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Inflation Dynamics Under The Sticky Information Phillips Curve

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Abstract

This paper aims to present the theoretical foundation of the sticky information Phillips curve as outlined by Mankiw and Reis (2002) and to investigate the empirical validity of the model on Romanian data following the methodology proposed by Coibion (2010). The analysis is performed in comparison with the forward looking new keynesian Phillips curve. This allows us to stress the differences between the two models and to asses whether the sticky information framework outperforms the sticky prices framework. The estimation of the two models is done conditional on the same expectations data set which is obtained by simulation following the methodology proposed by Khan and Zhu (2006). The results suggest that the sticky information Phillips curve is consistent with the data, but, compared with the sticky price model, it has an inferior ability to predict inflation. This comes mainly from the fact that the model relies on an weighted average of past forecasts of inflation which generates a substantial degree of inertia. Formally, the two models are compared using the nonnested Davidson-Mackinnon J test.

1 Introduction

Mankiw and Reis (2002) (MR (2002) hereafter) have proposed the sticky information model as a response to some of the failures[1] of the standard forward looking new keynesian Phillips curve model formulated on the Calvo (1983) assumption of staggered price formation. The two models are directly comparable because they both draw upon the common assumption of a monopolistic competition framework, but differ in the mechanism that explains imperfect price adjustment: the assumption of sticky prices brings forth the new keynesian Phillips curve (NKPC), while the assumption of sticky information yields the sticky information Phillips curve (SIPC).

The sticky price model postulates that the price adjustment mechanism in the economy is sluggish as a result of price adjustment costs faced by firms. By contrast, the sticky information model puts no restriction on price adjustments, but imposes that only a fraction of the agents update their information in the current period. MR (2002) motivate this assumption by stating that information diffuses slowly throughout the population as a result of the existence of costs of acquiring new information or reoptimization. Both models illustrate extreme cases that explain price adjustment giving total weight to one of the two rigidities, when in practice it is likely that both of them influence, to some extent, the price adjustment process.

Although the theoretical background and the simulation results in MR (2002) are in favor of the sticky information model, some important issues remain regarding the empirical implementation and the extent to which the assumptions of the model are consistent with the data. The empirical evidence on the validity of the model is mixed. Mankiw and Reis (2001), Carroll (2003), Khan and Zhu (2006) (KZ (2006) hereafter) and Dopke et al. (2008) find in their studies a degree of informational rigidity close to the one proposed for calibration in MR (2002). However, the recent work of Coibion (2010) on USA data finds poor evidence in favor of the sticky information

[1] Specifically, the sticky prices model has problems in explaining the following stylized facts: inflation is highly persistent, disinflations always have contractionary effects and monetary policy shocks affect inflation with a substantial delay. For details on the literature concerning these issues and the illustration of these failures using simulations see MR (2002).

model and, after investigating a wide range of specifications, concludes that the NKPC statistically dominates the SIPC. The author argues that the estimates of the degree of informational rigidity in the SIPC are severely distorted by the existence of real-time forecast errors specific to expectations data and by the excessive degree of inflation inertia implied by the model.

All the methodological approaches mentioned earlier diverge to some degree. The most straightforward method of estimation is that of Dopke et al (2008). The authors use Consensus expectations for France, Germany and UK and estimation is employed individually, using nonlinear least squares, and pooled, using seemingly unrelated regressions. KZ (2006) preffer to use as a proxy for expectations out-of-sample forecasts and similarly employ a nonlinear least squares estimation. In addition to that, KZ (2006) draw attention upon the "generated regressors problem", as formulated by Pagan (1986) and Murphy and Topel (1985), and propose a bootstrap procedure to form confidence intervals. Coibion (2010) uses both survey expectations and simulated data set similar to that of KZ (2006) but he argues that nonlinear least squares is not appropiate to estimate the SIPC due to the endogeneity problem of output gap and he uses an instrumental variable (IV) estimator. However, he does not mention the "generated regressors problem" when using simulated expectations.

In the following, I will test the sticky information model on Romanian data by applying the methodology described by Coibion (2010). This consists in estimating both SIPC and NKPC conditional on the same measures of inflation expectations. In order to generate inflation and output gap expectations, I will use the methodology outlined by Stock and Watson (2003) and applied by KZ (2006) in the case of the sticky price model. Briefly, the procedure consists in constructing measures of expectations as VAR out-of-sample forecasts. This methodology is consistent with the testing procedure of Coibion (2010), as he uses the VAR expectations data set as an alternative to survey data.

The empirical estimation of the SIPC brings sensible results, in the sense that they are consistent with the underlying theory and the results and they are similar to ones reported in the earlier mentioned studies that bring arguments in favor of the SIPC. For robustness, I perform all estimates using two representative samples and I also include the results corresponding to simple AR-based expectations. The main drawback of the analysis is the small data sample, which brings some difficulties in simulating a reliable expectations series.

Next, the NKPC is estimated using the corresponding expectations data generated for the SIPC. Most empirical studies follow the approach of Gali and Gertler (1999) were ex-post inflation data is used as a proxy for expectations. This imposes upon the model the assumption that agents form their expectations rationally, which has brought an unnecessary restriction for the NKPC and, hence, reduces the chance for the model to perform well empirically. According to Adam and Padula (2003), this problem can be mitigated using survey data. In the absence of a quarterly expectations data set, I will use as a proxy the simulated VAR expectations. In this way both models of inflations will be estimated conditional on the same data set.

Although the literature has brought forth many exensions of the baseline NKPC[2], in the following we use as a competing model for SIPC the forward looking NKPC, the model which the former was designed to replace. The estimation of the NKPC is performed both in reduced and structural form and we obtain parameters that are statistically significant and close to the expected values. Finally, having estimated the two models, we proceed in comparing them using the Davidson-Mackinnon J test, as proposed by Coibion (2010). To test the critique of Coibion (2010) regarding the artificial increase of the informational rigidity coefficient, I also perform a robustness check of the estimates to different degrees of strategic complementarity.

The rest of the paper is structured as fallows: section 2 aims to give some insight on the theoretical derivation of the two Phillips and some intuition upon the differences between the two models, section 3 describes the methodology regarding the estimation of the SIPC, the expectations simulation procedure and the econometric approach considered in comparing the two models, section 4 presents the empirical results of model estimation and their comparison on statistical grounds and section 5 concludes.

[2]One of the most influential extensions of the forward looking NKPC is the hybrid Phillips curve in Gali and Gertler (1999) where a backward looking component is derived. A recent literature review on the empirics of the NKPC can be found in Vasicek (2009).

2 Theoretical derivation

This section aims to expose the main theoretical features of the two competing models of inflation, the NKPC and the SIPC. In the first part I will expose the optimization problems faced by households and firms in the monopolistic competition framework that is common to both models. In the case of the NKPC imperfect price adjustment is explained by a Calvo pricing rule, while in the case of the SIPC price adjustment is explained by the MR (2002) assumption of infrequent information arrival.

2.1 A simple model of aggregate supply

The monopolistic competition model of aggregate supply is presented in a form similar to the one in Khan and Zhu (2002) and Mankiw and Reis (2010). This framework describes a closed economy and does not account for capital accumulation. These simplifying assumptions are commonly employed in deriving the aggregate supply that is used to express the Phillips curve.

2.1.1 Households

Suppose that the preferences of a representative agent for households are described by the utility function:

$$U_t(C_t, H_{it}) = \frac{C_t^{1-\sigma}}{1-\sigma} - \int_0^1 \frac{H_{it}^{1+\phi}}{1+\phi} di \tag{1}$$

where

- C_t is aggregate consumption:

$$C_t = \left(\int_0^1 C_{it}^{(\epsilon-1)/\epsilon} di \right)^{\epsilon/(\epsilon-1)} \tag{2}$$

- H_{it} is the labor supply for product variety i,
- σ is the intertemporal elasticity of substitution,
- ϕ is the Frisch labor elasticity,
- ϵ is the rate of substitution between products.

We formulate consumer's maximization function:

$$U = \sum_{t=0}^{\infty} \beta^t U_t \tag{3}$$

with budget constraint:

$$\int_0^1 C_{it} P_{it} di + B_t = \int_0^1 W_{it} H_{it} di + B_{t-1}(1 + R_t) \tag{4}$$

The problem can be solved in two steps:

a) maximization of total spending given consumtion C_t; we form the following Lagrange function

$$L(C_{it}) = \int_0^1 P_{it} C_{it} di + \lambda_1 \left[C_t - \left(\int_0^1 C_{it}^{(\epsilon-1)/\epsilon} di \right)^{\epsilon/(\epsilon-1)} \right] \tag{5}$$

First order conditions with respect to C_{it} yield the demand for good i:

$$\left(\frac{P_{it}}{P_t} \right)^{-\epsilon} = \frac{C_{it}}{C_t} \tag{6}$$

where P_t is the aggregate price index

$$P_t = \left(\int_0^1 P_{it}^{1-\epsilon} di \right)^{1/(1-\epsilon)} \tag{7}$$

b) maximization of total utility given the budget constraint; to solve the problem we formulate the Lagrange function:

$$L(C_t) = U + \lambda_2 \left[\int_0^1 C_{it} P_{it} di + B_t - \int_0^1 W_{it} H_{it} di - B_{t-1}(1 + R_t) \right] \tag{8}$$

First order conditions with respect to C_{it} and H_{it} yield labor supply:

$$\frac{C_t^{-\sigma}}{H_{it}^{\phi}} = \frac{P_t}{W_{it}} \tag{9}$$

2.1.2 Firms

We assume that each firm i uses the the Cobb-Douglas technology $Y_{it} = H_{it}^a$, $0 < a < 1$, having as input only labor (the model does not account for capital accumulation).

The objective of the firm is to maximize the function of real profit:

$$\pi_{it} = C_{it}P_{it}/P_t - H_{it}W_{it}/P_t \tag{10}$$

taking as given labor supply and demand for good i. After substituting (6) and (9) in (10) we obtain a function of Y_{it}, the produced quantity of good i:

$$\pi_{it}(Y_{it}) = \frac{Y_{it}^{1-1/\epsilon}}{Y_t^{-1/\epsilon}} - \frac{Y_{it}^{(1+\phi)/a}}{Y_t^{-\sigma}} \tag{11}$$

Firm i faces a total cost that depends only on the quantity of labor employed: $W_{it}H_{it}$. Using the production function, the cost is expressed in terms of Y_{it}:

$$TC_{it}^n = W_{it}Y_{it}^{1/a} \tag{12}$$

In order to express nominal marginal cost, expression (12) is differentiated with respect to Y_{it}. Real marginal cost is obtained by dividing nominal marginal cost by the price index P_t:

$$MC_{it}^r = \frac{1}{a}\frac{W_{it}}{P_t}Y_{it}^{1/a-1} \tag{13}$$

After real price of labor $\frac{W_{it}}{P_t}$ is substituted with (9), we employ the notation $\omega = \phi/a + 1/a - 1$ and relation (13) becomes:

$$MC_{it}^r = \frac{1}{a}Y_{it}^{\omega}C_t^{\sigma} \tag{14}$$

To derive the optimal price desired by the firm, we take the first order conditions in (11). After rearranging, this leads to:

$$\left(\frac{\widehat{Y}_{it}}{Y_t}\right)^{-\frac{1}{\epsilon}} = \frac{\epsilon}{\epsilon - 1}(1+\phi)\frac{1}{a}\widehat{Y}_{it}^{\omega}Y_t^{\sigma} \tag{15}$$

Given that we assume a closed economy and no capital accumulation, production is equal to consumption, i.e. $Y_t = C_t$ and $Y_{it} = C_{it}$. Using this observation, (6) is expressed as:

$$\widehat{Y}_{it} = \left(\frac{P_{it}}{P_t}\right)^{-\epsilon} Y_t \tag{16}$$

Taking together (14) in (15) and (16), we can express the optimum price of the firm as a markup over marginal cost:

$$\frac{\widehat{P}_{it}}{P_t} = \mu MC_{it}^r \tag{17}$$

where $\mu = \frac{\epsilon}{\epsilon-1}(1+\phi)$ is the fixed markup of firm i.

For convenience, we express equations (14), (17) and (6) in deviation from the steady state. We define a value of steady state for each of these variables, and we use the following notations: $mc_{it} = \log(MC^r_{it}) - \log(\bar{MC}), y_t = \log(Y_t) - \log(\bar{Y}_t), p_{it} = \log(P_{it}), p_t = \log(P_t)$. This gives the following equations analoguous to (14), (17) and (6), respectively:

$$mc^r_{it} = \omega \widehat{y}_{it} + \sigma y_t \tag{18}$$

$$\widehat{p}_{it} = p_t + mc^r_{it} \tag{19}$$

$$y_{it} = -\epsilon(p_{it} - p_t) + y_t \tag{20}$$

We express relation (19) using (18) and (20):

$$\widehat{p}_{it} = p_{it} + \alpha y_t \tag{21}$$

where $\alpha = \frac{\omega+\sigma}{1+\omega\epsilon}$. The resulting equation expresses the desired price of the firms as moving one to one with the aggregate price level and having a semi-elasticity to output gap equal to α, the coefficient of real rigidity.

To understand more thoroughly the significance of α, we have to introduce the equation of aggregate demand. MR (2002) use in their simulations the general equation for the aggregate demand derived from the quantity theory of money. Taking logs and supposing that the velocity of money is equal to one, the equation can be written as:

$$m_t = p_t + y_t \tag{22}$$

Aggregate demand y_t is negatively related to the aggregate price level p_t and positively related to the monetary aggregate m_t. It is apparent that m_t can be interpreted as a substitute for any variable that can shift the aggregate demand. We express the desired price of the firm using (22) and we obtain:

$$\widehat{p}_{it} = (1-\alpha)p_t + \alpha m_t \tag{23}$$

From (23) we see that the optimal price level is an weighted average between the conditions of aggregate demand and the aggregate price level. A low α, i.e. a high degree of real rigidity, implies that firms give low weight in their pricing decisions to the conditions of aggregate demand. This is equivalent to a low degree of strategic complementarity, in the sense of Cooper and Andrew (1988).

Generally, the optimal price expressed in (21) is not the one practiced by firms. This pricing rule corresponds to the case in which prices in the economy are perfectly flexible, that is firms can reset their prices every period according to the result of their maximization problem. To illustrate this, we set P_{it}, the price practiced by firms, equal to $\widehat{P}_{it}$. Equation (17) is rearranged as follows:

$$P_{it} = P_t k Y_t^q \tag{24}$$

where $k = (\frac{\mu}{a})^{1/(1+\omega\epsilon)}$ and $q = \frac{\omega\sigma}{1+\omega\epsilon}$. We raise the previous expression to power $1-\epsilon$, integrate between 0 and 1 and raise to power $1/(1-\epsilon)$, resulting the expression

$$P_t = P_t k Y_t^q \tag{25}$$

This yields $P_t = P_{it}$ and

$$Y_t = \left(\frac{\omega}{\mu}\right)^{\frac{1}{\omega\sigma}} = \bar{Y} \tag{26}$$

We see that in (26) we have deduced the vertical aggregate supply curve (output does not depend on prices).

In the following two subsections we will drop the assumption of perfectly flexible prices and adopt two competing models of price adjustment: the sticky price model and the sticky information model. The derivation of the models follows Gali and Gertler (1999) and MR (2002).

2.2 The Sticky Prices Phillips Curve

In this framework, firms face costs to adjust prices in each period. The most commonly used assumption in modeling firms' price adjustment pattern is the Calvo pricing rule. According to this, in each period only a fixed fraction $1-\theta$ of firms adjust prices. Knowing that they don't have the opportunity to reset prices in each period, firms set their price x_t taking into account all expected future discounted optimal prices. Given the subjective discount factor β, this can be modeled by defining a quadratic loss function:

$$L(x_t) = \sum_{j=0}^{\infty} (\theta\beta)^k E_t (x_t - \widehat{p}_{t+k})^2 \tag{27}$$

The optimal price x_t is chosen as to minimize the future expected discounted losses that would appear as a result of price stickiness. The expected future losses are weighted geometrically with the ratio $\theta\beta$. As the firm looks further into the future, the weighting term $(\theta\beta)^k$ declines as the probability of not being able to change price for k periods, θ^k, and the discount term for this horizon, β^k, become smaller. Taking the first order condition with respect to the control variable x_t in (27) yields the following pricing rule:

$$x_t = (1 - \beta\theta) \sum_{j=0}^{\infty} (\beta\theta)^j E_t \widehat{p}_{t+j} \tag{28}$$

Note that in the limiting case of $\beta = 1$ the weights used denote the probabilities associated with the opportunity of price adjustment. Given that the events arrive independently from one period to another, the probabilities corresponding to a price change in $t, t+1, \ldots, t+k$, will be, respectively $1-\theta, \theta(1-\theta), \theta^2(1-\theta), \ldots, \theta^k(1-\theta)$. Analogously, if we take into account a general value for β, we see that the k periods future expected price is weighted with $\theta\beta$ to quantify both price adjustment probability and subjective discounting of future incomes. Summing up these probabilities for $k \to \infty$ we get 1, which explains why the sum in (28) is a weighted average. Knowing from the pricing rule in (28) all the prices x_t in the economy, it is straightforward to express the aggregate price level:

$$p_t = (1 - \theta) \sum_{j=0}^{\infty} \theta^j x_{t-j} \tag{29}$$

As it can be seen, the aggregate price level is formed as a weighted average of all the prices in the economy. Only a proportion $1 - \theta$ of these prices are settled in the current period. The rest of them are fixed in different moments of the past. The weights used represent the proportion of firms that fixed their price in each period $(t, t-1, \ldots)$. As they sum up to 1, we take into account the prices of all firms.

The structure of the model presented so far enables us to calculate the average time of price change. Let τ denote the period between two price changes of a firm. The weight associated to τ is the proportion of firms that changed prices after τ periods, that is $(1-\theta)\theta^{\tau-1}$. We range τ from 1 to ∞ and sum up all the terms. Taking limit to infinity of this series we obtain the average time of price change to be equal to $1/(1-\theta)$.

The NKPC is derived using (21), (28) and (29). Each of the equations (28) and (29) can bee seen as a solution of a specific recursive equation:

$$p_t = \theta p_{t-1} + (1-\theta)x_t \tag{30}$$

$$x_t = \beta\theta E_t x_{t+1} + (1-\beta\theta)\widehat{p}_t \tag{31}$$

Iterating equation (30) by recursive substitution yields equation (29). Analogously, if we additionally use the law of iterated expectations in (31), we obtain (28). We use (21) and (29) to express $\widehat{p}_t$ and x_t in (28) and, after some manipulation, the forward looking NKPC is obtained:

$$\pi_t = \frac{(1-\theta)(1-\beta\theta)}{\theta}\alpha y_t + \beta E_t \pi_{t+1} \tag{32}$$

where inflation is defined as $\pi_t = p_t - p_{t-1}$.

Note that the forward looking term of the equation is a consequence of the fact that firms are forward looking when setting price x_t.

2.3 The Sticky Information Phillips Curve

In contrast with the sticky prices model, the sticky information model does no longer restrict agents to reset their prices in each period. Instead, the model postulates that the aquisition of updated information is costly and, consequently, not all the agents in the economy optimize their plans according to the latest information. Analogously to the sticky prices model, this framework uses a mechanism similar to that proposed by Calvo, here dealing with informational rigidity: in each period a proportion $1-\lambda$ of all agents set prices using updated information; the rest of them also change prices, but taking account of older information. According to this framework, a value of λ close to 1 denotes a high degree of informational rigidity, while a value of λ close to 0 denotes a low degree of informational rigidity.

Agents use the same price maximization rule outlined in (21). Given that information is not always updated, firms set prices in period t according to the information set from $t - j$:

$$x_t^j = E_{t-j}\widehat{p}_t \tag{33}$$

where $j = \overline{0, \infty}$ corresponds to the time periods since information was last updated. Averaging all the prices in the economy using as weights the proportion of firms that use the corresponding price level, we get:

$$p_t = (1 - \lambda) \sum_{j=0}^{\infty} \lambda^j x_t^j \tag{34}$$

Note that the average time of information arrival can be calculated similar to the average time of price change, as outlined in section 2.2. After going through the same steps, the average time of price change is found to be equal to $1/(1 - \lambda)$.

Using equations (21) and (33), the price level equation can be written as:

$$p_t = (1 - \lambda) \sum_{j=0}^{\infty} \lambda^j E_{t-j} (p_t + \alpha y_t) \tag{35}$$

We obtain inflation by expressing p_t and p_{t-1} from (35). After some manipulation of the resulting equation, eventually the SIPC is obtained:

$$\pi_t = \frac{(1 - \lambda)\alpha}{\lambda} y_t + (1 - \lambda) \sum_{j=0}^{\infty} \lambda^j E_{t-j-1} (\pi_t + \alpha \Delta y_t) \tag{36}$$

3 Methodology

This section aims to give some insight on the empirical approach that is undertaken in section 4. In the following subsections, I illustrate the general problems related with the empirical estimation of the SIPC, the expectations simulation procedure and the criteria employed to compare the SIPC with the NKPC.

3.1 General issues regarding the estimation of the SIPC

In order to estimate the SIPC, one is confronted with several difficulties, as mentioned by KZ (2006). First, from a technical point of view, the SIPC equation cannot be estimated in the theoretical form outlined in (36) because the second term on the right side is an infinite sum in the past. The solution employed in the empirical studies is to make a truncation of the expectations series up to a j_{max} distance into the past. As a result, the empirical counterpart of (36) is written as:

$$\pi_t = \frac{(1-\lambda)\alpha}{\lambda} y_t + (1-\lambda) \sum_{j=0}^{j_{max}-1} \lambda^j E_{t-j-1} (\pi_t + \alpha \Delta y_t) + \epsilon_t \tag{37}$$

From (37) it can be seen that the estimated SIPC equation takes into consideration only past expectations of current output gap and inflation that are formed from $t - j_{max}$ up to $t - 1$. Nevertheless, when adopting this approach, one needs to analyze which j_{max} is sufficiently distant in the past to account for the infinite sum and if this truncation brings into the equation persistent disturbances.

Second, one important issue is which measure of expectations should be used in the estimations. Some studies use survey data (see for example Dopke et al (2008)), while others use simulated data (ZK (2006)). Both options have their drawbacks. Usually, expectations survey data is unavailable on a quarterly basis and they do not cover horizons longer than 4 to 6 quarters. Furthermore, for the case of Romania, up to 2009, no quarterly inflation or output survey is publicly available. The alternative option of simulated data can be criticized on the grounds that it does not take account of many events, such as press news, that cannot be incorporated in the simulation procedure. Another important issue is related to what Mankiw et al. (2003) identified as inflation expectations disagreement, that is expectations do not converge across different categories of individuals. This brings further complications into the problem, as one has to choose between expectations relevant to all the agents in the economy, or only for a specific category.

Finally, one has to use for estimation a numeric procedure due to the nonlinear form of the equation. The numerical procedure employed could yield misleading results, as the minimized function is likely to have points of local minima that differ substantially from the global minimum. Consequently, we might come across different results when using different starting values.

3.2 Expectations simulation procedure

Due to the data limitations mentioned earlier, I will estimate the SIPC using simulated data as outlined by ZK (2006) and further employed by Coibion (2010). I will use the same set of variables as Coibion (2010) did in generating forecasts for inflation and output gap. First we define two sets of bivariate VARs of the form:

$$\begin{bmatrix} Z_t \\ X_t \end{bmatrix} = \mu + \beta(L) \begin{bmatrix} Z_t \\ X_t \end{bmatrix} \tag{38}$$

where X_t corresponds to output or inflation and Z_t is one of the indicators that is believed to be relevant for output, in the first set, and inflation, in the second set. Specifically, for inflation I will use the interbank offer rate for one month maturity, capacity utilization, oil price, registered unemployment, industrial production and output gap. For output gap I take the same variables as for inflation, but I replace the oil price with the monetary base.

The length of the VAR is chosen as to minimize the root-mean-square error in forecasting. Next, each VAR is estimated up to a certain time point in the data sample and is used to generate out-of-sample forecasts for inflation and output gap. A similar set of forecasts is generated using AR models. All the forecasts for a given variable are averaged excluding the minimum and the maximum values and imposing the AR forecast as one of the forecasts to be averaged over. Ultimately we obtain two sets of mean out-of-sample forecasts, one for inflation and the other for output gap. The procedure is repeated recursively as to obtain forecasts in each period for a fixed horizon.

For convenience, I arrange this data in a form of a matrix which contains at each line all the expectations formed at a given point in time, column j denoting the length of the forecast horizon. The forecasts matrix for inflation will be:

$$F_\pi = \begin{bmatrix} E_{t_0}(\pi_{t_0+1}) & E_{t_0}(\pi_{t_0+2}) & \cdots & E_{t_0}(\pi_{t_0+j_{max}}) \\ E_{t_0+1}(\pi_{t_0+2}) & E_{t_0+1}(\pi_{t_0+3}) & \cdots & E_{t_0+1}(\pi_{t_0+j_{max}+1}) \\ E_{t_0+2}(\pi_{t_0+3}) & E_{t_0+1}(\pi_{t_0+4}) & \cdots & E_{t_0+2}(\pi_{t_0+j_{max}+2}) \\ \vdots & \vdots & \ddots & \vdots \\ E_{t_0+s}(\pi_{t_0+s+1}) & E_{t_0+s}(\pi_{t_0+s+2}) & \cdots & E_{t_0+s}(\pi_{t_0+j_{max}+s}) \end{bmatrix} \tag{39}$$

where $s+1$ denotes the length of the estimation sample of the SIPC. Each series of expectations from the SIPC, denoted as $E_{t-j}(\pi_t)$ with $j = \overline{1, j_{max}}$, is obtained from the j column of F_π. The first observation of the sample is determined as to have observations for all of the expectations series. This is conditioned by the first observation of $E_{t-j_{max}}$ and the last historical observation on inflation. From here we can see than very long forecasting horizons are not convenient, as they shrink the sample length. In an analogous manner we form F_y, the matrix of forecasts for the output gap.

3.3 Model comparison

A first criteria in comparing the fit of the SIPC and the NKPC is the extent to which each of them explains the variabilty in inflation. The most straightforward criteria is the magnitude of R-squared. However, both models of inflation are estimated in the form that corresponds to their theoretical derivation, excluding the intercept from the equation. To use the definition of R-square to measure the fraction of inflation variability explained by the model, both models need to be reestimated including an intercept in the equation.

Coibion (2010) proposes for model comparison the use of the nonnested Davidson-Mackinnon J test (DM test)[3]. Specifically, we can test the null of the NKPC using equation (40) and the null of the SIPC using equation (41):

$$\pi_t = ky_t + E_t\pi_{t+1} + \delta_{SI}\widehat{\pi}_t^{SI} + \epsilon_t \tag{40}$$

$$\pi_t = \frac{(1-\lambda)\alpha}{\lambda}y_t + (1-\lambda)\sum_{j=0}^{j_{max}-1}\lambda^j E_{t-j-1}\left(\pi_t + \alpha\Delta y_t\right) + \delta_{SP}\widehat{\pi}_t^{SP} + \epsilon_t \tag{41}$$

where π_t^{SI} is the fitted value from the SIPC and π_t^{SP} is the fitted value from the NKPC. Each of the two models can be rejected if the fitted values from the competing model are significant in the augmented equation corresponding to its specification.

[3]The cited paper also uses an encompasing model to test for the two models jointly. However, due to the small data sample, using for this model a nonlinear GMM procedure yeilded imprecise results.

4 Empirical application

This section presents the empirical results obtained by applying the outlined methodology. The SIPC and the NKPC are estimated using data on the Romanian economy and several specification tests are performed. Additionally, the two models are compared on statistical grounds using two DM nonnested tests. In the last subsection, I analize the robustness of the models to different calibration values of the coefficient of real rigidity.

4.1 Data and organization of the series

The two central variables[4] of the empirical application are the inflation rate and the output gap. Inflation is calculated using the consumer price index (CPI)[5] and output gap is calculated using a HP filter[6].

The available data sample covers the 1998Q1 - 2009Q4 period. However, one cannot estimate the SIPC for the entire sample because he needs an initial sample starting from 1998Q1 for which to estimate the first VARs. It is preferable to have a sufficiently long initial data sample to have reliable estimations for the first VARs, but we also have to take into consideration that the length of this sample shrinks the estimation sample for the SIPC. Given these drawbacks, I chose to estimate the initial VARs from 1998Q1 to 2002Q4 corresponding to the first 20 observations.

In a similar manner, I form expectations using an AR(2) model for inflation and an AR(1) model for output gap. To expand the estimation sample of the SIPC as much as possible, I estimate the first AR models using data up to 2000Q4. This generates a set of AR expectations formed at periods ranging from 2002Q4 to 2009Q4.

The results from the two simulations are very similar, at least for the first

[4]For a description of the source of all the series and their calculation see appendix A.

[5]Although this choice can be criticized on the grounds that the CPI is also determined by administred and volatile prices that are weakly correlated with the output gap, its advantage is that inflation expectations are more likely to be related to the CPI.

[6]It is worth mentioning that output gap is filtered using the data of the whole sample, which contradicts the hypothesis that agents form expectations using only real time data. The same criticism can be formulated for seasonal adjustments and data revisions that are incorporated in our data set.

part of the VAR expectations sample. VAR simulations begin to incorporate the additional information only in the second part of the sample, as it can be seen in figures 3 and 4 from appendix C. This observation motivates the use AR expectations to increase the sample size of the expectations series for the 2002Q4 2004Q4 period. Up to 2003Q1, the expectations will be formed only from AR forecasts. Subsequently, VAR forecasts will be added as the sample expands up to 2004Q4, afterwards all the observations being formed exclusively as described in section 3.2 [7].

4.2 Estimation of the SIPC using nonlinear least squares

In the baseline estimation I estimate the SIPC using nonlinear least squares, setting as starting values the coefficients proposed for calibration in MR (2002), i.e. $\lambda = 0.75$ and $\alpha = 0.1$. In order to asses the robustness to different expectations series, I reported in table 1 the estimations corresponding to the AR forecasts, averaged VAR forecasts (referred to as VAR_1) and the combined AR and VAR expectations formed as outlined in sections 3.2 and 4.1 (referred to as VAR_2). Due to the fact that the VAR_2 expectations series is constructed using only AR forecasts up to 2002Q4, I also reported the sensitivity of the estimates to restricting the sample from 2005Q1 onwards. To see how the estimates respond to different truncation values, I use in each case a j_{max} of 4,6, and 8 quarters.

First we examine the implications of the global results. All estimates of λ with one exception are statistically significant and comparable to the benchmark value proposed by MR (2002). The average time of information arrival, $1/(1-\lambda)$, ranges between 2.4 and 5.6 quarters. The sum of the weights in (37) is in most cases close to 1, the lowest value reported being 0.79. A lower value of S is expected to be associated with a higher degree of autocorrelation of the residuals, as the omitted regressors have a greater contribution in explaining the variability of inflation.

The degree of real rigidity is statistically significant at levels that vary substantially from case to case, exceeding the 10% threshold in five out of

[7] From here on, if not otherwise mentioned, we will refer to this series as simply the VAR-based expectations series.

fifteen cases. Most estimates of α are grater than the 0.1 benchmark value proposed by MR (2002). This implies a lower degree of real rigidity, meaning that firms give a bigger weight to aggregate demand when optimizing their prices, as it can be observed from (23). Using the terminology of Cooper and John (1988), this is equivalent to a lower degree of strategic complementarity, that is each firm is less influenced in setting prices by the decisions of their peers and, consequently, by the aggregate price level.

Table 1: Estimates of the SIPC using nonlinear least squares

	estimation sample				
	2002Q4-2009Q4		2005Q1-2009Q4		
	expectations series		expectations series		
	AR	VAR_2	AR	VAR_1	VAR_2
			$j = 8$		
λ	$0.78^{***}(0.03)$	$0.82^{***}(0.02)$	$0.69^{***}(0.08)$	$0.81^{***}(0.12)$	$0.79^{***}(0.04)$
α	$0.23^{*}(0.12)$	$0.37^{***}(0.13)$	$0.14^{**}(0.07)$	$0.38^{***}(0.12)$	$0.35^{***}(0.12)$
S	0.87	0.79	0.95	0.82	0.84
Q	0.15	0.10	0.12	0.09	0.10
			$j = 6$		
λ	$0.73^{***}(0.04)$	$0.77^{***}(0.02)$	$0.59^{***}(0.12)$	$0.73^{***}(0.05)$	$0.72^{***}(0.05)$
α	0.17(0.11)	$0.26^{***}(0.09)$	0.07(0.05)	$0.25^{***}(0.07)$	$0.23^{***}(0.07)$
S	0.84	0.80	0.96	0.85	0.86
Q	0.09	0.08	0.15	0.10	0.11
			$j = 4$		
λ	$0.58^{***}(0.05)$	$0.62^{***}(0.03)$	$-0.50^{***}(-0.05)$	$0.62^{***}(0.07)$	$0.60^{***}(0.08)$
α	0.06(0.04)	$0.12^{***}(0.04)$	-0.00(0.01)	$0.14^{***}(0.05)$	$0.12^{***}(0.05)$
S	0.88	0.86	0.94	0.86	0.87
Q	0.22	0.20	0.72	0.12	0.13

For λ and α Newey-West standard errors are reported in brackets. S denotes the sum of the coefficients of the second right hand side term of (37). Q denotes the asymptotic p-value of the Ljung-Box statistic for one lag autocorelation test of the residuals.

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

Second, we can examine how the pattern of the estimates varies from one case to the other. We distinguish four important observations: (i) in both samples the estimates corresponding to the autoregressive expectations indicate a lower degree of informational stickiness; (ii) if we compare the corresponding estimates in the two samples, we find that in all cases the expanded sample indicates a higher degree of informational stickiness; this means that the average arrival time was higher in the 2002Q4 - 2005Q4 period; (iii) using the VAR_2 series we find lower values for λ than when using the VAR_1 series, as a result of incorporating the AR information; (iv) in all cases a lower j_{max} yields a lower degree of informational stickiness and a higher degree of real rigidity, but surprinsingly, it does not have a clear effect on the value of S, as we might expect.

The estimates of informational rigidity are comparable the ones in the recent literature.[8] Mankiw and Reis (2001) generate their expectations assuming univariate stochastic processes for inflation and productivity growth and estimate λ to be equal to 0.75. Carrol (2003) shows that under the proposed model of epidemiological expectations λ is estimated to be 0.73. Khan and Zhu (2006) estimate the SIPC using different lags and different measures of inflation expectations and obtain, in average, a value of λ of 0.76. Dopke et al. (2008) estimate that, conditional on survey data, information stickiness ranges between 0.8 - 0.7 for Germany, France and UK and between 0.5 - 0.6 for Italy. Consequently, the values obtained in this section indicate a slightly higher degree of informational rigidity than previously estimated.

4.3 Assesing the endogeneity problem in estimating the SIPC

Coibion (2010) argues that the output gap in (37) is subject to the endogeneity problem. This requires the use of an IV estimator such as TSLS or GMM. We have to define a set of relevant instruments which could be used in a GMM estimation in the case that output gap suffers from endogeneity. The choice of the instruments is subject to several issues.

First of all, instruments have to respect the orthogonality conditions. To address this issue, I will use the Hansen J test. Although this tests only if the overidentifying conditions hold, it is a useful tool in validating the orthogonality conditions. Second, Stock,Wright and Yogo (2002) stress that instruments that are not highly correlated with the endogeneous variables, that is weak instruments, can lead to unreliable inferences. The standard

[8] I express these results using $1-\lambda$ to denote the probability of information update.

approach to test for weak instruments is to use the Cragg-Donald statistic and the critical values proposed by Stock and Yogo[9]. However, this framework is valid only for linear IV and GMM estimation. This is not very convenient, as both the structural form of the NKPC and the SIPC have a nonlinear specification. Consequently, I will perform the weak instruments test only for the reduced form of the NKPC.

Finally, after the validity of the instruments is confirmed, endogeneity is tested using the Durbin-Wu-Hausman (DWH) test. This test is performed using an auxiliary estimation in which the variables which are tested for endogeneity are treated as exogenous by including them in the instrument list. The DWH statistic is calculated as the difference between J statistic of the original estimation and the J statistic from the auxiliary estimation. It is important to asses whether the suspect variables are truly endogenous to motivate the use of the GMM framework. If, contrary to apriori expectations, the suspect variables are exogenous, then OLS is the efficient estimator.

4.4 Estimation of the NKPC

In this section we investigate the empirical validity of forward looking NKPC, the benchmark model for inflation against which we will compare the SIPC. The NKPC can be estimated both in reduced and structural form. The structural form is the empirical counterpart of (32) and the reduced form is obtained from the structural form by substituting the coefficient of output gap:

$$\pi_t = ky_t + E_t\pi_{t+1} + \epsilon_t \tag{42}$$

Usually, the NKPC is estimated by imposing rational expectations upon the agents. Formally, this is done by defining the inflation expectations formed at the present and referring to the next period as the ex-post realised inflation plus a white noise error term[10]. Following Coibion (2010), the methodology addopted here does not impose rational expectations upon the

[9]The Cragg-Donald statistic allows weak instruments tests for more than one regressor. When oly one regressor is suspect to be a weak instrument, a simple F test of the first stage regression can be performed, but using the critical values of Stock and Yogo.

[10]See Gali and Gertler (1999).

NKPC. Instead, the estimation is done conditional upon the expectations series used to estimate the SIPC.

However, given that expectations of π_{t+1} are generated using π_t, the endogeneity problem of the expectations is not mitigated. Moreover, it is likely that a shock to the Phillips curve is contemporaneously correlated with the output gap. Consequently, I estimated the NKPC by GMM using as instruments two lags for the output gap and the series of inflation expectations for a quarter ahead formed in the previous quarter.[11] The estimates corresponding to the AR expectations and the VAR expectations series are reported in table 2. For reasons of comparability, results are shown for the two samples considered in estimating the SIPC.

In all cases, the high value of the Cragg-Donald statistic is considerably above the critical value of 5%, which leads to the rejection of the weak instruments hypothesis[12]. The J test indicates that the overidentifying restrictions in the GMM framework are valid. The possible endogeneity of the suspect regressors is investigated using tree DWH tests. H_1 statistic corresponds to the output gap endogeneity test, H_2 tests inflation expectations and H_3 tests the two variables jointly. The results for the first sample indicate that only in the case of inflation expectations the exogeneity is not confirmed. We distinguish here a certain difference between the results for the two samples, as for the 2005Q1-2009Q4 sample exogeneity of inflation expectations cannot be rejected. This could be caused by the power reduction of the test due to the small sample size.

These results indicate that output gap could be treated onwards as exogenous. Using in the list of instruments a constant, output gap and the same series of expectations as before, we obtain the estimates listed in table 3. It can be seen that, for the extended sample, the estimates of both parameters are statistically significant. The discount factor β does not differ significantly from unity, as we expected apriori from economic theory.

[11]According to Coibion (2010), the orthogonality condition for these instruments holds under the assumption of iid errors. This implies that past values of the output gap, respectively a subset of past expectations, are orthogonal to the error term of the equation.

[12]For the outlined specification, the 5% critical value corresponding to the simulations of Stock and Yogo is 16.78.

Table 2: GMM estimates of the reduced form NKPC.
Output gap treated as endogenous

	estimation sample				
	2002Q4-2009Q4		2005Q1-2009Q4		
	expectations series		expectations series		
	AR	VAR_2	AR	VAR_1	VAR_2
k	0.003 (0.008)	0.02 (0.02)	0.001 (0.007)	0.02(0.03)	0.02(0.02)
β	1.01^{***}(0.01)	0.98^{***}(0.02)	0.99^{***}(0.02)	0.95^{***}(0.03)	0.95^{***}(0.03)
J	1.73 (0.42)	1.77(0.41)	2.89 (0.23)	2.45 (0.29)	2.52 (0.28)
CD	41.58	40.84	38.28	34.19	34.87
H_1	0.09 (0.77)	0.58 (0.45)	0.006(0.93)	0.16 (0.69)	0.18 (0.67)
H_2	3.25 (0.07)	3.38 (0.07)	1.35(0.24)	1.30 (0.25)	1.18 (0.17)
H_3	3.73 (0.15)	3.99 (0.14)	1.90(0.39)	2.09 (0.35)	1.88 (0.39)

In brackets are reported, for k and β, Newey-West standard errors, and for J,H_1,H_2 and H_3, asymptotic p-values. GMM estimation method: Newey West HAC weighting matrix, iteration to convergence.

* significant at 10%; ** significant at 5%; *** significant at 1%

Moreover, the coefficient of output gap is significant at the 10% level, thus validating the reduced form of the NKPC. However, the results for the second sample indicate that only the discount factor is statistically significant. The values of k are comparable with the ones obtained in the first sample, but they are not significant, probably because of the small size of the sample.

Note that, when comparing the values of the estimates in table 3 with the ones in table 2, we see that they are not very different, although the standard errors are bigger in the first case. This can result from the unnecessary use of instruments for the output gap and the loss of efficiency in estimation.

The next step is to estimate the NKPC using nonlinear GMM in structural form and to compare the estimates with the ones obtained in the reduced form. As a result of the previous discussion, I will treat onward output gap as exogenous [13]. The specification of the equation is the following:

$$\pi_t = \frac{(1-\theta)(1-\beta\theta)}{\theta}\alpha y_t + \beta E_t \pi_{t+1} + \epsilon_t \tag{43}$$

It can be seen that the coefficient of real rigidity is not identified. Therefore, the estimation of the equation in the structural form necessitates the

[13] If we consider output gap as endogenous, the results are qualitatively unchanged.

Table 3: GMM estimates of the reduced form NKPC.
Output gap treated as exogenous

	estimation sample				
	2002Q4-2009Q4		2005Q1-2009Q4		
	expectations series		expectations series		
	AR	VAR_2	AR	VAR_1	VAR_2
k	0.0007 (0.006)	0.025^{*} (0.01)	-0.0006 (0.006)	0.0226 (0.02)	0.019(0.01)
β	1.01^{***}(0.01)	0.96^{***}(0.03)	0.99^{***}(0.02)	0.91^{***}(0.06)	0.91^{***}(0.05)
J	1.56 (0.21)	0.06(0.93)	2.61 (0.11)	2.30 (0.13)	1.97 (0.16)
CD	490.58	483.2	195.44	165.55	178.49
H_2	3.34 (0.07)	4.36 (0.04)	1.40(0.24)	0.23 (0.63)	0.68 (0.41)

In brackets are reported, for k and β, Newey-West standard errors, and for J and H_2, asymptotic p-values. GMM estimation method: Newey West HAC weighting matrix, iteration to convergence.

* significant at 10%; ** significant at 5%;*** significant at 1%

calibration of α, the coefficient of real rigidity. We will take into consideration two values for α: 0.1 and 0.4. As mentioned earlier, 0.1 corresponds to the calibration value proposed by MR (2002) and the second value is consistent with our prior estimates of the SIPC. The calibration of α will not affect the fit of the curve, as the coefficient of output gap will remain unchanged. However, varying the values of α will be reflected in the magnitude of θ, the degree of price rigidity. This has important implication for the interpretation of the results, as θ is the key structural parameter of interest in the NKPC. The results are reported in table 4[14].

Analyzing the estimates in the structural form, we see that the ones corresponding to the AR-based expectations are not statistically significant in one case and in the others suggest an excessive degree of price rigidity. Turning to the results from the use of the AR-based expectations, we can formulate several observations: (i) The estimates are statistically significant and suggest a sensible average time of price change. (ii) Conditional on the degree of real rigidity, the average time of price change, $1/(1-\theta)$, rages between 2.6 and 3 quarters in the case of $\alpha = 0.1$ and between 5 and 5.9 quarters in the case of $\alpha = 0.4$; the estimates corresponding to a lower

[14]For analogous results considering endogenous output gap, see table 7 from appendix B.

Table 4: GMM estimates of the structural form NKPC
Output gap treated as exogenous

		estimation sample				
		2002Q4-2009Q4		2005Q1-2009Q4		
		expectations series		expectations series		
		AR	VAR_2	AR	VAR_1	VAR_2
$\alpha = 0.1$	θ	0.92^{***}	0.62^{***}	1.00	0.64^{***}	0.67^{***}
		(0.33)	(0.09)	(524.3)	(0.11)	(0.10)
$\alpha = 0.4$	θ	0.95^{***}	0.80^{***}	1.00	0.82^{***}	0.83^{***}
		(0.17)	(0.06)	68.3	(0.07)	(0.06)
	β	1.01^{***}	0.96^{***}	0.99^{***}	0.91^{***}	0.91^{***}
		(0.01)	(0.03)	(0.02)	(0.06)	(0.05)
	k	0.0006	0.025	0.000	0.0226	0.019

In brackets are reported, for k and β, Newey-West standard errors, and for J and H_2, asymptotic p-values. GMM estimation method: Newey West HAC weighting matrix, iteration to convergence.
* significant at 10%; ** significant at 5%;*** significant at 1%

degree of real rigidity are closer to the results in the literature [15]. (iii) In the second sample, the degree of price stickiness is lower than in the first sample, indicating that prices began to adjust more rapidly after 2005. (iii) In all cases, the values of k, resulting from the estimates θ and β are consistent with the ones that were directly estimated in the reduced form.

4.5 Choosing a benchmark expectations series

The results outlined up to this point indicate some differences between using a simple AR expectations series and a VAR expectations series. In estimating the SIPC we found that: (i) estimates using VAR-based expectations indicate a slightly greater degree of informational stickiness than AR-based expectations and other findings in the literature; in most cases both structural coefficients are statistically significant; (ii) when using simple AR-bases expectations, the coefficient of real rigidity is usually estimated imprecisely. Estimating the NKPC has revealed that: (i) when we treat output gap as exogenous, the only situation when we obtain significant co-

[15] Gali and Gertler (1999) obtain GMM estimates of θ ranging from 0.83 to 0.96. However, the authors suspect an upward bias in their estimates

efficients is the VAR expectations series over the extended sample; (ii) in the structural form, the estimated degree of price rigidity is closer to other estimates in the literature.

All these arguments are in favor of using the VAR expectations series as a benchmark series of expectations. For the sake of brevity, all further analysis will be performed using the VAR-based expectations series.

4.6 Comparing the two competing models

The empirical analysis from the previous section does not reject neither of the two models of inflation, namely the SIPC and the NKPC. The estimates conditional on the VAR-based expectations series (and, to a lesser extent, on the AR-based expectations series) are consistent with other results from the literature [16]. However, the two models are not compatible one with the other, as they rely on different assumptions. Consequently, we need to analyze on statistical terms if one of them excludes the other.

The estimates corresponding to the specifications described in section 3.3 are listed in table 5. First, it can be seen that in both cases the intercept is not statistically significant, thus motivating the use of the theoretical form as deduced in section 3. Second, the inclusion of the invalid regressor does not alter the quality of the results. In the case of the NKPC, this leads to an increase in the standard error of k, but the estimated value remains roughly the same. For the SIPC, both structural coefficients, λ and α suffer a slight increase, but this has no effect on the general fit of the curve.

The R-square criterion clearly favors the NKPC. In the case of the SIPC, the model explains 65% of the variability in inflation, while in the case of the NKPC the proportion raises to 87%. This difference between the ability of the two models to fit actual inflation can be vizualised graphically in figure 1. As we can see, the SIPC fails to adjust to surprise shocks in inflation and exhibits a substantial degree of inertia. This comes from the fact fitted inflation is constructed as a weighted average of past forecasts, causing recent information to be incorporated by agents all slowly. Turning to the NKPC, we see a different story. The equation relies on current expectations of future

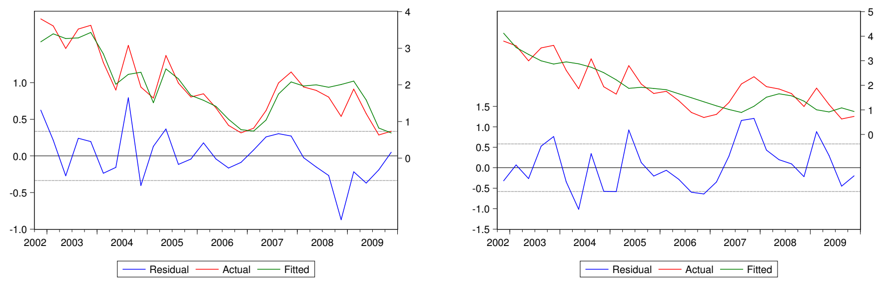
[16] See appendix C

Table 5: Estimates of the SIPC and NKPC including the intercept

estimation sample: 2002Q4 - 2009Q4					
	NKPC		SIPC	Nonnested model tests	
c	0.013 (0.17)	c	0.387 (0.38)	δ_{SI}	0.32 (0.24)
k	0.025 (0.015)	λ	0.879^{***} (0.03)	δ_{SP}	0.65^{***} (0.17)
β	0.952^{***} (0.07)	α	0.541^{*} (0.32)		
R^2	0.87	R^2	0.65		

Note: HAC standard errors are reported in brackets. All estimates are done by updating the HAC weighting matrix to convergence. See text for instruments.

Figure 1: Comparing the fit of the two models



(a) Fitted inflation from the NKPC (b) Fitted inflation from the SIPC

inflation, which is, by means of construction, highly correlated with current inflation. As a result, the NKPC is able to account for a much larger amount in inflation variability. The model follows closely the spikes of inflation from 2002 to 2005 and the major turnover in the disinflation process that took place in late 2006.

To compare the two models using the DM nonnested tests, we come across the endogeneity problem. Due to the fact that both informational and price rigidities are likely to influence inflation to some extent, we expect that the fitted values of one model are correlated with the residuals of the other. This is addressed by IV estimation, but doing so we will need for an equation instruments from both models, which is inconvenient giving the small data sample at hand.

The baseline results from the DM test are listed in table 5. The augmented NKPC is estimated using the following sets of instruments: a constant, output gap, $E_{t-2}(\pi_{t+1})$ and $E_{t-1}(\pi_t)$.[17] The value of $\hat{\delta}^{SI}$ is statistically insignificant, giving arguments to accept the null of the NKPC. In the case of the augmented SIPC, I use as instruments a constant, output gap, $E_{t-1}(\pi_t)$, $E_{t-1}(y_t)$, and $E_{t-2}(\pi_{t+1})$.[18] The value of δ^{SP} is statistically significant at the 1%, leading to the rejection of the SIPC.[19] According to these results, the SIPC is statistically dominated by the NKPC. However, due to the small data sample, the reported results must be interpreted with some degree of skepticism[20].

4.7 Robustness to the degree of real rigidity

The degree of real rigidity plays an important role in the estimation of the two models. To complete the comparative analysis, I will calibrate α in each equation. Coibion (2010) argues that a low degree of real rigidity favors the estimation of a high degree of informational rigidity, but simultaneously gives a substantial weight to past forecasts and causes a worsening of the fit in the SIPC. To respond to this critique, I follow Coibion (2010) and impose values of α ranging from 0.1 to 0.5 in the estimation of the two models. In the case of the NKPC this is done in the structural form of the equation. In order to compare the R-squared from the two models as a function of α, we need to have the same degrees of freedom. Consequently, I impose the value of β to be equal to 0.95, the estimated value from the unrestricted version

[17] It can be seen that past forecasts of output gap are missing from the list of instruments. This is motivated by the presence of the output gap. However, the estimation including past forecasts of output gap brings different results. Moreover, according to the DWH test, π_t^{SI} could be treated as exogenous. This leads to similar results as in the previous case. The estimates are reported in table 8.

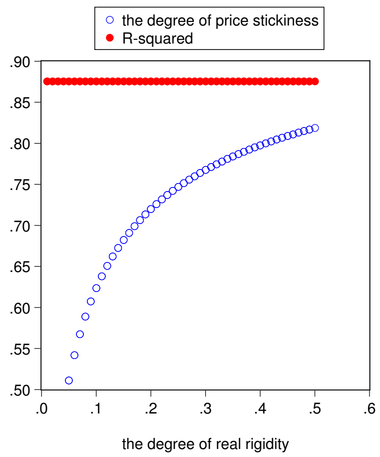
[18] Excluding $E_{t-1}(y_t)$ from the list of instruments, as I procedeed for the augmented NKPC, yeilds similar results.

[19] The result is similar when using as additional instruments $E_{t-2}(\pi_t)$, $E_{t-2}(y_t)$. Coibion (2006) argues that the use of a subset of past forecasts as instruments when estimating the SIPC does not alter considerably the estimation results.

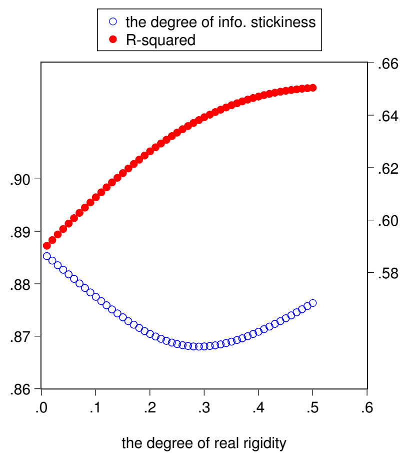
[20] If we accept as baseline results the ones reported in table 8, then the null of the NKPC is also rejected.

of the model.[21]

Figure 2: Comparing the sensitivity to α



(a) NKPC



(b) SIPC

As we can see, both λ and θ react to changing the coefficient of real rigidity. However, only the fit of the SIPC is influenced by the values α. In the case of the NKPC, the structural parameters are calculated as to obtain the same reduced form estimates, as we have already seen in section 4.4. Analyzing the dependence between α and λ, we see that in our case the observation formulated in Coibion (2010) does not hold. It can be seen that the degree of informational stickiness does not increase monotonically with α. Moreover, the general fit of the curve, as measured by R-square, improves for higher values of α.

[21]Another option would be to impose a value for θ and to estimate β. Coibion (2010) estimates the NKPC in the reduced form, imposing the value for θ and calibrating k.

5 Conclusion

The empirical results outlined in this paper are in favour of validating the hypothesis of informational stickiness formulated by Mankiw and Reis (2002). The analysis of the underlying model, the SIPC, is performed conditional on simulated expectations data obtained using out-of-sample forecasts. The empirical approach in assesing the validity of the SIPC follows the strategy of Coibion (2010). This consists in testing whether the data is consistent with the underlying theory and in comparing the statistical performance of the model relative to that of the forward looking NKPC.

The robustness of the estimates is tested by using alternative definitions of the expectations series and two different data samples. Consequently, I presented the results obtained using AR and VAR forecasts from 2002Q4 and, alternatively, 2004Q4.

The most straighforward approach employed was to estimate the SIPC using the nonlinear least squares procedure. The estimates were performed for different expectations lags. Almost all results indicate statistically significant coefficients. Using all the available forecasts we find both for the coefficient of informational rigidity and for the coefficient of real rigidity values slightly higher than the benchmark values proposed by Mankiw and Reis. As we drop series corresponding to older forecasts, the values of the estimates decrease considerably, indicating a certain dependence of the results on the truncation point.

The reduced NKPC enables us to perform several specification tests in order to address the weak instruments and endogeneity issues. Using simulated expectations favours the rejection of null of weak instruments in all cases and the DWH endogeneity tests brings arguments for using the output gap as exogenous. This contradicts the findings of Coibion (2010), who argues that output gap is correlated with the residuals. In our case, this finding might not hold due to the low correlation between inflation and output gap.

Finally, the two models are compared using the expectations series that fits best in both cases. Using the R^2 criteria, the NKPC is found to explain a much heigher proportion of inflation variability than the SIPC. The two models are compared on statistical grounds using the Davidson-Mackinnon J test. Again, the NKPC seems to dominate the SIPC, but the results are sensitive to the orthogonality conditions.

Although these results partially indicate that the SIPC is validated empirically, they should be interpreted with care. First of all, the Romanian economy is best illustrated by the model of a small open economy. This is not very convenient, as the SIPC and NKPC were designed to account for a closed economy. Second, data is available only for a very short sample, making the estimations subject to a high degree of uncertanty. Moreover, the unavailability of a quaterly survey for inflation and output does not allow us to estimate the degree of information stickiness implied by authentic expectations.

Given these drawbacks, the results outlined in this paper should be considered only a tentative to asses the role of informational rigidities in the dynamics of inflation. As stated before, it is unlikely that the price adjustment mechanism can be accounted only by informational rigidities. In this sense, it would be desirable to see the extent to which these relate to other rigidities documented in the recent literature.

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A Data description

All primary data series are collected in the form they were published in march 2010. The series that were not published in seasonal adjusted form were adjusted at quaterly frequency using the X12 multiplicative procedure. The series that were available at monthly frequency are converted to quarterly frequency by average. Most of the series can be downloaded from the NIS (National Institute of Statistics), NBR (National Bank of Romania) and Eurostat websites. Unless otherwise mentioned, all series are taken for the 1998Q1-2009Q4 sample.

1. Inflation (π_t) is calculated as difference of logs of the consumer price index (CPI): $100(\log(P_t) - \log(P_{t-1}))$. The consumer price index, P_t, is expresed as a quaterly fixed base series aggregated by averaging the monthly fixed base index; the series is seasonal adjusted at quaterly frequency.
   source: NIS Monthly Bulletin

2. Real output (y_t) is expressed in millions of national currency, chain linked volumes, reference year 2000, seasonal adjusted by NIS.
   source: for 2000Q1 - 2009Q4 data are taken from the published NIS series (also available at Eurostat). For 1998Q1 - 1999Q4 data are constructed using year on year volum indices published in older NIS bulletins and not included in the recently published series.

3. Output gap ($ygap$) is calculated from the real GDP series (y_t) by applying the HP filter with the smoothing parameter $\lambda = 1600$ using the 1998Q1 - 2009Q4 sample. First we generate the HP trend of the $100\log(y_t)$ series and output gap is calculated similarly to a log difference: $100(\log(y_t) - \text{hptrend}(\log(y_t)))$.

4. Registred unemployment rate ($ureg$) is expressed as a ratio of number of registred unemployed to total active population; aggregated by average from monthly data; seasonally adjusted at quarterly frequency.
   source: 2000Q1 - 2009Q4 NIS Monthly Bulletin. For 1998Q1 - 1999Q4 data are taken from older NIS bulletins and not included in the recently

published series.

5. Interbank offer rate for one month maturity ($buborm1m$) - aggregated by average from monthly data.
   source: NBR interactive database

6. Capacity utilization (cu) - expressed as a ratio; used in logs; aggregated by average from monthly data; seasonally adjusted at quarterly frequency.
   source: NBR Business Survey (Buletin de conjunctura)

7. Industrial production ($yind$) - fixed based index 2005, seasonally adjusted by NIS; used in logs; aggregated by average from monthly data.
   source: NIS monthly bulletin. Data are available only for the 2000Q1-2009Q4 period.

8. Monetary base ($m0$) - expressed in millions of national currency; aggregated by average from monthly data; seasonally adjusted at quarterly frequency; used in logs.
   source: NBR monthly bulletin

9. Crude oil price (oil) - aggregated by average from monthly data; used in logs.
   source: U.S. Energy Information Administration, http://www.eia.doe.gov/

B Alternative estimation results

Table 6: GMM estimates of the SIPC.
Output gap treated as endogenous

		estimation sample				
		2002Q4-2009Q4		2005Q1-2009Q4		
		expectations series		expectations series		
		AR	VAR_2	AR	VAR_1	VAR_2
	λ	0.79	0.81	0.72	0.76	0.76
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
j=8	α	0.32	0.50	0.12	0.20	0.18
		(0.00)	(0.00)	(0.12)	(0.00)	(0.02)
	S	0.84	0.81	0.92	0.88	0.89
	Q	0.16	0.11	0.08	0.06	0.06

In brackets are reported p-values calculated using the corresponding t-distribution and the Newey West standard errors. GMM estimation method: Newey West HAC weighting matrix, iteration to convergence. See text for instruments.

Table 7: GMM estimates of the structural form NKPC.
Output gap treated as endogenous

		estimation sample				
		2002Q4-2009Q4		2005Q1-2009Q4		
		expectations series		expectations series		
		AR	VAR_2	AR	VAR_1	VAR_2
$\alpha = 0.1$	θ	0.83	0.66	0.91	0.66	0.69
		(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
$\alpha = 0.4$	θ	1.09	0.81	0.96	0.82	0.83
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	β	1.01	0.98	0.99	0.95	0.96
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	k	0.003	0.018	0.00096	0.019	0.015

In brackets are reported p-values calculated using the corresponding t-distribution and the Newey West standard errors. GMM estimation method: Newey West HAC weighting matrix, iteration to convergence. See text for instruments.

Table 8: Alternative estimates of the augmented NKPC

	estimation sample: 2002Q4 - 2009Q4	
	$NKPC_1$	$NKPC_2$
c	-0.34** (0.15)	-0.30* (0.17)
k	-0.001 (0.01)	0.011 (0.02)
β	0.56*** (0.15)	0.57*** (0.15)
δ^{SI}	0.55*** (0.17)	0.53*** (0.17)

Note: HAC standard errors are reported in brackets. All estimates are done by updating the HAC weighting matrix to convergence .

List of instruments for $NKPC_1$: constant, ygap,$E_{t-1}(\pi_t)$, $E_{t-1}(y_t)$,$E_{t-2}(\pi_{t+1})$.

List of instruments for $NKPC_2$: constant, ygap,$E_{t-1}(\pi_t)$, $\hat{\pi}_t^{SI}$,$E_{t-2}(\pi_{t+1})$.

C Figures

Figure 3: VAR expectations, AR expectations, AR and VAR combined expectations and actual inflation

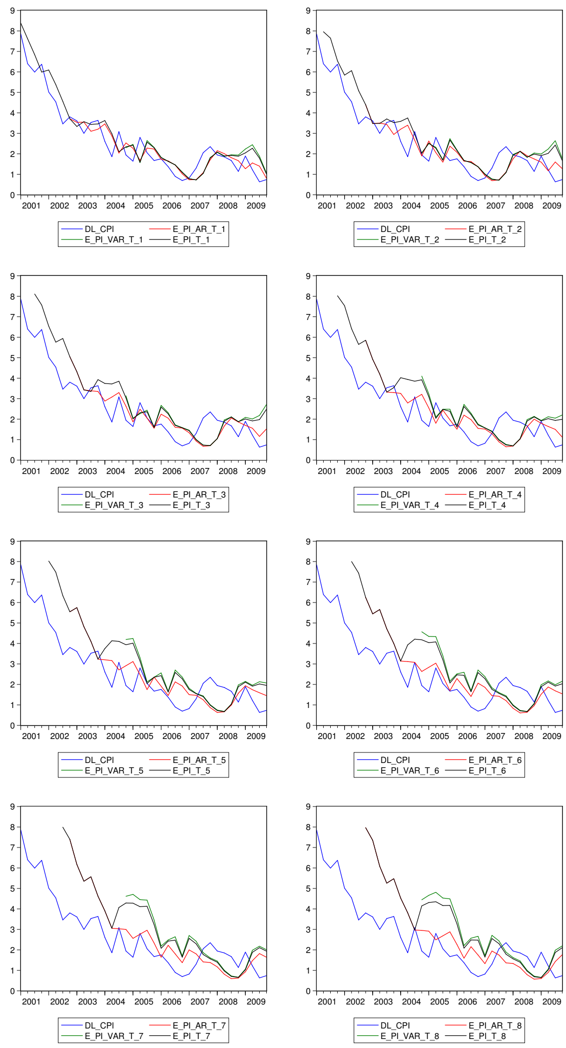

Figure 4: VAR expectations, AR expectations, AR and VAR combined expectations and actual output gap