FORECASTING INFLATION RATE: PROFESSIONAL AGAINST ACADEMIC, WHICH ONE IS MORE ACCURATE

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Abstract

This paper evaluates the professional forecasts, those made by financial and non-financial forecasters and the aggregate between them, by comparing their results to academic forecasts. The US quarterly inflation rate and the professional forecasts are considered for the period of 1981 third quarter to 2012 final quarter. This paper examines whether academic forecasts outperforms the professional forecasts.

For short term inflation forecasting the professional forecasters (non-financial, financial and the aggregate) proved to be the most accurate, however for long term inflation forecasting academic forecasts showed to be most accurate. The results also indicate that the long term aggregate forecasts related to information from the aggregate short term forecasts and current inflation rate. Furthermore, financial forecasters use the short term non-financial forecasts in their expectations and the non-financial forecasters use the short term financial forecasts in their long term expectations.

In addition, the results confirm causality between the short and long term forecasts of the non-financial forecasters. For the financial inflation forecasts, there is no causality between the short and long term financial forecasts.

Keywords: Forecasting inflation rate; professional forecast; causality

1. Introduction

Inflation is defined as a sustained increase in the general level of prices for goods and services. It is measured as an annual or quarterly percentage increase. Inflation is a sign that an economy is growing. In some situations, little inflation (or even deflation) can be just as bad as high inflation. The lack of inflation may be an indication that the economy is weakening. The inflation rate can be used as an important indicator for strength of economies, therefore forecasting inflation has always been important.

The purpose of the present paper is to provide a simple model, which explains how households form their inflation expectation. The model is based on a number of crucial recent empirical findings. There has been a heighten interests in how non-experts form their inflation expectations. This stems from two recent innovative developments in the literature that are distinct but related: i. rational inattentive behavior or sticky-information expectations and, ii. anchoring behavior of inflation expectations.

Reis (2006a and 2006b) argue that rationally inattentive agents update their information set sporadically. Subsequently, the slow diffusion of information among the population is due to the costs of acquiring information as well as the costs of re-optimization, resulting in the 'sticky-information expectations'. Distinguishing between experts and non-experts expectations, Carroll (2003 and 2006) put forward a specific form of 'sticky information' expectations that best explains how households form their expectations about the macro economy. 'Epidemiological expectations' argues that households form their expectations by observing the professionals' forecasts which are reported in the news media. They, however, observe the professionals' forecasts imperfectly by 'absorbing' over time and, eventually, the professional forecasts are transmitted throughout the entire population. The epidemiological model of expectations formation is analogous to observational or social learning (as described in Bikhchandani et al (1998)).

The 'anchoring' behavior of agents' inflation expectations is assessed in relation to monetary policy-making (see for example, Levin et al, 2004, Kelly, 2008, Blanchflower and Mac Coille, 2009, and references therein). This literature considers the issue of monetary policy credibility; specifically inflation targeting and the dynamics of the unobserved fundamental inflation rate. While definitions may vary, here we refer to Bernanke (2007) who provides an intuitive definition for anchored inflation expectations: if the public experiences a spell of inflation higher than their long-run expectation, but their long-run expectations of inflation changes little as result, inflation expectations can be considered to be anchored. This definition can be applied to expectations anchoring to inflation target set by the monetary authority in the long-run. Beechy et al (2011) specifically focuses on the anchoring behavior of experts' (or professionals') inflation expectations, while Easaw et al (2010), combines both strands of literature, analyzing the anchoring behavior of households set within the sticky-information expectations framework. Beechy et al (2011) find that credible monetary policy, especially explicit inflation targets, ensure that professional inflation forecasts and Easaw et al (2010) find that households inflation expectations are firmly 'anchored' on professional forecasts.

The paper presents a simple model explaining the dynamics of households expectations, in particular, how the household over-reacts in the short-run as they update their expectations. In the model we outline, household's inflation expectations are firmly anchored on the professional's forecast and current inflation rates. The professional inflation forecast is analogous to the expected change of the fundamental rate of inflation and the household uses it as a proxy for the unobserved fundamental rate of inflation.

2. Univariate SSA Forecasting

In the first part the univariate SSA forecasts is compared with aggregate, financial and non-financial forecasts.

2.1 Singular Spectrum Analysis

Singular Spectrum Analysis (SSA) is a non-parametric time series modelling and forecasting technique (Golyandina et al., 2001). Singular Spectrum Analysis (SSA) has proven to be a successful method to decompose and reconstruct time series, without noise. These reconstructed series are used for more accurate forecasting than e.g. the ARIMA or Holt-Winters forecasting models. The SSA method has been widely used in multiple research disciplines, including image processing, earth science, finance and economics, (Rodriguez-Aragon et al, 2010; Vautard et al, 1992; Golyandina et al, 2010; Hassani et al, 2009). A further introduction to the subject is given by Elsner and Tsonis (1996). SSA has proven to be effective forecasting with complex seasonal patterns and non-stationary trend(Sanei and Hassani, 2015). Forecasting based on time series without seasonality, e.g. stock markets or the inflation rate, is less predictive due to the chaotic/non-seasonal nature of the time series.

Short introduction of Univariate SSA

Let us now formally describe the algorithm for the SSA forecasting method. The SSA forecasting algorithm, as proposed in Golyandina *et al.* (2001), is as follows:

1. Consider a time series $Y_T = (y_1, \ldots., y_t)$ with length T.

2. Fix the window length L.

3. Consider the linear space $\mathfrak{L}_r \subset \mathbf{R}^L$ of dimension $r < L$. It is assumed that $e_L \notin \mathfrak{L}_r$, where $e_L = (0,0, \ldots.,1) \in \mathbf{R}^L$.

4. Construct the trajectory matrix $\mathbf{X} = [X_1, \ldots., X_K]$ of the time series Y_T .

5. Construct the vectors $U_i = (i = 1, \ldots., r)$ from the SVD of $\mathbf{X}$. Note that U_i is an orthonormal basis in $\mathfrak{L}_r$.

6. Orthogonal projection step: compute matrix $\hat{X} = [\widehat{X_1}: \dots.: \widehat{X_K}] = \sum_{i=1}^{r} U_i\, U_i' \mathbf{X}$. The vector $\widehat{X_i}$ is the orthogonal projection of X_i onto the space $\mathfrak{L}_r$.

7. Hankellization step: construct the matrix $\tilde{X} = \text{Ƕ}\hat{X} = [\widetilde{X_1}: \dots.: \widetilde{X_K}]$

8. Set $v^2 = \pi_1^2 + \cdots + \pi_r^2$, where π_i is the last component of the vector $U_i = (i = 1, \dots., r)$. Moreover, assume that $e_L \notin \mathfrak{L}_r$. This implies that $\mathfrak{L}_r$ is not a vertical space. Therefore, $v^2 < 1$.

9. Determine vector $A = (\propto_1, \dots., \propto_{L-1})$:

$$A = \frac{1}{1 - v^2} \sum_{i=1}^{r} \pi_i\, U_i^{\nabla}$$

where $U^{\nabla} \in \mathbf{R}^{L-1}$ is the vector consisting of the first $L - 1$ components of the vector $U \in \mathbf{R}^L$. It can be proved that the last component y_L of any vector $Y = (y_1, \dots., y_L)^T \in \mathfrak{L}_r$ is a linear combination of the first y_{L-1} components, i.e.

$$y_L = \propto_1 y_{L-1} + \cdots + \propto_{L-1} y_1$$

Moreover, this does not depend on the choice of a basis $U_1, \dots., U_r$ in the linear space $\mathfrak{L}_r$.

10. Define the time series $Y_{N+h} = (y_1, \dots., y_{N+h})$ by the formula

$$y_i = \begin{cases} \tilde{y}_i & \text{for } i = 1, \dots, T \\ \sum_{j=1}^{L-1} \propto_j y_{i-j} & \text{for } i = T + 1, \dots, T + h \end{cases}$$

where $\tilde{y}_i = (i = 1, \dots., T)$ are the reconstructed series. Then, $y_{T+1}, \dots., y_{T+h}$ are the h-step-ahead recurrent forecasts.

The advantage of Singular Spectrum Analysis as forecasting method is that it works well with small samples and processing time is minimal. Having historical available information, SSA may produce forecasts at least as good as the forecasts made by professional forecasters. SSA combines filtering techniques with forecasting (Hassani, 2007); and, assumptions of classical methods (e.g. normality) are not needed (Hassani et al., 2013b).

For all forecasts the data up to 2004 is used to model SSA and forecasts for the last 8 years (from 2005 until 2012, 32 observations) used to measure forecast accuracy. Two different forecast horizons have been made for the inflation rate, namely 1 year ahead (short-term) and 10 year ahead (long-term).

In addition, the three methods 1.) ARIMA 2.) Holt-Winters 3.) Random Walk forecasting methods have been used as a benchmark to test the accuracy.

3. Empirical Results

3.1 Data

Inflation rate forecasting using actual inflation and professional forecasts received from reference (year), which includes and is based on the US 'CPI' inflation rate 1981 Q3 to 2012 Q4. Being able to forecast 1 year ahead (short term) it is only possible to use e.g. Q1 and all before to forecast Q1 of next year. In this paper that would be the case from 1981 Q3 up to 2004 Q1 to forecast 2005 Q1 and shifting 1 quarter forward for each new forecast. This is 1 year (4 step) ahead forecasting and in testing the data it has been performed for the last 32 points from the forecast of 2005 Q1 until 2012 Q4. In the same manner 10 year ahead forecasting (long term) has been done, however to forecast the same last 8 years, 2005 – 2012, only data from 1995 Q1 to forecast 2005 Q1 are used.

3.2 Results

To assess which forecasting method, academic or professional is more accurate, the results are compared with the actual inflation. The RMSE criterion is used, based on the last 30 observation, to assess the accuracy.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{y}_t - y_t)^2}$$

The lowest RMSE represents the method that has forecasted the inflation for last 8 years in the time series most accurately.

Short term and long term inflation forecasting

The short term forecasting of inflation has been done in several ways. The aggregate is a combination of the financial and non-financial forecasts, which are respectively the second and third forecast to which we compare 4 other methods; Singular Spectrum Analysis (SSA), Random Walk, ARIMA and Holt Winters. In Table 1 below the correlation between the forecasts and the actual inflation are shown and the results of forecasting accuracy of all the methods using RMSE are shown. Firstly, the correlation has been tested to see the interdependence of inflation and the forecasting methods. As can be seen the highest correlation is between the inflation and the aggregate forecasts, and, the highest negative inflation is between the actual inflation and the SSA forecasts. The correlation is just an indicator as expectation of how well a method should perform as it proves the interdependence, therefore it is important to measure the accuracy. In this case the lowest Root Mean Squared Error has been provided by the non-financial forecasts and closely followed by the aggregate forecasts. The Holt Winters (HW) method proves that it is not capable of outperforming even the naive Random Walk (RW) forecasts, and the ARIMA forecasts barely outperform the RW forecasts. SSA is doing well, however the financial, non-financial and the aggregate between them prove to be the most accurate forecasting methods in this case.

Table 1: Root Mean Squared Errors (RMSE) for all Short term forecasts

Short term 1 year ahead forecast (2005-2012)		
	Correlation	RMSE
CPI1_mean aggregate	0.613	1.476
CPI1_mean1 financial	0.597	1.542
CPI1_mean2 non-financial	0.582	1.467
SSA	-0.497	1.705
Random Walk	-0.262	2.561
ARIMA	-0.374	2.473
Holt Winters	-0.233	3.240

The long term forecasting of inflation has been done in similar ways. In Table 2 below the correlation between the long term forecasts and the actual inflation are shown and the results of forecasting accuracy of all the methods using RMSE are shown. Also the correlation has been tested to see the interdependence of inflation and the long term forecasting methods. As can be seen the results differ from the short term forecasts, the highest correlation is still between the inflation and the aggregate forecasts, however the highest negative inflation is between the actual inflation and the Holt Winters forecasts. SSA in this case has a higher correlation with inflation than the non-financial forecasts. Again the lowest Root Mean Squared Error has been produced by the SSA forecasts and then followed by the aggregate, financial and non-financial forecasts. The Holt Winters (HW) method and ARIMA do not perform well to forecast the inflation rate on the long term and even the simple naive Random Walk (RW) producing better forecasts.

Table 2: Root Mean Squared Errors (RMSE) for all Long term forecasts

Long term 10 year ahead forecast (2005-2012)		
	Correlation	RMSE
CPI10_mean aggregate	0.415	1.579
CPI10_mean1 financial	0.409	1.581
CPI10_mean2 non-financial	0.281	1.587
SSA	0.385	1.492
Random Walk	-0.101	1.817
ARIMA	-0.192	3.714
Holt Winters	-0.346	5.953

4. Multivariate SSA

Multivariate (or multichannel) SSA is an extension of the standard SSA to the case of multivariate time series. The use of MSSA for multivariate time series was proposed theoretically in the context of nonlinear dynamics in Broomhead and King (1986a), and examples of successful application of MSSA are given in Hassani et al. (2009b) and Patterson *et al.* (2010). MSSA here is applied as explained in Hassani et al. (2013a).

Assume that we have an M-variate time series $(y_j^{(1)}, \dots, y_j^{(M)})$, where $j = 1, \dots, T$ and let L be window length. Similar to univariate version, we can define the trajectory matrices $\mathbf{X}^{(i)} (i = 1, \dots, M)$ of the one-dimensional time series $\left\{y_j^{(i)}\right\} (i = 1, \dots, M)$. The trajectory matrix $\mathbf{X}$ can then be defined as $\mathbf{X} = (\mathbf{X}^{(1)}, \dots, \mathbf{X}^{M})'$. Now; it is straightforward to expand the univariate approach of SSA to the multivariate domain. The other stages of MSSA are similar to the stages of the univariate SSA; the main difference is in the structure of the trajectory matrix $\mathbf{X}$ and its approximation; these matrices are now block-Hankel rather than simply Hankel (for more information see Sanei and Hassani, 2015).

Long-Horizon (Fundamental Rate of Inflation) and Short-Horizon (Actual Inflation) Inflation Expectations: Theoretical Issues

We assume that professional forecasters use long-horizon forecasts to forecasts the underlying fundamental inflation rate (π_t^f). This rate is equivalent to the long-run inflation target set by monetary authorities is the target is credible and, therefore, inflation expectations is anchored. Agents use short-horizon forecasts to forecasts actual inflation rate (π_t), which deviates from this fundamental rate due to a transitory shock (ε_t) as follows:

$$\pi_t = \pi_t^f + \varepsilon_t$$

Hence, the actual rate of inflation comprises of two components: a transitory and more permanent component. The fundamental inflation rate also changes due to any permanent innovation (η_t):

$$\pi_t^f = \pi_{t-1}^f + \eta_t$$

We are now able to consider inflation expectations: agent's long-horizon forecasts in *t* for *t+10* the agent his forecasts as follows:

$$E_t\,(\pi_{t+10}^f) = E_{t-1}(\pi_{t+9}^f) + E_t\,(\eta_{t+1})$$

where $E_t\,(\eta_{t+1})$ denotes the agents forecast permanent innovation. Hence, the agent effectively updates his inflation expectations if he expects a permanent innovation to the fundamental rate of inflation in the next period. Equation (3) is also assumed to be optimal, Full-Information Rational Expectations (FIRE):

$$E_t^*(\pi_{t+10}^f) = E_t^{FIRE}(\pi_{t+10}^f) = E_t\,(\pi_{t+10}^f) = E_{t-1}(\pi_{t+9}^f) + E_t\,(\eta_{t+1})$$

At this point we can introduce inattentiveness. We assume that agents do not observe information perfectly and, therefore, unable to update their expected permanent innovation instantly:

$$E_t\,(\pi_{t+10}^f) = (1-\lambda)E_t^{FIRE}(\pi_{t+10}^f) + \lambda E_{t-1}(\pi_{t+9}^f)$$

where $E_t^*(\pi_{t+10}^f) = E_t^{FIRE}(\pi_{t+10}^f) = \pi_{t+10} + \varepsilon_t$ and from this we are able to derive:

$$\pi_{t+10} - E_t\,(\pi_{t+10}^f) = \frac{\lambda}{1-\lambda}\Delta E_t\,(\pi_{t+10}^f) + \varepsilon_t$$

where $\Delta E_t\,(\pi_{t+10}^f) = [E_t\,(\pi_{t+10}^f) - E_{t-1}(\pi_{t+9}^f)]$.

Following Gefang *et al* (2011) question is whether short-horizon forecasts, i.e. the forecasts of actual inflation, may also determine long-horizon forecasts, especially if the latter is not anchored and this also can be derived:

$$\pi_{t+10} - E_t\,(\pi_{t+10}^f) = \frac{\lambda}{1-\lambda}\Delta E_t\,(\pi_{t+10}^f) + \frac{\lambda}{1-\lambda}\phi[E_{t-1}(\pi_{t+9}^f) - E_{t-1}(\pi_t\,) + \varepsilon_t\,]$$

Now there is an additional term which the difference the long-horizon and short-horizon forecasts made in *t-1*. This would now incorporate the position from where we started.

There are several theories about the professional forecasters and there attentiveness to data releases or macroeconomic news. Clements (2012) researched the attentiveness of agents to data releases and concluded that due to negative correlations between discrepancies and revisions, inattentiveness to data releases could be the explanation. According to the 'sticky information' model (SIM) by Mankiw and Reis (2002), professional forecasters do not always update their estimates, because this is a too time consuming and cost intensive activity of collecting and processing. The rational expectations hypothesis (REH) implies that the agents update their expectations continuously. According to Mankiw et al. (2003) the REH assumes too much of agents as it is impossible to update expectations as it turns outdated the second afterwards. Noisy information models are again an alternative to the SIM and the REH. The noisy information models state that forecasters only ever observe the true state of the economy with error (Clement, 2012; Mackowiak et al, 2009; Sims, 2003; Woodford, 2001). The main point here is that it is difficult to continuously update inflation expectations due to errors or time and money restraints, and, that the forecast becomes outdated the second after making it. This shows that it would be helpful to have an accurate forecasting method which can use historical data by itself to forecast accurately.

Causality criteria based on forecasting accuracy

A question that frequently arises in time series analysis is whether one economic variable can help in predicting another economic variable. One way to address this question was proposed by Granger (1969), in which he formalized the causality concept. The first criterion we use here is based on out-of-sample forecasting, which is very common in the framework of Granger causality. Here, we compare the forecast values obtained by the univariate procedure, SSA and MSSA. If the forecasting errors using MSSA are significantly smaller than those of univariate SSA, we can conclude that there is a causal relationship between these series (for more information about SSA causality based approach, see Sanei and Hassani, 2015, Huang et al., 2017).

In Table 3 below the RMSE results for the short and long term SSA and MSSA test are shown. The time series 1 is the basis for the Univariate forecast and together with time series 2 the basis for the Multivariate forecast. By performing MSSA there are two possible results, it must be noted that only the most accurate one is shown in Table 3. The horizon h shows to which horizon the forecast was made, 1 year ahead (4 steps) or 10 year ahead (40 steps) to measure both short and long term performance and causality.

Table 3: SSA and MSSA test RMSE results to measure causality

			RMSE	
timeseries 1	timeseries 2	h	Univariate SSA	Multivariate SSA
Long term Aggregate	Actual	1 year	0.115	0.449
		10 year	0.872	0.864*+
	Short term aggregate	1 year	0.115	0.548
		10 year	0.872	0.704*+
Long term Financial	Short term non-financial	1 year	0.152	0.143*
		10 year	0.640	0.735
	Long term non-financial	1 year	0.152	0.263
		10 year	0.640	0.839
Long term Non-Financial	Short term financial	1 year	0.140	0.178
		10 year	0.978	0.880*+
	Long term financial	1 year	0.140	0.355
		10 year	0.978	0.914

*Where there is believed to be causality due to the smaller RMSE for the MSSA than the Univariate SSA result.

+The causality has been tested statistically significant using the Diebold Mariano test statistic (1995) with the corrections that were suggested by Harvey *et al.* (1997). The quality of a forecast is to be judged on some specified function $g(e)$ as a loss function of the forecast error e. Then, the null hypothesis of equality of expected forecast performances is $E(d_t) = 0$, where $d_t = g(e_{\mathrm{SSA}}) - g(e_{\mathrm{O}})$. e_{SSA} and e_{O} are the forecast errors that are obtained with SSA and the other methods respectively. In our case, g is the quadratic loss function. The Diebold and Mariano statistic S for h-step-ahead forecasts and the n forecasted points is given by

$$S = \sqrt[\bar{d}]{\left\{\frac{n+1-2h+h(h-1)/n}{n\widehat{\mathrm{var}}(\bar{d})}\right\}}$$

where $\bar{d}$ is the sample mean of the d_t-series, $\widehat{\mathrm{var}}(\bar{d})$ is, asymptotically, $n^{-1}(\hat{\gamma}_0 + 2\sum_{k=1}^{h-1}\hat{\gamma}_k)$ and $\hat{\gamma}_k$ is the kth autocovariance of d_t. $\hat{\gamma}_k$ can be estimated by

$$n^{-1}\sum_{t=k+1}^{n}(d_t - \bar{d})(d_{t-k} - \bar{d}).$$

The S-statistic follows the asymptotic standard normal distribution under the null hypothesis and its correction for finite samples follows the Student t-distribution with n−1 degrees of freedom. We consider the above test at 1% and 10% confidence levels.

The results show that the long-term aggregate forecasts (financial and non-financial combined) have a causal relationship with the actual inflation and the short term aggregate for long term forecasting. For short term forecasting the results show that there is no causal relationship between the long term aggregate neither with the actual inflation nor with the short term aggregate.

Secondly, the results also show that the long-term financial forecasts have a causal relation with the short-term non-financial forecasts. This proves that the financial forecasters use the non-financial forecasters' short-term forecasts in their own long-term expectations, however it has to be noted that the result is not significant according to the Diebold Mariano test. Interestingly, the long-term forecasts of the non-financial forecasters show a significant causal relation with the long-term financial forecasts. This shows that the non-financial forecasters' look at the long-term expectations of the financial forecasters' and consider this in their own expectations. There were no further causal relationships between the aggregate, financial and non-financial forecasts.

The next section is testing if financial and non-financial forecasters incorporate their own long term forecasts in their short term forecasts. Again by using MSSA and comparing the outcome with the univariate SSA outcome to see whether or not there exists a causal relationship between the short and long term expectations of both the financial and the non-financial forecasters.

Table 4: Causality tests results.

Univariate SSA	Multivariate SSA	Univariate SSA	Multivariate SSA
Short term financial	With Actuals **	9.9511	9.7669
Short term non-financial	With Actuals **	9.7163	9.6056*
Short term Aggregate	With Actuals **	9.6599	9.6777
Long term financial	With Actuals	9.3924	9.5467
Long term non-financial	With Actuals	9.2856	9.4213
Long term Aggregate	With Actuals	9.2874	9.5237
Long term financial	With short term financial *	9.3924	9.3661*
Long term non-financial	With short term non-financial *	9.2856	9.1199*
Aggregate	With short term aggregate *	9.2874	9.2321*
Short term financial	With short term non-financial **	9.9511	9.4929*
Short term non-financial	With short term financial **	9.7163	9.4929*
Long term financial	With long term non-financial	9.3924	9.0872*
Long term non-financial	With long term financial	9.2856	9.0872*

*Where there is believed to be causality due to the smaller RMSE for the MSSA than the Univariate SSA result. ** expect to have causality.

Table 5: Causality between short term and long term forecasts

	Univariate SSA	Multivariate SSA
Financial forecasts	9.770588	9.951134
Non-financial forecasts	9.716331	9.32209*+

*Where there is believed to be causality due to the smaller RMSE for the MSSA than the Univariate SSA result. +The causality has been tested statistically significant using the Diebold Mariano test statistic (1995) with the corrections that were suggested by Harvey *et al.* (1997).

The MSSA outcomes show causality between the short and long term forecasts of the non-financial forecasters. For the financial inflation forecasts, there is no causality between the short and long term financial forecasts as the multivariate forecasts underperformed the univariate forecasts. The non-financial forecasters do use their long term expectations in their short term expectations as the multivariate forecasts outperformed the univariate forecasts.

Are the financial and the non-financial forecasts related?

In this section of the paper, the short term forecasts from the financial sector and the non-financial sector are tested using univariate SSA and multivariate SSA in order to show whether one uses information of the other in their forecasting. If the forecasting errors using MSSA are significantly smaller than those of univariate SSA, we can conclude that there is a causal relationship between these series. However, before that we first look at the correlation between the forecasts for each method with the actual inflation. The financial and non-financial have higher correlation with each other than the univariate SSA of each of them and the multivariate SSA (MSSA) even has a lower correlation. It should be noted that there are some other statistical measures that can be used here; however, the correlation is used to measure the association.

Table 6: Correlation

	Correlation between financial and non-financial	Correlation Univariate SSA	Correlation MSSA
Short term financial	0.854	0.748	0.594
Short term non-financial	0.854	0.493	0.292

Table 7: RMSE of the short term forecasts to measure causality

	Univariate SSA	Multivariate SSA
Short term financial	0.302	0.313
Short term non-financial	0.351	0.352

As can be seen form Table 7 above, the multivariate SSA is less accurate than the univariate SSA for the financial forecasts and for the non-financial it is the same. Therefore it can be concluded that for short-term the financial forecasts do not have a causal relationship with the non-financial forecasts.

Granger causality

Using a granger causality test to show causality between the short and long term forecasts of the non-financial forecasters with 99% confidence levels, proves that the non-financial forecasters use the long term forecasts in their short term expectation. In contrast with the MSSA outcomes, the financial forecasters also seem to use the long term forecasts in their short term expectation using the granger causality test at a 95% significance level. The results can be seen in Table 8 below:

Table 8: Granger causality test result for long term and short term inflation forecasting.

Test	Granger value	Significance
Long term to short term financial	4.1553*	0.01928
Short term to long term financial	0.3649	0.6954
Long term to short term non-financial	5.077**	0.008458
Short term to long term non-financial	2.0214	0.1394

* significant at 95%
** significant at 99%

Furthermore, the results show that neither the non-financial nor the financial forecasters use the short term forecasts in their long-term expectations.

Noise or News

Finally in this section we test to see whether the short and long term forecasts are efficient forecasts and can be viewed as 'news' or 'noise'. To do this, we check if the difference between the actual inflation and short/long forecasts are orthogonal to the actual inflation or to the inflation forecasts. We do this by obtaining the correlation between these series and also testing the joint significance of the parameters of bivariate regressions of the differences on the actual or long/short inflation forecasts. The results in Table 9 and 10 show that the Differences are mainly orthogonal to long/short inflation forecasts, indicating towards the efficient forecast hypothesis. See Patterson and Heravi (1992) and Patterson et al. (2011) for more details of these tests in the context of data revision.

Table 9: Correlation between differences (D1) and the actual or short/long term forecasts

	Short	Long	Actual
D1 aggregate	0.59318**	0.14665	-
D1 financial	0.763813**	0.353221**	-
D1 non-financial	0.508709**	0.06378	-
D2 aggregate	-	-0.17154	0.919945**
D2 financial	-	-0.17502	0.92211**
D2 non-financial	-	-0.17795	0.918715**
D3 aggregate	-0.09016	-	0.873422*
D3 financial	-0.20975	-	0.830539*
D3 non-financial	-0.05722	-	0.885605

** significant at a 99% confidence level, *significant at a 95% confidence level

Table 10: Testing the significance of regression parameters between differences (D1) and the actual or short/long term forecasts. * shows any significant results for the joint test.

Regression	b0	b1	F Joint test
D1 agg > short term aggregate	-0.94	0.281	45.06*
D1 agg > long term aggregate	-0.469	0.085	1.82
D1 fin > short term financial	-1.24	0.397	116.24*
D1 fin > long term financial	-1.01	0.266	11.83*
D1 nonfin > short term non-financial	-0.802	0.231	28.98*
D1 nonfin > long term non-financial	-0.297	0.034	0.34
D2 agg > actual	-2.514	0.909	457.01*
D2 agg > long term aggregate	0.959	-0.426	2.52
D2 fin > actual	-2.446	0.914	471.39*
D2 fin > long term financial	1.046	-0.441	2.62
D2 nonfin > actual	-2.572	0.91	449.18*
D2 nonfin > long term non-financial	0.963	-0.439	2.71
D3 agg > actual	-2.007	0.801	267.01*
D3 agg > short term aggregate	0.449	-0.169	0.68
D3 fin > actual	-1.829	0.789	184.57*
D3 fin > short term financial	0.998	-0.350	3.82
D3 nonfin > actual	-2.112	0.808	301.79*
D3 nonfin > short term non-financial	0.228	-0.112	0.27

5. Discussion

This paper presented that at least for the data was used in this study, the aggregate of financial and non-financial forecasts are most accurate for short term inflation forecasting, and for long term forecasting the SSA method is a more accurate forecasting technique compared to the other methods used. It needs to be noted that SSA was applied in the most basic form in this paper and all other academic methods were applied in the most optimal version.

MSSA uses a combination of historical information, based on the actual inflation rate and the aggregate, financial or non-financial forecasts. Normally MSSA is used to forecast a certain time series more accurate using more information. However, in this paper we are using MSSA to look at a causal relationship between two time series. In the case of the inflation forecasting, it shows that the long term aggregate forecasts (financial and non-financial combined) have a causal relationship with the actual inflation and the short term aggregate for long term forecasting. For short term forecasting this is not the case. The results also show that the long term financial forecasts have a causal relation with the short term non-financial forecasts. This proves that the financial forecasters use the non-financial forecasters' short term forecasts in their own long term expectations. Interestingly, the long term forecasts of the non-financial forecasters show a causal relation with the long term financial forecasts. This shows that the non-financial forecasters' look at the long term expectations of the financial forecasters' and take this into account in their own expectations. There were no further causal relationships between the aggregate, financial and non-financial forecasts.

Why has SSA not been used very often in economics and finance, even though the method has proven to be accurate and of good use in natural sciences and dynamical systems analyses? Hassani et al. (2013b) speculates that there are four main reasons behind this: First, tradition is a possible cause since SSA is not the common used method. Second, In SSA, there are many options for an automatic choice of parameters but it may lead to serious mistakes. SSA builds models and then uses them on the same data. If the computations are performed without proper testing of the adequacy of the models built then the conclusions may be very wrong. In analyzing complex time series (which is the case with many financial time series) SSA must be used with great care, which requires serious work by the statisticians performing SSA. Third, SSA is too flexible and is difficult to formalize. Four, SSA demands more computing power than the traditional methods and requires specialized application software, which is not always available. However, computing power has improved recently with the result that SSA is becoming more popular (Hassani et al., 2015, Silva and Hassani, 2015, Ghodsi et al., 2017).

6. Conclusions

In this paper, it is demonstrated that for forecasting the US Inflation rate the short term forecasting was most accurately produced by the non-financial forecasts and closely followed by the aggregate forecasts. Univariate SSA is performing well compared to ARIMA, the Holt Winters (HW) method and Random Walk (RW). HW proves that it is not capable of outperforming even the naive forecasts RW, and the ARIMA forecasts barely outperform the RW forecasts. However, the financial, non-financial and the aggregate between them prove to be the most accurate forecasting methods for short term (1 year ahead) inflation forecasting over a period of 8 years from 2005 Q1 until 2012 Q4. The SSA method proves to be almost as good as the forecasts made by professional (financial and non-financial) forecasters, so it is worth to use the SSA method since the costs and time involved are less.

For long term (10 year ahead) forecasting, it is demonstrated that Univariate SSA forecasts the US Inflation rate most accurately and is followed by the aggregate, financial and non-financial forecasts over a period of 8 years from 2005 Q1 until 2012 Q4. The Holt Winters (HW) method and ARIMA prove they have more difficulty to forecast the inflation rate on the long term as even the naive Random Walk (RW) forecasts are performing better. Therefore, it can be concluded that for forecasting with long horizon the univariate SSA forecasting technique outperformed the other methods .

MSSA can be used, based on accuracy RMSE of the forecasts, if one time series uses information of another time series in their expectations. The results show that aggregate forecasts have a causal relationship with the actual inflation and the short term aggregate. For short term forecasting there is no causal relationship. Furthermore, the long-term financial forecasts have a causal relation with the short-term non-financial forecasts. This proves that the financial forecasters use the non-financial forecasters' short-term forecasts in their own long-term expectations. Interestingly, the long-term forecasts of the non-financial forecasters show a causal relation with the long-term financial forecasts. This shows that the non-financial forecasters look at the long-term expectations of the financial forecasters and consider this in their own expectations. There were no further causal relationships between the aggregate, financial and non-financial forecasts. The MSSA outcomes were used to show whether financial and non-financial forecasters incorporate their own long term forecasts in their short term forecasts by testing for causality. For the financial inflation forecasts, there is no causality between the short and long term financial forecasts. However, the non-financial inflation forecasters do use their long term expectations in their short term expectations.

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