298483	0.172207

Note. RMSE: Root Mean Squared Error; MAE: Mean Absolute Error; MAPE: Mean Absolute Percentage Error; BIAS: Bias; VAR: Variance; COV: Covariance; Theil: Theil Inequality Coefficient. "*Conv.*" represents the iterative to convergence weight updating procedure.

In addition, also when the kalman-filtered output gap is used in Model 2 as a regressor, the iterative to convergence method has produced unexpected results in terms of not providing the normality assumption at the 5% significance level for set2 and obtaining negative-signed coefficients for output gap and import price index variables.

Dynamic in-sample forecasting performances for some of the Model 2 specifications are given in Table 7. Bold values imply the lowest metrics for forecasting evaluation, excluding the COV component which gives the highest value. According to the Theil inequality coefficient and RMSE, MAE & MAPE metrics, first regression output is seen to exhibit a good fit. Since close-to-zero coefficients are also observed for the other regression outputs, it would be more suitable to examine also BIAS, VAR and COV components before deciding about a possible reliable specification for Model 2. Although the minimum systematic bias (0.0574%) belongs to output 11 where the instrument set 7 is performed in the analysis, VAR [0.000001] and COV [0.995838] components indicate the output 2 where the instrument set 1 is used as the best forecasting performance model. However, when this specification is evaluated, it is seen that the output gap coefficient (1.398132) is not less than 1 and the magnitude of import price index coefficient takes a really low value of 0.294385. As a conclusion, it can be said that in the models selected for forecasting, the forward and backward behaviour coefficients differ significantly from one another in explaining inflation dynamics for the 5% significance level, and forward-looking pricing behaviour is dominant in Model 2.

4. CONCLUSION

This paper provides theoretical and empirical augmentations of the traditional hybrid PC model in a way to account for inflation dynamics in Turkey by using GMM procedure that is widely used to estimate rational-expectations models. More obviously, we estimate two variants of the traditional hybrid PC model based on the observed value π_{t+1} to approximate the future expected term $E_t\pi_{t+1}$ by taking rational expectations as basis. In order to check whether instruments are valid, we employed J-statistics to test the validity of over-identifying restrictions in the estimated models (for instruments exogeneity). Undoubtedly, the role of exchange rate in this research as an indicator of supply-side shocks is undeniable for Model I and Model II. Besides the original main regression variables, adding also nominal effective exchange rate series into the instrumental variables has been superior to the results that are generated only with the usage of main regression variables as instrumentals.

To summarize for Model I, different trials have shown that results are very sensitive to the instrumental variable choices so that many unreported findings have produced the unexpected signs with insignificant coefficient estimates. Besides, in the general sense, forward price-setting behavior becomes predominant for Model I and apart from the volatile import coefficients, a reliable forecasting model appears as the one which does not include any output gap measure in the instrument set. Moreover, other things being equal, the model reveals an increase of 6.8% in inflation approximately for a 1% increase in import. If necessary to evaluate the Model 2 results, the usage of the HP-filtered output gap as a regressor has produced better results than the output gap being calculated with KF algorithm. As a matter of fact, while the dominant pricing behavior in Model 2 is forward-looking; all the findings have been found to be significant and coefficient signs have been in line with the expectations for the only one output in which set 4 is used out of 13 outputs. We can say that the results show great variability for Model 2 and the iterative to convergence method does not generate desirable results, the usage of "kalman" series as an explanatory variable renders a meaningless output gap, and even if it makes the output gap meaningful, the results do not conform with the theoretical recommendations due to the finding of a negative coefficient. Besides, also when the best forecasting performance output is considered according to the VAR and COV components, the output gap coefficient is greater than 1 and the magnitude of import price index coefficient takes a very low value.

To sum up, this study evaluates two variants of hybrid NKPC model that takes import price index as basis depending on the examination of forecasting performances of two different models, and it is expected to guide the researchers for the quest of a suitable model with respect to explaining Turkish inflation dynamics based on the different applicational components.

APPENDIX A

Table A1. Sets of Instrumental Variables for Model I

Sets	Instrumental Variables

1	inf(-1) inf(-3) inf(-4) inf(-5) inf(-7) inf(-8) dlnmc(-1) dlnmc(-2) dlnmc(-4) imp(-1) imp(-2) imp(-3) imp(-5) dexch(-1) dexch(-2)
2	inf(-1) inf(-3) inf(-4) inf(-5) inf(-7) inf(-8) dlnmc(-1) dlnmc(-2) dlnmc(-4) imp(-1) imp(-2) imp(-3) imp(-5) dexch(-1) dexch(-5)
3	inf(-1) inf(-2) inf(-3) inf(-4) dlnmc(-4) dlnmc(-6) dlnmc(-8) imp(-1) imp(-3) imp(-4) imp(-5) dexch(-3) dexch(-5) dexch(-10)
4	kalman(-2) inf(-1) inf(-3) inf(-4) inf(-5) inf(-7) dlnmc(-1) dlnmc(-4) dlnmc(-7) imp(-1) imp(-4) imp(-7) dexch(-2) dexch(-4) dexch(-5)
5	inf(-1) inf(-4) inf(-5) dlnmc(-1) dlnmc(-4) dlnmc(-6) dexch(-1) dexch(-2) dexch(-4) dexch(-5) dexch(-6) dexch(-8) imp(-1) imp(-10)
6	inf(-1) inf(-3) inf(-4) inf(-6) dlnmc(-1) dlnmc(-5) dlnmc(-6) dexch(-1) dexch(-2) dexch(-5) dexch(-6) imp(-1) imp(-3) imp(-5) imp(-6)
7	inf(-1) inf(-2) inf(-3) inf(-4) dlnmc(-1) dlnmc(-5) dlnmc(-6) dexch(-1) dexch(-2) outgap(-1) outgap(-5) imp(-1) imp(-3) imp(-5) imp(-6)
8	inf(-1) inf(-2) inf(-3) inf(-4) dlnmc(-1) dlnmc(-5) dlnmc(-6) outgap(-1) outgap(-3) outgap(-4) outgap(-5) dexch(-1) dexch(-2)

Table A1 (*Continued*)

9	inf(-1) inf(-2) inf(-3) inf(-4) dlnmc(-1) dlnmc(-5) dlnmc(-6) outgap(-1) outgap(-3) outgap(-4) outgap(-5) dexch(-1)
10	inf(-1) inf(-2) inf(-3) inf(-4) dlnmc(-1) dlnmc(-5) dlnmc(-6) outgap(-1) outgap(-3) outgap(-4) outgap(-5) dexch(-1) dexch(-6)

Table A2. Poor GMM Estimations of the Model 1 Including Only Original Variables as Instrumentals

Sets	inf(1)	inf(-1)	dlnmc	imp	Prob (J-Stat)	Adjusted R^2	N-step
1	0.585845*	0.422941*	0.417254*	-6.726688*	0.559298	0.899665	1
2	0.559594*	0.439336*	1.848014	3.006501	0.162897	0.884954	1
3	0.592656*	0.416622*	0.381892*	-7.019324*	0.644749	0.899180	1
4	0.639380*	0.362998*	0.741819*	-3.778438*	0.654261	0.879326	1
5	0.639984*	0.357736*	0.218823	0.689125	0.422237	0.867278	1
6	0.658821*	0.334761*	0.033384	0.188468	0.487699	0.863040	1

7	0.652030*	0.350982*	0.453923*	-2.724429*	0.628856	0.872037	1
8	0.639609*	0.363935*	0.506331*	-0.623979	0.517203	0.868988	1
9	0.624850*	0.379109*	0.037867	1.440715	0.411149	0.864172	1
10	0.652486*	0.351047*	0.110750	1.865604	0.565082	0.855640	1
11	0.350746*	0.637417*	0.865453	33.62712*	0.743808	0.595513	1
12	0.511479*	0.478521*	0.291830	12.70478	0.459163	0.819737	1
13	0.448504*	0.541339*	-0.870581	27.66779**	0.521419	0.651133	15
14	0.816010*	0.185751*	1.000302***	-12.15658	0.276897	0.838997	15

Note. *, ** and *** represent 1%, 5% and 10% significance levels respectively (Since the general results are the same, in order to save space only the results based on N-step iterative weight updating procedure and Bartlett kernel are reported here). Estimation weighting matrix, standard errors and covariance computed using HAC weighting matrix (Newey-West fixed bandwidth = 4).

Table A3. Sets of Instrumental Variables Used in Table A2

Sets	Instrumental Variables
1	inf(-1) inf(-2) inf(-3) inf(-4) inf(-5) dlnmc(-1) dlnmc(-2) dlnmc(-3) dlnmc(-4) imp(-1) imp(-2) imp(-3) imp(-4) imp(-5)
2	inf(-1) inf(-2) dlnmc(-1) dlnmc(-3) dlnmc(-5) imp(-2) imp(-5)
3	inf(-1) inf(-2) inf(-3) inf(-4) inf(-5) dlnmc(-1) dlnmc(-2) dlnmc(-3) dlnmc(-4) dlnmc(-5) imp(-1) imp(-2) imp(-3) imp(-4) imp(-5)
4	inf(-1) inf(-2) inf(-3) dlnmc(-1) dlnmc(-2) dlnmc(-3) dlnmc(-4) dlnmc(-5) dlnmc(-6) imp(-1) imp(-2) imp(-3) imp(-4) imp(-5)
5	inf(-1) inf(-2) dlnmc(-1) dlnmc(-2) dlnmc(-3) dlnmc(-4) dlnmc(-5) dlnmc(-6) imp(-1) imp(-2) imp(-3)
6	inf(-1) inf(-2) dlnmc(-1) dlnmc(-2) dlnmc(-3) dlnmc(-4) dlnmc(-5) dlnmc(-6) imp(-1)
7	inf(-1) inf(-2) inf(-4) inf(-6) dlnmc(-1) dlnmc(-2) dlnmc(-3) dlnmc(-4) dlnmc(-5) dlnmc(-6) dlnmc(-7) imp(-1) imp(-3) imp(-5) imp(-7)

8	inf(-1) inf(-2) inf(-4) inf(-6) dlnmc(-1) dlnmc(-3) dlnmc(-4) dlnmc(-5) dlnmc(-6) dlnmc(-7) imp(-1) imp(-3) imp(-5) imp(-7)
9	inf(-1) inf(-2) inf(-4) inf(-6) dlnmc(-1) dlnmc(-5) dlnmc(-6) dlnmc(-7) dlnmc(-8) imp(-1) imp(-3) imp(-5) imp(-7)
10	inf(-1) inf(-2) inf(-3) inf(-6) dlnmc(-1) dlnmc(-2) dlnmc(-5) dlnmc(-6) dlnmc(-7) dlnmc(-8) imp(-1) imp(-3) imp(-5) imp(-7)
11	inf(-1) dlnmc(-1) dlnmc(-4) dlnmc(-8) imp(-1) imp(-2) imp(-5)
12	inf(-1) dlnmc(-1) dlnmc(-4) dlnmc(-8) imp(-1)
13	inf(-1) inf(-8) dlnmc(-2) dlnmc(-4) dlnmc(-6) imp(-1) imp(-5)
14	inf(-1) inf(-3) inf(-8) dlnmc(-2) dlnmc(-4) dlnmc(-6) imp(-1) imp(-5)

Table A4. Sets of Instrumental Variables for Model II

Sets	Instrumental Variables
1	inf(-1) inf(-3) inf(-4) inf(-5) inf(-7) inf(-8) outgap(-1) outgap(-2) outgap(-3) outgap(-4) imp(-1) imp(-2) imp(-3) imp(-5) dexch(-1)
2	inf(-1) inf(-3) inf(-4) inf(-5) inf(-7) inf(-8) outgap(-1) outgap(-2) outgap(-4) imp(-1) imp(-2) imp(-3) imp(-5) dexch(-1) dexch(-2)
3	inf(-1) inf(-3) inf(-4) inf(-5) inf(-7) inf(-8) outgap(-1) outgap(-2) outgap(-4) imp(-1) imp(-2) imp(-3) imp(-5) dexch(-1) dexch(-5)
4	inf(-1) inf(-3) inf(-4) inf(-5) inf(-7) outgap(-2) dlnmc(-1) dlnmc(-4) dlnmc(-7) imp(-1) imp(-4) imp(-7) dexch(-2) dexch(-4) dexch(-5)
5	inf(-1) inf(-3) inf(-4) inf(-6) outgap(-1) outgap(-5) outgap(-6) imp(-1) imp(-3) imp(-5) imp(-6) dexch(-1) dexch(-2) dexch(-5) dexch(-6)
6	inf(-1) inf(-2) inf(-3) inf(-4) outgap(-1) outgap(-3) outgap(-4) outgap(-5) dlnmc(-1) dlnmc(-5) dlnmc(-6) dexch(-1) dexch(-2)

7	inf(-1) inf(-2) inf(-3) inf(-4) outgap(-1) outgap(-3) outgap(-4) outgap(-5) dlnmc(-1) dlnmc(-5) dlnmc(-6) dexch(-1)
8	inf(-1) inf(-2) inf(-3) inf(-4) outgap(-1) outgap(-3) outgap(-4) outgap(-5) dlnmc(-1) dlnmc(-5) dlnmc(-6) dexch(-1) dexch(-6)
9	inf(-1) inf(-2) inf(-3) inf(-4) inf(-5) outgap(-1) outgap(-3) outgap(-4) outgap(-5) dlnmc(-1) dlnmc(-3) dlnmc(-5) dexch(-1) dexch(-2)

REFERENCES

Bari, B., & Şıklar, İ. (2021). An estimation of the open economy hybrid new Keynesian Phillips curve for Turkey. Fiscaoeconomia, 5(3), 1081-1100.

Baser, S., Kucuk, H., & Ogunc, F. (2013). Inflation dynamics in Turkey: In pursuit of a domestic cost measure (No. 1311). Research and Monetary Policy Department, Central Bank of the Republic of Turkey.

Baum, C. F., Schaffer, M. E., & Stillman, S. (2003). Instrumental variables and GMM: Estimation and testing. The Stata Journal, 3(1), 1-31.

Clark, P. K. (1987). The cyclical component of US economic activity. The Quarterly Journal of Economics, 102(4), 797-814.

D'Amato, L., & Garegnani, M. L. (2009). Studying the short-run dynamics of inflation: Estimating a hybrid new-keynesian Phillips Curve for Argentina (1993-2007) (Working Paper No. 2009/40), Banco Central de la República Argentina (BCRA).

Du Plessis, S., & Burger, R. (2006, October). A New Keynesian Phillips Curve for South Africa. In SARB conference.

Dupuis, D. (2004). The new Keynesian hybrid Phillips curve: An assessment of competing specifications for the United States (No. 2004-31). Bank of Canada.

Eruygur, A. (2011). Analysis of inflation dynamics in Turkey: a New Keynesian Phillips curve approach.

Faff, R., & Gray, P. (2006). On the estimation and comparison of short-rate models using the generalised method of moments. Journal of Banking & Finance, 30(11), 3131-3146.

Furuoka, F. (2017). A new approach to testing unemployment hysteresis. Empirical economics, 53(3), 1253-1280.

Furuoka, F., Pui, K. L., Chomar, M. T., & Nikitina, L. (2021). Is the Phillips curve disappearing? Evidence from a new test procedure. Applied Economics Letters, 28(6), 493-500.

Gali, J., & Gertler, M. (1999). Inflation dynamics: A structural econometric analysis. Journal of monetary Economics, 44(2), 195-222.

Guay, A., & Pelgrin, F. (2004). The US new Keynesian Phillips curve: An empirical assessment (Working Paper No. 2004-35). Bank of Canada.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. Econometrica: Journal of the Econometric Society, 50(4), 1029-1054.

Hansen, L. P., & Sargent, T. J. (1980). Formulating and estimating dynamic linear rational expectations models. Journal of Economic Dynamics and control, 2, 7-46.

Harvey, A. C. (1985). Trends and cycles in macroeconomic time series. Journal of Business & Economic Statistics, 3(3), 216-227.

Imbens, G. W. (2002). Generalized method of moments and empirical likelihood. Journal of Business & Economic Statistics, 20(4), 493-506.

Johnston, J., & Dinardo, J. (1997). Econometric methods (4th ed.). McGraw-Hill Companies, Inc.

Jondeau, E., & Le Bihan, H. (2005). Testing for the new Keynesian Phillips curve. Additional international evidence. Economic Modelling, 22(3), 521-550.

Korkmaz, S. (2010). Yeni Keynesyen Phillips Eğrisinin Türkiye'ye Uygulanması. Uluslararası Yönetim İktisat ve İşletme Dergisi, 6(11), 141-162.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?. Journal of Econometrics, 54(1-3), 159-178.

MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. Journal of applied econometrics, 11(6), 601-618.

Narayan, S., Cirikisuva, S., & Naivutu, R. (2023). A hybrid NKPC inflation model for the small Island state of Fiji. Economic Analysis and Policy, 78, 873-886.

Nason, J. M., & Smith, G. W. (2005). Identifying the new Keynesian Phillips curve (No. 1026). Queen's Economics Department Working Paper.

Nason, J. M., & Smith, G. W. (2008). Identifying the new Keynesian Phillips curve. Journal of Applied Econometrics, 23(5), 525-551.

Perron, P., & Vogelsang, T. J. (1992). Nonstationarity and level shifts with an application to purchasing power parity. Journal of Business & Economic Statistics, 10(3), 301-320.

Sümer, A. L. (2020). Discussion of hybrid new Keynesian Phillips curve methodology on inflation dynamics. İşletme Ekonomi ve Yönetim Araştırmaları Dergisi, 3(2), 254-260.