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INFLATION, INFORMATION RIGIDITY, AND THE STICKY INFORMATION PHILLIPS CURVE

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The Great Moderation is characterized as a period of stable macroeconomic conditions, especially with regard to inflation. Under the sticky information theory, this environment may provide a few incentives for agents to update information on inflation, thus, producing a new slope of the sticky information Phillips curve. We estimate the degree of information rigidity implied by the sticky information Phillips curve. Using threshold models, we identify two regimes of high and low inflation, finding that each identified regime is associated with a specific degree of information stickiness. This evidence is consistent with agents that update information faster when inflation is higher.

Keywords: Inflation, Sticky Information, Phillips Curve, Threshold Model.

1. INTRODUCTION

In 2004, Ben Bernanke highlighted the substantial decline in the variability of growth in real output and in the variability of inflation as one of the most striking features over "the past twenty years." Bernanke also pointed out that this decline, "the Great Moderation," bore similarities to other declines that occurred around the same time in other major industrial countries.[1] Not only the variability, but also the level of inflation, became steadily low for a long period of time. Figure 1 illustrates how inflation became steady and low for both developed countries and emerging economies. In this new environment, several questions arise: Is there a new relationship between inflation and output (i.e., Phillips curve)? If so, do previous modeling strategies remain valid descriptors for this structural

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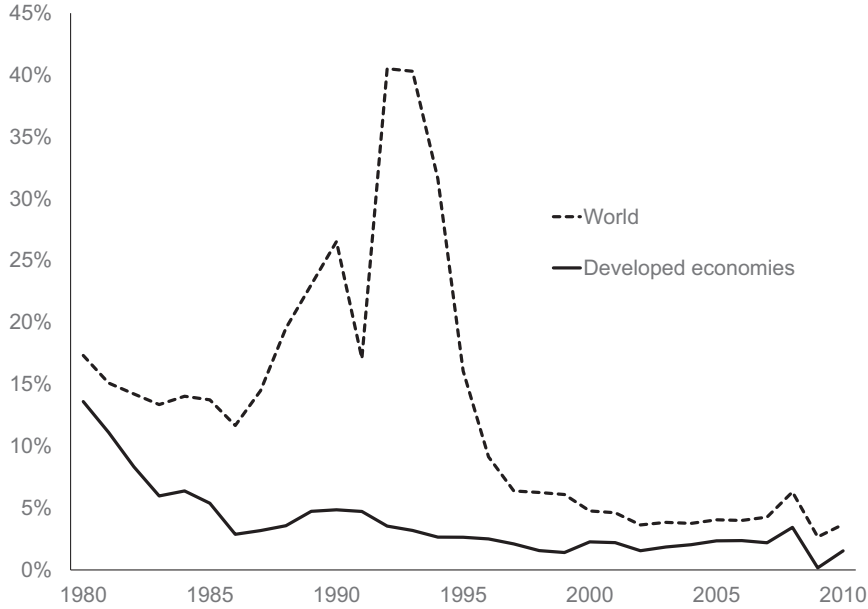


FIGURE 1. Inflation by regions. Source: IMF International Financial Statistics (IFS).

relationship? Moreover, does this new scenario imply that models relying on inflation information are better in terms of describing monetary policy frameworks? Here, we present evidence in favor of a change in the slope of the Phillips curve suggested by Mankiw and Reis (2002).

The sticky information model proposed by Mankiw and Reis (2002) is based on the argument that information on macroeconomic conditions diffuses slowly through the population. Thus, while prices are always changing based on current information, price-setting decisions are not. In other words, information is sticky. The sticky information modeling approach is part of the family of models with informational rigidities. In this regard, models with noisy information proposed by Woodford (2002) and Sims (2003) have become more widely used in the literature on the behavior of macroeconomic expectations and its implications for policy making decisions.[2]

As a matter of fact, the gradual diffusion of information across the population assumed by the sticky information model has received empirical support by using survey data. Carroll (2003) uses a two-agent epidemiology expectation model of information transmission and estimates the rate of diffusion of inflation forecasts from professional forecasters to households. He finds results in line with those in Mankiw and Reis (2002). Döpke et al. (2008b) and Carrera (2012) provide similar estimates using the Carroll's approach. Döpke et al. (2008b) study the case of European countries, and Carrera (2012) presents the case for the diffusion from professional forecasters to firms' general managers, arguing that the rigidity of

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managers' expectations is the key to the Phillips curve. They all find that the data support the epidemiology expectation model.

In the context of the Phillips curve, the sticky information model implies that the price level depends on expectations of the current price level formed in the past, as some price setters set prices based on past decisions, due to the costs of either acquiring or processing new information. These concepts are formally known as the sticky information Phillips curve (SIPC).

A more stable monetary policy and low inflation around the globe are both reasonable arguments for isolating and estimating the SIPC. This does not deny its potential role as a complementary form of rigidity to price stickiness (some literature has emphasized the need to model both price and information stickiness), but rather highlights the role of the use of information for modeling the Phillips curve. Therefore, estimating the degree of information rigidity by itself provides more insight about the transmission mechanism in a new international environment. In this regard, Klenow et al. (2007) find that price changes in the United States Consumer Price Index (US CPI) microdata reflect information older than that predicted by a flexible information model; Kiley (2007a) finds that the SIPC and the one-lag hybrid new Keynesian Phillips curve (NKPC) exhibit similar performance; and Korenok (2008) cannot formally reject the SIPC.

Our work provides consistent SIPC estimates for the United States and for Organisation for Economic Co-operation and Development (OECD) countries. We find evidence that rejects the flexible information hypothesis in favor of sticky information. This result is consistent with that found in Khan and Zhu (2006), who estimate the SIPC for the United States, and in Coibion and Gorodnichenko (2012), who use survey data analysis.

We use threshold models to identify high- and low-inflation regimes and estimate the SIPC for each identified regime. The slope of the SIPC changes between regimes. Indeed, the information updating process seems to be higher when the inflation rate is higher. This evidence suggests that economic agents are more aware of macroeconomic conditions when inflation is higher; that is, missing information during high-inflation periods is costly. During low-inflation regimes, on the other hand, there are few incentives for updating information; that is, stable macroeconomic conditions make the information updating process slow. Our result is also consistent with that of Maćkowiak and Wiederholt (2009). In their view, rational inattention is related to the level of information because agents must decide how much attention they should devote to information while constantly updating their information set. In ours, information is sticky because the logistics behind new information (acquisition, processing, and absorption) has different costs (from low to high) when the observed inflation is in different regimes. For instance, it is not more costly to work with new information if observed inflation is low but the gains of paying for new information are higher when inflation is at high levels.

Our findings support the hypothesis that firms in countries with higher inflation pay more attention to changes in price level. As a matter of fact, there is a

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well-documented positive correlation between inflation and its volatility [see for example Okun (1971), Taylor (1981), and Kiley (2000, 2007b)]. With this in mind, Reis (2006) models firms that update their information more frequently when the volatility of aggregate prices is higher. In the sticky information literature, updating information becomes more costly for firms when inflation is lower because a firm must acquire, process, and absorb new information in order to update its current information set. As such, firms may remain inattentive. By the same token, Reis (2006) concludes that planning ahead becomes easier if low uncertainty provides few incentives to update information on macroeconomic conditions.

In line with the discussion by Lucas (1973), Ball et al. (1988), and Kiley (2007a) regarding the exogeneity of the degree of price stickiness, our results support a similar discussion in terms of the degree of information stickiness. We find evidence that suggests a positive relationship between the degree of information stickiness and the level of inflation. Thus, our work also contributes to the existing literature by providing further evidence of state-contingent and time-dependent inflation processes in the context of the Phillips curve.

The rest of this paper is structured as follows: Section 2 contains the baseline model of Mankiw and Reis (2002). In Section 3, we estimate the SIPC. In Section 4, we present the results of threshold estimations for high- and low-inflation regimes. Section 5 concludes the paper.

2. BASELINE STICKY INFORMATION PHILLIPS CURVE

Every firm sets its price every period, but firms gather information and recompute optimal prices slowly over time. In each period, a fraction λ of firms obtain new information about macroeconomic conditions (such as inflation and output) and $(1 - \lambda)$ firms continue to set prices based on old plans (outdated information). Firms with updated information compute a new path of optimal prices.

Each firm has the same probability of being one of the firms updating its information set, regardless of how much time has passed since its last update. Thus, on average, the expected time for a firm to update its prices is $1/\lambda$.[3]

A firm's optimal price that maximizes expected profits at any given point in time is $p_t^* = p_t + \alpha y_t$, where p_t is the overall price level and y_t is the output gap (or aggregate demand-related variable).[4] The desired price depends on the overall price level and output gap, so a firm's desired relative price rises in booms and falls in recessions. Also note that a small α means that each firm gives more weight to the changes in prices set by other firms rather than to the level of aggregate demand.

A firm that last updated its plans j periods ago sets its price as the expected value of the optimal price j periods ago: $x_t^j = E_{t-j} p_t^*$. The aggregate price level is the average of the prices of all firms in the economy: $p_t = \lambda \sum_{j=0}^{\infty} (1 - \lambda)^j x_t^j$. The aggregate price level is then defined by $p_t = \lambda \sum_{j=0}^{\infty} (1 - \lambda)^j E_{t-j}(p_t + \alpha y_t)$

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and the baseline SIPC is defined as

$$\pi_t = \frac{\lambda\alpha}{1-\lambda} y_t + \lambda \sum_{j=0}^{\infty} (1-\lambda)^j E_{t-1-j}(\pi_t + \alpha \Delta y_t), \quad (1)$$

where $\Delta y_t = y_t - y_{t-1}$ is the growth rate of output and $\pi_t = p_t - p_{t-1}$ is the growth rate of prices (inflation). Note that $\frac{\lambda\alpha}{1-\lambda}$ is the slope of the SIPC. In this setup, inflation depends on output, past expectations of current inflation, and changes in current output growth.

3. ESTIMATION METHODOLOGY

The usual procedure used to estimate a SIPC is nonlinear Ordinary Least Squares (OLS) [Khan and Zhu (2006), Döpke et al. (2008a), and Coibion (2010)]. Khan and Zhu's (2006) method uses publicly available data for estimating expectations. Döpke et al. (2008a) and Coibion (2010) use information from survey data and plug the responses into forecasts of inflation and economic growth. It is important to mention that the use of survey data limits the truncation value of the Phillips curve. Döpke et al. (2008a) consider only two levels of truncation (at four and six periods), and Coibion (2010) additionally uses the forecasts from estimated VAR's in order to expand the level of truncation to 12 periods.

Most survey data on macroeconomic variables allow at most only two forecasting windows (typically the questioning concerns expected inflation at the end of the current year and end of the next year), reducing the scope of these types of studies. Some research, i.e., Coibion (2010), shows consistency in results between artificial time series expectations and those coming from survey data. Thus, artificial expectations are useful for elaborating different forecasting windows. In the context of the SIPC, we use older information about inflation from previous periods to forecast inflation for the current period. As in Mankiw and Reis (2002), we use old but rationally forward-looking expectations.

There is also some discussion regarding the real rigidity parameter α. Taking into account both microevidence and aggregate evidence, Woodford (2003) concludes that a value for α between 0.10 and 0.15 is adequate. Reis (2006) cites Chari et al. (2000) and sets $\alpha = 0.17$. Another reasonable value is 0.13, used by Rotemberg and Woodford (1997) and Ball and Romer (1990).[5] Some other values used in the literature for estimating the SIPC for the United States are Khan and Zhu (2006), α equal to 0.10; Reis (2006), α equal to 0.11; and Coibion (2010), α equal to 0.20. For European countries, Döpke et al. (2008a) use two values of α, 0.10 and 0.20, as a way to test for robustness.

Thus, we estimate the SIPC for 1971–2007 using quarterly data for 12 OECD countries, where we estimate—in this section and throughout this paper—the information rigidity parameter by holding constant the real rigidity level; that is, we estimate λ subject to α equal to 0.10, a value that is consistent with the literature.

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3.1. Data

We collect quarterly data for 12 OECD countries from 1958–2007[6] and use an 8-year data period for iteratively forecasting inflation and the output gap. Given those forecasts and the level of truncation required for each SIPC (5 years), our sample shrinks to the period 1971–2007. We build this database in line with Khan and Zhu (2006) and Stock and Watson (2003).[7]

The main source of the data is the International Financial Statistics (IFS) database from the International Monetary Fund. Other secondary sources are the OECD (for data on core inflation) and the Federal Reserve System (for data on capacity utilization). We also consider the global financial database for long-time series, when they are not available in the IFS.[8]

For the United States inflation forecasts, we follow Khan and Zhu (2006) and use the short-term interest rate (federal funds rate, level), dividend yield (S&P 500 stock dividend yield, logarithm), term spread (difference between the 10-year government bond rate and the short-term interest rate, level), unemployment rate (level), capacity utilization (level), and the output gap (logarithm). For the United States output gap forecasts, we use the short-term interest rate (level), dividend yield (logarithm), term spread (level), stock market price index (S&P stock price index, growth), capacity utilization (level), and inflation (level).

3.2. Estimation Strategy

Khan and Zhu's (2006) strategy consists of the truncation of equation (1). The empirical approach to the SIPC is as follows:

$$\pi_t = \frac{\lambda\alpha}{1-\lambda} y_t + \lambda \sum_{j=0}^{j^{\max}} (1-\lambda)^j E_{t-1-j}(\pi_t + \alpha \Delta y_t) + u_t, \qquad (2)$$

where $u_t = \lambda \sum_{j=j^{\max}+1}^{\infty} (1-\lambda)^j E_{t-1-j}(\pi_t + \alpha \Delta y_t)$.

For a given λ, the approximation error, u_t, becomes theoretically smaller with an increase in the truncation level ($j^{\max}$). The truncation level considered is between 4 and 19 quarters.

A total of ($j^{\max}+1$) past expectations (or forecasts) of current variables π_t and Δy_t for each t is needed to estimate equation (2). Each of these forecasts is based on past information from periods $t-1, t-2, \cdots, t-1-j^{\max}$, respectively.

The baseline case considers an output gap that is estimated by the quadratic detrending method (quadratic detrended output gap) and an inflation that is measured by the consumer price index (CPI). Our results hold even if we instead consider a Hodrick–Prescott output gap and either the core inflation or the gross domestic product (GDP) deflator as the measure of inflation.

For generating out-of-sample forecasts for inflation and output gap, we estimate: (i) univariate autoregressive models; and (ii) bivariate VAR's.[9] In keeping with Stock and Watson (2003), we eliminate the largest and the smallest forecast when

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determining the average in order to reduce the sensitivity to large outliers and use the forecast of the output gap growth as the output gap forecast.[10]

Khan and Zhu (2006) estimate the degree of information stickiness (parameter λ), conditional on an imposed degree of real rigidity (parameter α). Parameter λ can be estimated by using IV nonlinear least squares. In other words, we minimize the following objective function for different values of that parameter:

$$\widehat{\lambda} = \underset{(\lambda)}{\operatorname{argmax}} \sum_{t=1}^{T} \left[\pi_t - \frac{\lambda\alpha}{1-\lambda} y_t - \lambda \sum_{j=0}^{j^{\max}} (1-\lambda)^j E_{t-1-j}(\pi_t - \alpha \Delta y_t) \right]^2 . \quad (3)$$

Note that the output gap, y_t, is endogenous in Phillips curve models. We then replace y_t by $\widehat{y}_t$ in equation (3), where $\widehat{y}_t$ are predicted values (uncorrelated with the error term u_t). We use y_{t-1} as an instrument, so in the first step we regress $y_t = \theta y_{t-1} + e_t$, then $\widehat{y}_t = \widehat{\theta} y_{t-1}$.

Finally, we test the null hypothesis H_0: $\lambda = 1$ (no information stickiness) against the alternative, H_1: $\lambda < 1$ (some information stickiness) in order to conclude our evaluations.

3.3. Evidence from OECD Countries

In line with Khan and Zhu, 2006, Döpke et al., 2008a and Coibion, 2010, we estimate the SIPC for OECD countries, imposing a degree of real rigidity and taking into consideration the availability of data. We reject the null hypothesis of flexible information in all cases. It seems fair to say that sticky information theory implies that countries with higher inflation levels or higher inflation volatility experience lower levels of inattentiveness. A simple cross-country analysis supports this hypothesis.

In Figure 2, we plot $\widehat{\lambda}$ and average inflation for each country. This figure suggests that in countries with higher inflation, price setters are expected to update information more frequently. In line with Reis (2006), it is more costly for firms in countries with lower inflation to update information because updating requires acquiring, processing, and absorbing information, such that they remain inattentive. Reis (2006) suggests that it is easier to plan ahead in a context of lower uncertainty, which reduces the incentives to update information on macroeconomic conditions.

Even though it is possible to argue that high inflation should not be costly if inflation is "chronic,"[11] we also consider the volatility of inflation. The positive relationship between $\widehat{\lambda}$ and this measurement of uncertainty still holds (see Figure 3), which suggests an additional factor that affects $\widehat{\lambda}$.

Note that the information rigidity estimates for OECD countries consider four truncation levels ($j^{\max} = 4$). The information rigidity estimates are very much alike when we consider higher truncation levels. We also get similar patterns to those in Figures 2 and 3 when we use different truncation levels.

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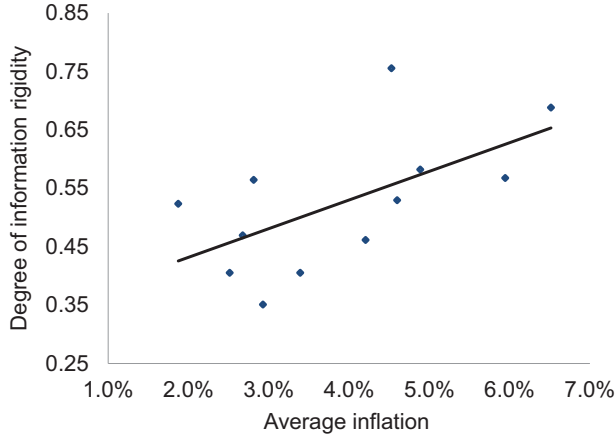


FIGURE 2. Information rigidity and inflation for OECD countries. The information rigidity estimate is the value considering four truncation ($j^{\max}$) levels. The average inflation is the average of the quarterly inflation within the sample.

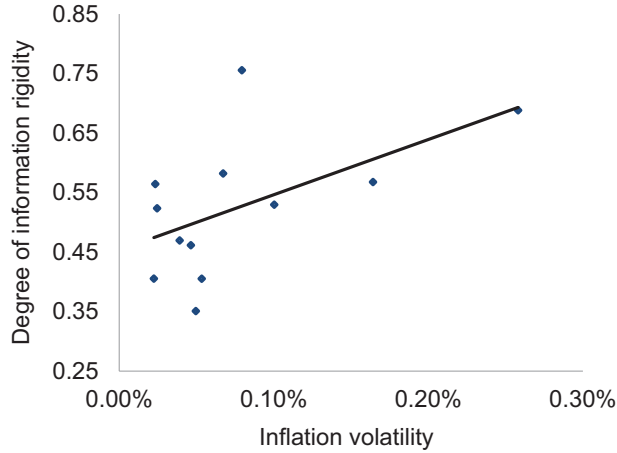


FIGURE 3. Information rigidity and inflation volatility for OECD countries. The information rigidity estimate is the value considering four truncation ($j^{\max}$) levels. Inflation volatility is measured as the variance of the quarterly inflation within the sample.

4. THRESHOLD MODELS

As suggested in the previous section, there is evidence that points to a change in the slope of the SIPC. This change may have implications for the design of optimal monetary policy. Walsh (2010) presents an exercise on the difference in the dynamics of inflation and the output gap for different degrees of information stickiness for the United States in response to a monetary policy shock. Following

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Mankiw and Reis (2002), Walsh (2010) shows that the maximum effect and the persistence of the shock are different when the slope of the SIPC is modified.

Even though a smooth transition threshold model (a more general case for a threshold model) would capture the slope of the SIPC (given the fact that looking at new information pays off more the higher the inflation is), our focus is on a single change in this slope because of the great moderation in variables such as inflation that lead to a change from a high- to a low-inflation regime. That single change in regimes is captured well in the particular case of a threshold model in which the threshold inflation is estimated.[12]

Figure 4 shows the US CPI, core, and GDP deflator inflation. All the measures suggest that it is possible to contrast periods of high inflation (from the 1970s to the early-1980s) with periods of low inflation (from the mid-1980s to 2007), suggesting a change in the regime (state) of the inflation patterns, as pointed out in Kiley (2007a).

In this section, we estimate both time and inflation threshold models over the SIPC empirical approach. We evaluate whether two regimes are present in the United States data and whether the change in regime has any effect on the slope of the SIPC, as discussed in preceding sections.

4.1. Time and Inflation Threshold Models

Here, we set the threshold models to be estimated. We first set a threshold model in which time is the threshold variable:

$$\pi_t = \begin{cases} \frac{\lambda_1 \alpha}{1-\lambda_1} y_t + \lambda_1 \sum_{j=0}^{j^{\max}} (1-\lambda_1)^j E_{t-1-j}(\pi_t + \alpha \Delta y_t) + u_t & \text{if} \quad t > \tau + j^{\max} \\ \frac{\lambda_2 \alpha}{1-\lambda_2} y_t + \lambda_2 \sum_{j=0}^{j^{\max}} (1-\lambda_2)^j E_{t-1-j}(\pi_t + \alpha \Delta y_t) + u_t & \text{if} \quad t \leq \tau, \end{cases} \tag{4}$$

where λ_1 and λ_2 are information rigidity parameters for low- and high-inflation periods, respectively, and τ is the threshold parameter.[13]

Note that if the regime changes at time τ, the measure of the firms that updated their information at $\tau - j$ is determined under the previous regime. To address this issue, in equation (4), for the second period, we consider the model t periods after $\tau + j^{\max}$; that is, until the model converges completely with the second regime (the transition period depends on the truncation, and is between 1 and 5 years).

We consider two estimations of model (4). We first impose a τ = 1982Q4, splitting the sample from 1971 to 1982 (period of high inflation, with an average of 7.6%) and from 1983 to 2007 (period of low inflation, with an average of 3.1%).[14] In the second estimation, we internally allow the threshold parameter τ in the model to be estimated.

We also propose a second model in which high inflation is determined for inflation rates higher than a threshold value. A natural candidate for the threshold variable is the current level of inflation, but by construction, this variable is endogenous to the model. A key assumption in these types of models is that the threshold variable must be exogenous. Thus, we consider the lag of inflation

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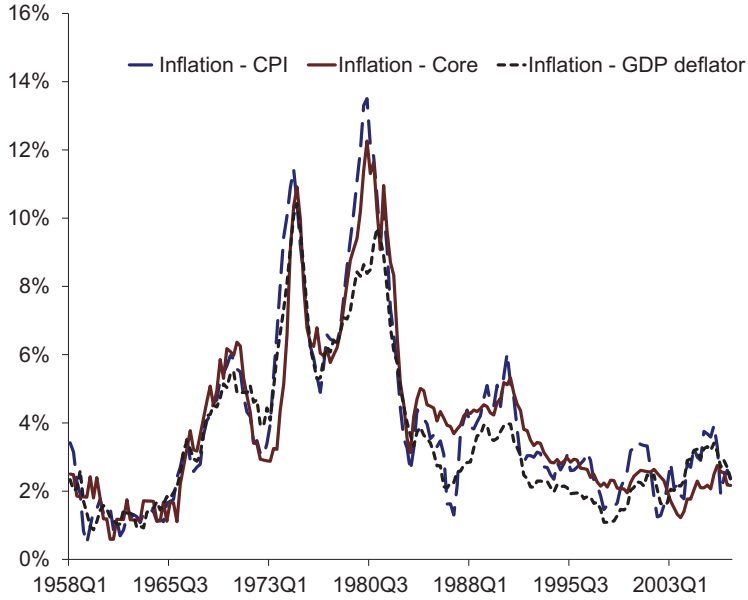


FIGURE 4. The United States inflation.

as the threshold variable. We then set the following model:

$$\pi_t = \begin{cases} \frac{\lambda_1\alpha}{1-\lambda_1} y_t + \lambda_1 \sum_{j=0}^{j^{\max}} (1-\lambda_1)^j E_{t-1-j}(\pi_t + \alpha\Delta y_t) + u_t & \text{if} \quad \pi_{t-1} \leq \gamma \\ \frac{\lambda_2\alpha}{1-\lambda_2} y_t + \lambda_2 \sum_{j=0}^{j^{\max}} (1-\lambda_2)^j E_{t-1-j}(\pi_t + \alpha\Delta y_t) + u_t & \text{if} \quad \pi_{t-1} > \gamma, \end{cases} \tag{5}$$

where λ_1 and λ_2 are information rigidity parameters for low and high inflation, respectively, and γ is the threshold parameter.[15] In addition, we consider inflation volatility instead of inflation as a threshold variable; thus, we split the sample into periods of high- and low-inflation volatility.

Note that equation (5) may be misspecified, since the measure of the firms that update their information at $\tau - j$ is determined under the previous periods, which could be the other regime. On the other hand, as in the model with time as a threshold variable, we expect that periods of high inflation or high-inflation volatility to be periods before 1982.[16]

4.2. Results

Table 1 presents the regressions for equation (4) in which a cut-off point between high and low inflation is imposed in 1982Q4. We reject the null of flexible information in each sub-period. For the period 1971–1982, the degree of information stickiness ($\widehat{\lambda}_2$) is 0.52, which implies 1.9 quarters of inattentiveness during a high inflation period. In contrast, the degree of information stickiness ($\widehat{\lambda}_1$) is around 0.39

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TABLE 1. Information rigidity and inflation regimes

Inflation regimes	Low inflation ($t > 1984Q1$)	High inflation ($t \leq 1982Q4$)
Information rigidity ($\widehat{\lambda}$)	0.39	0.52
	(0.064)	(0.034)
Duration in quarters	2.6	1.9
Z-test (p-value)	0.007	

Note: We set $\alpha = 0.1$ and $j^{\max} + 1 = 5$ quarters. Standard errors are in parentheses. The Z-test shows the probability value for the null hypothesis of $\widehat{\lambda}_1 = \widehat{\lambda}_2$.

TABLE 2. Breaking-point time threshold estimate

Threshold estimate ($\widehat{\tau}$)	90% confidence interval	95% confidence interval
1981Q2	(1979Q4;1985Q2)	(1979Q4;1985Q4)

Note: Asymptotic critical values are reported in Hansen (2000).

in the second period, which implies an average duration of information stickiness of 2.6 quarters, considering low inflation. This result suggests that price setters update information more frequently when inflation is higher, a result that seems to be robust to different measures of inflation and output gap.[17]

In addition, we perform a Z-test as suggested by Paternoster et al. (1998) to test the null hypothesis of $\widehat{\lambda}_1 = \widehat{\lambda}_2$. Table 1 also shows the probability value for that null hypothesis. In all the cases, we reject the null, indicating that both parameters are different at a confidence level of 90%. This result is robust to other measures of output gap and inflation.

We estimate equation (4) when the time change-point is unknown and needs to be calculated, so that it defines either high- or low-inflation time periods. In Table 2, we report the estimated τ ($\widehat{\tau}$) for the change from high to low inflation and its asymptotic 90 and 95% confidence interval. The estimate of the threshold time is 1981Q2. We conclude that there are two classes of regimes separated by the point estimate: (i) "high inflation" for periods before $\widehat{\tau}$; and (ii) "low inflation" for subsequent years. The asymptotic confidence intervals for the time threshold values are small, suggesting a lower level of uncertainty about the division of the data.

For the threshold estimates, we present the concentrated likelihood ratio function $\mathrm{LR}(\tau)$ (see Figure 5). The function $\mathrm{LR}(\tau)$ is a normalization of the objective function, which minimizes at $\widehat{\tau}$ = 1981Q2. This date holds even if we consider other measures of output gap and inflation. The confidence level is defined as the values of τ (time) for which $\mathrm{LR}(\tau)$ is smaller than the critical value (the flat line in the confidence level in Figure 5).[18]

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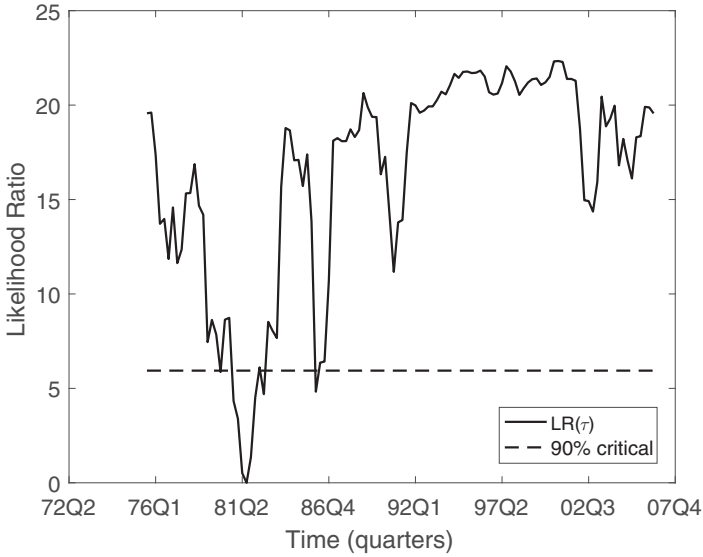


FIGURE 5. Likelihood ratio for threshold models with time as a threshold variable. The LR(τ) minimizes at 1981Q2. The confidence level is defined as the values of τ for which LR(τ) is smaller than the flat line (the critical value).

Table 3 shows these λ_1 and λ_2 for the implied high- and low-inflation periods. We reject the flexible information hypothesis in all cases. For high inflation, $\widehat{\lambda}_2$ equals 0.54. This result suggests that price setters update information about every two quarters when inflation is higher. On the other hand, $\widehat{\lambda}_1$ equals 0.36 in low-inflation periods. This result implies an average duration of information stickiness of 2.8 quarters. In general, Tables 1 and 3 are consistent with the hypothesis that agents update information faster at higher levels of inflation.

Table 3 also shows the probability value for the null hypothesis of $\widehat{\lambda}_1 = \widehat{\lambda}_2$. In all cases (when we also consider other measures of output gap and inflation), we reject the null, which indicates that both parameters are different at a confidence level of 99%. That is, we find strong evidence that agents update information faster in high-inflation environments.[19]

We estimate a threshold model in which inflation is the threshold variable, i.e., equation (5). Table 4 reports the point estimate for $\widehat{\gamma}$ and its asymptotic 90% confidence interval. The inflation threshold tends to be at 1.7%. We identify two classes of regimes based on the point estimates: (i) "high inflation" for inflation rates higher than $\widehat{\gamma}$; and (ii) "low inflation" for inflation rates lower than $\widehat{\gamma}$.

We further estimate a threshold model for inflation volatility as the threshold variable.[20] Table 4 reports the inflation volatility point estimate for $\widehat{\gamma}$ and its asymptotic 90% confidence interval. The inflation volatility threshold tends to be at 0.09%. Thus, we identify two classes of regimes, "high-inflation volatility" and "low-inflation volatility," by using the inflation variance threshold estimate $\widehat{\gamma}$.

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TABLE 3. Information rigidity and inflation regimes

Inflation regimes	Low inflation ($t > 1982Q3$)	High inflation ($t \leq 1981Q2$)
Information rigidity ($\widehat{\lambda}$)	0.36	0.54
	(0.053)	(0.035)
Duration in quarters	2.8	1.9
Z-test (p-value)	0.005	

Note: We set $\alpha = 0.1$ and $j^{\max} + 1 = 5$ quarters. Standard errors are in parentheses. The Z-test shows the probability value for the null hypothesis of $\widehat{\lambda}_1 = \widehat{\lambda}_2$.

TABLE 4. Inflation threshold estimates

Inflation as a threshold		Variance of inflation as a threshold	
Threshold estimate ($\widehat{\gamma}$)	90% confidence interval	Threshold estimate ($\widehat{\gamma}$)	90% confidence interval
1.67%	(0.88%; 2.46%)	0.09%	(0.01%; 0.17%)

Note: Asymptotic critical values are reported in Hansen (2000).

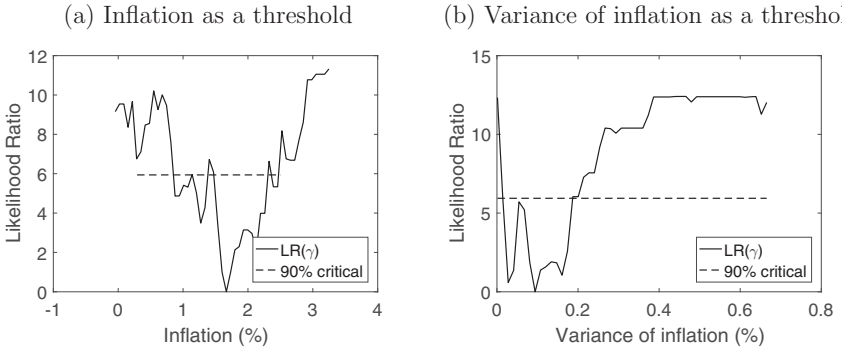


FIGURE 6. Likelihood ratio for threshold models. (a) Inflation as a threshold and (b) variance of inflation as a threshold. The $\mathrm{LR}(\gamma)$ minimizes at 1.7% for the inflation as a threshold variable, and at 0.09% for the variance of inflation as a threshold variable. The confidence level is defined as the values of γ for which $\mathrm{LR}(\gamma)$ is smaller than the flat line (the critical value).

Figure 6 shows the concentrated likelihood ratio function $\mathrm{LR}(\gamma)$ for the threshold estimates. The function $\mathrm{LR}(\gamma)$, a normalization of the objective function, minimizes at $\widehat{\gamma} = 1.7\%$ and $\widehat{\gamma} = 0.09\%$ when we use inflation and inflation volatility as threshold variables, respectively.

Table 5 shows the estimation of the degree of information rigidity for inflation values higher (or lower) than $\widehat{\gamma}$, under the specification of

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TABLE 5. Information rigidity and inflation regimes

Inflation regimes	Low inflation ($\pi_{t-1} \leq 1.7\%$)	High inflation ($\pi_{t-1} > 1.7\%$)
Information rigidity ($\widehat{\lambda}$)	0.37	0.57
	(0.047)	(0.034)
Duration in quarters	2.7	1.8
Z-test (p-value)	0.001	

Note: We set $\alpha = 0.1$ and $j^{\max} + 1 = 5$ quarters. Standard errors are in parentheses. The Z-test shows the probability value for the null hypothesis of $\widehat{\lambda}_1 = \widehat{\lambda}_2$.

TABLE 6. Information rigidity and inflation volatility regimes

Inflation volatility regimes	Low inflation volatility (Variance inf. $\leq 0.09\%$)	High inflation volatility (Variance inf.$> 0.09\%$)
Information rigidity ($\widehat{\lambda}$)	0.36	0.54
	(0.041)	(0.031)
Duration in quarters	2.8	1.9
Z-test (p-value)	0.001	

Note: We set $\alpha = 0.1$ and $j^{\max} + 1 = 5$ quarters. Standard errors are in parentheses. The Z-test shows the probability value for the null hypothesis of $\widehat{\lambda}_1 = \widehat{\lambda}_2$.

equation (5). This generates two parameters, λ_1 and λ_2, under high- and low-inflation regimes, respectively. The point estimates suggest that the degree of information rigidity parameter changes when inflation rates are either lower or higher than $\widehat{\gamma}$.

We reject the null of flexible information, a result that is robust to different measures of inflation and output gap. Our estimations suggest that under a low-inflation regime, $\widehat{\lambda}_1$ is 0.37 (consistent with 2.7 quarters of inattentiveness), while for high-inflation environments, $\widehat{\lambda}_2$ is 0.57 (approximately 1.8 quarters). This result supports our hypothesis that economic agents update information faster in high-inflation environments, while in low-inflation environments, those agents lack incentives to update information.

Table 6 shows similar results when we consider inflation volatility as a threshold variable. The results suggest that under a low-inflation volatility regime, $\widehat{\lambda}_1$ is 0.36 (consistent with approximately 2.8 quarters of inattentiveness), while for high-inflation volatility environments, $\widehat{\lambda}_2$ is 0.54 (approximately 1.9 quarters of inattentiveness).

The Z-test to evaluate the null hypothesis of $\widehat{\lambda}_1 = \widehat{\lambda}_2$ is shown in Tables 5 and 6. The probability value in all cases allows us to reject the null at the confidence level of 90%. This result holds even when we consider alternative measures for output gap and inflation.

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5. CONCLUSIONS

As emphasized by Lucas (1976), a model's ability to fit past data, especially when it relies on ad hoc assumptions about individuals' or firms' behavior, is not sufficient grounds for using it to analyze future changes in policy. The recent work on imperfect information, which includes sticky information, has focused on providing microfoundations, leading to reduced forms.

We provide direct estimations of the degree of information rigidity following the sticky information theory. Our results suggest different degrees of information rigidity across countries and across different time periods. We 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.

We obtain consistent estimates of the slope of the SIPC for 12 OECD countries, following the strategy of Khan and Zhu (2006). Our results are in line with those of Döpke et al. (2008a), who consider a small sample of countries and a different way of incorporating inflation and output expectations; and with Coibion and Gorodnichenko (2012), who find information rigidity in a cross-country analysis based on the data of professional forecasters. We are able to reject the hypothesis of flexible information in favor of a degree of stickiness for all countries in the sample. Furthermore, we find evidence that suggests that periods of high inflation are associated with a higher degree of information stickiness. On the other hand, a lower degree of information stickiness is also associated with periods of low inflation. These results also hold for different measures of inflation and the output gap.

The United States shows differences in the duration of information stickiness between high- and low-inflation periods. Estimates of the degree of information stickiness for OECD countries suggest that countries that have suffered relatively high average inflation or highly volatile inflation would tend to have a higher degree of information stickiness. We split the sample between periods with high and low inflation by estimating threshold models. We consider two scenarios: (i) estimating a date that splits the sample between high and low inflation; and (ii) estimating an inflation level (and inflation volatility) that splits the sample between two regimes.

In all cases, we reject the hypothesis of flexible information. In all cases, a higher degree of information stickiness is associated with high-inflation scenarios. These results are robust to different measurements of inflation and output gap.

A pertinent area of future research would be to test the exogeneity of slope of the Phillips curve in line with the discussion in Lucas (1973), Ball et al. (1988), and Kiley (2000), but in the context of the sticky information framework.[21] Other topics that remain for future research include the use of measures of marginal cost rather than the output gap, and estimating the SIPC for developing countries.

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NOTES

1. Remarks by Governor of the FED Ben Bernanke at the meetings of the Eastern Economic Association in Washington, DC on February 20, 2004.

2. For applied work in this literature, see Nimark (2014) for signal extraction and business cycle implications; see Boco et al. (2016) for competition between traders and noisy information; and Crucini et al. (2015) for distance between cities and noisy signals across them.

3. Similar to the sticky price literature, it is assumed that the arrival of decision dates for each firm is a Poisson process.

4. For a similar relationship of optimal price setting in the context of rational inattention, see Reis (2006).

5. See also Gali and Gertler (1999) for a discussion of α in the context of the new Keynesian Phillips curve.

6. Due to availability, the sample is not the same for the 12 OECD countries. For Canada, United States and United Kingdom, the sample starts in 1958; for Australia in 1960; for Germany in 1963; for Austria in 1965; and for Finland, France, Korea, Norway, Spain, and Switzerland in 1970.

7. Forecasts are in turn considered expectations for those variables. The starting point for each forecast series is 1966. In our estimations for the SIPC, for each country, we considered different $j^{\max}$ up to 5 years. Thus, in order to pick up the first forecast for a $j^{\max}$ equal to 19, the sample estimation period must be 1971–2007.

8. See the appendix for details on the sample and data involved.

9. Khan and Zhu (2006) estimate bivariate VAR's using six forecasting variables and then take a simple average of the forecasts from each VAR. One advantage of this procedure is that it reduces the sensitivity of forecasts to different time periods and potential changes in the informational content of the variables.

10. Rather than using the forecasting power for estimating expectations, we use the log likelihood function. We use the Schwarz information criterion for the optimal length of the autoregressive integrated moving average (ARIMA) model and VAR estimations. Similar methods and variables are considered by Canova (2007) for forecasting inflation rate in the G-7 countries.

11. If the inflation rate is high every year, agents expect high inflation every year. Therefore, their level of inattentiveness remains the same every year as well.

12. Moreover, a smooth transition threshold model would also require additional assumptions about the function that smooths the indicator variable. Zhang (2017) uses such models to investigate the nonlinear dynamics of the inflation-output Phillips curve in China.

13. Here, the date that splits the sample into low and high inflation is identified by τ.

14. We also note that the variance in the inflation rates decreases, going from 0.09 in the first period to 0.01% in the second period. Thus, the first period, from 1971 to 1982, and the second period, from 1983 to 2007, can be seen as high- and low-inflation volatility regimes, respectively.

15. For a theory of least squares estimation and inference on models similar to equations (4) and (5), see Chan (1993) and Hansen (2000).

16. Although the degree of misspecification increases with the level of truncation, the overall effect of this problem on the information rigidity parameter in previous periods gets smaller.

17. The second period differs according to the level of truncation ($j^{\max}$). For four quarters of truncation, the second estimation period ranges from 1984Q1 to 2007Q4.

18. In all remaining exercises, we also consider $j^{\max}$ equals to 4, which implies 5 quarters as the lag structure in the model specification.

19. Note that estimations with higher $j^{\max}$ do not significantly change these results, because new terms in equation (2) get smaller as the truncation level increases. Thus, we expect our results to hold when higher truncation levels are considered.

20. We use the variance of the monthly year-on-year inflation within the corresponding quarter as a measure of inflation volatility.

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21. Kiley (2000) points out that, in the literature, sticky prices help generate persistent output fluctuations in response to aggregate demand shocks. However, Kiley builds a model in which price stickiness is endogenous and generates persistent output fluctuations. Since the degree of price stickiness should be lower in high-inflation economies, Kiley argues that output persistence should also be lower in high-inflation economies.

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APPENDIX: DATABASE FOR FORECASTING

The main criterion for choosing the countries in the sample is the availability of data on GDP at constant prices for the estimation of the output gap. We build a database following Khan and Zhu (2006) and Stock and Watson (2003).

The main source of the data is the IFS database. Other secondary sources are the OECD (for data on core inflation) and the Federal Reserve System (for data on capacity utilization for the United States). We also consider the global financial data database for long-time series when they are not available in the IFS.

From countries other than the United States, as suggested by Stock and Watson (2003), we use the nominal effective exchange rate devaluation (level) and the terms of trade (level) to account for any pass-through from import prices to inflation and to capture possible effects of external shocks on the productive sector in the context of open economies.

In Table A.1, we present the data used for forecasting inflation and the output gap for different countries.

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TABLE A.1. Available information for forecasting

	Short interest rate	Spread term	Stock market index	Devaluation exchange rate	Terms of trade
Australia	x	x	x	x	x
Austria	x	x	x	x	x
Canada	x	x	x	x	x
Finland	x		x	x	x
France	x	x	x	x	x
Germany	x	x	x	x	x
Korea	x	x	x	x	x
Norway	x	x	x	x	x
Spain	x	x	x	x	x
Switzerland	x	x	x	x	x
United Kingdom	x	x	x	x	x
United States1/	x	x	x		

1/ Information on unemployment and capacity utilization are available.

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