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MASTER THESIS

DOES THE FED FOLLOW THE PREDICTIONS OF THE PROFESSIONAL FORECASTERS?

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Does the Fed follow the predictions of the professional forecasters?

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Abstract

Yes, it does very closely. The baseline model presented in this paper is a modification of the asymmetric preference model suggested by Ruge-Murcia (2003a) to investigate how policy makers use the predictions of the professional forecasters data available and revised data when making their decisions. In this model, the central banker targets a weighted average of revised and professional forecaster inflation together with a weighted average of revised and professional forecaster output. Moreover, in this paper we consider an extended model to allow the central bank to react differently depending on whether the economy is doing good or not.

1 Introduction

Economic forecasting is the process of making predictions about the economy. Forecasts can be carried out at a high level of aggregation or at a more disaggregated level, for specific sectors of the economy or even specific firms. Many institutions engage in economic forecasting, including international organizations such as the International Monetary Fund, World Bank and the OECD, national governments and central banks, and private sector entities. Some forecasts are produced annually, but many are quarterly predictions.

The economist typically considers risks; these risks help illustrate the reasoning process used in arriving at the final forecast numbers. Forecasts are used for a variety of purposes. Governments and businesses use economic forecasts to help them determine their strategy, their plans, and budgets for the upcoming year. Stock market analysts use forecasts to help them estimate the valuation of a company and its stock.

In this thesis, we focus our attention on the forecasts collected in the Survey of Professional Forecasters (SPF) is a quarterly survey done in the USA by the Reserve Bank of Philadelphia. The survey began in 1968 and was conducted by the American Statistical Association (ASA) and the National Bureau of Economic Research (NBER). The Federal Reserve Bank of Philadelphia took over the survey in 1990. In its early days (prior to the takeover by the Federal Reserve Bank of Philadelphia) the survey was often referred to in the academic literature as the ASA-NBER survey.

The SPF reports predictions for different kind of economic variables, such as the real GDP and its components, the consumer price index (CPI) and the price consumption expenditure (PCE), long-term inflation forecasts, etc.

This paper considers the theoretical and empirical investigation of optimal monetary policy in an extended asymmetric preference model similar to the type suggested by Ruge-Murcia (2003a, 2004) in which policy makers consider both predictions of the professional forecasters and their expectations on revised data to base their decisions on. Our aim is to analyze the behaviour of the central banker when defining the targets of inflation and output as weighted averages of SPF and revised data. This paper can be considered as a replication of the model suggested by Cassou, Scott and Vázquez (2016) where real time data was considered instead of the predictions reported in the SPF used in this paper. This model allows us to analyze if the results obtained in this paper are similar to the ones obtained in Cassou, Scott and Vázquez (2016).

The main objectives of this project are the following:

(i) to study the properties of forecast errors associated with the predictions of the professional forecasters,

(ii) to analyze the importance of the predictions in the SPF to characterize the optimal monetary policy, and

(iii) to study whether its importance depends on whether the economy is doing well or not.

In this paper we develop the baseline model and an extended model. In both models the empirical results obtained are really similar: the Fed follows very closely the predictions of the professional forecasters. The estimation of these models is done by the ordinary least square estimation and constraint maximum likelihood estimation method.

2 The Model

The theoretical model developed in this project consists of a monetary planner that weighs inflation and output differently in making their decisions. We regard the revised data, the one that appears in conventional databases such as the Federal Reserve Economic Data base (Fred) available at the website of the Federal Reserve Bank of St. Louis, as describing the true state of the economy. However, these revised data is not observed at the time monetary policy is implemented. In this scenario, the policymaker may well consider the predictions of the professional forecasters in their decision making in addition to their predictions on revised data.

To analyze the potential weight of the predictions of professional forecasters issued by policy makers and the possibility that this weight may be different during good or bad economic times, we investigate an extension of the model in Cassou, Scott and Vázquez (2012, 2016) which itself is an extension of the inflation-unemployment asymmetric preference model suggested in Ruge-Murcia (2003a, 2004). In this section we focus on a baseline model, which consists on a simple equation. This equation is found using methods similar to Surico (2007) where a second order Taylor approximations to the planner's first order condition is derived.

This approach is simpler in the structure for estimation purposes than the one suggested by Ruge-Murcia (2003a, 2004). For developing this model we consider the baseline model used in Cassou, Scott and Vázquez (2016). However, and in contrast to Cassou, Scott and Vázquez (2016), we use the predictions of the professional forecasters on output and inflation instead of their real-time data counterparts.

The model starts with the equation suggested by Lucas (1977). This equation is not affected by the lag issue associated with revised data,

$$Y_t = Y_t^p + \alpha(P_t - P_t^e) + \eta_t,$$

where Y_t is the output produced at time t, Y_t^p is the potential output at time t, P_t is the price level at time t, P_t^e is the expected price level at time t (based on information at $t-1$), η_t is a supply disturbance and α reflects the sensitivity of firm output to unexpected price changes. Variables are expressed in log terms. Adding and subtracting P_{t-1} inside the parenthesis term on the right gives

$$y_t = \alpha(\pi_t - \pi_t^e) + \eta_t, \tag{1}$$

such that $y_t = Y_t - Y_t^p$ is the output gap, and $\pi_t = P_t - P_{t-1}$ and $\pi_t^e = P_t^e - P_{t-1}^e$ are the inflation and expected inflation respectively. To understand why the structure of these equations is not affected by the lag issue, it is important to remember where they come from.

By using the model proposed in Ruge-Murcia (2003a, 2004), in particular, by considering i_t the policy variable, the central bank is going to choose the policy variable to monitor the weighted average of the SPF inflation and revised inflation,

$$\lambda^{\pi}\pi_t + (1-\lambda^{\pi})\pi_t^{SPF} = i_t + \varepsilon_t, \tag{2}$$

where ε_t is serially uncorrelated disturbance with zero mean and standard deviation σ_ε. We model the inflation target as a weighted average of the two data types and use a parameter $\lambda^{\pi} \in [0,1]$. That is, $\lambda^{\pi} = 0$ express that the policy target is entirely based on the professional forecasters prediction, $\lambda^{\pi} = 1$ means that the target is entirely revised data and $\lambda^{\pi} \in (0,1)$ indicates that the two data types are averaged in determining the target. So the parameter $(1-\lambda^{\pi})$ is the measure of the short-term pressure the central bank gets from the government and other economic agents react to SPF inflation data.

Similarly to (2), the policymaker targets a weighted average of the SPF output and revised output,

$$\lambda^{Y} Y_t + (1-\lambda^{Y}) Y_t^{SPF}, \tag{3}$$

where $\lambda^{Y} \in [0,1]$ and we allow $\lambda^{\pi} \neq \lambda^{Y}$. The different weights of the SPF inflation and SPF output (i.e $(1-\lambda^{\pi})$ and $(1-\lambda^{Y})$, respectively) will reflect the different ability of the initial predictions of inflation and output to forecast final revised inflation and output, respectively. From here we know that $\lambda^{Y} = 0$ means that policy maker only takes into account the SPF output, $\lambda^{Y} = 1$ means that only takes into account the revised output and $\lambda^{Y} \in (0,1)$ indicates that policy takes into account an average of this two data types.

The following two equations show the relationship between the two types of data:

$$\pi_t = \pi_t^{SPF} + r_t^{\pi} \tag{4}$$

and

$$Y_t = Y_t^{SPF} + r_t^{Y} \tag{5}$$

where r_t^{π} and r_t^{Y} are the forecast errors of the professional forecasters at date t for the inflation and output of period t, respectively. Using (4) and (5), (2) and (3) can be rewritten as,

$$\pi_t - (1-\lambda^{\pi}) r_t^{\pi} = i_t + \varepsilon_t \tag{6}$$

and

$$Y_t - (1-\lambda_b^{Y}) r_t^{Y}, \tag{7}$$

respectively. So from these two equations can be concluded that the weighted average of SPF and revised data captured by the central bank is expressed linearly as a function of revised data (π_t and Y_t) and data revisions (r_t^{π} and r_t^{Y}). Equations (6) and (7) are extensively used will in the algebra below.

The policy maker has to choose i_t such that the minimization problem takes into account the weighted averages given by (2) and (3) according to,

$$\min_{i_t} E_{t-1}\left\{(\frac{1}{2})[\widehat{\pi}_t - \pi_t^*]^2 + \frac{\phi}{\gamma^2}\left(exp\left(\gamma[Y_t^* - \widehat{Y}_t]\right) - \gamma[Y_t^* - \widehat{Y}_t] - 1\right)\right\} \tag{8}$$

such that the inflation and output indicator are

$$\widehat{\pi}_t = \lambda^\pi \pi_t + (1-\lambda^\pi)\pi_t^{SPF}$$

and

$$\widehat{Y}_t = \lambda^Y Y_t + (1-\lambda^Y)Y_t^{SPF}.$$

In this minimization problem E_{t-1} represents the expectations at the end of the period $t-1$. In this minimization problem it is assumed that $\gamma \neq 0$ and $\phi > 0$. Taking into account Ruge-Murcia (2003) we assume that π^* is constant over time, so it will be denoted as π^* so as to simplify the notation. By solving the minimization problem, the first order condition is described by the following equation,

$$E_{t-1}[i_t] + E_{t-1}[\varepsilon_t] - \pi^* - \Big(\frac{\phi\alpha}{\gamma}\Big)E_{t-1}\bigg(\exp\Big[\gamma(-y_t + (1-\lambda^Y)r_t^Y)\Big] - 1\bigg) = 0. \tag{9}$$

We assume that output target is potential output: $Y_t^* = Y_t^p$ and y_t denotes the output gap ($y_t = Y_t - Y_t^*$, to represent the revised output gap).

Following Surico (2007), by taking a second order Taylor approximation of equation (9) around $y_t = 0$ and $r_t^Y = 0$. So we get,

$$\begin{aligned} i_t - \pi^* - \Big(\frac{\phi\alpha}{\gamma}\Big)E_{t-1}\Big[\gamma y_t + \gamma(1-\lambda^Y)r_t^Y + \\ +\frac{\gamma^2}{2}y_t^2 + \frac{\gamma^2(1-\lambda^Y)^2}{2}(r_t^Y)^2 + R_2(.) + \gamma^2(1-\lambda_b^Y)y_t r_t^Y\Big] \end{aligned} \tag{10}$$

where $R_2(.)$ represents the error term of the second order approximation. In order to get a regression equation, we next substitute $i_t = \pi_t - (1-\lambda^\pi)r_t^\pi - \varepsilon_t$ (this equation is a modification of (2)) into (10) to obtain,

$$\pi_t = d_0 + d_1 y_t + d_2 r_t^Y + d_3 y_t^2 + d_4 (r_t^Y)^2 + d_5 y_t r_t^Y + (1-\lambda^\pi)r_t^\pi + \zeta_t \tag{11}$$

where ζ_t is the error term , which is the linear combination of the forecast errors and the error of higher orders of Taylor approximation series. Indeed, equation (11) is a reduced form, so each of the coefficients defined above are related to the structural parameters as follows: $d_0 = \pi^*$, $d_1 = \phi\alpha$, $d_2 = \phi\alpha(1-\lambda^Y)$, $d_3 = \frac{\phi\alpha\gamma}{2}$, $d_4 = \frac{\phi\alpha\gamma(1-\lambda^Y)^2}{2}$, $d_5 = \phi\alpha\gamma(1-\lambda^Y)$.

It is important to remark that, as we have used the asymmetric model suggested by Ruge-Murcia (2003a), the quadratic elements must be on the baseline model so as to reflect the policymaker preference asymmetries but also this reduced form contains components associated with the predictions errors of professional forecasters, such as $(1-\lambda^\pi)r_t^\pi$ which is related to the inflation forecast errors produced by the professional forecasters.

Next as an extension of the baseline model described previously, we allow for different weighting targets depending on whether the economy is in good or bad economic times, as in Cassou, Scott and Vázquez (2016). Formally, we create a new variable I_t, which is a dummy variable indicating whether the economy is performing well or not,

$$I_t = \begin{cases} 0, & u_t \leq u^T, \\ 1, & u_t > u^T. \end{cases} \tag{12}$$

In this model we use the unemployment rate as the indicator variable and the threshold value is 6.5. So, if the economy is doing well (i.e. unemployment rate is low or moderately low) the dummy variable will take value 0 and if the economy is doing bad (i.e. the unemployment rate is high) it takes value 1.

Using (12), the inflation and output weighted average targets, (2) and (3), can be generalized to take into account that the policymaker can accommodate her targets to economic circumstances as follows,

$$I_t[\lambda_b^\pi \pi_t + (1-\lambda_b^\pi)\pi_t^{SPF}] + (1-I_t)[\lambda_g^\pi \pi_t + (1-\lambda_g^\pi)\pi_t^{SPF}] = i_t + \varepsilon_t, \tag{13}$$

and

$$I_t[\lambda_b^Y Y_t + (1-\lambda_b^Y)Y_t^{SPF})] + (1-I_t)[\lambda_g^Y Y_t + (1-\lambda_g^Y)Y_t^{SPF}], \tag{14}$$

where $\lambda_j^Y \in [0,1]$ for any j ($j = b, g$) for good and bad times and we allow $\lambda_j^\pi \neq \lambda_j^Y$ for $j = b, g$. The different weights of the SPF inflation and SPF output (i.e $(1-\lambda_j^\pi)$ and

$(1-\lambda_j^Y)$, respectively) will reflect the different ability of the initial predictions of inflation and output to forecast final revised inflation and output, respectively. From here we know that $\lambda_j^Y = 0$ means that the policy maker only takes into account the SPF output under economic situation j, $\lambda_j^Y = 1$ means that only takes into account the revised output on situation j and $\lambda_j^Y \in (0,1)$ indicates that takes into account an average of these two data types similar reasoning applies to λ_j^π.

Using (4) and (5), (13) and (14) can be rewritten as,

$$\pi_t - (1-\lambda_b^\pi)I_t r_t^\pi - (1-\lambda_g^\pi)(1-I_t)r_t^\pi = i_t + \varepsilon_t \tag{15}$$

and

$$Y_t - (1-\lambda_b^Y)I_t r_t^Y - (1-\lambda_g^Y)(1-I_t)r_t^Y, \tag{16}$$

respectively. So from these two equations can be concluded that the weighted average of SPF and revised data captured by the central bank is expressed linearly as a function of revised data (π_t and Y_t) and predictions errors of professional forecasters (r_t^π and r_t^Y).

The policy maker has to choose i_t such that the minimization problem takes into account the weighted averages given by (13) and (14) according to,

$$\begin{aligned}
&\min_{i_t} E_{t-1}\Bigg\{ (\frac{1}{2})(I_t[\lambda_b^\pi \pi_t + (1-\lambda_b^\pi)\pi_t^{SPF}] + (1-I_t)[\lambda_g^b \pi_t + (1-\lambda_b^\pi)\pi_t^{SPF}] - \pi_t^*)^2 \\
&+\frac{\phi}{\gamma^2}\Bigg(exp\Bigg(\gamma(Y_t^* - I_t[\lambda_b^Y Y_t + (1-\lambda_b^Y)Y_t^{SPF}] - (1-I_t)[\lambda_g^Y Y_t + (1-\lambda_g^Y)Y_t^{SPF}])\Bigg) \\
&-\gamma\Bigg(Y_t^* - I_t[\lambda_b^Y Y_t + (1-\lambda_b^Y)Y_t^{SPF}] - (1-I_t)[\lambda_g^Y Y_t + (1-\lambda_g^Y)Y_t^{SPF}]\Bigg) - 1\Bigg)\Bigg\}.
\end{aligned}$$

The following regression equation can be obtained by solving this minimization problem

$$\begin{aligned}
\pi_t &= d_0 + d_1 y_t + d_2^b r_t^Y + d_2^g(1-I_t)r_t^Y + d_3 y_t^2 + d_4^b(I_t r_t^Y)^2 + d_4^g((1-I_t)r_t^Y)^2 \\
&+ d_5^b y_t I_t r_t^Y + d_5^g y_t (1-I_t) r_t^Y + (1-\lambda_b^\pi)I_t r_t^\pi + (1-\lambda_g^\pi)(1-I_t)e_{t,t+s}^\pi + \zeta_t,
\end{aligned} \tag{17}$$

where ζ_t is the error term , which is the linear combination of the forecast errors and the error associated with higher orders of Taylor approximation series. Indeed, equation (17) is a reduced form, so each of the reduced-form coefficients are related to the structural parameters as follows,

$$d_0 = \pi^* \;\;,\;\; d_1 = \phi\alpha \;\;,\;\; d_2^b = \phi\alpha(1-\lambda_b^Y) \;\;,\;\; d_2^g = \phi\alpha(1-\lambda_g^Y) \;\;,\;\; d_3 = \frac{\phi\alpha\gamma}{2},$$

$$d_4^b = \frac{\phi\alpha\gamma(1-\lambda_b^Y)^2}{2} \;\;,\;\; d_4^g = \frac{\phi\alpha\gamma(1-\lambda_g^Y)^2}{2} \;\;,\;\; d_5^b = \phi\alpha\gamma(1-\lambda_b^Y) \;\;,\;\; d_5^g = \phi\alpha\gamma(1-\lambda_g^Y).$$

As in the baseline model, where no distinction between good and bad time was considered, some components of equation (17) capture the interactions of policymaker actions with the forecast errors of professional forecasters. For instance, $(1-\lambda_b^\pi)I_t r_t^\pi$ and $(1-\lambda_g^\pi)(1-I_t)r_t^\pi$ capture the interactions with inflation forecast errors that depend on whether the economy is doing good or not.

3 Empirical Results

This section is divided into several subsections. In the first one, we describe the main sources of the data and some basic transformation that we have done into the variables for being able to use the data. The second subsection explains the data revision process. In the third subsection we show the results of the empirical model.

3.1 Data

The empirical model needs revised data and SPF data for both output and inflation as well as data for the unemployment rate which will be our indicator in the extension of the baseline model, to distinguish between good and bad times. The revised data used include quarterly Gross Domestic Product (GDP), the GDP deflator and the unemployment rate. The revised GDP and the revised GDP deflator, as well as the unemployment rate, are obtained from the Federal Reserve Economic Data base (FRED) maintained by the St. Louis Federal Reserve Bank. All the variables related to the predictions of the professional forecasters were obtained from the official website of the SPF maintained by the Philadelphia Federal Reserve Bank. Because the models require inflation rates rather than price indexes, the inflation rates were obtained as the first difference of the log of the price index which was then multiplied by 4 to obtain annualized rates.

The data of the predictions of the professional forecasters, both GDP and GDP deflator, are available since the fourth quarter of 1968. On the other hand, the revised data proved to be the binding constraint for the end period of the analysis. Although data that is called revised data was available up to 2016:1 when started to carry out the empirical analysis, the earlier end date for the long sample was chosen so as to be consistent with the timing of the last revision for the data, ignoring comprehensive or benchmark revisions that can be carried out in the future. In particular, there is a three-year lag before output data is revised for the last time. This lag means that only the data up to 2013:1 can be considered as truly revised data. Together these data constraints implied a data set which ran from 1966:2 to 2013:1.

One further complication with the SPF data empirical analysis carried out here, relative to an empirical analysis that uses purely revised data or purely SPF data, is that the SPF data for GDP has several different construction characteristics than the revised level data for GDP, so computing GDP forecast errors as in (5) is not a straightforward exercise. Two particularly problematic aspects are that the two series have different benchmark revision characteristics and different trends. Both of these features mean that a simple differentiation of (the logs of) the two raw series to get the forecast error series is more likely to reflect these construction differences than the forecast error process itself. To remedy this issue, we recompute the SPF output series using the raw SPF data and revised data trend base. In particular, we compute

$$\widehat{Y_t^r} = [1 + ln(\frac{Y_t^r}{Y_{t-1}^r})] * Y_{t-1}^{HP}$$

where Y_{t-1}^{HP} is the trend component of the revised GDP data, Y_t^r is the SPF output data at date t and $\widehat{Y_t^r}$ is our notation for the recomputed SPF GDP data. This recomputed SPF data now has the same trend features as the revised data, and thus can be combined with the revised output series to get a forecast error series of GDP that is not sensitive to different trends, yet the recomputed series still maintains the same deviation from the trend inherent in the original SPF GDP series. In this application, we considered the popular Hodrick and Prescott (1997) filter to obtain the trend component of GDP, Y_t^{HP}.

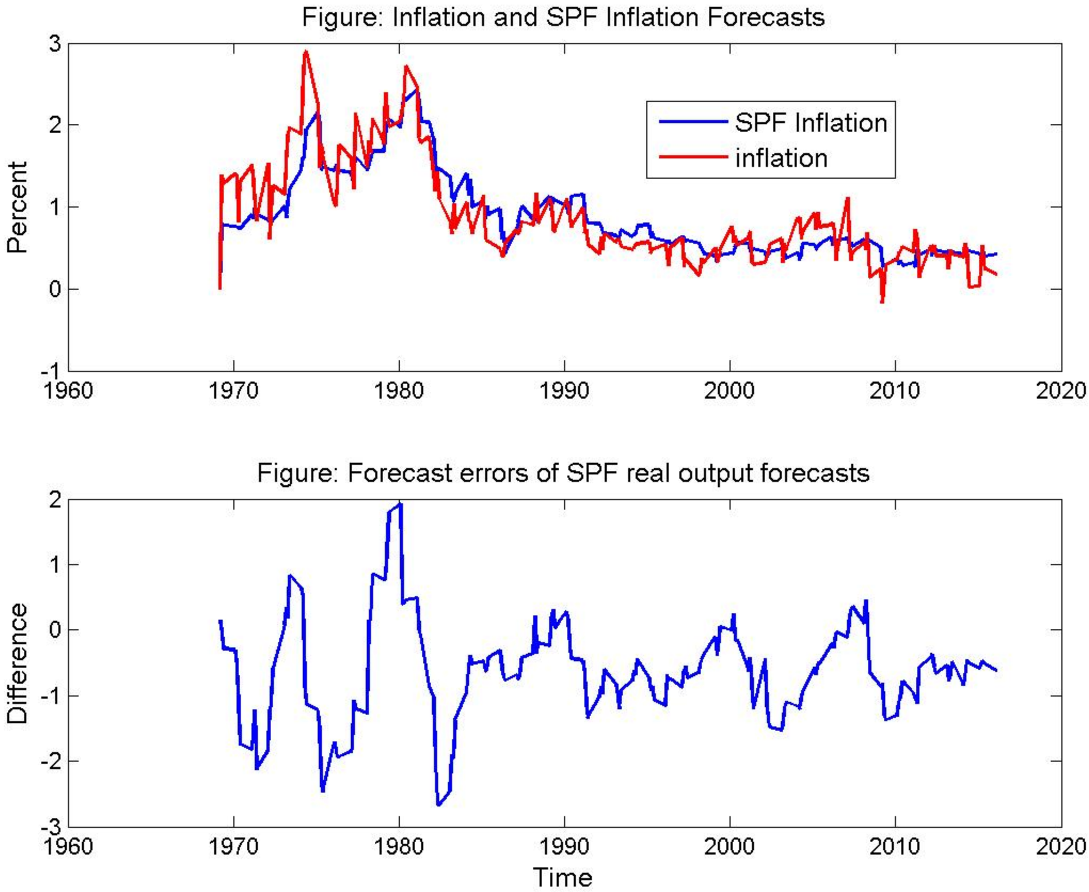

Figure 1: Different properties of variables.

Figure 1 contains two plots, with the top graph plotting the revised inflation series and the SPF inflation series and the bottom graph plotting the forecast errors of the SPF real output forecasts. These plots highlight a few important features of the data. The revised inflation is more volatile than SPF inflation. On the second plot, it can be seen the forecast error of the output is around 0 and it takes values from -3 to 2.

3.2 Properties of the forecast error processes

Before starting to analyze the results of the empirical model, it is important to undertake some investigations of the forecast errors in order to see (i) if the forecast errors of output and inflation are white noise, and (ii) if the forecast error processes look different depending on whether the economy is doing well or not. As noted in Croushore (2011) and many others, the distinction between real-time and revised data would not be an issue as long as revisions are not large, so it is important to analyze if the same happens with the predictions of the professional forecasters.

Table 1: Estimation of the revision process.

	Output		Inflation	
	linear	non-linear	linear	non-linear
Const.	-0.8260 (0.0455)	-0.6990 (0.0926)	-0.1416 (0.1819)	-0.1587 (0.1802)
AR(1) good	0.8864*** (0.0455)	0.9102*** (0.0542)	0.6267*** (0.0717)	0.7395*** (0.1367)
AR(1) bad		0.8517*** (0.0624)		0.4006*** (0.1367)
AR(2) good	-0.1579* (0.0974)	-0.0628 (0.1191)	0.0998 (0.1120)	0.0826 (0.1471)
AR(2) bad		-0.3109*** (0.1454)		0.1217 (0.1757)
AR(3) good	-0.1415 (0.1270)	-0.0211 (0.1586)	0.2751 (0.1746)	0.0373 (0.2112)
AR(3) bad		-0.3529 (0.1931)		0.2627 (0.3187)
R^2	0.7528	0.7541	0.3818	0.3938

Note: standard errors are in parenthesis. We use the convention that tests that are significant at 10 *percent level only have a * while those that are significant at* 5 *percent are marked by ***.*

Table 1 shows that forecast errors of professional forecasters are predictable. So, they are not rational forecasters. This preliminary investigation suggested an AR(1) process for the baseline model and for the extended model for the forecast error of output and inflation. The results for the output forecast error regression are presented in the first column and the inflation forecast error regression in the second column. It can be seen that the in the linear forecast error output regression we are not considering any difference between bad and good economic times, and in the non-linear model, we allow for a distinction between this two possible economic situations. For this issue, we consider an indicator variable as described above with a threshold $u^T = 6.5$.

Both columns of the non-linear regressions model of output and inflation forecast errors show that the two forecast errors are predictable. In particular, the second column shows that the forecast error output is significantly predicted by its own first lag. A similar result is found for as well as the inflation forecast error. These results reject the null hypothesis that the forecast error of output and inflation are white noise, which means that the forecast errors are predictable and may matter in the analysis of the central banker preference asymmetries. Moreover, Table 1 shows that distinction between good and bad times provides similar conclusions to those reached with the linear forecast error regressions.

3.3 Empirical equation results

We next undertook the estimation of the baseline inflation model (11) and the extended model (17) using OLS. The estimation of the baseline model and extended model are presented in Tables 2 and 3.

OLS regressions do not impose any restrictions on the reduced-form parameters. Nevertheless, it is useful to study the associated estimation results. Thus, all reduced-form parameters are statistically significant. The two unrestricted models show four important conclusions can be drawn from this analysis.

First, the estimate of d_0 $(= \pi^*)$ suggests that the annual inflation target is around 3.8%. Second, the null hypothesis $H_0 : d_3 = 0$ is rejected, which is consistent with the hypothesis that the monetary authority has asymmetric preferences, indicating that the monetary authority takes stronger action when output is below its permanent level than when it is above (i.e. a positive and significant estimate of $d_3 = \frac{\phi\alpha\gamma}{2}$ implies that the asymmetric preference parameter γ is also positive). This finding is in line with the results in Ruge-Murcia (2003a) and Cassou, Scott and Vázquez (2012, 2016). Third, the different estimated values for $1-\lambda^{\pi}$ indicate there is also an asymmetric response to SPF inflation data. Fourth, the implied values of λ^{π} are positive and around 0, which implies that the Fed weighs the SPF inflation much more heavily than revised data.

Table 2: OLS estimation of the baseline model (11).

Coefficient	Variable	Inflation	$\lambda^Y = 1$	$\lambda^{\pi} = 1$
d_1	y_t	-1.0053***	-0.3191*	-0.7751***
		(0.2159)	(0.1622)	(0.2645)
d_2	r_t^Y	3.1616***	1.0212***	3.2166***
		(0.4147)	(0.3183)	(0.5114)
d_3	$(y_t)^2$	0.4349***	0.1852***	0.4440***
		(0.0903)	(0.0388)	(0.1114)
d_4	$(r_t^Y)^2$	2.2404***	-	2.4532***
		(0.3280)	(-)	(0.4035)
d_5	$y_t r_t^Y$	-1.5451***	-	-1.6086***
		(0.3301)	(-)	(0.4070)
$1-\lambda^{\pi}$	r_t^{π}	0.9570***	1.0296***	-
		(0.1014)	(0.1154)	(-)
d_0	Const.	3.8379***	3.8170***	3.7528***
		(0.2402)	(0.2750)	(0.2960)
R^2		0.56	0.41	0.32
F-stat		35.78	30.46	16.52

Obs: 175

Note: standard errors are in parenthesis. We use the convention that tests that are significant at 10% *only have a * while those that are significant at* 5% *are marked by ***.*

Now it is time to analyze the extended model (17) in which we distinguish between good and bad economic times. First, the estimate of $d_0(=\pi^*)$ suggests that the annual inflation target is around 4.2%. As it can be seen in Table 3, the great majority of the estimated parameters obtained are consistent with the ones reported in Table 2. The estimated value for the coefficient involving the asymmetric preference parameter, d_3, in both models, is around 0.4 and in the case of $1 - \lambda^{\pi}$ takes a value nearby 1. This implies that λ^{π} is around 0, so in both models the Fed weighs very heavily the predictions of the professional forecasters.

Table 3: OLS estimation of the extended model (17).

Coefficient	Variable	Inflation	$\lambda^Y = 1$	$\lambda^\pi = 1$
d_1	y_t	-1.2312***	-0.2987*	-1.0695***
		(0.2168)	(0.1575)	(0.2731)
d_2^b	r_t^Y	4.5955***	0.4535	5.1514***
		(0.6739)	(0.3475)	(0.8390)
d_2^g	r_t^Y	3.3705***	1.5800***	3.1182***
		(0.4118)	(0.3450)	(0.5191)
d_3	$(y_t)^2$	0.4412***	0.1178***	0.5116***
		(0.0901)	(0.0425)	(0.1119)
d_4^b	$(r_t^Y)^2$	3.4226***	-	3.8807***
		(0.4658)	(-)	(0.5820)
d_4^g	$(r_t^Y)^2$	1.5398***	-	1.6939***
		(0.3733)	(-)	(0.4701)
d_5^b	$y_t r_t^Y$	-2.0197***	-	-2.2516***
		(0.3557)	(-)	(0.4452)
d_5^g	$y_t r_t^Y$	-1.3873***	-	-1.3059***
		(0.3529)	(-)	(0.4445)
$1-\lambda_b^\pi$	r_t^π	0.8230***	1.0304	-
		(0.1672)	(0.1887)	(-)
$1-\lambda_g^\pi$	r_t^π	1.1082***	1.1707	-
		(0.1294)	(0.1487)	(-)
d_0	Const.	4.2151	3.8507***	4.1042***
		(0.2540)	(0.2675)	(0.3205)
R^2		0.61	0.45	0.37
F-stat		25.75	23.82	12.28

Obs: 175

Note: standard errors are in parenthesis. We use the convention that tests that are *significant at* 10% *only have a * while those that are significant at* 5% *are marked by ***.*

We can conclude that allowing for a distinction between good and bad times does not add anything important.

OLS estimation does not impose any kind of restriction on the reduced-form parameters of the inflation empirical equation. It is important to remark that in the baseline model as well as in the extended model, the coefficient obtained for the output gap has a negative sign, which it does not make sense from a theoretical point of view. A similar argument applies to the estimates of coefficient d_5. These caveats motivate the use of a constraint maximum likelihood (CML) approach were the structural parameters are directly estimated and the theoretical restrictions on these parameters are also imposed. Imposing all the restrictions for (11), we are able to estimate the values of some structural parameters that we were not able to identify under OLS, such as γ. In the OLS analysis, we were able to know the value of d_3, which is a convolution of structural parameters, now thanks to the CML, we can estimate the value of the parameter that reflects the asymmetric preference of the Fed.

Table 4: CML estimation of the baseline model (11).

Parameters	Values
σ_π	1.8353 (0.1302)
d_0, Const.	3.0005 (0.1540)
d_1, y_t	0.2510 (0.0735)
γ	0.9804 (0.2597)
λ^Y	0.0000 (.)
λ^π	0.0000 (.)

Note: the standard errors are in parenthesis.

One of the problems that we had with the OLS was the negative sign of the estimated value of the output gap. With the CML, the estimated value for the output gap is 0.2510. So by imposing the restriction on the parameters, we can obtain an identification of all structural parameters, which is not possible under the OLS estimation. By looking to the rest of parameters, we see that the value of λ^Y and λ^π is 0, so for both, for output and inflation the Fed entirely considers the SPF forecast, which is consistent with the results obtained in the OLS analysis.

In the case of the CML for (17), all the results obtained are very similar to the ones obtained for the baseline model (11). Indeed, the main difference is the value of λ_b^π is not 0, but is quite near to 0, so even that we do not obtain the same results, are quite similar. This means that the extended model built to distinguish between good and bad times does not provide any additional insight.

Table 5: CML estimation of the extended model (17).

Parameters	Values
σ_π	1.8333 (0.1518)
d_0, Cons.	2.9891 (0.1597)
d_1, y_t	0.2549 (0.0752)
γ	0.9552 (0.2639)
λ_g^Y	0.0000 (.)
λ_b^Y	0.0000 (.)
λ_g^π	0.0000 (.)
λ_b^π	0.1166 (0.3154)

Note: the standard errors are in parenthesis.

4 Conclusions

In this paper, we have shown that the Fed follows very closely the predictions of the professional forecasters. We study a variant of the Cassou, Scott and Vázquez (2016) model where the policymaker takes into acount the predictions of the professional forecasters in order to define her output and inflation targets instead of real-time data used in their paper. Following, by assuming that the central banker targets a weighted average of both revised and SPF data as in Cassou, Scott and Vázquez (2016).

We interpret this empirical finding as the result of the Federal Open Market Committee (FOMC) following a forward guidance approach to monetary policy. The forward guidance is a tool used by a central bank to exercise its power to monitor monetary policy by shaping with their own announcements, market expectations of future levels of interest rates. So, the FOMC make announcements related to the monetary policy and professional forecasters will follow closely these announcements when making their predictions.

The empirical inflation model is estimated using two alternative approaches: ordinary least square estimation and constraint maximum likelihood estimation. Our empirical results of our baseline model show consistent results for the two estimation approaches. More precisely, there are only a few small differences between the estimated coefficients obtained from the two estimation procedures. The most remarkable is that a pair of theoretical counterintuitive reduced-form estimated coefficients under OLS are overcomed by carrying out a CML estimation, which imposes a correct set of theoretical restrictions on the structural parameters. OLS analysis are corrected by imposing all the restrictions in the baseline model. If we consider the extended model allowing for different weights in the targets depending on whether the economy is doing good or bad, the results from the OLS and CML approaches are also consistent.

Our empirical results in the baseline and the extended model show evidence that the Fed focuses only on the SPF data. Moreover, the empirical results show that the extended model built to distinguish between good and bad times does not provide any important insight. This finding is in contrast with the results found in Cassou, Scott and Vázquez (2016) using real-time instead of the predictions of professional forecasters used in this paper.

More generally, this paper shows evidence that optimal decisions made by arguably well-informed agents, such as the Fed, are likely to be consistent with the professional forecaster predictions even though these are not rational (i.e. they are somewhat predictable).

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