FORECASTING EMERGING MARKETS INTEREST RATES USING OPTIMAL TIME-VARYING FINANCIAL CONDITIONS INDEX

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ABSTRACT

This paper aims to optimise the financial conditions index (FCI) indicator that best describes the monetary policy interest rate setting behaviour of twelve emerging market central banks. This is achieved by analysing and looking at the background of modelling interest rates and forecasting interest rate setting behaviour from various regions globally. Following the credit crisis of 2008, the conventional wisdom and foundations that prevailed before were profoundly shaken. Particularly the conduct and behaviour of central banks in response to financial conditions assumed centre stage. Consequently, there has been a consensus among economists and policymakers on the importance of financial conditions, and the influence thereof, on the interest rate setting.

However, in order for central banks to achieve their financial stability objectives, they need to construct an optimal indicator that best describes financial conditions. To construct such an optimal indicator, this paper firstly investigates whether the central banks of emerging markets follow the Taylor rule in setting their interest rates. Secondly, it investigates whether the FCI with optimal time-varying weights better describes interest rate movements in emerging markets, when incorporated in the Taylor rule. Lastly, it evaluates interest rate predictability by comparing various models that include non-optimized FCIs.

The paper finds that the majority of emerging countries follow the Taylor rule. It also finds that most emerging markets take into account the information contained in FCIs and the majority of these countries, optimize the variables that enter the FCIs. When evaluating the forecasting accuracy of these models, the paper finds that the optimized model ranks superior in most countries in terms of forecasting accuracy. The optimization and allocation of the variables that enter the optimized FCI happen in a similar manner that was proposed by Markowitz in portfolio allocation theory.

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1. CHAPTER 1: INTRODUCTION

1.1 Background of the study

The credit crisis of 2008 raised financial stability concerns and has turned attention to the conduct and behaviour of central banks in response to certain financial indicators (Castro, 2011). Smaghi (2009) and Hatzius et al. (2010) note that the credit crisis has profoundly shaken the conventional wisdom that prevailed before the crisis, and has brought to the fore the importance of financial conditions to macroeconomic outcomes. Accordingly, policymakers, investors and researchers alike have been paying increased attention towards financial conditions indices (FCIs) in their effort to understand channels of financial stress in the economy. This is because the FCIs provide a useful tool when assessing the likely setting of monetary policy stance, and its impact on the financial markets (Charleroy and Stemmer, 2015).

In this regard, the purpose of this paper is to optimise the financial conditions index in order to best describe the interest rate setting behaviour of central banks in emerging markets. Hatzius et al. (2010) highlight that FCIs summarize the information about the future state of the economy contained in current financial variables. Additionally, FCIs allow not only for the analysis of monetary policy but also for an assessment of the evolution of overall financial conditions and their impact on the real economy. The FCIs are largely understood in the context of the monetary transmission mechanism. This is because monetary policy influences the economy by changing the financial conditions that affect economic behaviour. As such, the structure of the financial system is a key determinant of the importance of various channels of transmission mechanism (Hatzius *et al.*, 2010).

The forecasting of interest rates and the optimizing thereof is important because interest rates underpin monetary policy of many central banks. Monetary policy largely works via its influence on aggregate demand on the economy, in the long run, monetary policy determines the value of money. Movements in the general price level indicate how much the purchasing power of money has changed over time. When the central bank decides on a route or action to be taken, it sets in motion a series of economic events. The sequence of events starts with the initial influence on the financial markets, which in turn slowly works its way through to changes in current expenditure levels. Changes in domestic demand influence the current production levels, wages and employment. This process eventually leads to a change in the domestic prices. Economists refer to this chain of developments as the transmission mechanism of monetary policy.

Monetary policy rules around the world have undergone significant changes over the last four decades from ad-hoc discretionary, erratic, monetary targeting, eclectic to inflation targeting. An increasing number of emerging markets central banks have adopted the inflation targeting as their monetary policy framework (Hammond, 2012), although with varying several characteristics (Svensson, 1997). In particular, empirical studies have shown that most monetary policies follow the popular Taylor (1993) rule. The rule specifies how central banks adjust repo rates in relation to inflation and output gap. Accordingly, there have been various studies that sought to test the validity of the rule for various economies. The appeal to the Taylor rule is largely due to its simplicity in approximating monetary policy decisions.

However, the rule has seen various modifications in its application so far, such as; the inclusion of lagged interest rates to allow for interest rate smoothing (Clarida *et al.*, 2000a); and the inclusion of backward and forward-looking variables (Rudebusch and Svensson, 1999). In essence, Taylor-type rules have become the customary way through which central banks policies are introduced in macroeconomic models (Asso et al. 2007). Although the Taylor rule has been very influential, there have been more debates regarding further modifications.

More specifically, in the years leading up to the financial crisis of 2008, Gameiro *et al.* (2011), the extension of the Taylor rule to include financial conditions stirred a huge debate in the literature. Various economists proposed including additional financial variables to take into account financial conditions such as exchange rates, interest rates, stock prices, house prices, interest rate spreads among others.

Whereas other authors consider it important that central banks target asset prices, others disagree (see Clarida, et al. (2000), Montagnoli (2004), Disyatat (2005), Driffill et al. (2006), and Castro (2011) among others). Consequently, the general benchmark of monetary rules has been the subject of intense debates over the past years. While the central banks focused mainly on achieving and maintaining price stability in the past, the financial crisis has illustrated the importance of financial conditions in preserving financial stability. In the United States and the United Kingdom, for instance, the credit crisis resulted, amongst other reasons, from central banks not paying close attention to financial variables. Hence the credit crisis was more pronounced in these countries than in the Eurozone (Castro, 2011).

Following from the above-mentioned evidence, there appears to be some consensus that financial markets indicators have a role to play in guiding central banks' interest rate setting behaviour. To capture that role, this paper draws and extends on the previous studies by augmenting the traditional Taylor rule with the optimal time-varying financial condition index (FCI) derived from portfolio theory techniques. The resulting rule will further be used to test the significance and information content of the variables by way of forecasting. In addition, the paper seeks to fill a particular gap identified in the literature (see chapter 2 below). That is, while various scholars have looked at the experiences of different countries separately, they have not explored in comparison the common features or peculiarities amongst countries regarding the consistency in setting interest rates

1.2 Statement of the problem

The importance of financial conditions, and their influence thereof, on the monetary policy interest rate setting behaviour of central banks, have been established in various countries. However, in order for central banks to achieve their financial stability objectives, the question arises on how they should construct an indicator that best describes financial conditions. The various forecasting currently being employed in literature when constructing FCI uses ad-hoc (or arbitrary) fixed weights to construct the FCI. There lies the problem because ad-hoc (or arbitrary) weight allocation is not objective and is not optimized. Thus, the paper seeks to test among other things the severity of this problem and attempts to optimize the financial conditions index derived from an optimal portfolio with time-varying weights to forecast interest rates.

1.3 Objectives of the study

This research investigates whether central banks of emerging markets respond differently to optimized financial conditions in their interest rate setting behaviour. In the main, the objective is to evaluate the out of sample interest rate predictability by employing optimal portfolio with time-varying weights in emerging markets. The study will aid in policy forecasting of interest rates, which will be useful for professional practitioners, policymakers, investors and researchers among others.

1.4 Research questions

Consistent with research objectives, this paper seeks to answer the following questions:

- Do the emerging market central banks follow the Taylor rule in setting their interest rates?
- Does the FCI with optimal time-varying weights better describe interest rate movements in emerging markets?

1.5 Hypotheses

- Null hypothesis: Optimal time-varying FCI better explains interest rate movements compared to non-optimized optimal FCI
- Alternative hypothesis: There's no difference between optimized FCI and non-optimized FCI

1.6 Outline of the study

The rest of the paper is organised as follows:

In section 2, the literature will be reviewed proving evidence of the role that financial markets indicators have on monetary policy setting. The findings are summarised and the gap identified in literature is presented in this section. Section 3 outlines the research methodology and theoretical framework followed in developing the optimized FCI and how is augmented in the Taylor rule. Other methods used are also briefly outlined.

Section 4 presents the data description, sources used, transformations made on the variables, evolution of the main variables and unit root tests performed on the variables. Section 5 provides the results and analysis of the data including examining the significance of variables and their information content by way of forecasting. Lastly, conclusions are presented in section 6 from the findings obtained from the initial objectives of the study.

2. CHAPTER 2: LITERATURE REVIEW

This section briefly outlines the evolution of the Taylor rule and its application. It shows that despite its prominence, it has undergone various extensions and modifications. The debate on whether central banks should respond to asset prices and financial variables is also outlined. Notwithstanding some disagreements in this debate, economists seem to agree on the role of the financial market in determining inflation and economic performance.

2.1 Taylor rule evolution in emerging markets

Asso *et al.* (2007) point out that the Taylor rule was a direct result of a long history that debated the merits of monetary policy based rules vs discretion. In his setup, Taylor (1993) articulated a rule that changed the way in which policymakers and central banks alike think about monetary policy setting. The rule was the result of the United States experience during the period 1980 – 1990s period, and suggested a linear algebraic interest rate rule that specifies how central banks should adjust their nominal interest rate in response to changes in economic conditions, specifically inflation and the output gap. To this end, the appeal of the Taylor rule stems from its intuitiveness, simplicity, and focus on short-term nominal interest rates as the instrument for monetary policy Asso *et al.* (2010).

The former governor of the Central Bank of Chile, De Gregorio (2014), notes that when central banks are faced with a decision on whether to loosen or tighten monetary policy, the most traditional answer is that Taylor rule, and inflation targeting framework is efficient to conduct monetary policy. In South Africa, Ellyne and Veller (2012), show that the Taylor rule gives a good fit for the period after the inflation target regime was implemented and a poor fit for the period before. On the other hand, Hammond (2012), observe generally that an increasing number of emerging markets central banks have adopted the inflation targeting as their monetary policy framework. According to Galimberti and Moura (2013), a large fraction of emerging countries that follow inflation targeting pursue more rigorous monetary policies than similar economies that do not.

2.2 Extensions of the Taylor rule

Gameiro et al. (2011) point out that the 2008 financial crisis activated the need to understand the role of central banks in addressing financial stability. The crisis made it clear that monetary stability is not a guarantor of financial stability and that finance plays a bigger role in macroeconomic dynamics than previously thought. According to (Castro, 2011), the financial crisis posed a challenge to simple Taylor rule models. However, long before the financial crises, there have been numerous studies in the literature that sought to modify and/or extend the simple Taylor rule to take into account financial conditions. Earlier extensions included lagged interest rates to allow for interest rate smoothing (Clarida et al., 2000). Other extensions included backward and forward-looking (see Rudebusch and Svensson, 1999; and Carlstrom and Fuerst, 2000), mainly to test whether the central banks should respond proactively to movements in expected future inflation, or base interest rate changes on past movements in inflation.

Subsequent extensions sought to augment the Taylor rule with exchange rates. In this regard, Batini *et al.* (2001) gives evidence and finds that the descriptive power of the Taylor rule augmented with exchange rates is higher than standard Taylor rule for small countries. Svensson (2003) arrives at a similar conclusion and proposes the Taylor rule augmented with the exchange rate for small open economies. Ghadha et al. (2004) give evidence of the reaction of central banks to deviations from the average exchange rate. In these papers, they show that exchange rates and asset prices are important to offset deviations from equilibrium levels. Mohanty and Klau (2005) and Galimberti and Moura (2013b) provide some evidence for central banks of emerging markets that they respond to exchange rate deviations. There's consensus on the role of the exchange rate as a financial variable to be incorporated into the Taylor role.

However, have been debates regarding other asset prices that should enter into the rule, more especially in the years leading up to the 2008 financial crisis. The proponents of augmenting the Taylor rule with asset prices particularly, Cecchetti *et al.* (1999), argue that a central bank concerned about maintaining its inflation stable and within its target range is likely to attain superior performance by responding to asset prices in addition to inflation and output gap in the Taylor rule. In this way, policymakers will be reacting to reduce the chance of asset price bubbles forming and misalignments in the financial markets. Others such as Goodhart and Hoffmann (2000,

2002) and Goodhart (2001) also argue that the future price developments information is contained in the current asset prices. With this knowledge, that current asset prices can assist to predict future inflation. They propose a broader measure of inflation, which will include housing and stock prices, instead of the conventional measure of inflation.

Those who are against the inclusion of asset prices in the Taylor rule like Bernanke and Gertler (1999), Bullard and Schaling (2002) and Gameiro *et al.* (2011) propose the “benign neglect” approach, where the central banks leave financial stability to be addressed by the self-discipline of the markets and the central banks be only concerned with their primary objectives of inflation and output among others. They argue that when the predictive content of asset prices has taken into account inflation, central banks should not respond to asset price movements. Instead, central banks should only respond when it is expected that the asset prices will affect forecast of inflation to prevent damages to the real economy. More specifically, Bernanke and Gertler (2001) contend that since asset prices are excessively volatile in relation to their information content, the cost of responding to asset prices might be substantial.

Castro (2008) reasons, that instead of central banks trying to target different individual asset prices, they could be observing asset prices in a form of a composite, the financial conditions index (FCI). This motivation follows from the works of Rudebusch (2002) who raises the issue of an omitted variable problem by bringing out that the reason for the significance of interest rate persistence in the monetary policy rule might be due to omitting a financial spread variable from the estimated regression. In this endeavour, the FCI has been identified as an indicator with the potential to foresee turning points in the business cycle as it summarises the information about the future state of the economy contained in a range of current financial variables.

2.3 Financial Conditions Index (FCI)

Considering the above discussion, the recent financial crises sparked an interest in the development of accurate measurements of financial shocks in the real economy. Furthermore, the need for policymakers to closely monitor financial conditions is quite clear. As a response to this need, the recent literature has developed several methods to construct financial conditions indices (FCIs). The aim is for policymakers to use FCIs to provide early warning of future financial crises (Koop and Korobilis,2014).

Montagnoli *et al.* (2004) put it markedly, that the FCI is able to capture the current development of financial markets, and gives a good indication of future economic activity. The methodologies to estimate FCIs have expanded over the years. They range from simple weighted averages of financial variables through sophisticated econometric estimates. Many financial institutions and policymakers produce closely-watched FCI (Koop and Korobilis, 2014). An important recent contribution is by Hatzius *et al (*2010), proposes principal components methods to extract an FCI from a large number of quarterly financial variables.

These approaches either use constant weights approach or employ time-varying weights using Kalman-Filter algorithm to determine the varying weights of financial variables. However, these weights are not optimized from a portfolio theory perspective. On this subject Akram and Eitrheim (2008) comment that the determination of the weights is not straightforward since there is no widely accepted definition of the financial stability indicator. In the effort of finding a more appropriate way of developing time-varying weights, an attempt is made in the next chapter using a different approach borrowed from portfolio optimization theory developed by Markowitz (1952). Using this approach, optimized time-varying weights of financial variables in the FCI are estimated. This will relax the assumption of fixed weights that enter the FCI and will allow for the possibility of structural changes over time. Furthermore, the weights that will be chosen will be optimized weights as per Markowitz portfolio selection theory.

3. CHAPTER 3: THEORETICAL FRAMEWORK & METHODOLOGY

In this section, we consider as proposed by Castro (2011), the contribution of asset prices and financial variables (collectively named financial variables henceforth) in a form of an index (FCI), where each variable will be assigned different optimal weights using the mean-variance portfolio optimization developed by Markowitz (1952). In essence, under this framework, the paper posit that central banks set interest rates in a way that maximises returns for a particular level of risk, similar to rational investors. To further elaborate, rational investors, seek to invest in a portfolio that maximizes the returns and minimize the risk. As such, they allocate the available capital to a portfolio that constitutes an optimal allocation of that capital in order to achieve maximum risk adjusted returns. Similarly, central banks seek to minimize financial instability when setting interest rates, and they achieve this by allocating optimal weights to the FCI that then influences interest rate setting. The first part of this section will be devoted to developing the optimal time-varying FCI, which will enter the Taylor rule that will be used in our analysis later on. Other FCIs that are predominantly in use will be also discussed later in the section.

3.1 Time-varying optimal weights using DCC –GARCH Model

The usage of dynamic conditional correlation (DCC) model in constructing time-varying optimal weights for efficient portfolio allocation is to some extent limited, as noted by El-Edel (2010). This study uses DCC because unlike other models, it guarantees that the time-dependent conditional correlation matrix is positive definite for each point in time. Furthermore, the number of parameters growth linearly and the DCC model is relatively parsimonious.

Among other authors, it was Tse and Tsui (1997) who introduces a time-varying correlation matrix instead of the traditional constant matrix assumed in earlier studies. In their setting, the conditional variable is restricted to be a VEC-diagonal M-GARCH, while the correlation matrix is an autoregressive moving average. It was Engle and Sheppard (2001) who extended a DCC by allowing for the correlation estimator to be time-varying.

In this paper, a DCC-GARCH that follows equation (3-1) and (3-2) is used to generate time-varying covariance matrix of financial variables and is estimated in two stages, as proposed by Engle and Sheppard (2001) and adapted from El-Edel (2010):

$$r_t \mid \mathcal{F}_{t-1} \sim N(0, H_t) \tag{3-1}$$

and,

$$H_t = D_t R_t D_t \tag{3-2}$$

Where r_t is the $k \times 1$ vector of asset returns with zero mean conditional upon information available at $t-1$, H_t is the $k \times k$ conditional variance-covariance matrix. D_t is a diagonal $k \times k$ matrix comprising of conditional standard deviations, $\sigma_{i,t}$, on the i^{th} diagonal and zeros everywhere else $(i = 1,2,\cdots,k)$, and R_t is $k \times k$ is a matrix of correlations, $\sigma_{ij,t}$, with ones on its main diagonal. For the case of 5 financial variables, $k = 5$, as is the case in this paper, H_t can alternatively be presented in a decomposed matrix form as follows:

$$H_t = \begin{bmatrix} \sigma_{1,t} & 0 & 0 & 0 & 0 \\ 0 & \sigma_{2,t} & 0 & 0 & 0 \\ 0 & 0 & \sigma_{3,t} & 0 & 0 \\ 0 & 0 & 0 & \sigma_{4t} & 0 \\ 0 & 0 & 0 & 0 & \sigma_{5,t} \end{bmatrix} \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \rho_{14,t} & \rho_{15,t} \\ \rho_{21,t} & 1 & \rho_{23,t} & \rho_{24,t} & \rho_{25,t} \\ \rho_{31,t} & \rho_{32,t} & 1 & \rho_{34,t} & \rho_{35,t} \\ \rho_{41,t} & \rho_{42,t} & \rho_{43,t} & 1 & \rho_{45,t} \\ \rho_{51,t} & \rho_{52,t} & \rho_{53,t} & \rho_{54,t} & 1 \end{bmatrix} \begin{bmatrix} \sigma_{1,t} & 0 & 0 & 0 & 0 \\ 0 & \sigma_{2,t} & 0 & 0 & 0 \\ 0 & 0 & \sigma_{3,t} & 0 & 0 \\ 0 & 0 & 0 & \sigma_{4t} & 0 \\ 0 & 0 & 0 & 0 & \sigma_{5,t} \end{bmatrix}$$

In the first stage, estimates of the mean equations of each asset returns are calculated, and a univariate GARCH model of asset returns conditional variances are estimated using equation 3-3:

$$h_{it} = w_i \sum_{p=1}^{P_t} \alpha_{ip}\, \varepsilon_{it-p}^2 + \sum_{q=1}^{Q_t} \beta_{iq} h_{it-q} \tag{3-3}$$

Where $\alpha_{ip} > 0$ and $\beta_{ip} > 0$, for non-negativity and $\left(\sum_{p=1}^{P_t} \alpha_{ip} + \sum_{q=1}^{Q_t} \beta_{iq}\right) < 1$, for stationarity. Imposing these restrictions, ensures that H_t becomes positive definite for all periods. The estimates from equation (3-3), are then used to compute D_t, where $D_t = diag(\sqrt{h_{it}}, \cdots \sqrt{h_{kt}})$ is the conditional variance of each asset.

In the second stage, the standardized returns obtained from the first stage are used to define R_t. Then the time-varying conditional correlation matrix is computed using equation (3-4) and (3-5) below:

$$R_t = \left[diag\left(\sqrt{Q_t^{-1}}\right)\right] Q_t \left[diag\left(\sqrt{Q_t^{-1}}\right)\right] \quad (3\text{-}4)$$

Where

$$Q_t = (1 - a - b)\bar{Q} + a\eta_{t-1}\eta'_{t-1} + bQ_{t-1} \quad (3\text{-}5)$$

Q_t is a $k \times k$ symmetric and positive definite matrix , η_{it} is the standardized innovations in which residuals are scaled by their standard deviations estimated in the first stage (i.e. $\varepsilon_{it}/\sqrt{h_{it}}$, and $\bar{Q}$ is the unconditional covariance of the standardized residuals from the first state. The non-negativity and stationarity restrictions are imposed also for this model to be mean reverting. In this second step, taking into consideration the parameters computed in the first stage, the log-likelihood function is estimated following equation (3 6):

$$\boldsymbol{L} = \frac{1}{2}\sum_{t=0}^{T}(k\log(2\pi) + 2\log(|D_t|) + \log(|R_t|) + \eta_t^{'}R_t^{'}\eta_t) \quad (3\text{-}6)$$

The maximization of the likelihood function is achieved using *Microfit and Eviews* to generate the time-varying covariance matrix of financial variables. The resulting time-varying covariance matrix is then used as an input in MATLAB code to generate for each period the efficient frontier of the portfolio optimal weights for each asset. The efficient frontier aims at minimizing the portfolio standard deviation, given the portfolio returns. We maximize the following problem following specifications by Cumby et al (1994) and El-Edel (2010):

$$\min_{w} \sigma_{pt}^2 = w_t' H_t w_t$$

$$s.t \quad w'\mu = r_t$$

Where $w_t = (w_1, w_2, w_3, w_4, w_5)'$ is the time-varying vector of portfolio weights and H_t is the 5x5 covariance matrix estimated using DCC–GARCH developed above. Additional constrains are $\mathrm{w}'I = 1$ and $\mathrm{w}'I \geq 1$, where I is an 5×5 vector array of ones.

The resulting optimal time-varying weights estimated are used to develop the optimal FCI (F_{OPT}) shown in equation (3-7):

$$F_{OPT} = w_t' x_t \quad (3\text{-}7)$$

Where $x_t = (REER_t, RHP_t, RSP_t, CS_t, FS_t)$ is a matrix of the financial variables i.e. real effective exchange rate ($REER_t$), real house prices (RHP_t), real stock prices(RSP_t), credit spread (CS_t) and future spread (FS_t).

Equation (3-7) gives the variable (FCI_{OPT}), which is used as a variable that into augmented in the Taylor rule, in the next section. Even though numerous central banks pursue financial stability as part of their objectives, they do not give an idea concerning the variables that they take into account when pursuing this objective. Therefore, it should be noted that in developing the (FCI_{OPT}) in equation 3-7, this study is guided by the views and proposals by various economic scholars such as Castro (2008), Goodhard and Hoofman (2001) among many others.

3.2 Time-varying weights using Kalman-Filter estimation

The predominant method largely used in literature to determine the time-varying weights of the components of the FCI is the Kalman-Filter approach. In this approach, the backwards-looking IS curve is assumed and the time-varying estimates of a state space are given by applying Kalman-Filter approach on the IS curve, see equation 3-8, Mantagnoli and Napolitano (2005) and Castro (2010).

$$\hat{y}_t = b_0 + \sum_{k=1}^{p} b_k \hat{y}_{t-k} + \sum_{l=1}^{q} b_l rir_{t-l} + \sum_{i=1}^{5} \sum_{j=1}^{n_i} b_{ij} x_{i,t-j} + u_t^d \quad (3\text{-}8)$$

Where rir is the real interest rate and x is a vector of financial variables as defined from section 3.1. Allowing for the parameters to evolve over time, the unobservable changes in coefficient $b_{ij,t}$ can be estimated using using Kalman-Filter over the measurement equation ($\hat{y}_t = X\beta_t + u_t$) and transitioning equation ($\beta_t = F\beta_{t-1} + \omega_t$). Where X is the matrix of independent variables and the constant. In this way β_t is the state vector comprising of time-varying coefficients and F is an identity matrix. The weight of each variable is computed as $\left[w_{i,t} = \frac{|\beta_{i,t}|}{\sum_{k=1}^{5} |\beta_{i,t}|}\right]$, where $\beta_{i,t}$ is the coefficient of variable x_t at time t. The FCI for the Kalman-Filter is then computed as

$$F_{KF} = w' \sum_{i=1}^{5} x_i. \quad (3\text{-}9)$$

3.3 Equal weights and constant weights from OLS estimation

As mentioned in previous sections, that other authors who attempt to construct FCI either use equal weights or OLS estimations. Following Kasaï and Naraidoo (2012), the FCI that results from equal weights average (F_{EW}) is shown in equation (3-10) where x_i is the vector of financial variables:

$$F_{EW} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3-10}$$

The FCI that results from estimating optimal weights using OLS estimation of the output gap on financial variables is shown in equation 3-11.

$$F_{OLS} = w' \sum_{i=1}^{5} x_i \tag{3-11}$$

where x_i is a matrix of financial variables. Using this approach, the weight of each variable depends on the importance it has in explaining the economic activity. The weight attached to each variable is measured as $\left[w_i = \frac{|\beta_i|}{\sum_{k=1}^{5}|\beta_i|}\right]$, where β_i are coefficients obtained from equation 3-12. Equation 3-12, follows similar logic used in equation 3-8 above:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \beta_1 reer_{t-1} + +\beta_2 rhp_{t-1} + \beta_3 rsp_{t-1} + \beta_4 cs_{t-1} + fs_{t-1} + \epsilon_t \tag{3-12}$$

Where $reer$, rhp, rsp, cs and fs respectively are the deviations from the long run equilibrium path of real effective exchange rate ($REER_t$), real house prices (RHP_t real stock prices(RSP_t), credit spread (CS_t) and future spread (FS_t).

In an attempt to best measure and obtain the FCI that best describes the behaviour of central banks of emerging countries, these models will be compared with the benchmark to determine whether the proposed time-varying optimal weights (FCI_{OPT}) obtained from portfolio estimation, perform better compared to equal weights FCI (FCI_{EW}), ordinary linear squares weights (FCI_{OLS}), and the Kalman-Filter FCI (FCI_{KF}).

3.4 Modelling the Taylor rule

The framework followed in this paper is adapted from the work that has been done by Castro (2011) and Vivian and Wohar (2013) among others. The original Taylor (1993) rule is shown in equation 3-13:

$$\hat{\imath}_t = r^* + \alpha_0 + \alpha_\pi(\pi_t - \pi^*) + \alpha_y(Y_t - Y_t^*) + \epsilon_t \tag{3-13}$$

Where $\hat{\imath}_t$ is the nominal target interest rate set by the central bank, r^* is the equilibrium value for $\hat{\imath}_t$, α_0 is the constant, α_π is the response coefficient on inflation gap, π_t is the inflation rate, π^* target inflation rate, α_y is the response coefficient on output gap, Y_t is output gap, Y_t^* and ϵ_t is error term. According to Taylor rule the coefficient α_π and α_y should both be positive.

From equation 3-13, if we make $\rho_0 = r^* - \alpha_\pi \pi^*$, $\rho_1 = 1 + \alpha_\pi$, $y_t = Y_t - Y_t^*$, augmenting with the FCI, and assuming backward-looking the Taylor rule takes the reduced form as shown in Equation 3-14. Where α_F is the response coefficient on financial conditions gap, and F_t is the financial conditions gap. In this way, the implied inflation target of the central bank can be computed as $\pi^* = \frac{(r^* - \rho_0)}{\alpha_\pi}$.

$$\hat{\imath}_t = \rho_0 + \rho_\pi \pi_{t-1} + \rho_y y_{t-1} + \rho_F F_{t-1} + \epsilon_t \qquad (3\text{-}14)$$

Following this version of the Taylor rule, equation 3-14, and allowing for partial adjustment mechanism, justified by empirical observation of the tendency of central banks to smooth interest rates, see Clarida *et al*, (2000), the Taylor rule takes the form of equation 3-15 and 3-16.

$$i_t = \rho_i(L) i_{t-1} + (1 - \rho_i)\hat{\imath}_t \qquad (3\text{-}15)$$

Where, $\rho_i(L) = \rho_{i1} + \rho_{i2} + \cdots + \rho_{in} L^{n-1}$ is the lag polynomial in the interest rate that shows interest rate persistence and ρ_i is interest rate smoothing parameter also thought of as the measure of policy inertia. When the value of the smoothing parameter (ρ_i) near unity, it shows that monetary policy interest rates adjust very slowly towards their policy target rate:

$$i_t = \rho i_{t-1} + (1 - \rho)[\rho_0 + \rho_\pi \pi_{t-1} + \rho_y y_{t-1} + \rho_F F_{t-1}] + \epsilon_t \qquad (3\text{-}16)$$

Taylor (1994) proposed that the ρ_π coefficient should be greater than one, this is commonly referred to as Taylor principle. In this regard if $\rho_\pi > 1$ the target real interest rate is adjusted to stabilize inflation. However, when $0 < \rho_\pi < 1$ the central bank moves to accommodate inflation. For that reason, the value of unity/one for ρ_π becomes an important differentiating criterion to assess the central banks behaviour in their inflation targeting pursuit. Likewise, a comparable distinction can be made regarding the output gap coefficient (ρ_y) where $\rho_y > 0$ implies monetary policy is stabilizing and $\rho_y < 0$ is accommodating changes to output gap. In this regard, the stability benchmark becomes ($\rho_\pi > 1, \rho_y > 0$) (Clarida et al, 2000).

4. CHAPTER 4: DATA DESCRIPTION

The data in this paper is presented on a monthly basis which is in line with the literature and is obtained largely from the Global Financial Data, Federal Reserve Economic Data (FRED) and from statistics published by the central banks under study. The emerging countries under study include South Africa, Malaysia, Chile, Poland, Turkey, Czech Republic, Mexico, Brazil, Russia, India, South Korea and China. The sample covers the periods when respective countries began adopting inflation targeting framework, mostly from the late 1990s. The choice of the in-sample period is also guided by the availability of historical data and the desire to reserve part of the remaining available data for out-of-sample analysis.

The repurchase/policy (repo) rate, is the policy instrument and measures the nominal interest rates. The inflation rate measures the annual change in the Consumer Price Index (CPI). In each case, the output gap is computed as the percentage deviation of the industrial production index from its Hodrick-Prescott trend. The proxy for the FCI is constructed using methods described in section 3 and comprises of (a) real effective exchange rate, (b) the real house price index, which is an average price of all houses in the country, deflated by CPI (c) the real stock price, is measured by the All Share Index, deflated by CPI (d) credit spread[1], is the spread between the yield on the long-term government bond and the yield on A-rated bonds, and (e) the future spread, is the change of spread between the 3-month interest rate futures contracts in the previous quarter and the current short-term interest rates.

Table 8-1 shows the descriptive statistics for the nominal repo rate, inflation, output gap and FCIs, see Appendix 8.1. Indicating how the variables have fluctuated over the periods including for each emerging country. All the means of the nominal repo rate and inflation rate are positive, indicating that interest rates and inflation increase overtime on average. The countries that show very large fluctuations in output gap include Malaysia, Chile, Brazil and South Korea. The results also indicate that the variables are not normally distributed for every emerging market country.

It is essential that the financial variables included in the estimated model are stationary. For this reason, the unit root test is performed on all of the time series, the

[1] For most emerging countries the corporate bonds were not readily available and the countries credit spread as determined from Emerging Market Bond Index (EMBI) was used as a proxy.

main variables results are shown in Table 8-2. The study utilizes Augmented Dicky-Fuller (ADF) to test for stationarity, and all variables are first differenced to evoke stationarity. The results reveal that all the series follow a stationary process.

Figures in Appendix 8.3 presents the evolution of the main retained variables considered in the analysis of the monetary policy in emerging market central banks under study. It can be seen that there's a close link between inflation and repo rate fluctuation over time, except for the case of China, Malaysia, Czech Republic, Russia and South Korea. The output gap shows a downturn in the years leading up to 2008, and recovers afterwards. The FCIs show similar movement pattern with interest rate and output gap although at a high level of volatility. The FCIs are expressed in a standardized form, the axis on the vertical shows standard deviation i.e. the measurement of one shows a one-standard-deviation difference from the mean.

5. CHAPTER 5: RESULTS

This section firstly investigates whether the emerging countries follow the Taylor rule when setting interest rates. Secondly, it examines whether these central banks respond differently to optimized FCIs in their interest rate setting behaviour compared to non-optimized FCIs. Table 5-1 reports linear regression results of estimation of the Taylor rule for South Africa (period 2000:01 – 2014:12), Malaysia (2003:11 – 2013:05), Chile (2004:11 – 2013:07) and Poland (2002:04 – 2013:05). The t-statistics are presented in parentheses and the estimates of the implicit inflation target (π^*) pursued by each central bank is computed. The Adj. R^2, Durbin-Wartson (DW) statistic for autocorrelation and the Schwartz Bayesian Information Criterion (SBIC) are also reported for each regression.

5.1 In-sample analysis for South Africa, Malaysia, Chile and Poland

South Africa:

The first column, in Table 5-1, presents the results of the simple Taylor rule, i.e. without allowing for interest rate smoothing and FCIs. The monetary policy response coefficients for inflation response $\rho_\pi = 0.58$ and for output gap response $\rho_y = 0.02$ are both positive and significant but below unity for the sample period. The estimate for implied inflation target ($\pi^* = 5.15$) seem plausible and is within the South African Reserve Bank (SARB) target range of 3-6%.

However, despite the outcome of the response coefficients being reasonable, Model 1 results indicate that the simple model is unable to capture the reaction of South African Reserve Bank to the output gap. Furthermore, Model 1 suffers from the problem of autocorrelation (DW = 0.03) and has low explanatory power (Adj. R^2 = 0.24). This implies that the SARB is not characterized by the simple Taylor rule, but by the monetary rule that partially adjusts interests to smooth interest policy rates. Hence we proceed with the estimation that allows for smoothing of interest rates following equation 3-15.

The results for the baseline Model 2 (column 2) smoothed estimation, show that all the response coefficients are positive, statistically significant and above unity. The estimates for smoothing parameter ρ_0 is high in all cases, indicating a considerable interest rate inertia i.e. only less than 2.5% of a change in the policy interest rate of the previous period is reflected in the current policy rate. The results also show evidence of significant reaction to inflation and is above unity, implying that SARB reacts to stabilize inflation. That is one percentage point rise in inflation from last period, induces SARB to raise the policy rate by more than one percentage point, sufficiently high to keep real interest rate from declining, to exert the desired stabilizing effect on inflation.

Table 5-1: In-sample estimates for South Africa, Malaysia, Chile and Poland

	South Africa						**Malaysia**					
Coefficients	**1**	**2**	**3**	**4**	**5**	**6**	**1**	**2**	**3**	**4**	**5**	**6**
ρ_0		0.975 *** (0.01)	0.961 *** (0.01)	0.967 *** (0.01)	0.950 *** (0.016)	0.963 *** (0.012)		0.94 *** (0.08)	0.93 *** (0.08)	0.93 *** (0.08)	0.93 *** (0.08)	0.94 *** (0.08)
ρ_π	0.575 *** (0.07)	1.93 *** (0.73)	1.95 *** (0.47)	2.40 *** (0.71)	1.876 *** (0.357)	1.751 *** (0.463)	0.02 (0.02)	0.48 ** (0.23)	0.29 * (0.15)	0.29 * (0.16)	0.32 * (0.19)	0.50 ** (0.23)
ρ_y	0.024 (0.060)	1.92 ** (0.904)	1.30 *** (0.45)	1.42 ** (0.57)	0.925 ** (0.370)	1.304 ** (0.509)	-0.00 (0.004)	0.049 (0.030)	0.06 ** (0.02)	0.03 (0.02)	0.06 ** (0.03)	0.05 * (0.03)
$\rho_{FCI,OPT}$			2.24 *** (0.82)						-0.4 * (0.24)			
$\rho_{FCI,EW}$				2.57 ** (1.22)						0.25 (0.16)		
$\rho_{FCI,OLS}$					2.178 *** (0.726)						-0.3 (0.307)	
$\rho_{FCI,KF}$						1.516 ** (0.723)					0.000	0.16 (0.24)
π*	5.15	6.10	5.94	5.94	5.86	5.98	2.30	2.41	2.42	2.40	2.41	2.35
Adj. R^2	0.24	0.98	0.98	0.98	0.98	0.98	-0.01	0.95	0.95	0.95	0.95	0.95
DW	0.03	2.14	2.22	2.21	2.24	2.18	0.07	2.03	2.02	2.02	2.01	2.03
SBIC	4.63	0.76	0.75	0.76	0.77	0.77	1.43	1.49	1.48	1.47	1.46	1.62
	Chile						**Poland**					
ρ_0		0.97 *** (0.09)	0.97 *** (0.09)	0.96 *** (0.09)	0.96 *** (0.09)	0.97 *** (0.09)		0.94 *** (0.08)	0.94 *** (0.08)	0.94 *** (0.08)	0.94 *** (0.08)	0.95 *** (0.08)
ρ_π	-0.13 (0.09)	-0.15 (0.46)	-0.23 (0.68)	-0.19 (0.39)	-0.66 (0.46)	-0.16 (0.51)	0.01 (0.08)	0.20 (0.21)	0.51 * (0.28)	0.39 (0.25)	0.31 (0.23)	-0.0 (0.30)
ρ_y	0.03 * (0.01)	0.23 (0.14)	0.38 (0.43)	0.19 (0.11)	0.21 * (0.11)	0.24 (0.18)	0.08 ** (0.03)	0.31 *** (0.10)	0.25 ** (0.10)	0.26 ** (0.10)	0.27 *** (0.10)	0.40 *** (0.15)
$\rho_{FCI,OPT}$			1.20 (2.77)						0.71 * (0.38)			
$\rho_{FCI,EW}$				-0.65 (0.74)						0.48 (0.33)		
$\rho_{FCI,OLS}$					-2.12 ** (1.06)						0.35 (0.310)	
$\rho_{FCI,KF}$						0.06 (1.08)						-0.5 (0.49)
π*	3.37	5.65	5.20	5.14	4.05	5.51	5.84	5.91	4.21	4.56	4.97	-89.69
Adj. R^2	0.01	0.98	0.98	0.98	0.98	0.98	0.02	0.98	0.98	0.98	0.98	0.98
DW	0.05	1.95	1.96	1.95	1.93	0.26	0.03	1.96	1.91	1.92	1.93	2.00
SBIC	4.29	0.33	0.37	0.36	0.31	0.19	3.55	0.58	0.58	0.56	0.55	0.55

Notes i) In column 1 the LS regression is presented following the basic Taylor rule: $i_t = \rho_0+\rho_\pi\pi_{t-1}+ \rho_y y_{t-1} +\varepsilon_t$. All the regressors are lagged one period.
ii) All other columns present the Taylor rule LS regression with interest rate smoothing, up to 3 lagged periods remove autocorrelation, and includes lagged FCI. The general formular is $i_t = \rho_0 i_{t-1}+\rho_1 i_{t-2}+\rho_2 i_{t-3}+(1-\rho_0-\rho_1-\rho_2)(\rho_\alpha+\rho_\pi\pi_{t-1}+\rho_y y_{t-1}+ \rho_f F_{t-1}) +\varepsilon_t$.
iii) The values reported in parentheses are standard erros and *(**)[***] indicate the parameter is significant at 10%(5%)[1%]
iv) The implied inflation target rate π* is computed as $\pi^* = (i^*-\rho_0)/\rho_\pi$, where i* is the sample mean. i* = 8.2% is for South Africa 2.9% for Malaysia, 4.2% for Chile, and 5.0% for Poland for respective periods. The SBIC is the Schwartz Bayesian Information Criterion.
v) FCI developed: time-varying optimal weights using DCC –GARCH Model (FCI_{OPT}), time-varying weights using Kalman-Filter estimation (FCI_{KF}), constant equal weights (FCI_{EW}), and weights from OLS estimation (FCI_{OLS}).

Additionally, from Figure 1, the evolution of inflation rate is consistent with this result as it can be seen that inflation has been outside the desired target range during the sample period. This outside of the target range result is an indication of hardening of the upper bound of the inflation target, and SARB relaxes repo rate as soon as it reaches 6% upper bound of the target zone. Indeed these results are consistent with the findings of Burger and Marinkov (2008) for the case of SARB.

Next, we consider Model 3-6 taking into consideration financial indicators that central banks consider when setting interest rates. The results show that SARB is reacting to all FCIs when setting interest rates, and attaches a positive, higher than unity to the financial conditions gap coefficient, this evidence is provided in column 3-6. The models indicate the statistically significant effect on all FCIs. Using optimized FCI_{OPT} for example, a one standard deviation increase in the index relative to its mean triggers the SARB to increase the interest rate to above 2.24%.

It is important to note that these findings also reveal that the models that do not include FCIs results in higher SBIC. In this sense, the models that are augmented with the FCI describe the behaviour of SARB better than those that ignore the information contained in the FCIs. It is interesting to note that the FCI_{OPT} developed in this paper, yields the lowest SBIC amongst all reported FCIs, which indicates that it describes the SARB's behaviour better than any other tested models.

As pointed out in section 3, the FCI_{OPT} is developed by employing portfolio theory, under Markowitz framework, and it assumes that central banks in their interest setting behaviour allocate weights in the portfolio of financial variables in order to minimize risk for a given return. These findings indicate that the SARB is targeting FCIs and allocates the variables that enter the FCI in a similar manner as would a rational investor.

In order to keep the in-sample analysis for other emerging countries briefly, we discuss only the critical findings in the following paragraphs. The foregoing detailed discussion on the results for South Africa described, were intended to outline the rationale followed when analysing the in-sample analysis presented in Table 5-1.

Malaysia:

The estimate results for Model 1 indicate that Malaysia monetary policy setting is not characterized by the simple Taylor rule. However, for smoothed estimation Model 2 the results indicate that Malaysia central bank reacts to lagged interest rates[2]. The results indicate that less than 7% of a change in the policy interest rate of the previous period is reflected in the current policy rate. Inflation is also significant and positive, although less than unity, indicating that the central bank in Malaysia accommodates inflation.

The output gap is not significant in Model 2, however, when it is augmented with optimal FCI (Model 3), the output gap becomes significant. The optimal FCI is significant and negative indicating that one standard deviation increase in the index relative to its mean triggers the central bank in Malaysia to decrease the interest rate by 0.4%. Other FCIs (Model 4-6), do not affect the results when augmented and are not significant.

Between the two competing regression results (Model 2 and 3), the optimized Model 3 yields the lower SBIC. This shows that this model better describes the interest rate setting behaviour of the central bank of Malaysia. Even though the central bank of Malaysia does not set a fixed target or a range for its inflation rate, the results show that the implied inflation target rate has been at around 2.4% for all models.

Chile:

The estimate results for Model 1 indicate that Chile monetary policy setting does not follow the simple Taylor rule. However, for smoothed estimation Model 2 the results indicate that the central bank of Chile reacts to lagged interest rates[2]. The results indicate that less than 3% of a change in the policy interest rate of the previous period is reflected in the current policy rate. Both the output gap and inflation are not significant, indicating that the central bank of Chile does not follow the Taylor rule in their monetary policy setting.

Nonetheless, interestingly, when we augment the Taylor rule with the FCIs, the output gap becomes statistically significant and positive, and the FCI_{OLS} (Model 5) becomes significant and negative. This means that one standard deviation increase in the index relative to its mean triggers the central bank in Chile to decrease the interest rate by 2.12%. Furthermore, Model 5, has the lowest SBIC for all competing models. The

[2] The regression model was regressed with three lags of interest rates, as the model was suffering from autocorrelation when only one lag of interest rate was used.

results show that the implied inflation target rate has been ranging between 4.05 and 5.65 % for all models, which is above the 3±1% target range for Chile.

Poland:

The estimate results for Model 1 indicate that Poland monetary policy setting is not characterized by the simple Taylor rule. However, for smoothed estimation Model 2 the results indicate that the central bank of Poland reacts to lagged interest rates[2]. The results indicate that less than 3% of a change in the policy interest rate of the previous period is reflected in the current policy rate. The results for Model 2 show that Poland does not react to inflation but to the output gap.

However, when augmented with FCIs, the inflation become significant and less than unity. The only FCI that is significant is the optimized FCI, Model 3, and its coefficient is negative indicating that one standard deviation increase in the index relative to its mean triggers the central bank of Poland to increase the interest rate by 0.7%. Other FCIs (Model 4-6) are not significant.

The results show that the implied inflation target rate has been above the 2.5±1%. The optimized FCI yields the lowest SBIC amongst all reported FCIs, which indicates that it describes the behaviour of Poland central bank better than any other tested models. Model 3 yields the lowest SBIC and shows that this model better describes the interest rate setting behaviour of Poland central bank.

5.2 In-sample analysis for Turkey, Czech Republic, Mexico and Brazil

Table 5-2 reports linear regression results of the Taylor rule for Turkey (period 2001:10 – 2013:05), Czech Republic (2001:10 – 2014:12), Mexico (2000:01 – 2014:12) and Brazil (2000:01 – 2014:12) in respective periods.

Turkey

The results for the central bank of Turkey without lagged interest rate suffers from autocorrelation (Model 1). But the results for smoothed estimation Model 2 indicate that the central bank of Turkey reacts to lagged interest rates. Less than 5% of a change in the interest rate target is reflected in repo rate from the previous period. The output gap is not significant for all models, and the only significant FCI is the ordinary least squares FCI_{OLS} (Model 5). This indicates that one standard deviation increase in the FCI relative to its mean triggers the central bank in Turkey to decrease the interest rate by 12.2%.

Inflation is also significant and positive, for all models and just above unity for Model 5, indicating that the central bank in Turkey accommodates inflation, just sufficiently high to keep the real interest rate from declining, to exert the desired stabilizing effect on inflation. Furthermore, Model 5, has the lowest SBIC for all competing models. The results show that the implied inflation target rate has been ranging between 3 and 10.3 % for all models, which is outside the 5.5±2% target range for Turkey.

Czech Republic

The results for Czech Republic central bank without lagged interest rate suffers from autocorrelation (Model 1). But the results for smoothed estimation Model 2 indicate that the central bank of Czech Republic reacts to lagged interest rates. Less than 3% of a change in the interest rate target is reflected in repo rate from the previous period. The monetary policy coefficients for inflation response is positive but less than unity for most of the models (except Model 5 and 6).

The output gap response is negative for all models and becomes significant only for Model 3, 4 and 6. Amongst these competing models, Model 3, has the lowest SBIC indicating that it best describes the monetary behaviour of Czech Republic. The results show that the implied inflation target rate has been ranging between 2 and 3% for all models, which is within the 3±1% target range for the central bank.

Table 5-2: In-sample estimates for Turkey, Czech Republic, Mexico and Brazil

	Turkey						**Czech Republic**					
Coeff	**1**	**2**	**3**	**4**	**5**	**6**	**1**	**2**	**3**	**4**	**5**	**6**
ρ_0		0.95 ***	0.95 ***	0.95 ***	0.96 ***	0.95 ***		0.97 ***	0.96 ***	0.96 ***	0.95 ***	0.94 ***
		(0.01)	(0.01)	(0.01)	(0.013)	(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ρ_π	0.88 ***	0.66 ***	0.63 ***	0.62 ***	1.08 ***	0.72 ***	0.37 ***	0.93 *	0.86 ***	0.73 ***	1.09 **	0.638 ***
	(0.03)	(0.15)	(0.17)	(0.15)	(0.24)	(0.16)	(7.57)	(0.54)	(0.29)	(0.24)	(0.45)	(0.19)
ρ_y	0.19	0.30	0.33	0.33	0.42	0.29	-0.00	-0.4	-0.29 *	-0.2 *	-0.34	-0.22 **
	(0.13)	(0.46)	(0.46)	(0.42)	(0.59)	(0.48)	(-0.14)	(0.370)	(0.16)	(0.12)	(0.22)	(0.09)
$\rho_{FCI,OPT}$			-1.1						0.70 *			
			(2.34)						(0.38)			
$\rho_{FCI,EW}$				-1.8						0.71 **		
				(2.18)						(0.31)		
$\rho_{FCI,OLS}$					-12.2 *						-0.14	
					(6.46)						(0.46)	
$\rho_{FCI,KF}$						-3.25						0.71 ***
						(2.65)						(0.24)
π^*	(1.65)	4.79	4.25	3.06	10.36	6.01	2.04	2.99	2.62	2.64	2.59	2.59
Adj. R^2	0.78	0.99	0.99	0.99	0.99	0.99	0.30	0.98	0.98	0.98	0.98	0.98
DW	0.08	1.55	1.56	1.56	1.64	1.55	0.05	1.96	2.10	2.09	2.06	2.08
SBIC	6.83	3.22	3.25	3.25	3.16	3.24	2.82	0.64	0.67	0.68	0.65	0.68
	Mexico						**Brazil**					
ρ_0		0.97 ***	0.96 ***	0.96 ***	0.96 ***	0.94 ***		0.98 ***	0.97 ***	0.97 ***	0.99 ***	0.98 ***
		(0.04)	(0.03)	(0.04)	(0.04)	(0.04)		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
ρ_π	1.49 ***	0.08	0.14	-0.3	-0.3	0.66	0.55 *	9.02	5.20 *	3.75	218	8.99
	(0.16)	(1.65)	(1.35)	(1.37)	(1.64)	(0.79)	(0.33)	(6.56)	(2.90)	(2.43)	(418)	(6.13)
ρ_y	0.20 **	1.34	1.01	0.77	1.18	0.44	-0.04	0.51	0.22	0.07	19.2	0.48
	(0.09)	(1.26)	(0.93)	(0.79)	(1.08)	(0.53)	(0.02)	(0.45)	(0.20)	(0.18)	(372)	(0.40)
$\rho_{FCI,OPT}$			3.14 *						2.61 *			
			(1.91)						(1.42)			
$\rho_{FCI,EW}$				2.15 *						2.80 **		
				(1.28)						(1.29)		
$\rho_{FCI,OLS}$					1.44						-141	
					(1.31)						(276)	
$\rho_{FCI,KF}$						1.70 **						2.39
						(0.70)						(2.92)
π^*	4.09	14.22	10.53	1.57	0.99	4.93	5.56	5.69	5.74	5.79	5.62	5.72
Adj. R^2	0.34	0.97	0.97	0.97	0.97	0.97	0.12	0.99	0.99	0.99	0.99	0.99
DW	0.16	1.96	2.01	1.93	1.94	1.98	0.03	2.18	2.21	2.24	2.12	2.18
SBIC	4.00	1.09	1.05	1.09	1.11	1.08	5.32	0.88	0.90	0.90	0.89	0.91

Notes i) In column 1 the LS regression is presented following the basic Taylor rule: $i_t = \rho_0 + \rho_\pi \pi_{t-1} + \rho_y y_{t-1} + \varepsilon_t$. All the regressors are lagged one period.
ii) All other columns present the Taylor rule LS regression with interest rate smoothing, up to 3 lagged periods remove autocorrelation, and includes lagged FCI. The general formular is $i_t = \rho_0 i_{t-1} + \rho_1 i_{t-2} + \rho_2 i_{t-3} + (1-\rho_0 - \rho_1 - \rho_2)(\rho_\alpha + \rho_\pi \pi_{t-1} + \rho_y y_{t-1} + \rho_f F_{t-1}) + \varepsilon_t$.
iii) The values reported in parentheses are standard erros and *(**)[***] indicate the parameter is significant at 10%(5%)[1%]
iv) The implied inflation target rate π^* is computed as $\pi^* = (i^* - \rho_0)/\rho_\pi$, where i^* is the sample mean. i^* = 8.2% is for Turkey, 1.5% for Czech Republic, 6.2% for Mexico, and 12.4% for Brazil for respective periods. The SBIC is the Schwartz Bayesian Information Criterion.
v) FCI developed: time-varying optimal weights using DCC –GARCH Model (FCI_{OPT}), time-varying weights using Kalman-Filter estimation (FCI_{KF}), constant equal weights (FCI_{EW}), and weights from OLS estimation (FCI_{OLS}).

Mexico

The results (Model 1) for Mexico central bank without lagged interest rate suffers from autocorrelation, and low explanatory power, even though both inflation and output gap are significant. The results for smoothed estimations indicate that the central bank of Mexico reacts to lagged interest rates. Less than 3% of a change in the interest rate target is reflected in repo rate from the previous period. The monetary policy coefficients for inflation and output gap response are not significant for all other models. This means the central bank of Mexico monetary policy setting behaviour is not explained by the Taylor rule. However, the results show that interest rates do respond to FCIs, as shown in Model 3,4 and 6. Amongst these competing models, Model 3, has the lowest SBIC indicating that it best describes the monetary behaviour of Mexico. The results show different implied inflation target rate for each model ranging from 1.57% to 10.5% versus the target range of 3±1%.

Brazil

The results for Brazil central bank without lagged interest rate suffers from autocorrelation (Model 1). But the results for smoothed estimation Model 2 indicate that the central bank of Brazil reacts to lagged interest rates. Less than 3% of a change in the interest rate target is reflected in repo rate from the previous period. The monetary policy coefficients for inflation response is only significant for Model 3 and is above unity, indicating that the central bank in Brazil acts to stabilize inflation. The output gap response is not significant for all the models. Model 3 best describes the monetary behaviour of Brazil. The results show that the implied inflation target rate has been above 5.5% for all models, which is outside the 4.5±1% target range for the central bank.

5.3 In-sample analysis for Russia, India, South Korea and China

Table 5-3 reports linear regression results of estimation of the Taylor rule for Russia (period 2003:11 – 2013:05), India (2000:01 – 2014:12), South Korea (2000:01 – 2014:12) and China (2003:09 – 2013:06).

Russia

The results (Model 1) for the central bank of Russia bank without lagged interest rate suffers from autocorrelation, and low explanatory power, even though both inflation and output gap are significant. The results for smoothed estimations indicate that the central bank of Russia reacts to lagged interest rates. Less than 3% of a change in the interest rate target is reflected in repo rate from the previous period. The monetary policy coefficients for inflation response is significant and positive for all models but is below unity, indicating that the central bank in Russia acts to accommodate inflation. The output gap response is significant for all the models. The only index that Russia responds to is that of Kalman-Filter (Model 6). Inter alia, all the models presented, Model 2 best describes the monetary setting of Russia, because it has the lowest SBIC and highest explanatory power compared to other models. The results show that the implied inflation target rate has been around 11.3 and 12.3% for all models.

India

The results (Model 1) for the central bank of India without lagged interest rate suffers from autocorrelation, and low explanatory power, even though both inflation and output gap are significant. The results for smoothed estimations indicate that the central bank of India reacts to lagged interest rates. Less than 4% of a change in the interest rate target is reflected in interest rate from the previous period. However, all other coefficients are not significant for all the models, indicating that India monetary policy setting might not be explained by the Taylor rule.

Interestingly, the implied inflation target shows a consisted inflation around 6%, which is close to the upper band of their 2-6% target range. It should be noted that India formally adopted inflation targeting framework in June 2016, which is outside the sample period under analysis. This highlights that explicit inflation targeting per se is not the only mechanism to achieve low and stable inflation.

Table 5-3: In-sample estimates for Russia, India, South Korea and China

	Russia						India					
Coeff	**1**	**2**	**3**	**4**	**5**	**6**	**1**	**2**	**3**	**4**	**5**	**6**
ρ_0		0.94 ***	0.94 ***	0.94 ***	0.94 ***	0.90 ***		0.99 ***	0.96 ***	0.96 ***	0.96 ***	0.96 ***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)		(0.08)	(0.09)	(0.09)	(0.09)	(0.09)
ρ_π	0.57 ***	0.49 ***	0.46 **	0.45 **	0.40 **	0.49 ***	0.03 *	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.04)	(0.15)	(0.18)	(0.17)	(0.19)	(0.09)	(0.02)	(0.00)	(0.01)	(0.006)	(0.01)	(0.01)
ρ_y	-0.13 **	1.02 **	1.09 **	1.06 **	1.21 **	0.39 **	0.18 ***	0.01	0.01	0.02	0.02	0.024
	(0.06)	(0.44)	(0.48)	(0.45)	(0.54)	(0.19)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
$\rho_{FCI,OPT}$			0.69						0.00			
			(0.54)						(0.02)			
$\rho_{FCI,EW}$				0.78						-0.00		
				(0.52)						(0.02)		
$\rho_{FCI,OLS}$					0.93						-0.00	
					(0.65)						(0.02)	
$\rho_{FCI,KF}$						1.09 ***						0.01
						(0.27)						(0.03)
π^*	10.02	12.31	12.70	12.70	13.29	11.27	6.84	6.21	6.05	6.04	6.04	6.05
Adj. R^2	0.58	0.99	0.98	0.98	0.98	0.98	0.13	0.96	0.93	0.93	0.93	0.93
DW	0.07	2.02	2.05	2.06	2.06	2.15	0.08	1.93	1.99	1.99	1.99	1.98
SBIC	3.65	0.34	0.47	0.47	0.47	0.40	2.45	0.37	0.01	0.12	0.12	0.13
	South Korea						**China**					
ρ_0		0.94 ***	0.94 ***	0.94 ***	0.94 ***	0.90 ***		0.92 ***	0.95 ***	0.95 ***	0.91 ***	0.92 ***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
ρ_π	0.57 ***	0.49 ***	0.46 **	0.45 **	0.40 **	0.49 ***	0.06 ***	0.32 **	0.61	0.60	0.27 *	0.33 *
	(0.04)	(0.15)	(0.18)	(0.17)	(0.19)	(0.09)	(0.01)	(0.13)	(0.54)	(0.53)	(0.14)	(0.17)
ρ_y	-0.13 **	1.02 **	1.09 **	1.06 **	1.21 **	0.39 **	-0.17 ***	-0.21 *	-0.37	-0.3	-0.18	-0.21 *
	(0.06)	(0.44)	(0.48)	(0.45)	(0.54)	(0.19)	(0.02)	(0.115)	(0.31)	(0.31)	(0.121)	(0.12)
$\rho_{FCI,OPT}$			0.69						-0.50			
			(0.54)						(0.71)			
$\rho_{FCI,EW}$				0.78						-0.4		
				(0.52)						(0.70)		
$\rho_{FCI,OLS}$					0.93						0.10	
					(0.65)						(0.18)	
$\rho_{FCI,KF}$						1.09 ***						-0.01
						(0.27)						(0.20)
π^*	10.02	12.31	12.70	12.70	13.29	11.27	2.93	2.77	2.83	2.82	2.75	2.77
Adj. R^2	0.58	0.99	0.98	0.98	0.98	0.98	0.26	0.92	0.92	0.92	0.92	0.92
DW	0.07	2.02	2.05	2.06	2.06	2.15	0.25	1.85	1.94	1.94	1.85	1.86
SBIC	3.65	0.34	0.47	0.47	0.47	0.40	1.10	1.03	1.01	1.01	1.00	0.99

Notes i) In column 1 the LS regression is presented following the basic Taylor rule: $i_t = \rho_0+\rho_\pi\pi_{t-1}+ \rho_y y_{t-1} +\varepsilon_t$. All the regressors are lagged one period.

ii) All other columns present the Taylor rule LS regression with interest rate smoothing, up to 3 lagged periods remove autocorrelation, and includes lagged FCI. The general formular is $i_t = \rho_0 i_{t-1}+\rho_1 i_{t-2} +\rho_2 i_{t-3}+(1-\rho_0- \rho_1 -\rho_2)(\rho_\alpha+\rho_\pi\pi_{t-1}+\rho_y y_{t-1}+ \rho_f F_{t-1}) +\varepsilon_t$

iii) The values reported in parentheses are standard erros and *(**)[***] indicate the parameter is significant at 10%(5%)[1%]

iv) The implied inflation target rate π^* is computed as $\pi^* = (i^*-\rho_0)/\rho_\pi$, where i^* is the sample mean. i^* = 10.6% is for Russia, 6.3% for India, 2.7% for South Korea, and 3.3% for China for respective periods. The SBIC is the Schwartz Bayesian Information Criterion.

v) FCI developed: time-varying optimal weights using DCC –GARCH Model (FCI_{OPT}), time-varying weights using Kalman-Filter estimation (FCI_{KF}), constant equal weights (FCI_{EW}), and weights from OLS estimation (FCI_{OLS}).

South Korea:

The results (Model 1) for the central bank of South Korea without lagged interest rate suffers from autocorrelation, and low explanatory power, even though both inflation and output gap are significant. The results for smoothed estimations indicate that the central bank of India reacts to lagged interest rates. Less than 3% of a change in the interest rate target is reflected in repo rate from the previous period. However, all other coefficients are not significant for all the models except Model 2, where output gap is significant and the financial coefficient of the Kalman-Filter (Model 6). Predominantly, however, the results indicate that the Korea central bank interest setting behaviour is not characterised by the Taylor rule. On the other hand, the implied inflation target shows a consisted inflation around below 4%, which is within the band of their 3±1% target range.

China

The results (Model 1) for the Central Bank of China without lagged interest rate suffers from autocorrelation, and low explanatory power, even though both inflation and output gap are significant. The results for smoothed estimations indicate that the central bank of India reacts to lagged interest rates. Less than 8% of a change in the interest rate target is reflected in repo rate from the previous period. However, all other coefficients are not significant for all the models except Model 2, where both inflation and output gap are significant. All other FCIs are not significant, indicating that China does not take into account financial conditions when setting interest rates. The implied inflation target shows a consisted inflation around below 3%, which is below the point target of 4%.

5.4 In-sample analysis summary

Table 5-4 below summarizes the overall implication of the in-sample analysis; it specifically shows models that best describes the behaviour of each country central bank monetary setting behaviour. In these results, ten out of the twelve emerging countries tend to follow the Taylor rule. It is only Chile and India that does not follow the Taylor rule. Furthermore, ten countries take into account the information contained in the FCIs and the majority of these countries, six specifically, optimize those variables that enter the FCIs, as per Model 3.

This is consistent with the hypothesis as suggested in this paper that optimal time-varying FCI better explains interest rate movements compared to non-optimized optimal FCIs. It should be noted that even though that Chile doesn’t follow Taylor rule, it does take into account FCI, as per Model 4, on the other hand, India does not react to all FCIs. Lastly, even though China follows the Taylor rule, it does not respond to all the FCIs.

Table 5-4: Summary of in-sample analysis

Countries	South Africa	Malaysia	Chile	Poland	Turkey	Czech Republic	Mexico	Brazil	Russia	India	South Korea	China	Total
Follows TR	√	√		√	√	√	√	√	√		√	√	**10**
Don't follow TR			√							√			**2**
Model 2													**0**
Model 3	√	√		√		√	√	√					**6**
Model 4													**0**
Model 5			√		√								**2**
Model 6									√		√		**2**

Notes: TR refers to the Taylor rule. Model 2 refers to the Taylor rule without augmenting with FCIs, Model 3 refers to Model 2 augmented with time-varying optimal weights using the DCC –GARCH method (FCI_{OPT}), Model 4 refers to Model 2 augmented with the constant equal weights method (FCI_{EW}), Model 5 refers to Model 2 augmented with the weights from OLS estimation method (FCI_{OLS}), and Model 6 refers to Model 2 augmented with the time-varying weights using the Kalman-Filter estimation method (FCI_{KF}).

5.5 Out-of-sample analysis forecast evaluation

In this section, the models developed in the previous section are used as a basis for a repeated forecasting exercise, where the out-of-sample forecasts are based on a recursive scheme, similar to the one employed by Naraidoo and Paya (2012). In order to compare the out-of-sample forecasting ability of different models, this paper employs test statistics MAE, MAPE and RMSE, however, only the last statistic is reported in this paper.

The number of observations in the in-sample is denoted I_{in} and for the out-of-sample analysis is denoted $I_{out.}$ This makes the total number of observations to be $I_T = I_{out} + I_{out}$. Using the recursive scheme, the in-sample observations increase from I_{in} to I_T – h, and the coefficients of the models/regressions are re-estimated by using the data up to time t, and the forecasts are generated for the horizon (*h*). The forecasting horizon calculated are for 1, 3, 6 and 12 step-ahead forecasts in period I_{out}.

Table 5-5 reports the evolution of the forecasting comparison and how each model ranks against the model that does not include financial conditions (Model 2) across different horizons. Using the RMSE test statistical method, the most accurate forecasting model amongst competing models will have the lowest RMSE, in this regard, that model has a better rank than the competing model.

The results show that the proposed optimized Model 3 (M3) outperforms the rest of the models for all forecasting horizons for the case of South Africa and India. Model 2 (M2) outperforms the rest of the models for all forecasting horizons in both Malaysia (except h=6) and Mexico.

For the case of Chile Model 4 outperforms other models for 1, 3, and 6 horizons. In Poland, Model 6 outperforms other models in horizon 1 and 3 but Model 3 performs better for horizon 6 and 12. In Russia, Model 2 outperforms other models in horizon 1 and 3 but Model 6 performs better for horizon 6 and 12. In South Korea, Model 5 outperforms other models in h=1 but Model 3 performs better for horizon 3, 6 and 12. In South Korea, Model 3 dominates (except at h=1). In Turkey and China, it is difficult to single out because each model dominates for each particular horizon.

Even though it is quite daunting to single out the outright dominating model in the results except for the case of South Africa and India where Model 3 was dominant, and for Mexico where for Model 1 was dominant. The results indicate that the majority of the central banks to take into account the information contained future FCIs (optimized and un-optimized) when setting interest rates, at least from the evidence presented in Table 5-5. Accordingly, we proceed to the next section where we test for forecasting predictability. We test whether two competing forecasts have equal predictive accuracy and whether this difference is significant or it is due to the specific choice of the data in the sample.

Table 5-5: Out-of-sample forecasting evaluation and ranks (MSPE)

	South Africa				Malaysia				Chile			
Steps	1	3	6	12	1	3	6	12	1	3	6	12
M2	0.21	0.39	0.70	1.33	**0.013**	**0.032**	0.026	**0.033**	0.015	0.182	0.112	0.382
M3	**0.15**	**0.16**	**0.14**	**0.20**	0.015	0.061	0.072	0.147	0.015	0.209	0.207	0.794
M4	0.16	0.21	0.29	0.44	0.040	0.074	**0.014**	0.044	**0.014**	**0.169**	**0.047**	0.137
M5	0.15	0.16	0.15	0.20	0.018	0.034	0.038	0.162	0.043	0.336	0.314	**0.035**
M6	0.16	0.18	0.21	0.31	0.016	0.040	0.044	0.081	0.015	0.190	0.131	0.420
	Poland				Turkey				Czech Republic			
Steps	1	3	6	12	1	3	6	12	1	3	6	12
M2	0.182	0.493	0.781	1.101	0.105	**0.761**	0.355	3.823	0.042	0.139	0.267	0.293
M3	0.166	0.434	**0.612**	**0.718**	0.066	0.768	0.268	3.402	0.044	0.151	0.266	0.275
M4	0.178	0.474	0.699	0.893	0.051	0.748	**0.171**	3.111	**0.041**	0.144	**0.258**	0.230
M5	0.182	0.487	0.733	0.976	**0.007**	0.892	0.412	**2.947**	0.043	**0.141**	0.268	0.293
M6	**0.151**	**0.395**	0.618	0.938	0.006	0.884	0.470	3.593	0.043	0.150	0.272	**0.199**
	Mexico				Brazil				Russia			
Steps	1	3	6	12	1	3	6	12	1	3	6	12
M2	**0.028**	**0.358**	**1.669**	**2.380**	0.389	0.597	0.833	1.398	**0.017**	**0.098**	0.275	0.564
M3	0.048	0.395	1.771	3.093	**0.383**	0.628	0.978	1.670	0.033	0.117	0.302	0.572
M4	0.040	0.430	1.866	3.138	0.396	0.657	0.952	1.702	0.038	0.128	0.322	0.599
M5	0.047	0.363	1.686	2.766	**0.383**	0.581	**0.734**	**0.855**	0.046	0.148	0.358	0.649
M6	0.033	0.396	1.814	2.387	0.388	**0.570**	0.763	1.263	0.047	0.125	**0.074**	**0.125**
	India				South Korea				China			
Steps	1	3	6	12	1	3	6	12	1	3	6	12
M2	0.160	0.259	0.303	1.756	0.038	0.143	0.320	0.890	0.008	**0.002**	**0.006**	0.069
M3	**0.157**	**0.257**	**0.302**	**1.751**	0.036	**0.095**	**0.208**	**0.558**	0.014	0.088	0.193	0.356
M4	0.162	0.258	0.312	1.718	0.037	0.108	0.238	0.659	0.011	0.083	0.187	0.350
M5	0.163	0.259	0.303	1.720	**0.029**	0.103	0.218	0.701	0.012	0.010	0.021	**0.065**
M6	0.161	0.260	0.301	1.857	0.054	0.212	0.466	1.158	**0.001**	0.025	0.040	0.140

Notes: 1 The table reports the out-of-sample forecasting rank of *Models* across the recursive windows, and the forecast horizon is h = 1, 3, 6 and 12 using MSPE criteria

2 M2 refers to the Taylor rule without augmenting with FCIs, M3 refers to M2 augmented with time-varying optimal weights using the DCC –GARCH method (FCI_{OPT}), M4 refers to M2 augmented with the constant equal weights method (FCI_{EW}), M5 refers to M2 augmented with the weights from OLS estimation method (FCI_{OLS}), and M6 refers to M2 augmented with the time-varying weights using the Kalman-Filter estimation method (FCI_{KF}).

5.6 Out-of-sample forecast accuracy comparison

In this section, the forecasting predictive accuracy is explored using the Diebold-Mariano (1995) and later modified by Harvey et al. (1997). In their formulation, suppose there are two forecasts $f_{1,}f_{2,\cdots,}f_n$ and $g_{1,}g_{2,\cdots,}g_n$ for a particular time series $y_{1,}y_{2,\cdots,}y_n$ the Diebold – Mariano statistic is defined as follows:

$$DM = \frac{\bar{d}}{\sqrt{\left[\gamma_0 + 2\sum_{k=1}^{h-1}\gamma_k\right]/_n}}$$

Where $\gamma_k = \frac{1}{n}\sum_{i=k+1}^{n}\left(d_i - \bar{d}\right)\left(d_{i-k} - \bar{d}\right)$ is the autocovariance at lag k, $\bar{d} = \frac{1}{n}\sum_{i=1}^{n} d_i$, $d_i = e_i^2 - e_j^2$ is related to the MSE error statistic, $e_i = y_i - f_i$, and $e_j = y_i - g_i$ are the residuals of the two forecasts and $h = n^{1/3} + 1$. Indeed, the Diebold – Mariano statistic tends to reject the null hypothesis for small samples. In this regard, Harvey et al. (1997) proposed a better test, which is defined as follows:

$$DM_t = DM\sqrt{[n + 1 - 2h + h(h-1)/n]} \sim T(n-1)$$

The DM_t takes on negative values if the forecast errors (e_i^2) of the benchmark model are lower than that of the competing model forecast erros (e_j^2). Under this DM_t test evolution, it is tested whether two competing forecasts have equal predictive accuracy, and whether this difference is significant or it is due to the specific choice of the data in the sample. More specifically, the DM_t test looks at the forecast errors differentials to test the null hypothesis that the difference between the benchmark model errors (Model 2) and other competing models (Model 3, M4, M5, and M6) is equal.

In this way, when the Diebold-Mariano test statistic is negative and statistically significant, it indicates evidence in favour of the predictive power of the benchmark model (Model 3). Table 5-6 provides a detailed forecasting performance of a pairwise out-of-sample forecast comparison based on recursive estimates for forecast horizon (h = 3, 6 and 12). Where the results are not shown (-), it means the DM_t statistic is not available. The evidence suggests that for most emerging countries, the information contained in the optimized FCI have marginal extra information regarding the forecasting predictability of interest rate setting behaviour as shown in Table 5-6.

While other central banks tend to optimize their interest rates, others do not. In the majority of the emerging countries under study namely South Africa, Poland, Turkey, Brazil, India and South Korea the optimized FCI (M3) dominates forecasting accuracy performance and predictive power for all horizons considered. Therefore, these emerging countries are concerned with optimizing the information contained in the financial conditions when setting interest rates. The opposite occurs in Malaysia, Czech Republic, and China, the evidence shows that the central banks in these countries see no gain to use information contained in optimized FCI.

Table 5-6: Interest rates forecasting accuracy evolution

	South Africa			Malaysia			Chile		
Steps	3	6	12	3	6	12	3	6	12
M2 vs.									
M3	**3.58***	**2.77****	**2.89****	-2.08	-3.89***	-3.51***	-1.79	-2.32*	-2.25**
M4	**3.30***	**2.38***	**2.86****	-7.54**	-0.79	-1.11	1.40	2.04*	2.30**
M5	**3.21***	**2.65****	**2.96****	-3.93*	-1.89*	-1.78*	-2.56	-4.74***	-0.83
M6	**3.81***	**2.64****	**3.12*****	-3.18*	-3.11**	-2.96**	-2.40	-2.86**	-3.28***
	Poland			**Turkey**			**Czech Republic**		
Steps	3.00	6.00	12.00	3.00	6.00	12.00	3.00	6.00	12.00
M2 vs.									
M3	**3.12***	**2.78****	**2.99****	**0.14**	**1.74**	**2.00***	-3.33*	-2.05*	**0.50**
M4	**2.76**	**2.29***	**2.63****	-	**2.04***	**2.17***	-1.58	**0.61**	**1.60**
M5	**2.26**	**1.96***	**2.45****	-0.91	-3.34**	**0.98**	-3.16*	-16.34***	-3.45***
M6	**3.4***	**4.27*****	**6.08*****	-0.80	-3.74***	-0.30	-2.47	-5.06***	**1.04**
	Mexico			**Brazil**			**Russia**		
Steps	3.00	6.00	12.00	3.00	6.00	12.00	3.00	6.00	12.00
M2 vs.									
M3	-	-1.97*	-1.98*	**5.53****	-	**1.20**	-18.54***	-8.17***	-6.46***
M4	-1.70	-2.11*	-2.25**	-1.72	-1.65	**0.54**	-9.56**	-5.93***	-5.64***
M5	-2.83*	-2.71**	-1.70	-2.31	-2.94**	**0.59**	-6.37**	-5.22***	-5.76***
M6	-1.44	-1.94*	-2.49**	-2.52	-3.11**	-1.28	-	**1.06**	**2.06***
	India			**South Korea**			**China**		
Steps	3.00	6.00	12.00	3.00	6.00	12.00	3.00	6.00	12.00
M2 vs.									
M3	**-**	**1.16**	**1.64**	**1.83**	**2.81****	**2.73****	-1.73	-2.74**	-3.3***
M4	**0.35**	**1.02**	**1.66**	**1.81**	**2.77****	**2.77****	-1.61	-2.66**	-3.22***
M5	**0.35**	**1.02**	**1.66**	**2.68**	**2.82****	**3.31*****	-4.16*	-6.13***	-0.04
M6	-1.02	-1.12	-1.69	-2.82*	-3.28**	-3.62***	-0.47	-2.26*	-2.75**

Notes: 1 The table presents Diebold-Mariano t-statistic,DM-t, values for each pair-wise out-of-sample comparison across recursive forecasting horizons h= 1, 3, 6 and 12.

2 A positive DM-t indicates that model M2 has less forecasting accuracy than M3/4/5/6 , while a negative sign indicates the opposite.

3 The DM-t tests for the null hypothesis that both forecasts have the same accuracy, agaist the alternative both Models forecasts do not have the same accuracy at 5%(**) and 10%(*) significant levels

Finally, there results for Chile, Czech Republic, and Russia indicates that the central banks take into account the information contained in FCIs although not optimized. In the case of Chile, Model 3 dominates the forecasting accuracy performance. In the case of Czech Republic, it is not clear which FCI dominates as the evidence shows that even though there’s no outright dominator, the FCIs are not significantly different from the benchmark Model 2 in horizon 6 and 12. In Russia, Model 6 dominates the forecasting accuracy performance. Thus, we conclude that the majority of the central banks take into account the FCIs when setting their interest rates, but more importantly, the majority optimize the information contained in these FCIs.

6. CHAPTER 6: CONCLUSION

Following the credit crisis of 2008, the conventional wisdom and foundations that prevailed before were shaken profoundly. The importance of financial conditions to macroeconomic outcomes were elevated. In particular, the conduct and behaviour of central banks in response to financial conditions. There has been a consensus among economists and policymakers on the importance of financial conditions, and the influence thereof, on the interest setting behaviour of central banks.

However, in order for central banks to achieve their financial stability objectives, this paper firstly investigates whether central banks of emerging markets follow the Taylor rule in setting their interest rates. Secondly, it investigates whether the FCI with optimal time-varying weights better describes interest rate movements in emerging markets, when augmented in the Taylor rule. Lastly, it evaluates interest rate predictability by comparing various models that include un-optimized FCIs.

To answer the first question, the paper finds that the majority of emerging countries, ten out of the twelve, which were investigated follow the Taylor rule. On the second question, the paper finds that ten of the emerging countries do take into account the information contained in the FCIs and the majority of these countries, six specifically, optimize those variables that enter the FCIs. This is consistent with the hypothesis suggested in this paper that optimal time-varying FCI better explains interest rate movements compared to non-optimized optimal FCIs.

Lastly, after evaluating central banks interest rate predictability, we conclude that the majority of the central banks do take into account the FCIs when setting their interest rates, but more importantly, the majority optimize the information contained in these FCIs. More specifically, nine out of twelve countries that use FCIs, we find that the Taylor rule incorporating FCIs perform better than those that omit FCIs. Out of the nine that use FCIs, six countries optimize. In this regard, when central banks set interest rates assume investors are rational in that they optimize their portfolio returns, thereby creating financial conditions.

The predominant response of emerging market policymakers to FCIs is remarkably telling and has important policy implications. It was perhaps this featuring of FCIs in the monetary policy rule of emerging markets that made them to be more resilient to the credit crises, compared to other developed countries.

7. REFERENCES

Akram, Q. F., and O. Eitrheim. 2008. “Flexible Inflation Targeting and Financial Stability: Is It Enough to Stabilize Inflation and Output?” Journal of Banking and Finance 32 (7): 1242–54.

Asso, F. et al. (2007) ‘Monetary Policy Rules: from Adam Smith to John Taylor - Taylor Conference 2007 - FRB Dallas’, (October), pp. 1–59.

Batini, N. et al. (2001) ‘Monetary Policy Rules for an Open Economy’.

Bernanke, B.S. and M. Gertler (1999), “Monetary Policy and Asset Price Volatility”, New challenges for monetary policy, Federal Reserve Bank of Kansas City, pp. 77-128.

Bullard, J., Schaling, E., 2002. Why the Fed should ignore the stock market. The Federal Reserve Bank of St. Louis, 35–41 (March–April)

Burger P and Marinkov M (2008) ‘Inflation Targeting and Inflation Performance in South Africa’, In Annual Forum, pp. 1–19. Available at: www.tips.org.za.

Carlstrom, C. T. and Fuerst, T. S. (2000) ‘Forward-Looking Versus Backward-Looking Taylor Rules’, Federal Reserve Bank of Cleveland, 9.

Castro, V. (2008). Are central banks following a linear or nonlinear (augmented) Taylor rule? The Warwick Economics Research Paper Series (TWERPS) 872, University of Warwick, Department of Economics.

Castro, V. (2011) ‘Can central banks’ monetary policy be described by a linear (augmented) Taylor rule or by a nonlinear rule?’, Journal of Financial Stability, 7(4), pp. 228–246.

Cecchetti, S. G., Genberg, H., Lipsky J. and Wadhwani, S. (2000). “Asset Prices and Central Bank Policy,” The Geneva Report on the World Economy, No. 2, Geneva: International Centre for Monetary and Banking Studies, May

Charleroy, R. and Stemmer, M. A. (2015) ‘An Emerging Market Financial Conditions Index: A VAR Approach Centre d ’ Economie de la Sorbonne Documents de Travail du’, pp. 1–15.

Clarida, R., Gali, J. and Gertler, M. (2000b) 'Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory', Quarterly Journal of Economics, 115(1), pp. 147–180.

De Gregorio, J. 2014. How Latin America weathered the global financial crisis. Washington, DC: Peterson Institute for International Economics.

Disyatat, P. (2005) 'Inflation targeting, asset prices and financial imbalances: conceptualizing the debate', (168).

Driffill, J. et al. (2006) 'Monetary policy and financial stability: What role for the futures market?', Journal of Financial Stability, 2(1), pp. 95–112.

El-Edel, D. M. R. (2010) 'International asset allocation and equity home bias in emerging markets', PQDT - UK & Ireland, p. 316.

Ellyne, M. and Veller, C. (2012) 'What is the SARB's inflation targeting policy, and is it appropriate?', Munich Personal RePEc Archive, (42134).

Engle, R. F. and Sheppard, K. (2001) 'Theoretical and Empirical properties of Dynamic Conditional Correlation Multivariate GARCH', NBER Working Paper Series, pp. 1–46.

Galimberti, J. K. and Moura, M. L. (2013a) 'Taylor rules and exchange rate predictability in emerging economies', Journal of International Money and Finance, 32(1), pp. 1008–1031.

Galimberti, J. K. and Moura, M. L. (2013b) 'Taylor rules and exchange rate predictability in emerging economies', Journal of International Money and Finance. Elsevier Ltd, 32(1), pp. 1008–1031.

Gameiro, I. M., Soares, C. and Sousa, J. (2011) 'Monetary policy and financial stability: an open debate'.

Ghadha, J., Sarno, L., Valente, G., 2004. Monetary policy rules, asset prices, and exchange rates. IMF Staff Papers 51, 529–552.

Goodhart. C. (2001) "What Weight Should be Given to Asset Prices in the Measurement of Infl ation?", The Economic Journal, 111: 335–356.

Goodhart, C. and B. Hofmann (2000), “Do Asset Prices Help to Predict Consumer Price Infl ation?”, Man- chester School, University of Manchester, vol. 68(0), pages 122-40, Supplement.

Goodhart, C. and B. Hofmann (2002), “Asset Prices and the Conduct of Monetary Policy”, Royal Eco- nomic Society Annual Conference 2002 88, Royal Economic Society.

Hammond, G. (2012) ‘State of the art of inflation targeting’, CCBS Handbook, Bank of England, 29(29), pp. 1–47.

Hatzius, J. et al. (2010) ‘Financial Conditions Indexes: A Fresh Look after the Financial Crisis proceedings of the U. U. monetary policy forum 2010 The Initiative on Global Markets the university of chicago booth school of business’.

Kasaï, N. and Naraidoo, R. (2012) ‘Financial assets, linear and nonlinear policy rulesAn in-sample assessment of the reaction function of the South African Reserve Bank.’, Journal of Economic Studies, 39(2), pp. 161–177.

Koop, G. andD.Korobilis (2014). "ANewIndex of FinancialConditions," European Economic Review, 71: 101-116.

Markowitz, H., 1952. Portfolio Selection. The Journal o f Finance, 7(1), 77-91

Mohanty, M. S. and Klau, M. (2005) ‘Monetary policy rules in emerging market economies: issues and evidence (pp. 205-245).’, Springer Berlin Heidelberg, (149).

Montagnoli, Alberto; Napolitano, O. (2004) ‘Financial Condition Index and interest rate settings: a comparative analysis’, pp. 1–24.

Rudebusch, Glenn D., 2002, “Term Structure Evidence on Interest Rate Smoothing and Monetary Policy Inertia,” Journal of Monetary Economics, Vol. 49, pp. 1161–87.

Rudebusch, G. and Svensson, L. E. O. (1999) Policy Rules for Inflation Targeting, NBER Chapters.

Smaghi, L. B. (2009) ‘Lorenzo Bini Smaghi : Monetary policy and asset prices’, (October), pp. 1–11.

Svensson, L. E. O. (1997) 'Inflation targeting in an open economy: Strict or flexible inflation targeting?', (November).

Svensson, L. E. O. (2003) 'What Is Wrong with Taylor Rules ? Using Judgment in Monetary Policy through Targeting Rules'.

Taylor, J. B. (1993) 'Discretion versus policy rules in practice', Carnegie-Rochester Confer. Series on Public Policy, 39(C), pp. 195–214.

Tse, Y.K. and Tsui, A.K.C., 1997. Conditional Volatility in Foreign Exchange Rates: Evidence from the Malaysian Ringgit and Singapore Dollar 1. Pacific Basin Finance Journal, 5(3), 345-356.

Vivian, A. and Wohar, M. E. (2013) 'The output gap and stock returns: Do cyclical fluctuations predict portfolio returns?', International Review of Financial Analysis. Elsevier Inc., 26, pp. 40–50.

8. APPENDICES

8.1 Descriptive statistics and unit root tests

Table 8-1: Main variables descriptive statistics for emerging countries

	Mean	Median	Max	Min	SD	Skew.	Kurt.	JB	Pr	Obs.	Mean	Median	Max	Min	SD	Skew.	Kurt.	JB	Pr	Obs.
	South Africa										**Malaysia**									
i_t	8.21	7.25	13.50	5.00	2.64	0.53	1.89	19.84	0.00	204	2.89	2.84	3.56	1.99	0.45	-0.32	2.64	2.98	0.23	130
π_t	5.55	5.60	12.23	0.16	2.25	0.28	3.75	7.37	0.03	204	2.46	2.31	8.17	-2.47	1.69	0.56	6.28	65.20	0.00	130
y_t	-0.02	0.32	8.15	-9.06	2.82	-0.74	4.58	39.89	0.00	204	-0.11	-0.33	24.84	-28.70	9.67	-0.32	4.59	16.03	0.00	130
$FCI_{t,OPT}$	0.00	-0.37	3.47	-1.01	1.00	1.19	3.62	51.44	0.00	204	0.00	-0.01	1.92	-3.42	1.00	-1.10	5.44	58.44	0.00	130
$FCI_{t,EW}$	0.00	-0.09	2.20	-3.10	1.00	-0.17	3.22	1.37	0.50	204	0.00	0.01	2.38	-1.92	1.00	0.16	2.31	3.10	0.21	130
$FCI_{t,OLS}$	0.00	-0.11	2.52	-2.10	1.00	0.50	2.71	9.25	0.01	204	0.00	0.08	1.75	-3.44	1.00	-1.27	5.59	70.95	0.00	130
$FCI_{t,KF}$	0.00	-0.24	4.44	-1.97	1.00	1.42	7.00	205	0.00	204	0.00	-0.11	2.47	-1.88	1.00	0.28	2.67	2.34	0.31	130
	Chile										**Poland**									
i_t	4.22	5.00	8.25	0.50	1.90	-0.42	2.85	3.60	0.17	118	4.79	4.50	11.50	2.50	1.57	1.39	5.99	103.4	0.00	149
π_t	3.42	3.21	9.40	-3.44	2.49	0.08	3.96	4.61	0.10	118	2.55	2.53	5.34	0.16	1.42	0.13	1.78	9.72	0.01	149
y_t	-0.37	-1.58	29.54	-39.8	13.54	-0.48	3.75	7.20	0.03	118	-0.02	0.23	8.70	-7.94	2.97	-0.01	3.33	0.69	0.71	149
$FCI_{t,OPT}$	0.00	-0.19	3.26	-2.33	1.00	0.85	3.82	17.37	0.00	118	0.00	0.22	1.65	-3.12	1.00	-1.07	4.07	35.62	0.00	149
$FCI_{t,EW}$	0.00	-0.03	2.44	-1.85	1.00	0.40	2.46	4.67	0.10	118	0.00	0.27	1.69	-3.38	1.00	-1.28	4.66	58.12	0.00	149
$FCI_{t,OLS}$	0.00	0.00	2.32	-1.95	1.00	0.14	2.28	2.92	0.23	118	0.00	0.26	1.88	-3.37	1.00	-1.23	4.56	52.66	0.00	149
$FCI_{t,KF}$	0.00	-0.47	3.15	-1.26	1.00	1.26	3.62	33.16	0.00	118	0.00	0.15	1.92	-3.67	1.00	-0.91	4.25	30.27	0.00	149
	Turkey										**Czech Republic**									
i_t	21.73	18.25	62.00	6.50	15.17	1.35	3.72	49.64	0.00	153	1.37	1.13	3.75	0.05	1.16	0.36	1.92	12.12	0.00	172
π_t	13.97	8.88	73.16	3.99	14.54	2.75	9.93	499.9	0.00	153	1.91	1.72	7.55	-0.40	1.69	1.37	5.03	83.59	0.00	172
y_t	-0.03	0.32	7.70	-18.3	4.42	-1.17	5.32	69.29	0.00	153	-0.03	0.41	7.60	-9.71	3.40	-0.28	3.16	2.38	0.30	172
$FCI_{t,OPT}$	0.00	-0.11	2.52	-2.27	1.00	0.19	2.52	2.34	0.31	153	0.00	-0.09	4.05	-3.40	1.00	0.08	6.62	94.10	0.00	172
$FCI_{t,EW}$	0.00	-0.01	2.82	-2.89	1.00	0.07	3.28	0.62	0.73	153	0.00	-0.14	2.16	-2.59	1.00	-0.08	2.80	0.46	0.79	172
$FCI_{t,OLS}$	0.00	-0.09	4.02	-1.81	1.00	1.34	5.69	91.93	0.00	153	0.00	-0.18	3.00	-3.52	1.00	0.25	5.22	37.23	0.00	172
$FCI_{t,KF}$	0.00	-0.09	3.19	-2.38	1.00	0.54	4.01	13.83	0.00	153	0.00	-0.16	2.24	-2.96	1.00	-0.01	2.41	2.47	0.29	172
	Mexico										**Brazil**									
i_t	6.23	5.64	10.98	3.19	2.07	0.38	2.04	11.07	0.00	179	6.60	5.99	13.73	0.66	3.24	0.33	2.15	6.55	0.04	136
π_t	4.11	4.06	6.59	2.16	0.95	0.45	2.89	6.11	0.05	179	5.54	5.67	10.45	2.91	1.26	0.20	3.94	5.99	0.05	136
y_t	-0.01	0.19	2.79	-5.53	1.43	-1.16	5.39	82.63	0.00	179	-0.26	-0.08	33.32	-27.86	13.97	0.25	2.56	2.55	0.28	136
$FCI_{t,OPT}$	0.00	-0.31	6.21	-1.49	1.00	2.71	14.09	1137.19	0.00	179	0.00	-0.27	2.39	-1.84	1.00	0.40	2.17	7.45	0.02	136
$FCI_{t,EW}$	0.00	-0.14	5.11	-1.97	1.00	1.39	7.30	195.48	0.00	179	-0.03	-0.02	3.44	-2.10	1.02	0.15	3.64	2.84	0.24	136
$FCI_{t,OLS}$	0.00	-0.27	5.36	-1.44	1.00	1.90	8.84	362.28	0.00	179	0.00	-0.03	2.85	-1.72	1.00	0.46	2.75	5.25	0.07	136
$FCI_{t,KF}$	0.00	-0.13	2.63	-2.58	1.00	0.31	2.71	3.44	0.18	179	0.00	-0.38	3.18	-2.40	1.00	0.78	3.45	15.0	0.00	136
	Russia										**India**									
i_t	10.36	10.00	16.00	7.75	2.26	0.54	2.24	9.3	0.01	129	6.51	6.00	10.25	6.00	1.03	1.88	4.94	111	0.00	149
π_t	9.52	9.39	15.16	3.58	2.97	0.10	2.09	4.6	0.10	129	7.35	6.78	16.22	2.23	3.16	0.49	2.42	7.97	0.02	149
y_t	-0.02	0.25	3.98	-6.17	2.06	-0.72	4.13	18.0	0.00	129	-0.01	-0.17	3.40	-2.95	1.47	0.19	2.69	1.49	0.47	149
$FCI_{t,OPT}$	0.00	-0.34	4.86	-1.29	1.00	2.34	10.02	382	0.00	129	0.00	0.00	2.70	-2.02	1.00	0.28	2.72	2.38	0.30	149
$FCI_{t,EW}$	0.00	-0.32	4.89	-1.26	1.00	2.32	9.94	375	0.00	129	0.00	-0.04	2.68	-2.22	1.00	0.30	2.97	2.24	0.33	149
$FCI_{t,OLS}$	0.00	-0.17	4.20	-1.35	1.00	2.04	8.34	242	0.00	129	0.00	-0.04	2.68	-2.22	1.00	0.30	2.97	2.24	0.33	149
$FCI_{t,KF}$	0.00	-0.06	3.71	-2.31	1.00	0.47	4.28	13.6	0.00	128	0.00	0.04	5.44	-3.55	1.00	0.46	8.60	199.8	0.00	149
	South Korea										**China.**									
i_t	2.84	2.50	5.25	1.25	1.01	0.87	2.84	22.86	0.00	180	3.29	3.33	4.14	2.70	0.45	0.26	2.12	5.67	0.06	131
π_t	2.59	2.57	5.90	0.37	1.20	0.13	2.53	2.21	0.33	180	2.98	2.63	8.44	-1.81	2.13	0.26	3.14	1.54	0.46	131
y_t	-0.02	0.21	6.63	-20.6	3.51	-2.61	14.92	1271	0.00	180	0.00	0.25	3.37	-4.59	1.46	-0.62	3.94	13.18	0.00	131
$FCI_{t,OPT}$	0.00	-0.03	3.32	-2.11	1.00	0.17	2.90	0.99	0.61	180	0.00	0.01	2.53	-2.14	1.00	0.01	2.22	3.34	0.19	131
$FCI_{t,EW}$	0.00	-0.02	3.69	-1.85	1.00	0.52	3.38	9.21	0.01	180	0.00	-0.02	2.59	-2.20	1.00	0.00	2.32	2.54	0.28	131
$FCI_{t,OLS}$	0.00	-0.11	3.20	-1.63	1.00	0.55	2.66	9.94	0.01	180	0.00	-0.09	2.36	-2.80	1.00	-0.06	3.09	0.11	0.95	131
$FCI_{t,KF}$	0.00	-0.24	6.77	-1.93	1.00	3.02	18.59	2096	0.00	180	0.00	0.07	2.30	-3.39	1.00	-0.56	3.90	11.17	0.00	131

Note: FCI developed, means: time-varying optimal weights using DCC –GARCH Model (FCI_{OPT}), time-varying weights using Kalman-Filter estimation (FCI_{KF}), Constant equal weights (FCI_{EW}), and weights from OLS estimation (FCI_{OLS}).

Table 8-2: Augmented- Dicky Fuller (ADF) unit root and stationary test

Variables	South Africa		Malaysia		Chile		Poland		Turkey		Czech Republic	
	ADF	Concl.	ADF	Concl.	ADF	Concl.	ADF	Concl.	ADF	Concl.	ADF	Concl.
i_t	-7.78***	I(0)	-5.44***	I(0)	-3.71***	I(0)	-9.33***	I(0)	-9.15***	I(0)	-12.4***	I(0)
π_t	-4.18***	I(0)	-7.3***	I(0)	-6.39***	I(0)	-8.87***	I(0)	-6.2***	I(0)	-6.23***	I(0)
y_t	-20.6***	I(0)	-10.6***	I(0)	-10.1***	I(0)	-14.4***	I(0)	-9.18***	I(0)	-17.4***	I(0)
$FCI_{t,OPT}$	-16.4***	I(0)	-7.81***	I(0)	-8.48***	I(0)	-8.35***	I(0)	-12.6***	I(0)	-14.5***	I(0)
$FCI_{t,EW}$	-6.09***	I(0)	-5.74***	I(0)	-9.87***	I(0)	-7.52***	I(0)	-11.7***	I(0)	-8.94***	I(0)
$FCI_{t,OLS}$	-15.8***	I(0)	-6.28***	I(0)	-9.55***	I(0)	-7.14***	I(0)	-11.2***	I(0)	-12.5***	I(0)
$FCI_{t,KF}$	-36.5***	I(0)	-5.61***	I(0)	-11.6***	I(0)	-15.3***	I(0)	-12.5***	I(0)	-10.8***	I(0)

Variables	Mexico		Brazil		Russia		India		South Korea		China.	
	ADF	Concl.	ADF	Concl.	ADF	Concl.	ADF	Concl.	ADF	Concl.	ADF	Concl.
i_t	-4.81***	I(0)	-7.53***	I(0)	-9.22***	I(0)	-7.36***	I(0)	-5.88***	I(0)	-9.49***	I(0)
π_t	-10.8***	I(0)	-7.39***	I(0)	-5.99***	I(0)	-10.5***	I(0)	-5.51***	I(0)	-5.5***	I(0)
y_t	-15.3***	I(0)	-8.29***	I(0)	-3.17**	I(0)	-6.62***	I(0)	-13.3***	I(0)	-10.5***	I(0)
$FCI_{t,OPT}$	-11.8***	I(0)	-10.9***	I(0)	-6.46***	I(0)	-13.34***	I(0)	-7.34***	I(0)	-7.21***	I(0)
$FCI_{t,EW}$	-10.5***	I(0)	-9.31***	I(0)	-6.57***	I(0)	-11.9***	I(0)	-7.14***	I(0)	-7.02***	I(0)
$FCI_{t,OLS}$	-5.43***	I(0)	-4.43***	I(0)	-7.69***	I(0)	-11.9***	I(0)	-10.9***	I(0)	-3.81***	I(0)
$FCI_{t,KF}$	-12.4***	I(0)	-10.7***	I(0)	-8.47***	I(0)	-19.6***	I(0)	-8.76***	I(0)	-9.16***	I(0)

The values reported in parentheses are standard erros and *(**)[***] indicate the parameter is significant at 10%(5%)[1%]

8.2 Evolution of the main variables

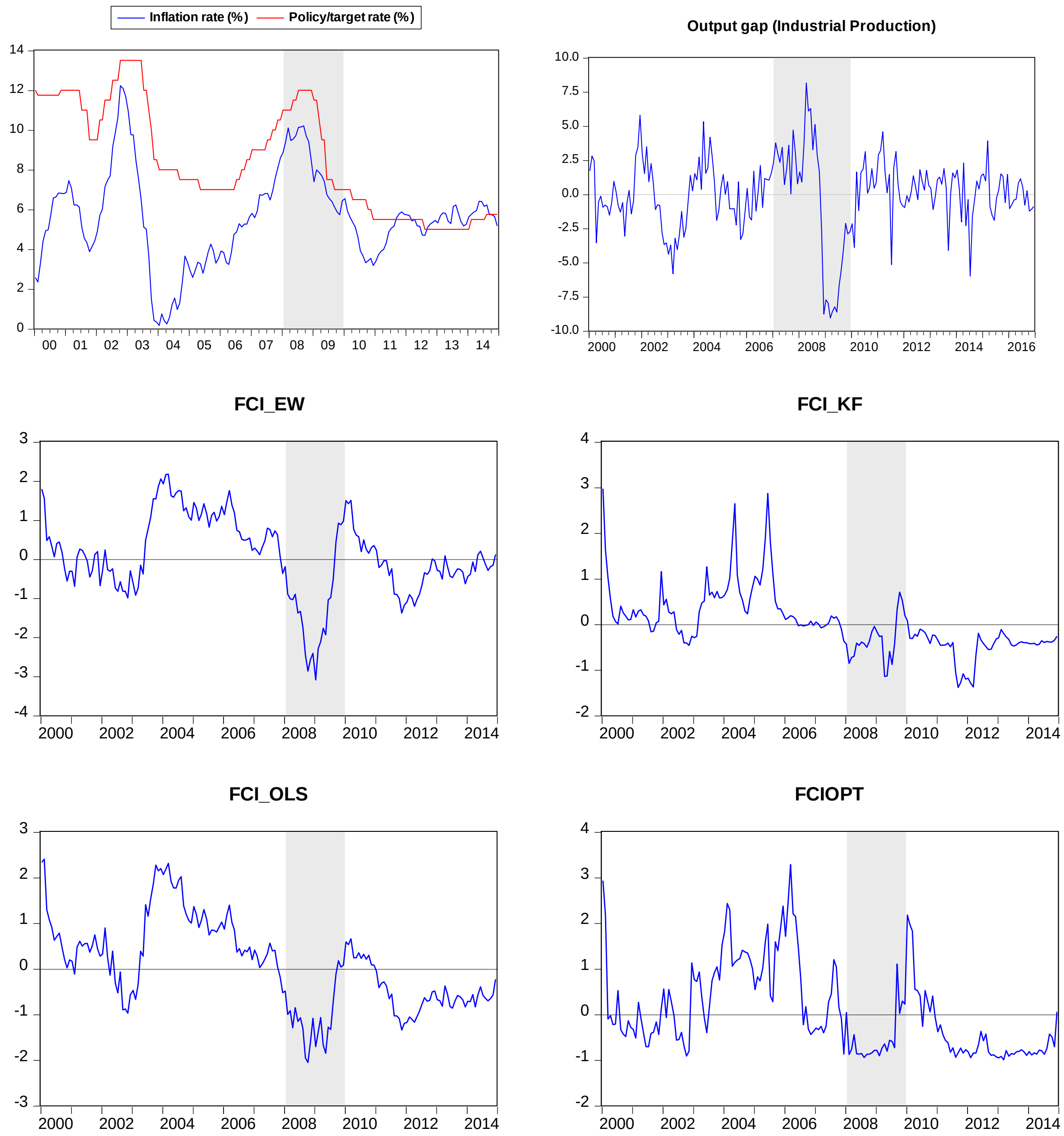

Figure 1: Evolution of policy rate, inflation, output gap and FCIs (South Africa)

Malaysia

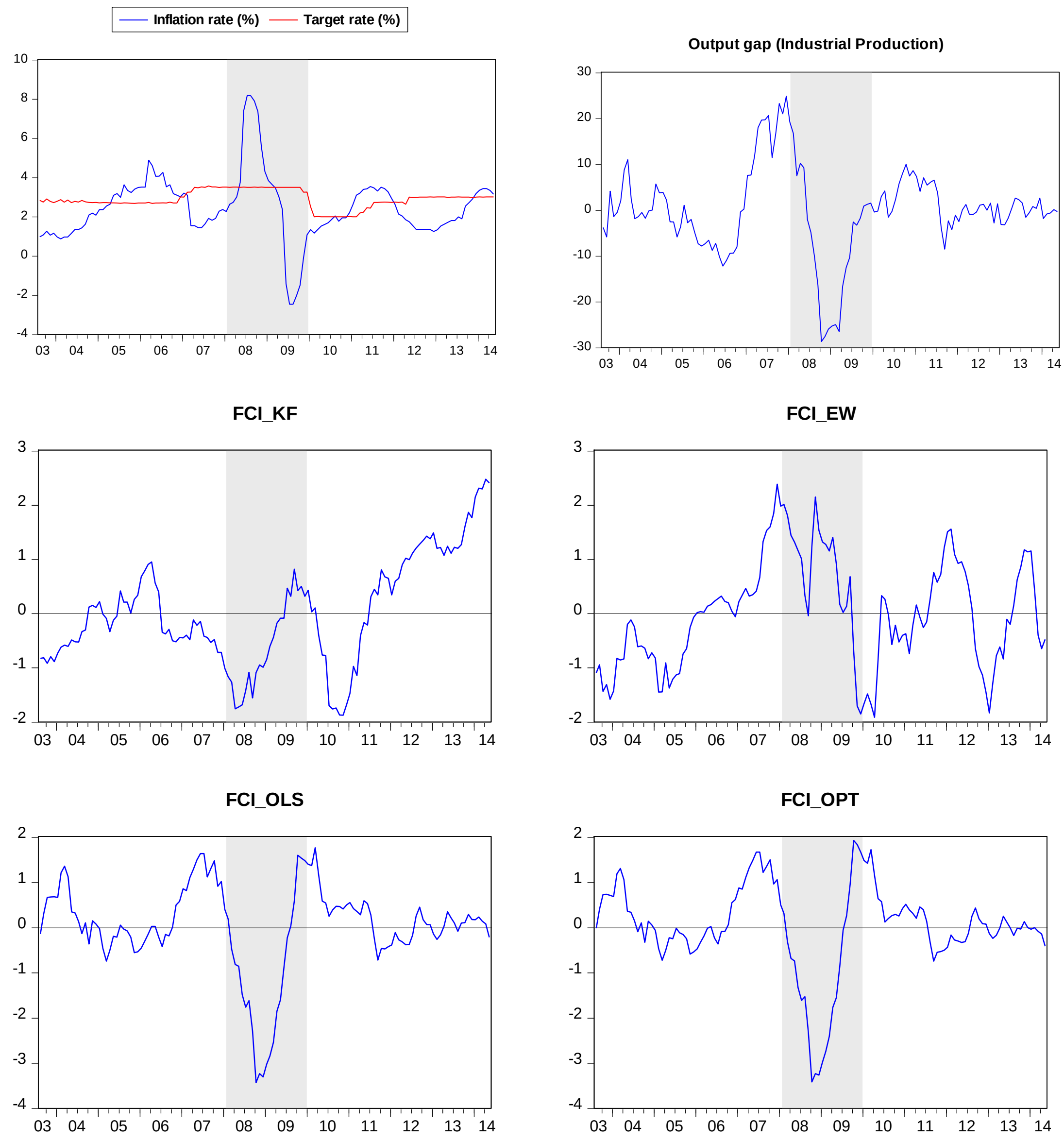

Figure 2: Evolution of policy rate, inflation, output gap and FCIs (Malaysia)

Chile

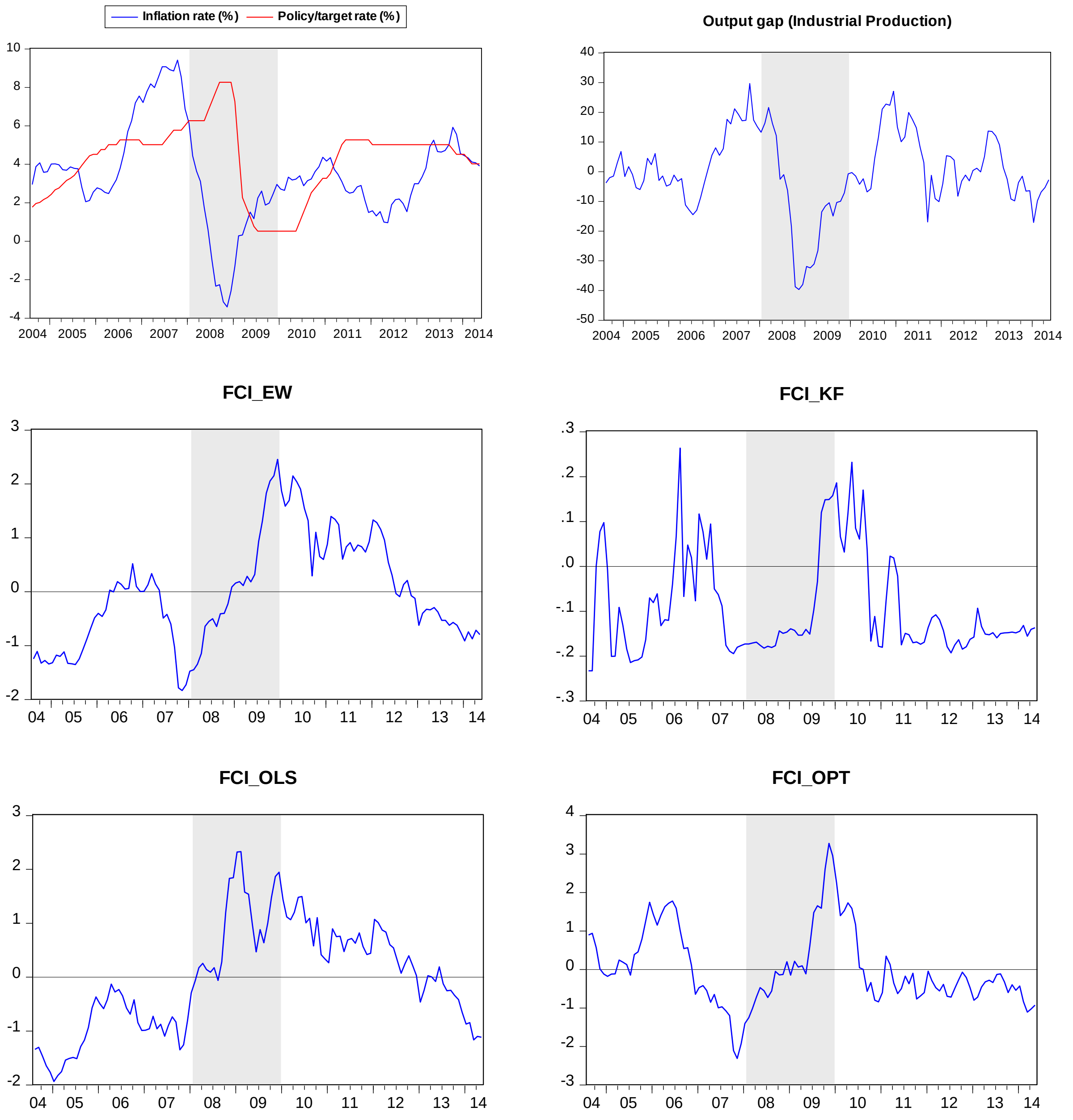

Figure 3: Evolution of policy rate, inflation, output gap and FCIs (Chile)

Poland

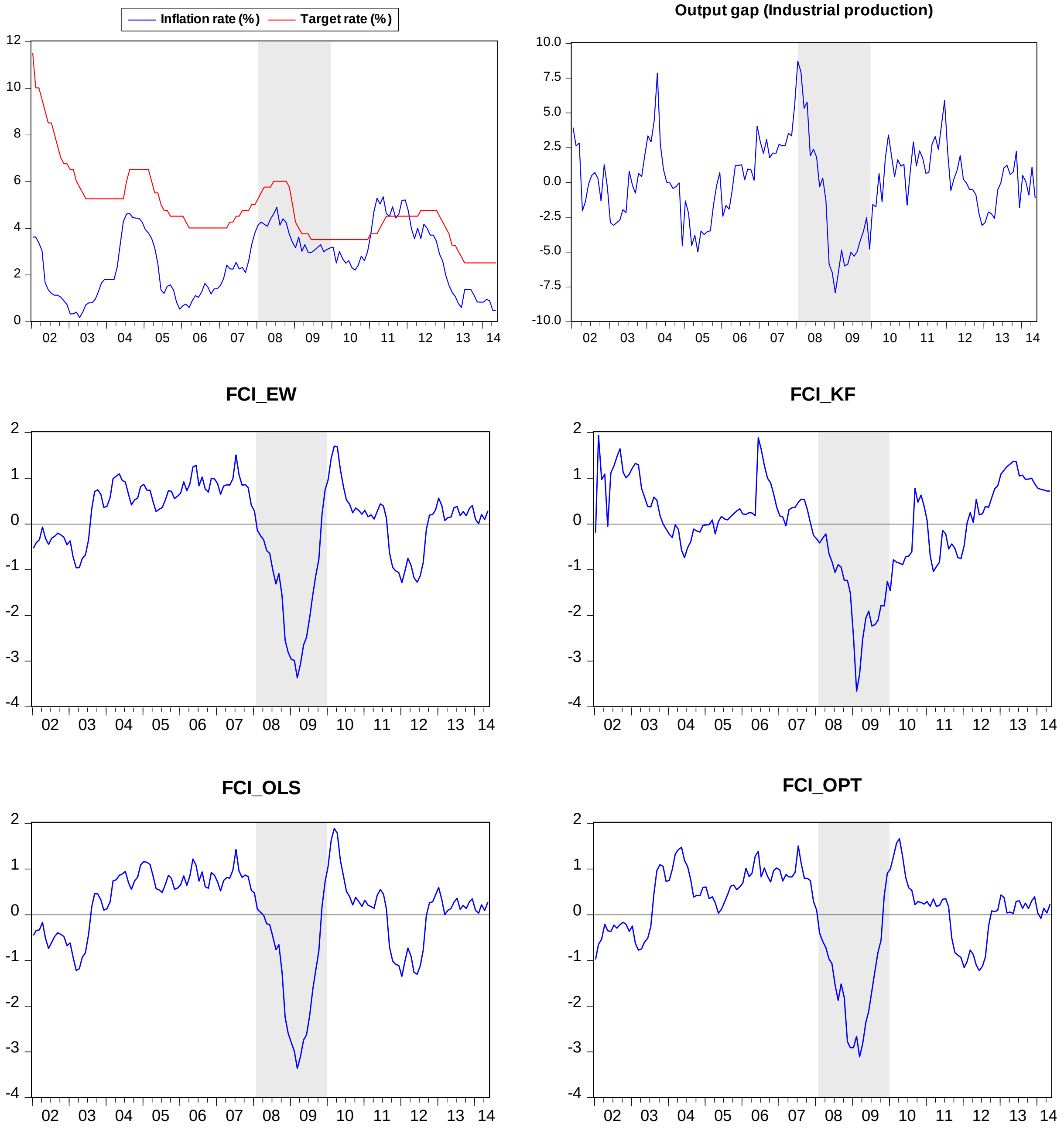

Figure 4: Evolution of policy rate, inflation, output gap and FCIs (Poland)

Turkey

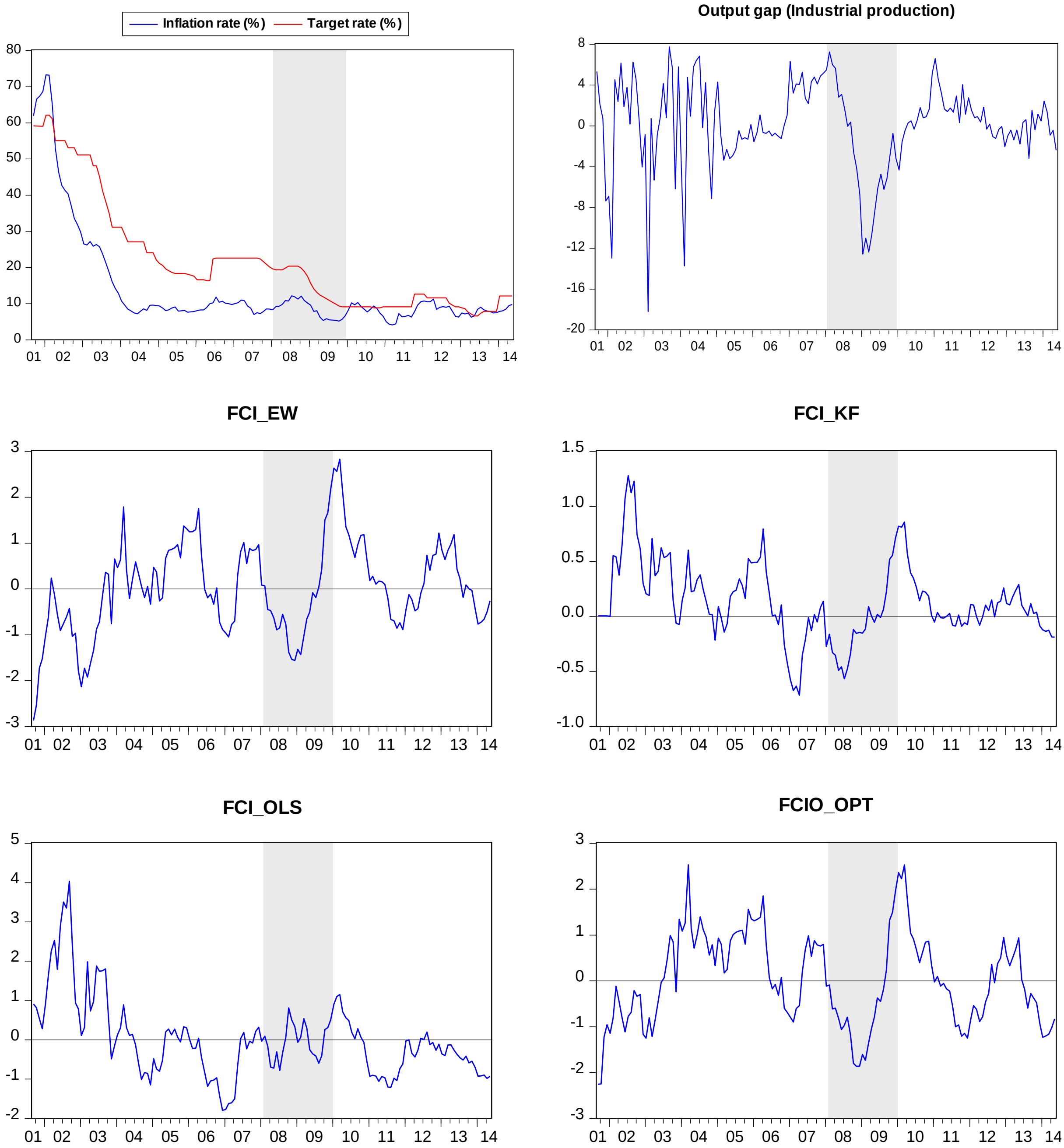

Figure 5: Evolution of policy rate, inflation, output gap and FCIs (Turkey)

Czech Republic

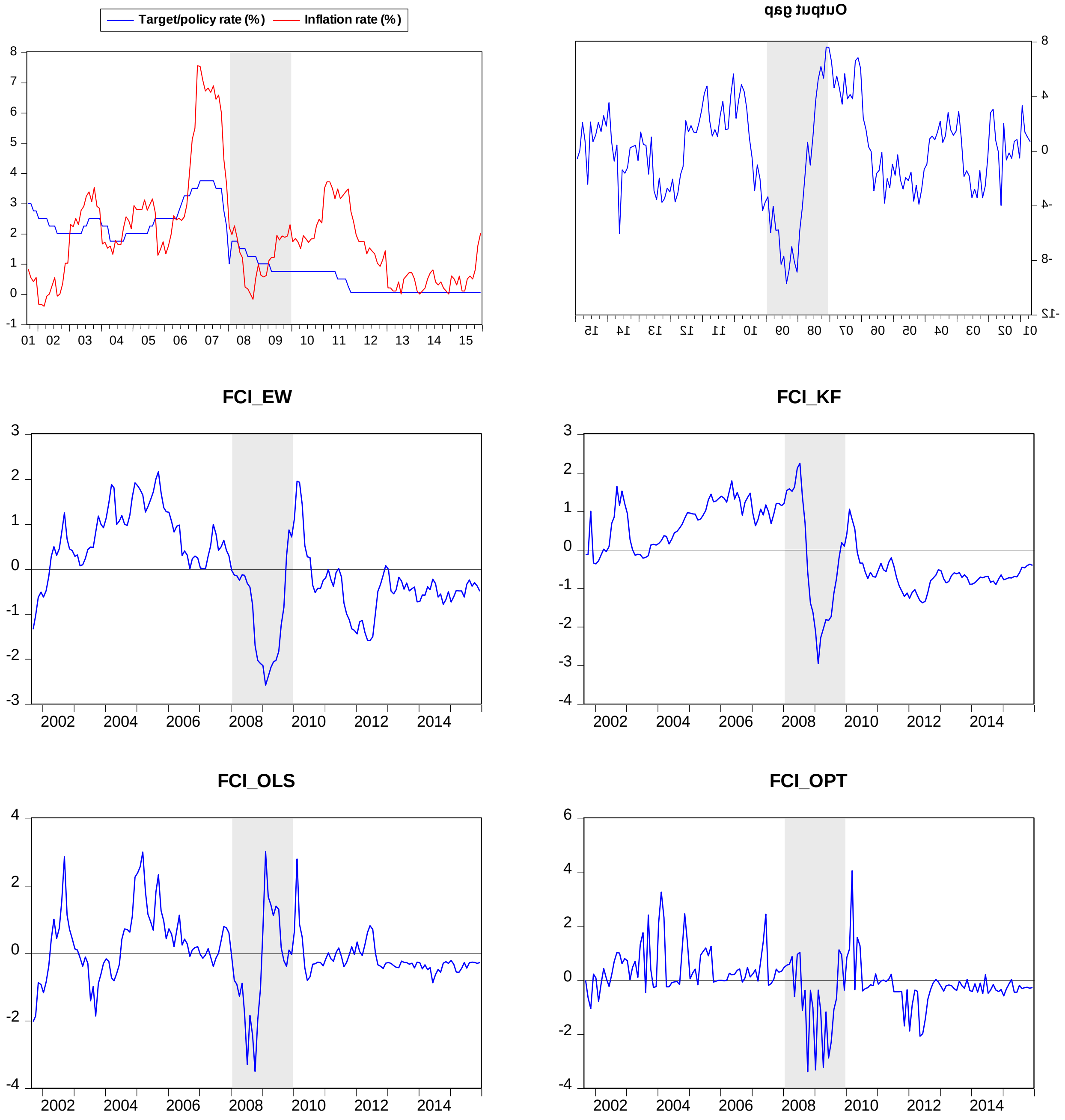

Figure 6: Evolution of policy rate, inflation, output gap and FCIs (Czech Republic)

Mexico

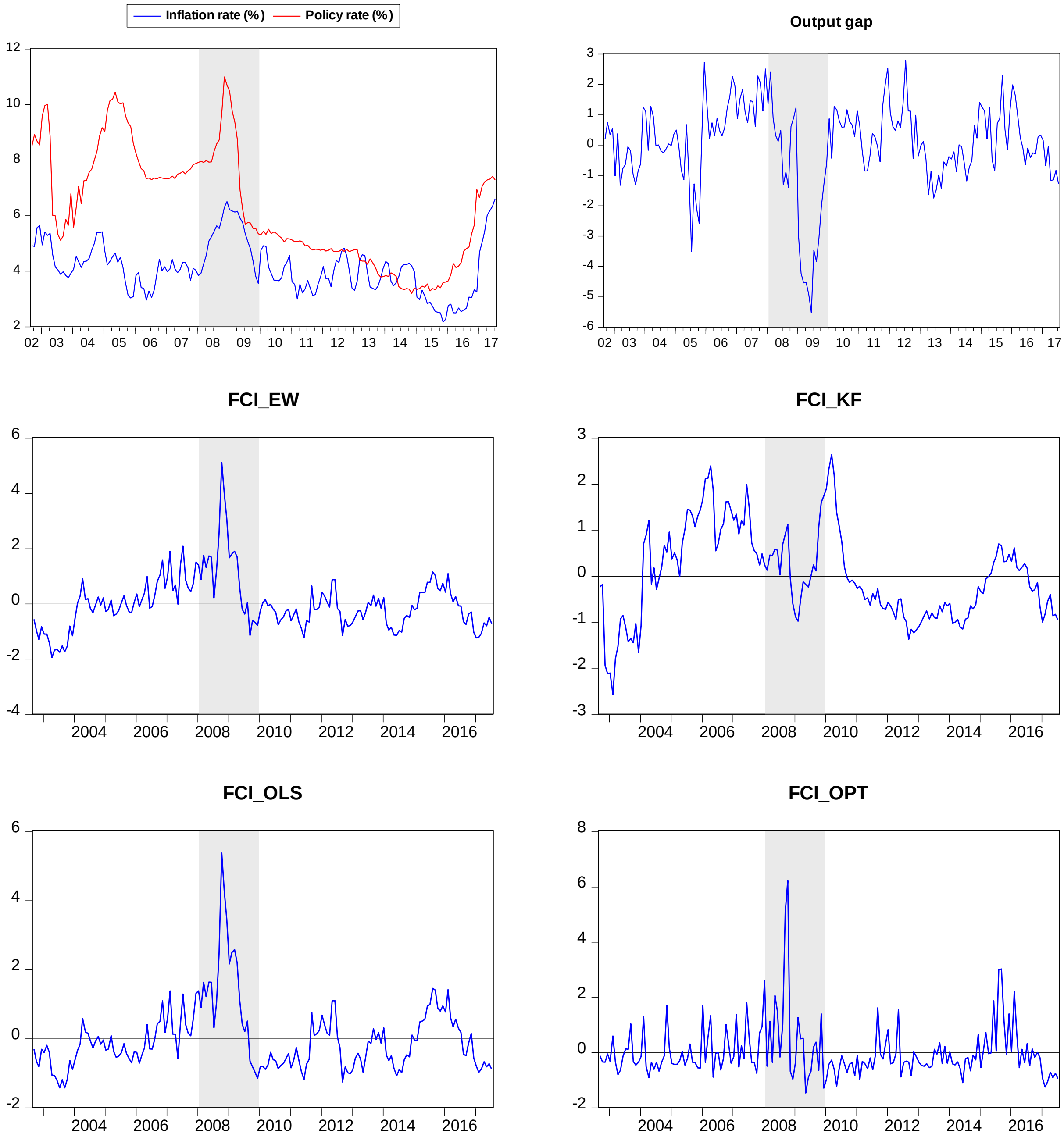

Figure 7: Evolution of policy rate, inflation, output gap and FCIs (Mexico)

Brazil

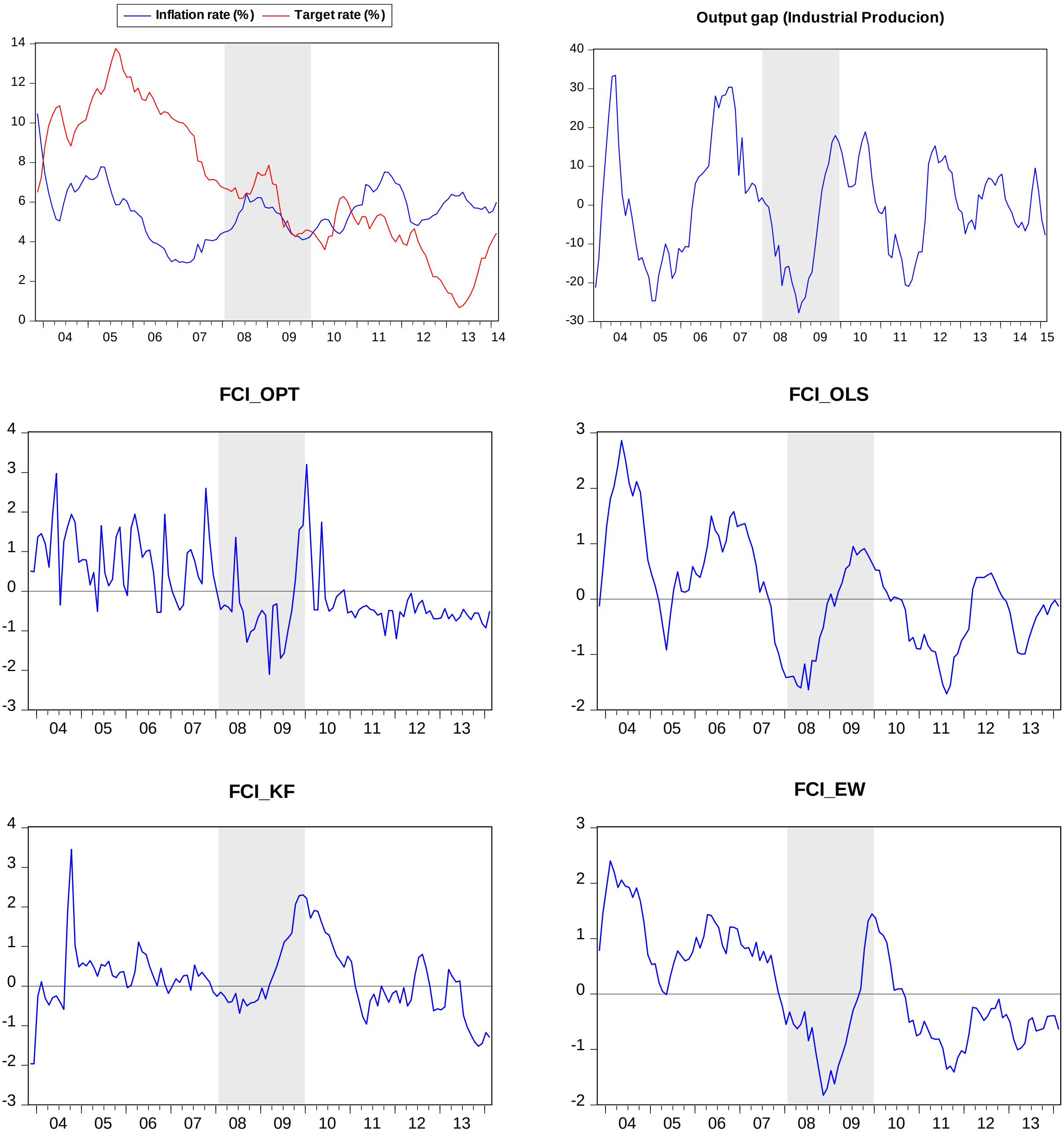

Figure 8: Evolution of policy rate, inflation, output gap and FCIs (Brazil)

Russia

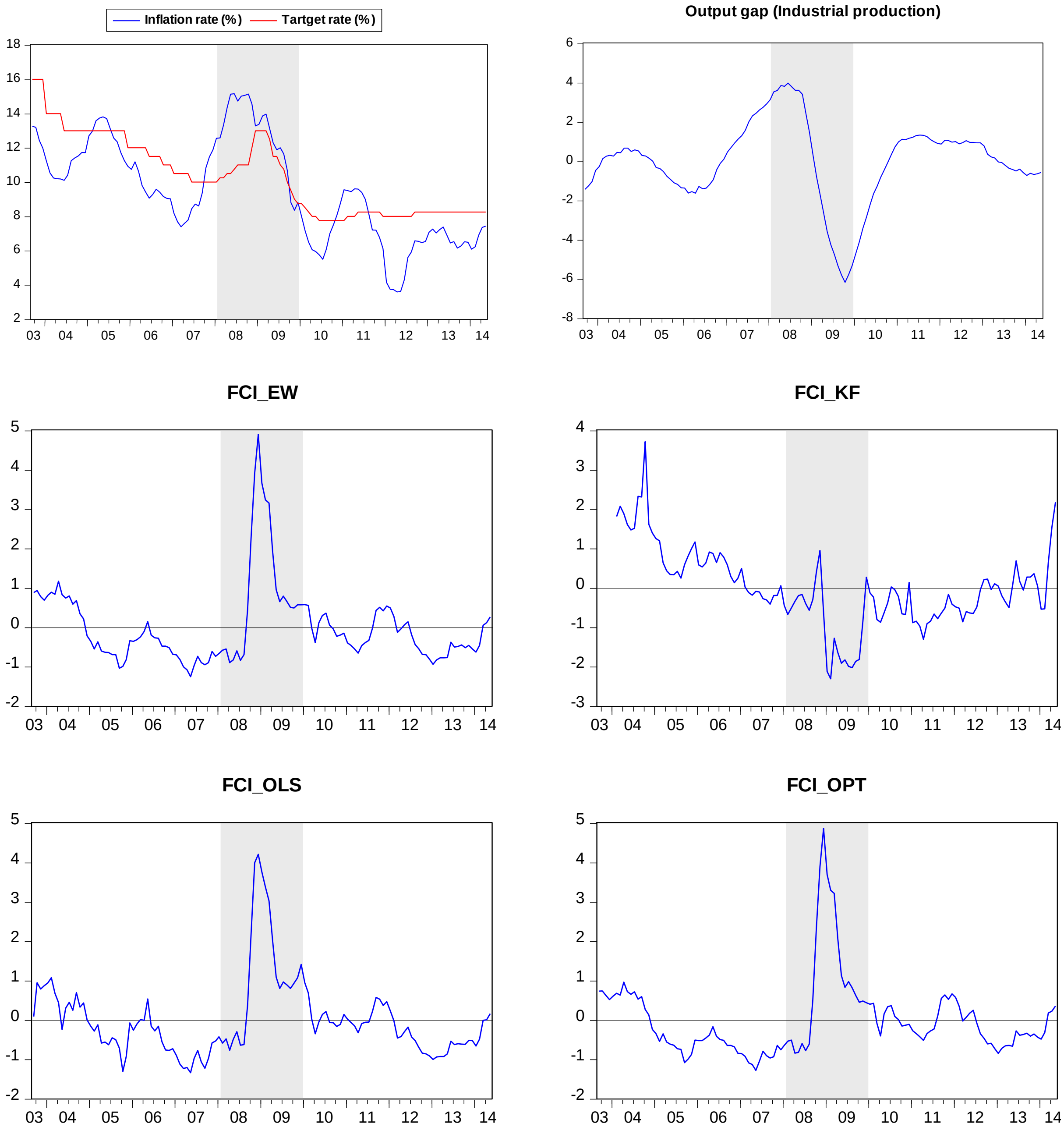

Figure 9: Evolution of policy rate, inflation, output gap and FCIs (Russia)

India

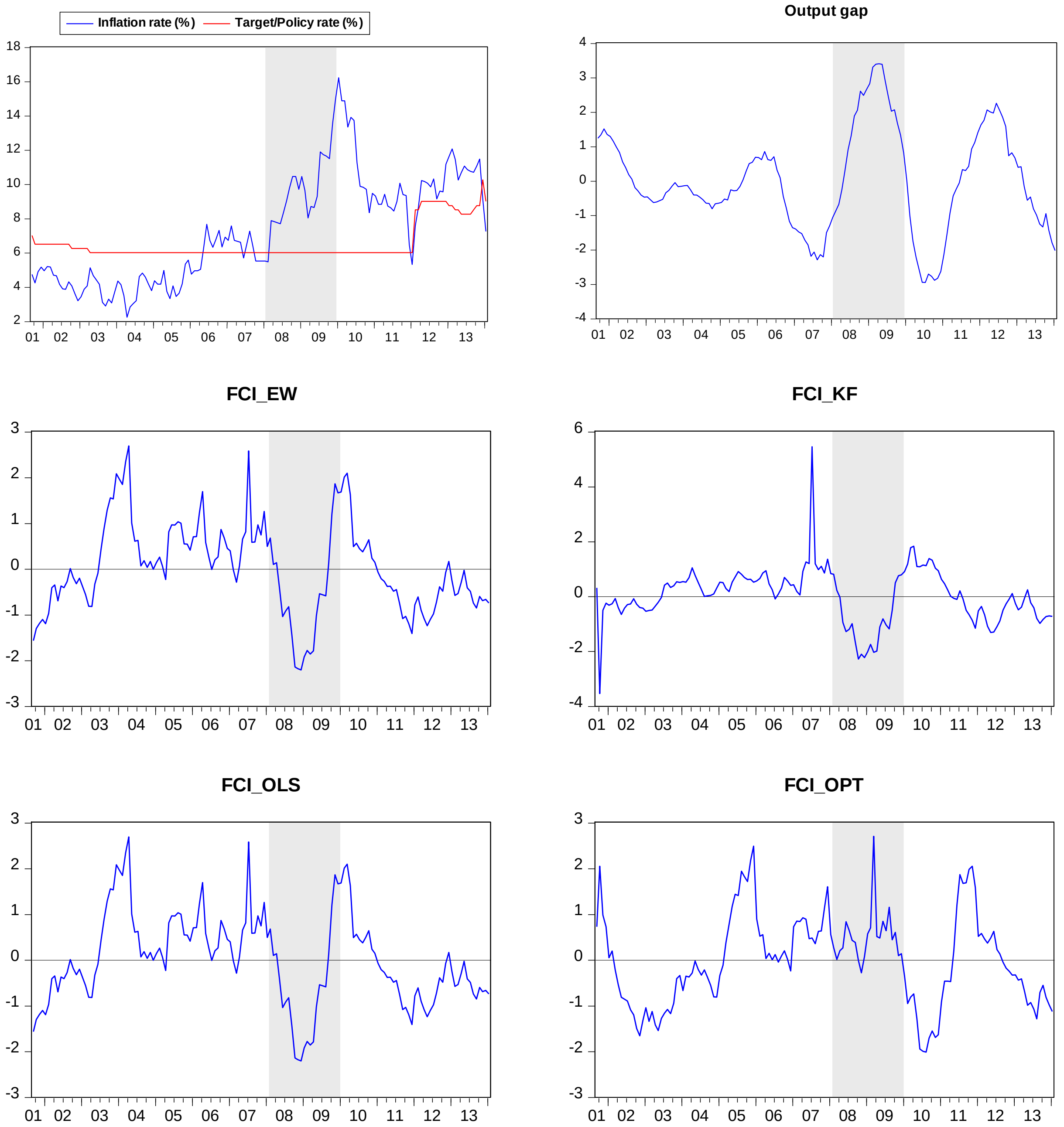

Figure 10: Evolution of policy rate, inflation, output gap and FCIs (India)

South Korea

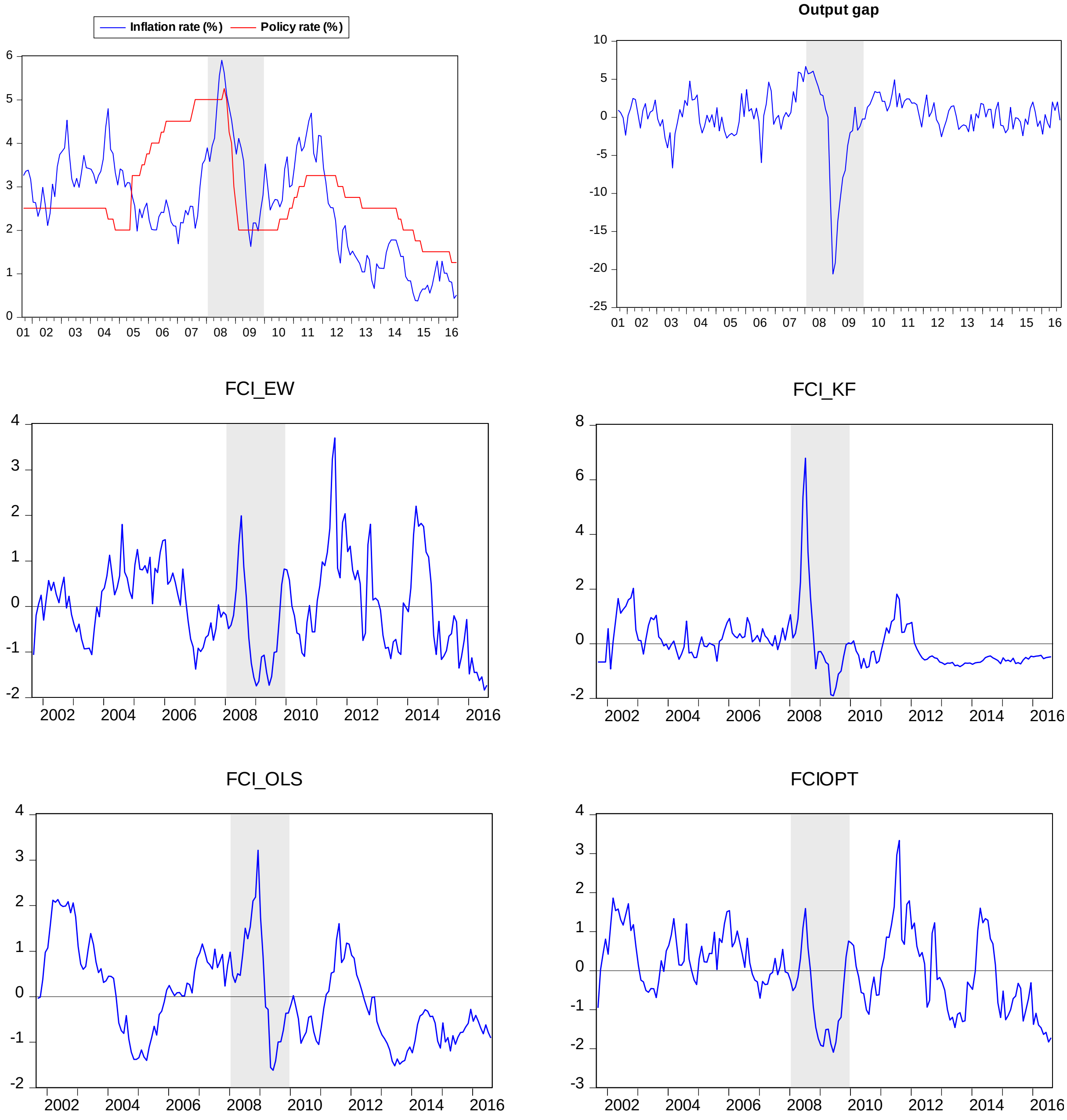

Figure 11: Evolution of policy rate, inflation, output gap and FCIs (South Korea)

China

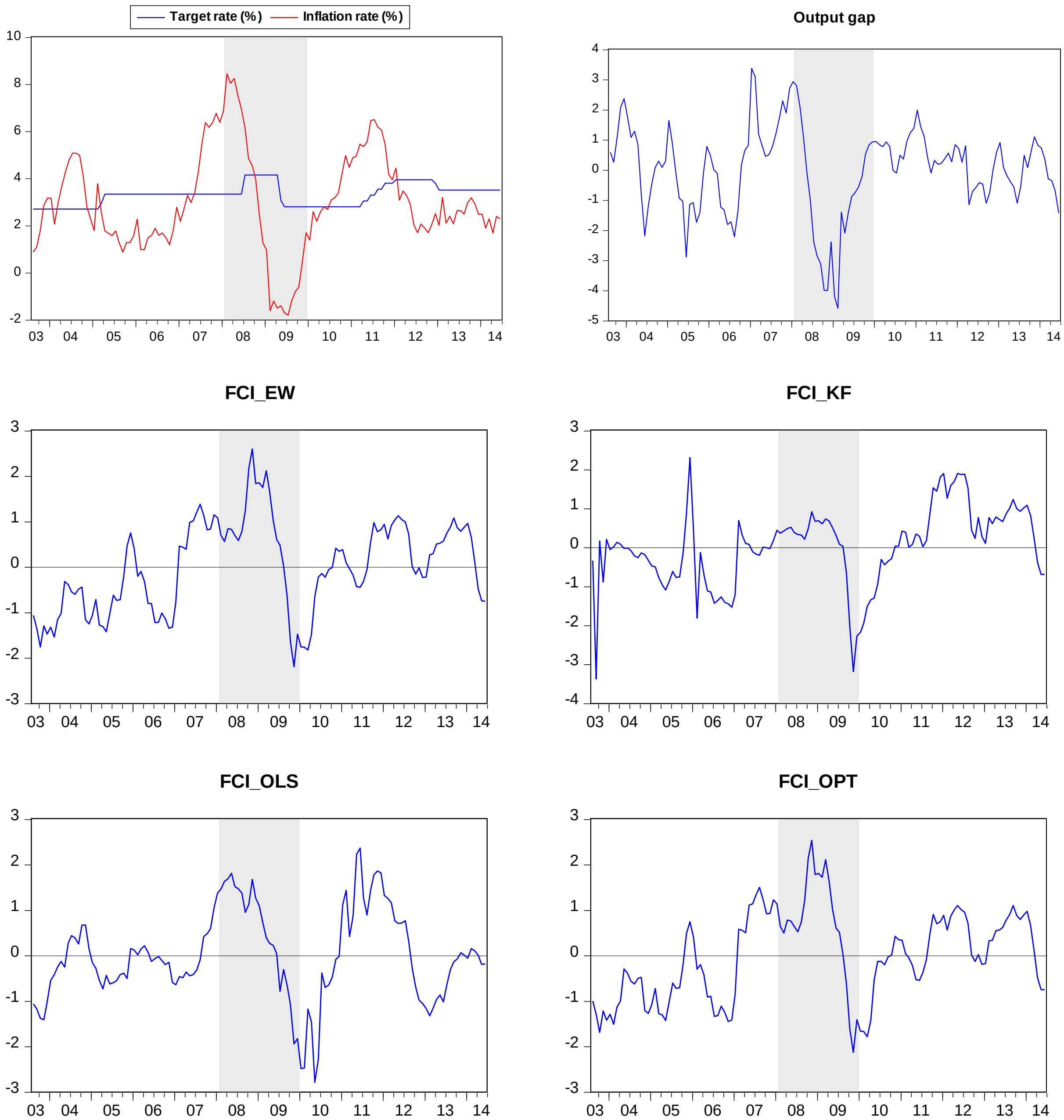

Figure 12: Evolution of policy rate, inflation, output gap and FCIs (Czech Republic)