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Threshold Effects in Sticky Information Philips Curve: Evidence from Iran

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Abstract

During the last decade, several studies have argued that sticky information model proposed by Mankiw and Reis (2002), in which firms update their information occasionally rather than instantaneously, explains some stylized facts about the inflation dynamics. Sticky information pricing model successfully captures the sluggish movement of aggregate prices in response to monetary policy shocks. Despite the importance of sticky information, no empirical studies have been done yet to estimate sticky information Philips Curve (SIPC) and its key parameter - the degree of information rigidity - in Iran. This paper is the first attempt to estimate the degree of information stickiness in Iran using the two stage empirical approach proposed by Khan and Zhu (2006). Having the correct structural parameter allows a better understanding of the dynamics of inflation. Results show that the average duration of information stickiness ranges from 3.2 to 4 quarters in Iran. In addition, the existence of threshold effects in SIPC is also tested in this paper. Based on the estimation of TAR model over 2002Q2- 2015Q1, firms update information faster when inflation is higher. This evidence suggests that firms are more aware of macroeconomic conditions when inflation is higher; that is, missing information during high inflation periods is costly.

Key Words: *Degree of information stickiness, Sticky information Philips Curve, Out of sample forecasting, Threshold model, Bootstrap*
JEL Classifications: *E31, E37, C53, D84*

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1. Introduction

The sticky information model proposed by Mankiw and Reis (2002) is based on the argument that information about macroeconomic conditions diffuses slowly through the agents. Thus, price-setting decisions are not always based on current (or updated) information. In other words, information is sticky. The gradual diffusion of information across the economic agents assumed by the sticky information model has received empirical support by using survey data [for example Carroll (2003) and Dopke et al. (2008)].

In the context of the Phillips curve, the sticky information model implies that the price level depends on expectations based on outdated information, because of the cost of acquiring and processing information. This is formally known as the sticky information Phillips curve (henceforth SIPC). Coibion (2006) argues that unlike Calvo (1983) model, the sticky information model of Mankiw and Reis (2002) can robustly deliver inflation inertia. He finds that two features of the model – including the frequency of information updating and the degree of real rigidities - play a key role in determining inflation inertia.

Despite the importance of sticky information pricing model, it has not been considered to analyze the effects of monetary policy shocks in Iran. In addition, no empirical studies have been done yet to estimate SIPC and its key parameter - the degree of information rigidity - in Iran. This paper is the first attempt to estimate the degree of information stickiness in Iran. Having the correct structural parameters allows a better understanding of the dynamics of inflation in various cases, such as in response to monetary policy shocks.

Following the two stage empirical approach proposed by Khan and Zhu (2006), the degree of information stickiness in Iran is estimated in this paper. In the first stage, past expectations are computed using combination of out of sample forecasting approach proposed by Stock and Watson (2003). In the second stage, using data and the generated regressors (past expectations), SIPC is estimated using non-linear least square. Based on results, the flexible information hypothesis is rejected in favor of sticky information. The average durations of information stickiness that range from 3.2 quarters to 4 quarters are estimated.

In addition, the existence of threshold effects in SIPC is also examined. In other words, it has been tried to find an answer to the question whether there is a significant relation between the degree of information stickiness and inflation rate. In this paper, by using threshold models, high and low inflation regimes and estimation of SIPC for each identified regime is identified. Based on the results, each regime is associated with a specific degree of information stickiness. Estimates show that firms update information faster when inflation is higher. In other words, the degree of information stickiness changes between two regimes. In fact, the frequency of information updating seems to be larger when the inflation rate is higher. This evidence suggests that firms are more aware of macroeconomic conditions when inflation is higher; that is, missing information during high inflation periods is costly.

Evidence suggests a negative relationship between the degree of information stickiness and the level of inflation. Thus, this paper also contributes to the existing literature by providing further evidence of state - contingent inflation processes in the context of the Phillips curve.

The remainder of this paper is organized as follows: Section 2 reviews the related literature. Section 3 describes the sticky information model proposed by Mankiw and Reis (2002) model. In Section 4, the estimation methodology is presented. Section 5 presents the results and robustness test. Section 6 concludes.

2. Literature Review

The first attempt to provide micro-foundations for sticky information model was carried out by Carroll (2003) and his epidemiological model of expectations. Carroll argues that the U.S. survey data on inflation expectations are consistent with a model in which each period, only a fraction of households adopt the superior inflation forecasts of experts. The experts' forecast is superior in the sense that they have better information. The remaining households find it costly to update their information and continue using their own past expectations rather than forming better predictions.

Reis (2006b) also provides micro - foundations for Mankiw and Reis model and argues that firms can rationally choose to be inattentive, and he derives the conditions for the optimal length of inattentiveness. Mankiw and Reis (2007) conclude that the assumption of sticky information can be justified by the costs of acquiring, absorbing, and processing information or by appealing to the epidemiology of expectations (as in Carroll, 2003).

In general, empirical studies on estimation of SIPC can be classified based on the data used for representing past expectations: 1) studies use Survey of Professional Forecasters (SPF) [for instance Carroll (2003), Dopke et al. (2008) and Carrera (2012)] and 2) studies apply direct estimation of past expectation using out of sample forecasting [e. g. Khan and Zhu (2006), Coibion (2010)[1], Carrera and Ramirez-Rondan (2014), Gillitzer (2015)]. Both these categories of studies will be reviewed below.

Carroll (2003), and Dopke et al. (2008) estimate an epidemiological model for European countries and provide similar support for the diffusion of information from forecasters to households in European countries. They also find that the information updating process of households is somewhat slower than for the U.S. economy. Using financial institutions' and firms' survey data from Peru and the model proposed by Carroll (2003) and Carrera (2012), the degree of information rigidity between financial institutions and the firm managers for the Peruvian economy is estimated. He found that firm managers' inflation expectations adjust slowly relative to the more precise expectations of professional forecasters. Based on his findings, the degree of information stickiness ranges between one and two quarters, and this result is robust to different specifications.

The SPF data provides an ideal source of expectations because they are a direct measure of what economists were forecasting and are available on a quarterly basis. The main limitation of SPF is that forecasts are provided for only the next four quarters. To extend the forecasting horizons, some studies follow the approach proposed by Stock and Watson (2003) and generate forecasts for each quarter in a way designed to closely replicate what forecasters would have believed for each time period.

Khan and Zhu (2006) proposed a methodology to estimate the structural parameters of the sticky information model directly. Using this methodology and data from the United States, they conclude that the evidence is not inconsistent with firms updating their information approximately once a year. They estimate average duration of information stickiness that range from three quarters (on the low side) to over seven quarters (on the high side).

Coibion (2010) evaluated the empirical support for the SIPC relative to the basic sticky price model. He found that the estimated structural parameters were inconsistent with an underlying sticky information model and the SIPC

1. Coibion also used median expectations data from the Survey of Professional Forecasters (SPF).

was statistically dominated by the new Keynesian Phillips curve. He argued that the poor performance of the sticky information approach was driven by two key elements. First, the sticky information model underestimated inflation in the 1970s and overestimated inflation since the 1980s. Second, prediction of inflation from the sticky information model is excessively smooth.

Gillitzer (2015) assessed the empirical performance of the SIPC for Australia. He discussed that there is only weak evidence in favor of the SIPC over the low-inflation period. Based on his results, parameter estimates are sensitive to inflation measures and sample periods, and are theoretically inconsistent for several specifications. The apparent poor performance of the SIPC in part reflects the fact that inflation has become difficult to model since the introduction of inflation targeting. Over sample periods including the early 1990s disinflation, the SIPC appears to fit the data better. The disappointing empirical performance of the SIPC can be in part explained by a change in the behavior of inflation since the introduction of inflation targeting. Accordingly, including data prior to the inflation targeting period in the estimation sample improves the performance of the SIPC.

Although some studies done in the context of sticky information Philips Curve implicitly indicate that there might be some kind of non-linearity in SIPC, a few studies test it. For the first time, Carrera and Ramirez-Rondan (2014) used threshold models to identify high and low inflation regimes and estimate the SIPC for each identified regime for 12 OECD countries, following the strategy of Khan and Zhu (2006). Their results suggest different degrees of information rigidity across countries and across different time periods. They argue that the estimated levels of information rigidity appear to be driven primarily by state-contingent conditions of low and high inflation scenarios. In other words, in low inflation environments, agents tend to be more inattentive to macroeconomic conditions.

3. Sticky Information Model

In the sticky information model [Mankiw and Reis (2002)], a firm chooses its optimal price in each period, but the information used to compute that optimal price is not necessarily the current one. In other words, it is assumed that the information is sticky. Unlike the sticky-price model, prices are always changing, but some chosen prices are based on the past or outdated information. Firms form their expectations rationally but because of costs associated with updating old information sets, the expectations do not change frequently.

Following Calvo (1983) pricing model, the probability that a firm updates its information to the current one in a given quarter is $(1 0\ o)$. This probability is independent of the history of past updates. The expected time between information updates is therefore $\frac{1}{(1 0\ o)}$ quarters. At a macro level, the parameter $(1 0\ o)$ also represents the fraction of firms that use updated information in their pricing decision. The remaining fraction, o , of firms uses past or outdated information. The optimal price of a firm in a given period is as follows:

$$p_t^o \cong p_t\ .\ \delta y_t \tag{1}$$

where y_t is the output gap and p_t is the price level. The parameter δ implies that if the output gap is positive, a firm's optimal price, p_t^o will be higher relative to the price level p_t . This parameter depends on the structure of the economy (for instance, the preference, technology, and the market structure parameters)[1]. The sticky information assumption implies that a firm that uses j-period old information sets the price:

$$x_t^j \cong E_{t0\,j}[p_t^o] \tag{2}$$

The price level in period *t* is the average of the prices of all existing firms:

$$\begin{aligned} p_t &\cong (1 0\ o)p_t^o\ .\ (1 0\ o)oE_{t01}[p_t^o]\ .\ (1 0\ o)o^2E_{t02}[p_t^o] \\ &.\ \ldots .\ (1 0\ o)o^jE_{t0\,j}[p_t^o]\ .\ \ldots \cong (1 0\ o)\Big|_{j\cong 0}^{\clubsuit} o^j x_t^j \end{aligned} \tag{3}$$

Combining equations (1)-(3), the SIPC is derived as follows:

$$\sigma_t \cong \frac{(1 0\ o)}{o}\delta y_t\ .\ (1 0\ o)\Big|_{j\cong 0}^{\clubsuit} o^j E_{t010\,j}[\sigma_t\ .\ \delta\Gamma y_t],\ \Gamma y_t \cong y_t\ 0\ y_{t01} \tag{4}$$

1. For more information about the structural components of δ see Woodford (2003).

where, Γy_t is the first difference of the output gap. According to equation (4), current inflation is determined by the current output gap, and past expectations of current inflation and the first difference of current output gap. The structural parameter o represents the degree of information stickiness at a given point in time. As o decreases, more and more firms use updated information when choosing prices, thereby implying a smaller degree of information stickiness. Therefore, from equation (4), inflation becomes more sensitive to the current output gap and less sensitive to the past expectations of current inflation and the first difference of the current output gap. The parameter δ in equation (4) captures the sensitivity of the optimal relative price to the current output gap. It can be interpreted as the degree of real rigidity, as discussed by Ball and Romer (1990). As Mankiw and Reis (2002) point out, firms which update their information set in a given period, realize that other firms are not updating their information, and this in turn limits the size of their price adjustment when δ takes a small value.

4. Methodology

Estimating o using equation (4) presents several difficulties. First, the time index, *j*, goes into the infinite past. This implies very long forecasting horizons for some firms. Given the limited data, a truncation point, $j^{\max}$, is necessary to set the forecasting horizons of the firms. Second, the SIPC involves past expectations of current values of inflation and changes in the output gap. These expectations (or forecasts) from past periods are required for the estimation. So, it is critical to have actual measures of past forecasts as regressors. The way this methodology addresses these issues is discussed in detail.

The empirical counterpart of equation (4) is:

$$\sigma_t \cong \frac{(1 0 o)}{o}\delta y_t \;.\; (1 0 o)\Big|_{j\cong 0}^{j^{\max}} o^j E_{t 0 1 0 j}[\sigma_t \;.\; \delta\Gamma y_t] \;.\; u_t \qquad (5)$$

where, u_t is the error term that includes the approximation error $(1 0 o)\Big|_{j\cong j^{\max} . 1}^{\clubsuit} o^j E_{t 0 1 0 j}[\sigma_t \;.\; \delta\Gamma y_t]$ due to the truncation point ($j^{\max}$). For a given

O, this approximation error gets theoretically smaller with an increase in the forecasting horizon. Based on the methodology and the sample period, the longest forecasting horizon is 8 quarters ($j^{\max} \cong 7$). In order to test the robustness of results, SIPC is re-estimated using different choices of the forecasting horizon (4 and 6 quarters).

4.1. Past expectations measures

In order to generate forecasts for each quarter, Stock and Watson (2003) is followed and combination of out of sample forecasts are computed. In this process, a set of bivariate ARDLs are run for both inflation and changes in the output gap with a set of predictive variables. These ARDLs are as follows:

$$\sigma_{t.\,h} \cong \varepsilon_{0i} \,.\, \varepsilon_{1i}(L)x_{it} \,.\, \varepsilon_{2i}(L)\sigma_t \,.\, \eta_{it.\,h}\,,\; i \cong 1,...,59 \qquad (6)$$

$$\Gamma y_{t.\,h} \cong \varphi_{0i} \,.\, \varphi_{1i}(L)x_{it} \,.\, \varphi_{2i}(L)\Gamma y_t \,.\, \theta_{it.\,h}\,,\; i \cong 1,...,59 \qquad (7)$$

where, x_{it} is the forecasting variable *i*. The choice of the forecasting variables is based on the findings of Atriyanfar and Barakchian (2011). They evaluated the information content of economic variables for inflation forecasting in Iran. The forecasting variables were selected from the following categories: 1) Real activity measures (such as GDP and consumption), 2) Wages and price indices, 3) Money and credit, 4) Asset price, 5) Constructing and housing sector, 6) Government budget and 7) Energy sector. These variables contain useful information about the state of the economy and also help to forecast the inflation rate and output gap.

The list of variables used in forecasting procedure is represented in appendix A (Table A1). The cyclical seasonal movements are removed from series by implementing a seasonal adjustment method[1]. All variables are transformed in logs and differentiated to get stationary time series - if necessary. These transformations are carried out on the basis of Unit Root Tests, both Augmented Dickey-fuller and Philips-Peron. Following Einian and Barakchian (2012), output gap is deifned as deviations of log of output (real GDP) from its trend using two stage Hodrick-Prescott iflter wit smoothing parameters (lambda = 677,1).

1. Census X12 adjustment method for removing the seasonal component of time series is used.

As mentioned earlier, an ARDL-based methodology is used in this paper to make out-of-sample forecasts of inflation and changes of output gap. Following forecast combination approach, a simple average of the forecasts from each bivariate ARDL is taken.[1] One advantage of this procedure over estimating a single ARDL is that it reduces the sensitivity of forecasts to potential changes in the informational content of the variables. Empirical research on combination forecasts has established that simple combinations, such as the average or median of a panel of forecasts, frequently outperform the constituent individual forecasts [Clemen (1989), Diebold (1998) and Newbold and Harvey (2002)]. Lagged forecasts going as far as 8 periods earlier for each quarter from 2002:Q2 until 2015:Q1 are created. The lag length in each ARDL is selected using the AIC.

To explain the out of sample forecasting procedure, consider the following example: Assume a forecasting horizon of 4 quarters (i.e. $j^{\max} \cong 3$). Then the earliest forecasts required to estimate equation (5) over the period 2002Q2-2015Q1 are the four-quarter-ahead forecast $E_{2001Q2}[\sigma_{2002Q2}]$. The ARDLs from the initial period, 1990Q2, till 2001Q2 is estimated and then, got the four-quarter-ahead average forecast. This procedure iteratively is repeated to obtain all the forecasts in equation (5).

Finally, following Coibion (2010) and khan and zhu (2006), a degree of real rigidity in the estimation of the SIPC as a way of more precisely estimating the degree of information rigidity is imposed. In particular, the case of 0.10, the value assumed by Mankiw and Reis (2002) is focused. Table B1 reports different amounts of real rigidity assumed in empirical studies. Based on this table, degree of real rigidity ranges from 0.1 to 0.2 in different studies. Low values of real rigidity imply substantial strategic complementarities in price setting among firms and are necessary for the sticky information model to deliver a delayed response of inflation to monetary shock. In robustness check section, also sensitivity test of results to the different amounts of real rigidity has been carried out.

1. This paper uses inflation forecasting package for producing out of sample forecasts. This package written in Matlab has been produced by Hooman Karami and Saeed Bayat and is sponsored by Monetary and Banking Research Institute (MBRI). The writer is so grateful for their helpful comments.

4.2. TAR model

In this paper, threshold model is used to identify high and low inflation regimes and estimate the SIPC for each identified regime. The hypothesis of this paper is that the slope of the SIPC changes between these two regimes. To be exact, the information updating process seems to be higher when the inflation rate is higher. This evidence suggests that firms are more aware of macroeconomic conditions when inflation is higher; that is, missing information during high inflation periods is costly. On the other hand, during low inflation regimes there are few incentives for updating information; that is, stable macroeconomic conditions make the information updating process about macroeconomic conditions slow.

4.2.1. Testing for non-linearity model

Following Carrera and Ramirez-Rondan (2014), the lag of inflation as a threshold variable[1] is considered. A threshold effect test is done to determine whether there is a statistically significant non-linearity in SIPC. In order to test the existence of nonlinearity, the approach proposed by Terasvirta (1994) is followed to test linearity in smooth transition auto-regressive models (STAR)[2] . The linearity test (with respect to first lag of inflation rate) is performed in the following regression:

$$\sigma_t \cong \varphi_0 Z_t \, . \sum_{i \cong 1}^{3} \varphi_i Z_t \sigma_{t01}^{i} \, . \; \xi_t \qquad (8)$$

where Z_t is the vector of explanatory variables on the right side of SIPC. If the Null hypothesis $H_0 \cong \varphi_1 \cong \varphi_2 \cong \varphi_3 \cong 0$ is not rejected, then the non-linear regression can be reduced to a linear form ($\sigma_t \cong \varphi_0 Z_t \, . \; \xi_t$). The results of these tests are reported in table (1).

1. A natural candidate for the threshold variable is the current level of inflation, but by construction, this variable is endogenous to the model. A critical assumption in threshold models is that the threshold variable has to be exogenous.
2. Since threshold regression is nested in smooth transition regression (STR), this test of linearity is more general than corresponding test in threshold regression.

Table 1: Results of Non-linearity Test

Horizons	Test Statistics (chi-square)	Probability
4	4.40***	0.0083
6	4.38***	0.0084
8	10.43***	0.0000

Note: Real rigidity is assumed to be 0.1. ***significant at 1%.

According to the results, the Null hypothesis regarding the linearity of regression with respect to lag of inflation rate is rejected within the 1% confidence level [1]. The test statistics on different horizons (4.40, 4.38 and10.43) and the P-value of the test (0.0083, 0.0084 and 0.0000) indicate that there is a statistically significant non-linearity in SIPC. Therefore, TAR model can be defined as follows:

$$\sigma_t \cong \begin{cases} \dfrac{(1 0\ o_1)}{o_1}\delta y_t\ .\ (1 0\ o_1) \sum_{j\cong 0}^{j\max} o_1^{\ j} E_{t010\,j}[\sigma_t\ .\ \delta\Gamma y_t]\ .\ \pi_t & if \quad \sigma_{t01} \infty \omega \\ \dfrac{(1 0\ o_2)}{o_2}\delta y_t\ .\ (1 0\ o_2) \sum_{j\cong 0}^{j\max} o_2^{\ j} E_{t010\,j}[\sigma_t\ .\ \delta\Gamma y_t]\ .\ \kappa_t & if \quad \sigma_{t01}\, \mathrm{A}\omega \end{cases} \tag{9}$$

where o_1 and o_2 are information rigidity parameters for low and high inflation regimes, respectively, and $\omega$is the threshold level. ω is allowed to be estimated.

In order to estimate ω, the approach suggested by Hansen (1996) is followed. The threshold ω can be estimated through sequential conditional least-squares estimation (CLS). For each possible value of the threshold level, the above equation is estimated and the sum of squared errors are kept. This procedure is repeated from the 15th up to the 85th percentile of the threshold variable (first lag of inflation rate) so that each regime includes an adequate number of observations. The LS estimator for ω is the value that minimizes the sum of squared errors:

1. The null hypothesis is tested using Wald test. The restrictions on coefficients are as follows: $\varphi_1 \cong \varphi_2 \cong \varphi_3 \cong 0$

$$\hat{\omega}^{*} \cong \arg\min SSR(\omega) \qquad (10)$$

Hansen (1996) has shown that a grid search that minimizes the total sum squared residuals will provide consistent estimates of both the thresholds and the model parameters.

5. Results

In this section, the results of estimating linear and non-linear SIPC are presented respectively. In addition, the sensitivity of the estimates of information rigidity to different amounts of real rigidity is tested in the final part of this section.

5.1. Estimation of linear SIPC

The degree of information stickiness (parameter o) in equation (5), conditional upon the imposed degree of real rigidity ($\delta \cong 0.1$), is estimated using non-linear least squares. The ordinary-least-square estimation of equation (5) using the forecast data is subject to the “generated regressors’’ problem discussed, in Murphy and Topel (1985) and Pagan (1986). The standard errors and confidence intervals would therefore be incorrect. Instead, bootstrapped confidence intervals[1] are provided for the estimates to address the generated regressors issue in the two-stage approach.

Table 2 reports the results of estimating linear SIPC for each forecasting horizon using Stata 13 software. Based on results, the sign of estimated degree of information stickiness is positive and its magnitude is less than one for all the horizons. Based on bootstrap standard errors, the values of o are significant at 95% confidence interval. Results indicate that the Null hypothesis of 'no information stickiness' can be rejected. Average durations of information stickiness range from 3.2 to 4 quarters.[2]

1. The number of repetitions of the bootstrapping procedure is 1000.

2. o and δ are also estimated jointly. Results show that the estimates of o are similar to those reported in table 2.

Table 2: Estimate of Linear SIPC

Forecasting horizon (quarters)	o	Bootstrap Standard Errors	R^2	S	D
4	0.69*	0.0878	0.67	0.77	3.2
6	0.75*	0.0579	0.70	0.82	4
8	0.74*	0.033	0.69	0.91	3.8

Note: Real rigidity is assumed to be 0.1. o is the degree of information rigidity.

* Significant at 5%. S equals the sum of the estimated coefficients of the SIPC. D is the duration of information stickiness and it is defined as $D \cong 1/(10\ o)$.

The estimated sum of the coefficients on past expectations in the SIPC, S, should be close to one as implied by the theoretical feature of the SIPC. Based on fifth column of table 2, S statistic is acceptably close to one in 8 quarter forecasting horizon. This means that in this forecasting horizon, selecting a truncation point does not lead to a large bias in the estimates.

5.2. Estimation of non-linear SIPC

As mentioned before, the non-linear SIPC is estimated using TAR model. The estimation period is 2002Q2- 2015Q1. The result of estimating the threshold level ω using Hansen (1996) approach is shown in table 3.

Table 3: Threshold Estimates

Forecasting horizon (quarter)	4	6	8
ω	0.0393	0.0444	0.0399

Note: Real rigidity is assumed to be 0.1. ω is the threshold level.

Based on the results, the inflation threshold tends to be between 3.93 and 4.44 percent. Therefore, two regimes can be defined: 1) High inflation: for inflation rates higher than ω, and 2) Low inflation: for inflation rates lower than ω.

Table 4: Degree of Information Rigidity in High and Low Inflation Regimes

Forecasting Horizon (Quarter)	**4**		**6**		**8**	
Inflation	Low	High	Low	High	Low	High
Degree of information stickiness	0.852*** (0.026)	0.385* (0.229)	0.868*** (0.017)	0.516*** (0.185)	0.889*** (0.289)	0.667*** (0.035)
Duration (Quarter)	6.8	1.6	7.6	2.1	9	3

Notes: Real rigidity is assumed to be 0.1, bootstrap standard errors are in parentheses.

* Significant at 10%;
** Significant at 5%; ***Significant at 1%.

Table 4 shows the estimates of the degree of information rigidity for inflation values higher (or lower) than ω, under the specification of equation (9). This generates two parameters: O_1 and O_2 under low and high inflation regimes, respectively. The point estimates suggest that the degree of information rigidity parameter changes when inflation rates are either lower or higher than ω . This result is robust for different forecasting horizons.Results indicate that under a low-inflation regime, O_1 ranges from 0.852 to 0.889 (consistent with approximately 6.8 and 9 quarters of duration of information stickiness), while for high-inflation regime, O_2 ranges from 0.385 to 0.667 (approximately 1.6 and 3 quarters). Based on bootstrap standard errors, O_1 and O_2 are statistically significant (all coefficients - instead of the case of 4 quarter forecasting horizon and high inflation regime - are significant at 1% level). This result supports the hypothesis that firms update information faster in high-inflation environments, while in low-inflation environments, those firms lack incentives to update information.

5.3. Robustness check

In this section, the sensitivity of the estimates of information rigidity to different amounts of real rigidity is investigated. By assuming two different values for real rigidity including 0.05, 0.2 non-linear SIPC is re-estimate. Based on Table 5, different amounts of real rigidity do not affect the result. The information rigidity is again larger in low inflation regimes in comparison with high inflation regime. Therefore, estimates of the degree of information rigidity in high and low inflation regimes are not sensitive to the amount of real rigidity.

Table 5: Degree of Information Rigidity in High and Low Inflation Regimes

Forecasting horizon (quarter)		**4**		**6**		**8**	
Inflation		**Low**	**High**	**Low**	**High**	**Low**	**High**
Real rigidity	0.1	0.852*** (0.0258)	0.385* (0.229)	0.868*** (0.0170)	0.516*** (0.185)	0.889*** (0.289)	0.667*** (0.035)
	0.2	0.850*** (0.0260)	0.454*** (0.0406)	0.867*** (0.0167)	0.551** (0.221)	0.888*** (0.207)	0.687*** (0.028)
	0.05	0.853*** (0.0257)	0.331* (0.226)	0.869*** (0.0161)	0.494* (0.255)	0.889* (0.467)	0.654*** (0.082)

Notes: Standard errors are in parentheses. * Significant at 10%; **; significant at 5%; ***significant at 1%.

6. Conclusion

Phelps (1970) proposed the idea that real effects of monetary policy are due to imperfect information. Lucas (1972) formalized this idea by assuming that agents observe the state of monetary policy with a delay. The Lucas model has been criticized on the grounds that information concerning monetary policy is published with little delay. However, Reis (2006) showed that a model with a fixed costs of acquiring, absorbing, and processing perfect information can provide a micro-foundation for the slow diffusion of information. Reis (2006) showed that the inattentiveness model provides a micro-foundation to the sticky-information Phillips curve. The inattentiveness model follows in the tradition of the menu cost models of Akerlof and Yellen (1985), Blanchard and Kiyotaki (1985), and Mankiw (1985). These researches interpreted menu costs as physical fixed costs of changing prices. The inattentiveness model instead stresses an interpretation of menu costs as fixed costs of acquiring information, and especially of absorbing and processing it.

Plans and information are then sticky, rather than prices. This change in interpretation may seem slight, but it turns out to imply a very different model and implications for inflation dynamics.

This paper is the first attempt to estimate the degree of information stickiness in Iran. Using the two stage empirical approach proposed by Khan and Zhu (2006), evidence that the flexible information hypothesis is rejected in favor of sticky information is found. It takes on average, 3.2 to 4 quarters for firms to update their information in setting prices.

The hypothesis that the slope of the SIPC changes between low and high inflation regimes is also tested. To be exact, the information updating process seems to be higher when the inflation rate is higher. Results suggest that under a low-inflation regime, duration of information stickiness ranges from 6.8 to 9 quarters, while for high-inflation conditions, the duration ranges from 1.6 to 3 quarters. This result supports the hypothesis that firms update information faster in high-inflation environments, while during low inflation regimes there are few incentives for updating information; that is, stable macroeconomic conditions make the information updating process about macroeconomic conditions slow.

This difference between the degree of information stickiness - or the firm's attention to the state of the economy - can be explained by the cost of acquiring information. In any period, a firm is faced with two choices (continuing with outdated information or updating information). Since it is costly for a firm to acquire and process information, the firm optimizes over these choices. In high inflation periods, cost and benefit analysis done by firms indicates that the benefit from changing prices exceeds the cost of acquiring information. So, firms collect and process information more frequently in high inflation regimes. Therefore, the degree of information rigidity is lower in high inflation regime. This result indicates that state dependent pricing models are more consistent with stylized facts in the economy of Iran.

Threshold effect in information stickiness suggests different lessons for monetary policy than standard sticky price and sticky information models. This study suggests that stabilizing monetary policy is good because the allocation of attention changes as monetary policy changes. In periods of monetary policy expansion (high inflation environment) firms decide to pay more attention to macroeconomic state and update their information more frequently. This process leads to more frequent price changes in the economy.

References

Akerlof, G. A., & J. L. Yellen, (1985). "A Near-rational Model of the Business Cycle, with Wage and Price Inertia". *The Quarterly Journal of Economics*, Vol. 100, 823-838.

Atrianfar, H. & M. Barakchian, (2011). "Evaluation of Information Content of Economic Variables for Inflation Forecasting in Iran", Journal of Monetary and Banking Research, Vol. 3, Number 8, 1-42, (in Persian).

Ball, L., & D. Romer, (1990). "Real Rigidities and the Non-Neutrality of Money". *Review of Economic Studies,* No. 57, 183-203.

Blanchard, O., & N. Kiyotaki, (1985). "Monopolistic Competition, Average Demand Externalities and Real Effects of Nominal Money", *NBER Working Paper,* No. 1770.

Calvo, G. A. (1983). "Staggered Prices in a Utility Maximizing Framework", *Journal of Monetary Economics,* XII (1983), 383–398.

Carrera, C. (2012). "Estimating Information Rigidity Using Firms' Survey Data". *The BE Journal of Macroeconomics*, 12(1).

Carrera, C., & N. Ramirez-Rondan, (2014). "Inflation, Information Rigidity and the Sticky Information Phillips Curve". *Peruvian Economic Association, Working Paper* No. 1, January 2014.

Carroll, C. (2003). "Macroeconomic Expectations of Households and Professional Forecasters". *Quarterly Journal of Economics,* 118, 269 – 298.

Clemen, R.T. (1989). "Combining Forecasts: A Review and Annotated Bibliography". *International Journal of Forecasting,* Vol. 5, pp. 559-583.

Coibion, O. (2006). "Inflation Inertia in Sticky Information Models". *Contributions in Macroeconomics,* 6(1), 1-29.

Coibion, O. (2010). "Testing the Sticky Information Phillips Curve", *Review of Economics and Statistics,* 92(1), 87–101.

Diebold, F. X. (1998). *Elements of Forecasting*. South-Western College Pub., 1–392.

Dopke, J., J. Dovern, U. Fritsche, & J. Slacalek, (2008). “The Dynamics of European Inflation Expectations”. *The BE Journal of Macroeconomics*, 8(1).

Einian, M. and M. Barakchian (2012). “Measuring and Dating Business Cycles of the Economy of Iran”, *Journal of Monetary and Banking Research*, Number 20, 161-194, (in Persian).

Gillitzer, C. (2015). “The Sticky Information Phillips Curve: Evidence for Australia” *Research Discussion Paper*, No. RDP 2015-04, Reserve Bank of Australia.

Hansen, B. E. (1996a). “Inference When a Nuisance Parameter is not Identiifed unde□the Null Hypothesis□, *Econometrica*, 64, 413□430.

Karami, H., & S. Bayat, (2013). “Evaluating and Comparing the Methods of Measuring Core Inflation in Iran”, *Journal of Monetary and Banking Research*, No. 17, 83-103, (in Persian).

Khan, H., & Z. Zhu, (2006). “Estimates of the Sticky-Information Phillips Curve for the United States,” *Journal of Money, Credit, and Banking*, 38:1, 195–207.

Lucas, R. E. (1972). “Expectations and the Neutrality of Money”. *Journal of Economic Theory*, 4, 103-124.

Mankiw, G. N. & R. Reis, (2002). “Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve”, *The Quarterly Journal of Economics*, Vol. 117, No. 4, 1295-1328.

Mankiw, N.G. & R. Reis, (2007). “Sticky Information in General Equilibrium”. *Journal of the European Economic Association*, 5 (2-3), 603 – 613.

Murphy, K. and R. Topel, (1985). “Estimation and Inference in Two-Step Econometric Models”. *Journal of Business and Economic Statistics* 3, 370-379.

Newbold, P., & D. I. Harvey, (2002). *Forecast Combination and Encompassing, in a Companion to Economic Forecasting*. M.P. Clements and D.F. Hendry, eds. Oxford: Blackwell Press.

Pagan, A. (1986). “Two Stage and Related Estimators and Their Applications”. *The Review of Economic Studies*, 53(4), 517-538.

Phelps, E. S. (1970). *Introduction: The New Microeconomics in Employment and Inflation Theory. In Microeconomic Foundations of Employment and Inflation Theory*, by Edmund S. Phelps, 1-23. New York: Norton.

Reis, R. (2006b). “Inattentive Producers”. *Review of Economic Studies*, 73 (3), 793-821.

Rotemberg, J., & M. Woodford, (1997). “An Optimization-based Econometric Framework for the Evaluation of Monetary Policy”. *NBER Macroeconomics Annual* 1997, Volume 12 (pp. 297-361). MIT Press.

Stock, J. H., & M. Watson, (2003). “Forecasting Output and Inflation: The Role of Asset Prices”, *Journal of Economic Literature*, 41:3, 788-829.

Terasvirta, T., (1994), “Specification, Estimation and Evaluation of Smooth Transition Autoregressive Models”, *Journal of the American Statistical Association*, Vol. 89, No. 425, 208-218.

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

Appendix A

Table A1: List of Variables Used in the Out of Sample Forecasting

Real Sector	Monetary and Credit Aggregates
Gross domestic product (at constant prices)	Notes and coins in circulation
Value-added of agricultural group (at constant prices)	Money base (MB)
Value-added of oil group (at constant prices)	Money supply (M1)
Value-added of manufacturing and mining group (at constant prices)	Liquidity (M2)
Value-added of service group (at constant prices)	Quasi money
Public consumption expenditure (at constant prices)	Demand deposit with banks and credit institutions
Private consumption expenditure (at constant prices)	Required reserves of banks (banks legal deposit with central banks)
Industrial production index (2011=100)	Excess reserves (banks sight deposit with central banks)
Wage and Price Indexes	Banking system claims on non-public sector
producer price index (PPI) (2011=100)	Central bank claims on public sector
PPI (agriculture, hunting, forestry)	Central bank claims on banks
PPI (fishing)	Net foreign asset (central bank)
PPI (manufacturing)	**Asset**
PPI (hotels and restaurant)	US Dollar USD/IRR (non-official market rate)
PPI (transport, storage and communication)	Price of coin (old scheme)
PPI (education)	Share price index (1990=100)
PPI (health and social works)	Value of share trading

Real Sector	Monetary and Credit Aggregates
CPI (food, beverages) (2011=100)	The average price of a square meter of residential infrastructure in Tehran
CPI (tobacco)	**Government Budget**
CPI (clothing and footwear)	Current payments
CPI (housing, water, fuel and power)	Development payments
CPI (rental equivalence of owner occupied houses)	Tax revenues
CPI (Rent of residential houses)	Oil revenues
CPI (Maintenance and repair services)	**Construction and Housing Sector**
CPI (household furnishings and operations)	Construction permits issued by municipalities in large cities
CPI (medical care)	Private sector investment in new building in urban areas
CPI (transportation)	Private sector investment in new building in Tehran
CPI (communication)	**Energy Sector**
CPI (recreation)	Electricity generation
CPI (education)	Crude oil production
CPI (hotel and restaurant)	Crude oil exports
CPI (miscellaneous goods and services)	Oil prices (West Texas)
Wage index of manufacturing workers	
Construction services index (2011=100)	

Appendix B

Table B1: Calibration of Real Rigidity in Empirical Studies

Study	Real rigidity
Ball and Romer (1990)	0.13
Rotemberg and Woodford (1997)	0.13
Mankiw and Reis (2002)	0.1
Woodford (2003)	0.1-0.15
Reis (2006b)	0.11
Khan and Zhu (2006)	0.1
Dopke et. al (2008)	0.1, 0.2
Coibion (2010)	0.2