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Citation

Non-Fundamental Expectations and Economic Fluctuations: Evidence from Professional Forecasts

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Abstract:
It is theoretically possible that non-fundamental idiosyncratic shocks to agents' rational expectations are a source of economic fluctuations. Studies using data on consumer and investor sentiment suggest that this is indeed a significant source of fluctuations. We present the results of a study that uses forecasts from professional forecasters to extract non-fundamental shocks to expectations. In contrast to previous studies, we show that non-fundamental expectations are not a significant source of output fluctuations.

1. Introduction

It is theoretically possible for non-fundamental idiosyncratic shocks to rational expectations to be a source of economic fluctuations. Such a view can be justified by dynamic models that generate multiple equilibria, e.g., Azariadis (1981), Cass and Shell (1983), Benhabib and Farmer (1994), and Farmer and Guo (1994). Under equilibrium indeterminacy, these "sunspot" shocks can affect the economy through endogenous forecast errors. If the resultant "animal spirit" fluctuations are empirically important, then there are implications for macroeconomic policy, forecasting and perhaps forecast evaluation. For instance, Carlstrom and Fuerst (2001a, 2001b) argue for monetary policy to be designed in a way that does not generate welfare-reducing sunspot fluctuations (see also Levin, Wieland and Williams, 2001). Macroeconomic forecasting models would need to focus more on capturing the driving force behind seemingly inexplicable shifts in expectations and its effects on the macroeconomy (Fuhrer, 1993; Throop, 1992; Carroll, Fuhrer and Wilcox, 1994).

One way to empirically verify the importance (or otherwise) of non-fundamental sources of economic fluctuations is to calibrate to data a structural model that allows for sunspots, and examine whether the model supports this possibility (e.g., Hamilton and Whiteman, 1985; Farmer and Guo, 1994; Lubik and Schorfheide, 2002). An alternative approach is to directly measure the importance of the non-fundamental component of expectations in business cycle fluctuations, without specifying the exact mechanism through which it affects the economy. This approach identifies shocks to an expectations variable that are orthogonal to a set of fundamental variables as sunspot shocks, and then evaluates the importance of these particular shocks as a source of economic fluctuations. For example, Oh and Waldman (1990) use revisions to the initial release of the U.S. Leading Index as expectational shocks and find that these shocks constitute 20% of the fluctuations in quarterly growth rates of industrial production; Matsusaka and Sbordone (1995) use a vector autoregressive (VAR) approach and find that between 13% and 26% of economic fluctuations can be explained by non-fundamental shifts in consumer sentiment; Chauvet and Guo (2003) consider both consumer and investor sentiment, and allow for asymmetric

effects of non-fundamental expectational shocks over different stages of the business cycle. They find that these shocks played an important role in several recessions.

This paper pursues the second approach. The results of empirical studies often depend on the dataset used, the sample period, and the method for identifying non-fundamental shocks. Our study differs from previous work in that we do not make use of data on consumer sentiment, nor of investor sentiment. Instead, we use forecasts of output and inflation from a survey of professional forecasters and interpret optimistic or pessimistic forecasts (relative to a set of fundamentals) as forecast shocks or sunspot shocks. We have several motivations for focusing on professional forecasts. One is that it allows us to make use of real-time, rather than revised, data in generating shocks to expectations, unlike previous studies which utilized revised data. While macroeconomic researchers today have available to them updated data, forecasters in real time do not; hence, the use of real-time data can sometimes lead to drastic reversals of results in forecasting studies (Diebold and Rudebusch, 1991; Croushore and Stark, 2001).

The identification of sunspots with forecast shocks can be justified via the "strategic complementarity" argument in Oh and Waldman (1990) whereby false announcements, i.e., inaccurate forecasts concerning the economy, can lead agents to increase (or decrease) production because they believe aggregate production will be high (low). [1] Furthermore, it seems reasonable to expect that economic forecasts from professional forecasters may be an important factor in agents' expectations formation since the former are given wide coverage in the financial and popular press. Optimism or pessimism showed by forecasters could well be a source of shifts in macroeconomic variables that capture sentiment. [2]

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[1] The notion that "a forecast can affect the subject of the forecast" is an old one, and several early papers discuss issues related to this (e.g., Grunberg and Modigliani, 1954; Devletoglou, 1961; Kemp, 1962 and Rothschild, 1964). Many of these were concerned with the possibility and desirability of accurate macroeconomic forecasting.

[2] It is not difficult to find comments in speeches, newspaper articles and books that allude to the importance of forecasts in generating business cycles. A light-hearted application of this idea is the R-word index – the number of times the word "recession" appears in British newspapers, compiled by The Economist (The Economist, 1998). Also, Farmer (1999) says "I like to think of sunspots as the predictions for the economy by the Wall Street Journal … these predictions can be self-fulfilling in some types of economies if agents believe in them."

The remainder of the paper is organised as follows. In the next section, we set out the empirical model and our assumptions. In Section 3, we describe the data and summarize the properties of the non-fundamental component of forecasts. In Section 4, the results of our study are presented and their robustness discussed. Section 5 concludes.

2.   The VAR Model

Following Matsusaka and Sbordone (1995) and Chauvet and Guo (2003), we generate non-fundamental idiosyncratic shocks to expectations using a VAR. The idea in these studies is to incorporate some measure of agents' expectations (either consumer or investor sentiment) into the VAR as an endogenous variable. Idiosyncratic shocks to the variable can then be interpreted as non-fundamental shifts in expectations and useful statistics such as variance decompositions can be computed to quantify the importance of these shocks to fluctuations in other macroeconomic variables. As explained earlier, we choose to use an average of forecasts from professional forecasters instead of sentiment measures.

The empirical model that we use can be written as

$$\begin{pmatrix} A_1 & 0 \\ 0 & A_2 \end{pmatrix} \begin{pmatrix} y_t \\ y^f_{t+1|t} \end{pmatrix} = \begin{pmatrix} b_1 \\ b_2 \end{pmatrix} + \sum_{i=1}^{p} \begin{pmatrix} C_{1i} & C_{2i} \\ 0 & C_{4i} \end{pmatrix} \begin{pmatrix} y_{t-i} \\ y^f_{t-i+1|t-i} \end{pmatrix} + \sum_{i=1}^{p} \begin{pmatrix} 0 \\ D_i \end{pmatrix} \tilde{y}_{t-i|t} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}, \ t = 1, 2, \ldots, T \qquad (1)$$

where $y_t = (y_{1t}, y_{2t}, \ldots, y_{nt})'$ is an ($n \times 1$) vector of variables and $y^f_{t+1|t} = (y^f_{1, t+1|t}, y^f_{2, t+1|t})'$ is a (2×1) vector of one-step ahead forecasts of a subset of the variables in y_t made by professional forecasters at time t. A_1 is an ($n \times n$) matrix of unobserved parameters, as are C_{1i}, $i = 1, \ldots, p$; C_{2i} is an ($n \times 2$) parameter matrix. A_2 and C_{4i} are (2×2) matrices of parameters, and b_1 and b_2 are ($n \times 1$) and (2×1) vectors of constants respectively. The '0's in (1) and in the rest of the paper represent zero matrices of the appropriate dimensions. The structural innovations $u_t = (u_{1t}', u_{2t}')'$ are assumed to be i.i.d. Gaussian with zero mean and a diagonal variance-covariance matrix:

$$\Gamma = \begin{pmatrix} \Gamma_1 & 0 \\ 0 & \Gamma_2 \end{pmatrix} \tag{2}$$

with $\Gamma_1 = diag(\sigma_{11}, \sigma_{12}, ..., \sigma_{1n})$ and $\Gamma_2 = diag(\sigma_{21}, \sigma_{22})$.

In our baseline model, y_t contains real output growth and inflation, an interest rate, stock returns, consumption growth and investment growth; later, we consider using other variables. We include two expectations variables in $y_{t+1|t}^f$, viz., one-step ahead forecasts of output growth and inflation. To correctly measure non-fundamental forecast shocks, the fundamentals entering into the forecast equations ought to be the vintage of the data that was available to the forecasters at the time the forecasts were made. Accordingly, the exogenous variables in $\tilde{y}_{t-i|t} = (\tilde{y}_{1,\,t-i|t}, \tilde{y}_{2,\,t-i|t}, ..., \tilde{y}_{n,\,t-i|t})'$, $i = 1, ..., p$, are real-time observations of y_{t-i} available to forecasters at time t, with corresponding $(2 \times n)$ parameter matrix given by D_i.[3]

Apart from a wider choice of variables, our empirical model is fairly similar to that in Matsusaka and Sbordone (1995). The other difference is that we explicitly specify a structural VAR model in (1) with plausible assumptions about the contemporaneous relationships that hold between macroeconomic variables. Since we wish to explore the separate impacts of our two expectations variables on macroeconomic fluctuations, the shocks in the model are orthogonalized by constraining A_2 to be a lower triangular matrix, so that output forecasts contemporaneously affect inflation forecasts but not vice versa. A_1 is similarly restricted so that the first six equations basically follow a recursive structure where the fundamental variables are ordered as interest rate, stock returns, consumption growth, investment growth, output growth and inflation, but modified slightly to allow for simultaneity between real output on the one hand and consumption and investment on the other.[4] The exact specification is

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[3] Note that by using real-time data, we do not attribute to "fundamentals" future revisions of $\tilde{y}_{t-i|t}$ that were not available to forecasters.

[4] To achieve exact identification of the structural VAR model, we have to impose two additional restrictions – real consumption growth has no contemporaneous effect on investment growth and stock returns only affect real output growth indirectly through their impact on consumption and investment.

$$A_1 = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & a_{35} & 0 \\ a_{41} & a_{42} & 0 & 1 & a_{45} & 0 \\ a_{51} & 0 & a_{53} & a_{54} & 1 & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & 1 \end{pmatrix}. \tag{3}$$

Unlike Matsusaka and Sbordone (1995) and Chauvet and Guo (2003), we do not carry out any specification searches, but enter all the endogenous variables into our model simultaneously. The coefficient matrix on the left-hand side of the VAR is also taken to be block diagonal. This assumption is natural given the way we have structured our equations: the upper-right zero restrictions are reasonable because forecasts should not have any impact on current realizations of y_t, while the bottom-left zero restrictions are appropriate since observations of y_t are generally not available to forecasters at time t.

To quantify the impact of sunspot shocks on economic fluctuations, consider the variance decomposition of the forecast errors from a VAR(1) specification of our model. We rewrite the model in reduced form as:

$$\begin{aligned} \begin{pmatrix} y_t \\ y^f_{t+1|t} \end{pmatrix} &= \begin{pmatrix} A_1^{-1}b_1 \\ A_2^{-1}b_2 \end{pmatrix} + \begin{pmatrix} A_1^{-1}C_{11} & A_1^{-1}C_{21} \\ 0 & A_2^{-1}C_{41} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ y^f_{t|t-1} \end{pmatrix} + \begin{pmatrix} 0 \\ A_2^{-1}D_1 \end{pmatrix} \tilde{y}_{t-1|t} + \begin{pmatrix} A_1^{-1}u_{1t} \\ A_2^{-1}u_{2t} \end{pmatrix} \\ &= \begin{pmatrix} \Pi_{01} \\ \Pi_{02} \end{pmatrix} + \begin{pmatrix} \Pi_{11} & \Pi_{12} \\ 0 & \Pi_{14} \end{pmatrix} \begin{pmatrix} y_{t-1} \\ y^f_{t|t-1} \end{pmatrix} + \begin{pmatrix} 0 \\ \Pi_{21} \end{pmatrix} \tilde{y}_{t-1|t} + \begin{pmatrix} A_1^{-1}u_{1t} \\ A_2^{-1}u_{2t} \end{pmatrix}. \end{aligned} \tag{4}$$

The 1-step ahead forecast error of y_t can be obtained by generating the reduced form VAR equations and substituting backwards once. Maintaining the i.i.d. assumption for the structural innovations u_{1t} and u_{2t}, the Mean Squared Forecast Error (MSFE) is

$$\begin{aligned} MSFE(y_{t+1} | \Omega_t) &= A_1^{-1}\Gamma_1 A_1^{-1\prime} + \Pi_{11} A_1^{-1}\Gamma_1 A_1^{-1\prime}\Pi_{11}{}' + \Pi_{12} A_2^{-1}\Gamma_2 A_2^{-1\prime}\Pi_{12}{}' \\ &= \sum_{j=1}^{n} \left\{ \sigma_{1j} \cdot \left[a_j a_j{}' + \Pi_{11} a_j a_j{}'\Pi_{11}{}' \right] \right\} + \sum_{k=1}^{2} \left\{ \sigma_{2k} \cdot \left[\Pi_{12} a_k a_k{}'\Pi_{12}{}' \right] \right\} \end{aligned} \tag{5}$$

where Ω_t represents information available at time t, a_j is the j-th column of A_1^{-1} and a_k is the k-th column of A_2^{-1} (see Hamilton, 1994). The contribution of the k-th forecast shock to the MSFE of $y_{t+1} \mid \Omega_t$ is then $\sigma_{2k} \cdot \left[\Pi_{12} a_k a_k{}' \Pi_{12}{}' \right]$.

3. Data and Preliminary Analysis

3.1 Data

The sample period of our study is from the fourth quarter of 1974 to the second quarter of 2002. The choice of sample period is partly due to data availability as we explain shortly. We will use three types of data: mean forecasts from professional forecasters and real-time data on fundamentals are used to generate forecast shocks, and later, we use the latest available data when measuring the impact of these forecast shocks on economic fluctuations. In the rest of the paper, we refer to the latter as "revised data".

Data on forecasts is obtained from the Survey of Professional Forecasters (SPF), maintained by the Federal Reserve Bank of Philadelphia. The SPF is the oldest quarterly survey of macroeconomic forecasts in the United States; the first survey was initiated in 1968. It was conducted by the American Statistical Association and the National Bureau of Economic Research prior to the Philadelphia Fed, who took over in 1990. The SPF covers one- to four-quarter ahead point forecasts of the major macroeconomic variables, as well as density and long-term forecasts of some of these variables.[5] We focus on one-quarter ahead forecasts of real output growth and inflation (as measured using the output deflator) and study non-fundamental shocks to these forecasts.[6]

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[5] A density forecast of a variable is a forecast of the probability distribution of possible values of that variable (see Tay and Wallis, 2000).

[6] Full details on the SPF and the Real-Time Data Set can be found in Croushore and Stark (1993, 2001), and on the Philadelphia Fed's website at http://www.phil.frb.org/econ/index.html. Every quarter, participating forecasters are provided with the advance release on the previous quarter's value for a range of macroeconomic variables and asked to provide forecasts for the current and following four quarters. For most of the variables in the dataset, seasonally-adjusted forecasts of levels are provided. We calculate mean one-step ahead forecasts of real output growth and inflation by taking the average of the individual forecasters' growth and inflation forecasts. As an example, the

An important feature of the forecast data is the changes in the definition of output over the sample period. Prior to 1992, the real output measure used in the survey was fixed-priced GNP. Survey data on real GNP were not available prior to 1981Q3, but as forecasts of both nominal GNP and the GNP deflator were available, we calculated the real GNP forecasts implied by these two series. Starting from 1992, the measure changed to fixed-priced GDP and from 1996 onwards, the data are chain-weighted. The deflator also follows the changes in the definition of output. We were careful to account for these definitional changes when calculating growth rates and constructing real-time and revised time series for output growth and inflation. Besides the changes in definition, we also accounted for changes in base years.

Real-time data on fundamentals is obtained from the Real-Time Data Set which is also compiled and maintained by the Philadelphia Fed. This dataset comprises numerous data files each associated with a particular date. These files contain time-series observations on a range of variables in the vintage that was available to forecasters at the date corresponding to the file. We use real-time data on real output, the price level, real consumption and real non-residential investment.[7] Other variables used as fundamentals in our analysis are an interest rate, the oil price and stock prices. There are no revisions in these three series. For these variables, we use the 3-month Treasury bill rate, the West Texas Intermediate spot oil price and the S&P 500 share price index. The 3-month T-bill rate, the oil price, and the revised versions of real output, the price level, real consumption and real investment are obtained from the Federal Reserve Bank of St. Louis' FRED II database. Data on the S&P 500 share price index are obtained from Datastream. Our choice of variables representing economic fundamentals was limited to a certain extent by the availability of real-time data. In particular, we would have included a fiscal variable in our model

current quarter's one-step ahead forecast of real output growth $y_{t+1|t}^f$ is computed as $y_{t+1|t}^f = 100 \sum_{i=1}^{n} \left[\left(Y_{i,t+1}^f / Y_{i,t}^f \right) - 1 \right] / n$ where $Y_{i,t}^f$ is forecaster i's forecasted level of real output, and n is the total number of respondents for period t.

[7] We faced a few instances of missing data. The reasons for the non-availability of these observations are carefully explained in the Fed's documentation that accompanies the dataset. We substituted these missing observations with suitable replacements. For instance, the government shutdown in early 1996 meant that no data for 1995Q4 was available for the 1996Q1 file. We replaced these observations with the advance release for 1995Q4 that was supplied to forecasters in the 1996Q1 survey (which was also delayed as a result of the shutdown).

had there been real-time data for it. Nonetheless, the variables we use are similar to those in typical VAR

forecasting models (e.g., Webb, 1985).

3.2   Preliminary Analysis

To obtain a preliminary indication of the importance of sunspots in expectations, we extract the

non-fundamental components in professional forecasts and analyze their properties. We do this by

regressing mean forecasts of output growth and inflation on real-time observations of our set of

fundamental variables. Setting the C_{4i} matrices to zero in (1), the forecast equations from the VAR are:

$$A_2 y^f_{t+1|t} = b_2 + \sum_{i=1}^{p} D_i \tilde{y}_{t-i|t} + u_{2t} \tag{6}$$

where $y^f_{t+1|t}$ = (forecasted real output growth, forecasted inflation)′ and A_2 is assumed to be lower

triangular. For the time being, we use fundamental information on interest rates, stock returns, real

consumption growth, real investment growth, real output growth and inflation. We consider $p = 4$ lags of

the fundamental variables.

We estimate (6) over 1974Q4 to 2002Q2 and plot both elements of $\hat{u}_{2t}$ in Figure 1, along with

the timing of recessions identified by the NBER. Table 1 reports summary statistics on $\hat{u}_{2t}$. The table

shows that non-fundamental output shocks reach minimum and maximum values of −0.8 and 0.8 percent,

which are fairly large when compared with our sample's output growth range of − 2.3 to 3 percent. The

range of the inflation expectations shocks is substantially smaller, ranging from just under −0.2 to just

over 0.2 percent. The mean inflation rate in our sample is 1 percent per quarter.

Visual inspection of the figures suggests that output expectations shocks are characterized by

cycles, which may be indicative of waves of optimism and pessimism. Our sample period covers four

recessions as dated by the NBER, and it is clear that the first and last of these recessions were preceded

by steep falls in the output shocks. This does not appear to be the case with the middle two recessions.

Cycles appear to be less prevalent in non-fundamental inflation shocks although all four recessions were

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preceded by deflationary expectations. Our visual inspection is corroborated by the summary statistics in Table 1. Both expectations shocks are autocorrelated although this is more persistent in the case of real output. Output shocks are also positively correlated with current values and leads of actual output growth, while inflation shocks are positively correlated with leads of both output growth and realized inflation.

4.   Empirical Evidence

The VAR model is estimated in two stages. In the first stage, the model's reduced form is estimated by ordinary least squares, equation by equation.[8] In the second step, the restrictions discussed in Section 2 are imposed and the structural model is recovered via the technique of full information maximum likelihood (see Hamilton, 1994).

4.1   Baseline Results

We report the results from the estimation of (1) and examine the role of non-fundamental expectations shocks using variance decompositions and impulse responses. Table 2 shows the percentage contributions of the non-fundamental output and inflation shocks to the MSFE of each of the six variables in our baseline model.[9] Figures 2 and 3 show the standardized impulse responses from these shocks. Table 3 displays the variance decompositions for real output growth and inflation.

Several regularities stand out from Table 2. First, the contributions of expectational shocks are small in all cases except for that of inflation forecast shocks to the MSFE of inflation. Second, the impact of non-fundamental output shocks on real output growth is only significant after 8 quarters. The corresponding effect on real consumption growth is also significant. It appears that output forecast shocks might be affecting actual output growth through their effect on consumption, as borne out by the impulse

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[8] The potential increase in efficiency from using the method of seemingly unrelated regressions is not likely to be significant given that the right-hand-side variables in our system are nearly identical. We use four lags of each variable as suggested by the usual VAR lag length selection statistics.
[9] Tests of significance of variance decompositions are based on bootstrapped standard errors obtained from 500 replications.

responses in Figure 2. If so, our results are qualitatively consistent with the findings of Matsusaka and Sbordone (1995) and Chauvet and Guo (2003). The magnitudes are small, however, and economically insignificant. Table 3 shows that the main driving forces in output fluctuations – at longer horizons – appear to be its own shocks (50%), interest rates (14%) and stock returns (11%), and not non-fundamental expectational shocks.

Our finding that forecast sunspot shocks do not matter much for output fluctuations is corroborated by Lubik and Schorfheide (2002). These authors took the first approach to the study of sunspot fluctuations by constructing and estimating a dynamic stochastic general equilibrium (DSGE) model that allows for equilibrium indeterminacy. Like us, they assume that sunspots trigger belief shocks that lead to a revision of forecasts and induce business cycle movements. They then develop a Bayesian posterior odds test for indeterminacy to assess the importance of sunspot fluctuations and conclude that while the U.S. was in a sunspot equilibrium before 1979, aggregate output fluctuations were not due to sunspot shocks.

The results indicate that inflation sunspot shocks are statistically significant, contributing nearly 15 percent to the 8-quarters ahead MSFE of inflation. But are they economically important? Table 3 shows that inflation is largely driven by its own shocks: at the 8-quarters horizon, the contribution of these shocks is 51 percent, while the next most important shocks are inflation expectations (14.5%) and interest rates (11%). To put some perspective on these magnitudes, we calculated the MSFE of an 8-step ahead forecast of quarterly inflation to be approximately 0.25 percent. A 95 percent confidence interval would be approximately 1 percent in length, so that 15 percent of this seems small. Using Livingston Survey data on expectations in conjunction with small VAR models, Leduc, Sill and Stark (2002) find that expectations shocks are much more important for the variability of inflation than exogenous oil, fiscal and monetary policy shocks, accounting for a much larger 30–50 percent compared to the 15 percent contribution from non-fundamental inflation shocks that we find.

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Figure 3 shows the impulse responses of a one-standard deviation shock to inflation forecasts in the model. This is a shock of about 0.1 of a percentage point on a quarterly basis, or 0.4 percent annually (from Table 1). The initial impact on actual inflation is an increase of about half a standard deviation, which amounts to an approximately one-to-one effect, i.e., 0.4 percentage points per annum, as compared to our sample's mean annual inflation rate of about 4 percent. The effect of the one-time shock on inflation dies down rapidly while the impact on the interest rate follows the same pattern. Our estimated impulse responses for these two variables, though less persistent, resemble the responses in Leduc, Sill and Stark (2002).

4.2   Robustness

To check the robustness of the results, we consider two extensions to the baseline model. In the first extension, we include the oil price as an exogenous variable in the VAR model. Most theories of inflation postulate that, in addition to excess demand and a measure of inflation expectations, the supply side is another important influence on the price level. In our sample period, there are three episodes when the oil price rose above US$30 per barrel. These were the second OPEC shock in the late 1970s which persisted into the early 1980s, the brief shocks in the early 1990s associated with the Gulf war, and another recent spike in the year 2000. There is a visible impact on inflation in the first case, although in the second and third episodes, inflation appears to have been less affected (see Hooker, 2002). We therefore incorporated the growth rate of the West Texas Intermediate spot oil price as an exogenous variable in the VAR model but do not report the results of this analysis in detail as they are very similar to those from the model excluding oil price inflation. In particular, expectational shocks continue to have only small and insignificant effects on output growth. At the same time, there remains a self-fulfilling element in inflation forecast shocks even after accounting for the effects of oil shocks on prices.

The second extension to the baseline model allows for the possibility that forecasters' information set might include fundamental variables that are not included as regressors in our VAR. If this were the

case, then the residuals in the forecast equations would pick up the effects of the omitted variables, which would then be interpreted as non-fundamental shocks. Although this is a criticism which can be leveled at any VAR, we address it partially by including in our model the U.S. Leading Index, compiled formerly by the Department of Commerce and more recently by The Conference Board (TCB). We added real-time observations of the index provided by TCB to the set of fundamentals used in the forecast equations of our VAR and re-estimated the model. Again, the impulse responses from this extension are virtually identical to those in the baseline model.

The variance decompositions are shown in Table 4. On the whole, the results are not much changed although, as expected, the contributions of the non-fundamental shocks to economic fluctuations are slightly reduced with the inclusion of the Leading Index in forecasters' information set. The impact of output forecast shocks on real output and consumption growth is even less economically significant than before. However, inflation sunspot shocks continue to influence actual outcomes, contributing 14 percent to the 8-quarters ahead MSFE of inflation.

5.   Conclusion

We evaluated in this paper the effects of non-fundamental expectations on economic fluctuations. The non-fundamental expectations were extracted from a survey of professional forecasters by regressing forecasts of real output growth and inflation on a list of variables representing economic fundamentals and viewing the residuals as non-fundamental shocks. Our results show that non-fundamental shifts in expectations have in general small effects on economic fluctuations, except in the case of inflation. This conclusion was obtained by studying variance decompositions and impulse responses from a vector autoregression of the U.S. macroeconomy, extended to incorporate forecasts.

Our empirical findings are similar to the results in Lubik and Schorfheide (2002), who concluded using a very different methodology that sunspot shocks increased the variability of inflation significantly prior to 1979, but essentially did not affect output fluctuations. The results are also consistent with the

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findings of Leduc, Sill and Stark (2002) and provide further evidence from an altogether different set of survey data to show that self-fulfilling expectations played a role in the U.S. inflation of the 1970s. On the other hand, the results of this paper are quite different from studies that use variables which measure agents' sentiments. Those studies generally find non-fundamental shifts in sentiment to be a significant factor in explaining economic fluctuations. As we used a different variable to extract non-fundamental shifts in expectations, our study should be viewed as complementary to these studies, and does not preclude the possibility that consumer and investor sentiment do play non-negligible roles in business cycle fluctuations. Neither does it preclude the possibility of sunspot fluctuations in general. However, it appears that we can rule out forecasts made and reported by professional forecasters as a significant source of these fluctuations.

Finally, we mention several caveats and avenues for further research. One drawback of our use of real-time data is that forecasters may actually have access to more timely information than we assume. In effect, this means that forecasts would be responding to contemporaneous developments. The forecast survey data might even reflect fundamental information not captured by historical data. There is little we can do about these inherent problems but we wish to emphasize that despite them, we do not find non-fundamental expectations to be a significant source of output fluctuations. Our research also ignores possible non-linear effects such as a greater role for non-fundamental expectations shocks around the time of recessions, and further analysis along the lines of Chauvet and Guo (2003) may provide interesting results. Finally, we have not fully exploited the richness of the data available in the Survey of Professional Forecasters. Although we focused on the sample average of forecasts from individual forecasters, it would be of interest to look at other statistics such as the skewness in the distribution of forecasts, which may better reflect optimism and pessimism.

Acknowledgements

References

Azariadis, C. (1981), "Self-Fulfilling Prophecies", *Journal of Economic Theory* 25, 380-396.

Benhabib, J. and Farmer, R.E.A. (1994), "Indeterminacy and Increasing Returns", *Journal of Economic Theory* 63, 19-41.

Blanchard, O.J. (1989), "A Traditional Interpretation of Macroeconomic Fluctuations", *American Economic Review* 79, 1146-1164.

Carlstrom, C.T. and Fuerst, T.S. (2001a), "Timing and Real Indeterminacy in Monetary Models", *Journal of Monetary Economics* 47, 285-298.

_____ and _____ (2001b), "Monetary Policy and Self-Fulfilling Expectations: The Danger of Forecasts", *Federal Reserve Bank of Cleveland Economic Review* 37, 9-19.

Carroll, C.D., Fuhrer, J.C. and Wilcox, D.W. (1994), "Does Consumer Sentiment Forecast Household Spending? If So, Why?", *American Economic Review* 84, 1397-1408.

Cass, D. and Shell, K. (1983), "Do Sunspots Matter?", *Journal of Political Economy* 91, 193-227.

Chauvet, M. and Guo, J-T. (2003), "Sunspots, Animal Spirits, and Economic Fluctuations", *Macroeconomic Dynamics* (forthcoming).

Croushore, D. and Stark, T. (1993), "Introducing: The Survey of Professional Forecasters", *Federal Reserve Bank of Philadelphia Business Review* Nov/Dec, 3-13.

_____ and _____ (2001), "A Real-Time Data Set for Macroeconomists", *Journal of Econometrics* 105, 111-130.

Devletoglou, E.A. (1961), "Correct Public Prediction and the Stability of Equilibrium", *Journal of Political Economy* 69, 142-161.

Diebold, F.X. and Rudebusch, G.D. (1991), "Forecasting Output with the Composite Leading Index: A Real-Time Analysis", *Journal of the American Statistical Association* 86, 603-610.

Farmer, R.E.A. (1999), *The Macroeconomics of Self-Fulfilling Prophecies*, Cambridge, Massachusetts: MIT Press.

Farmer, R.E.A. and Guo, J-T. (1994), "Real Business Cycles and the Animal Spirits Hypothesis", *Journal of Economic Theory* 63, 42-72.

Fuhrer, J.C. (1993), "What Role Does Consumer Sentiment Play in the U.S. Macroeconomy?", *New England Economic Review*, Jan/Feb, 32-44.

Grunberg, E. and Modigliani, F. (1954), "The Predictability of Social Events", *Journal of Political Economy* 62, 465-478.

Hamilton, J.D. (1994), *Time Series Analysis*, Princeton, New Jersey: Princeton University Press.

Hamilton, J.D. and Whiteman, C. (1985), "The Observable Implications of Self-Fulfilling Expectations", *Journal of Monetary Economics* 16, 353-373.

Hooker, M.A. (2002), "Are Oil Shocks Inflationary? Asymmetric and Nonlinear Specifications versus Changes in Regime", *Journal of Money, Credit, and Banking* 34, 540-61.

Keane, M.P. and Runkle, D.E. (1990), "Testing the Rationality of Price Forecasts: New Evidence from Panel Data", *American Economic Review*, 80, 714-735.

Kemp, M.C. (1962), "Economic Forecasting When the Subject of the Forecast Is Influenced by the Forecast", *American Economic Review* 52, 492-496.

Leduc, S., Sill, K., Stark, T. (2002), "Self-Fulfilling Expectations and the Inflation of the 1970s: Evidence from the Livingston Survey", Federal Reserve Bank of Philadelphia Working Paper No. 02-13.

Levin, A., Wieland, V., Williams, J.C. (2001), "The Performance of Forecast-Based Monetary Policy Rules under Model Uncertainty", Board of Governors of the Federal Reserve System Finance and Economics Discussion Series 2001-39.

Lubik, T. and Schorfheide, F. (2002). "Testing for Indeterminacy: An Application to U.S. Monetary Policy", Mimeo, University of Pennsylvania.

Matsusaka, J.G. and Sbordone, A.M. (1995), "Consumer Confidence and Economic Fluctuations", *Economic Inquiry* 33, 296-318.

Oh, S. and Waldman, S. (1990), "The Macroeconomic Effects of False Announcements", *Quarterly Journal of Economics* 105, 1017-1034.

Rothschild, K.W. (1964), "Cobweb Cycles and Partially Correct Forecasting", *Journal of Political Economy* 72, 300-305.

Salyer, K.D. and Sheffrin, S.M. (1998), "Spotting Sunspots: Some Evidence in Support of Models with Self-Fulfilling Prophecies", *Journal of Monetary Economics* 42, 511-523.

Sims, C.A. (1980), "Macroeconomics and Reality", *Econometrica* 48, 1-48.

Tay, A. S. and Wallis, K.F. (2000), "Density Forecasts: A Survey", *Journal of Forecasting* 19, 235-254.

The Economist (1998), "The Recession Index", Dec 10.

Throop, A.W. (1992), "Consumer Sentiment: Its Causes and Effects", *Federal Reserve Bank of San Francisco Economic Review*, 35-59.

Webb, R.H. (1985), "Towards More Accurate Forecasts from Vector Autoregressions", *Federal Reserve Bank of Richmond Economic Review* 71 (July/August) 3-11.

Figure 1
Non-Fundamental Expectations Shocks and NBER Recessions

Output Expectations Shock

Inflation Expectations Shock
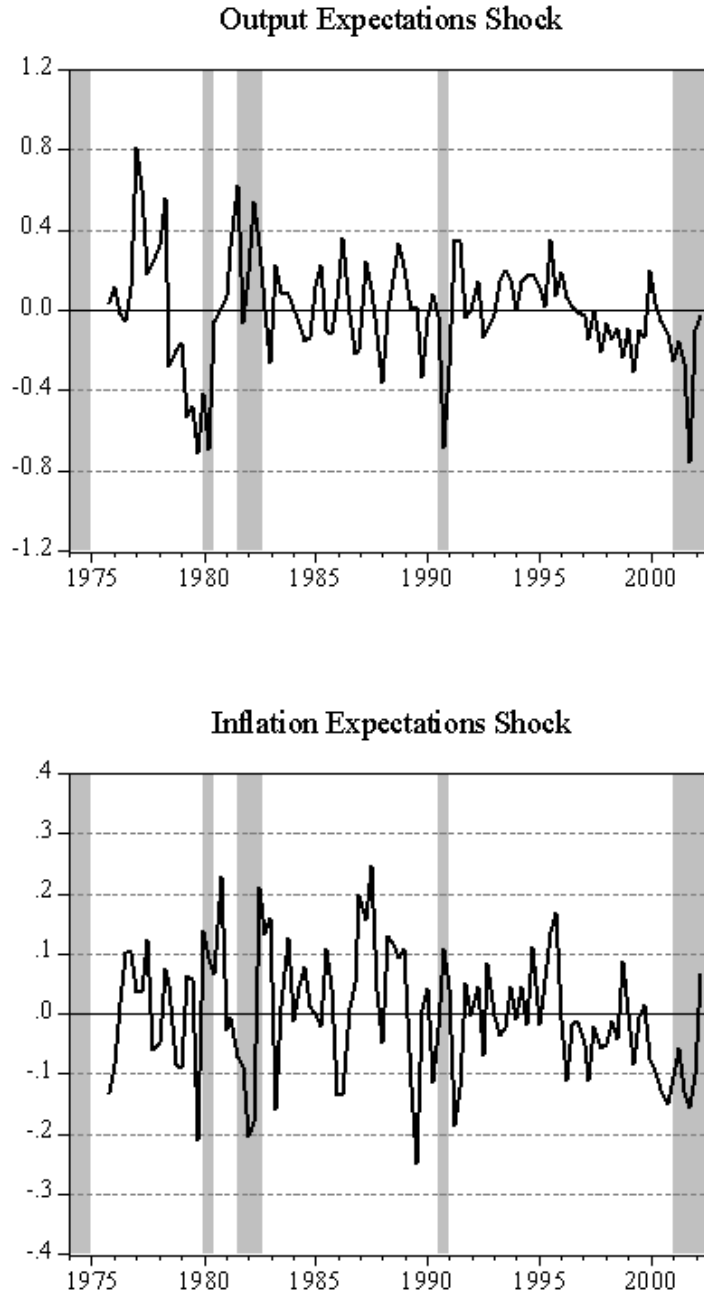
Note: The shaded regions refer to periods of recession as dated by the NBER. The graphs depict variation in mean one-step ahead forecasts that are not explained by fundamentals in real time.

Figure 2
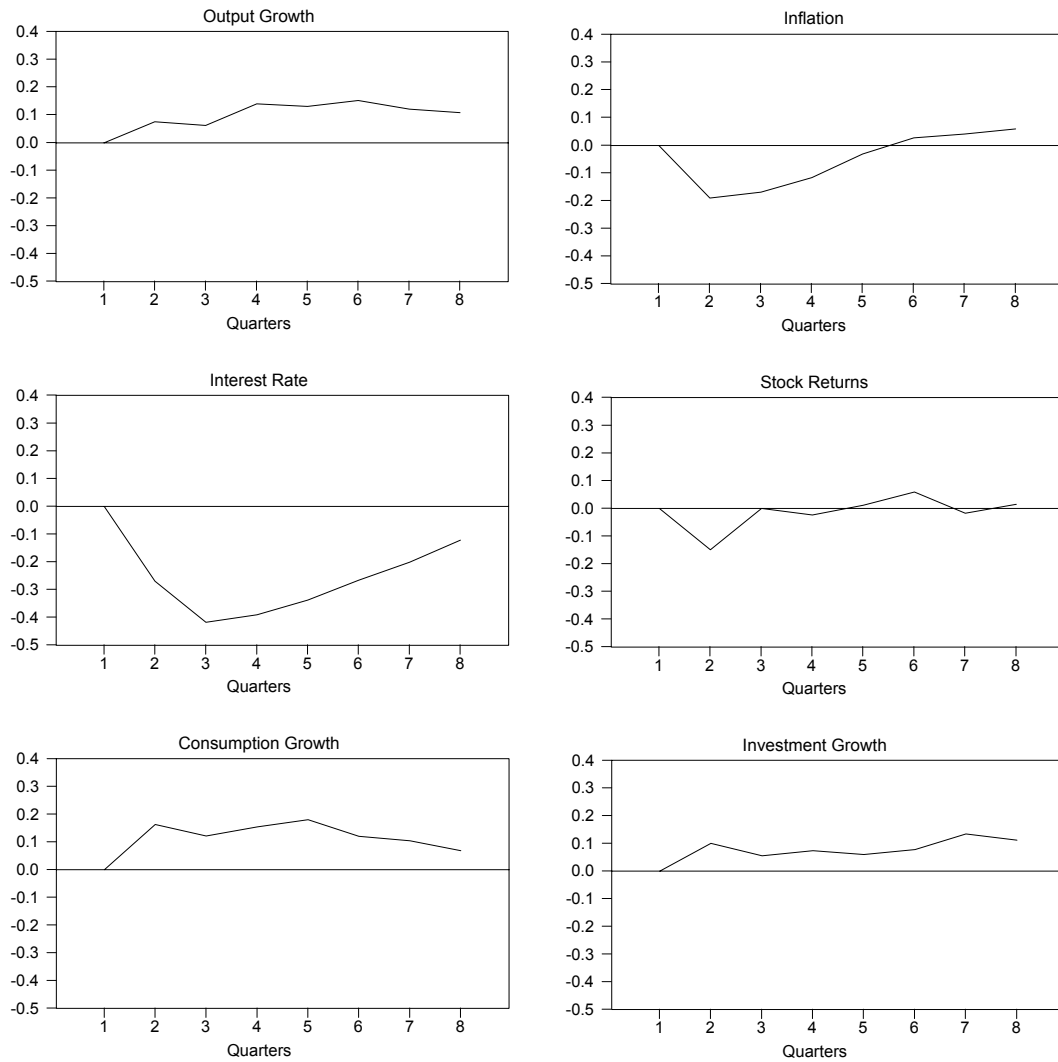**Standardized Impulse Responses of Output Forecast Shocks**

Figure 3
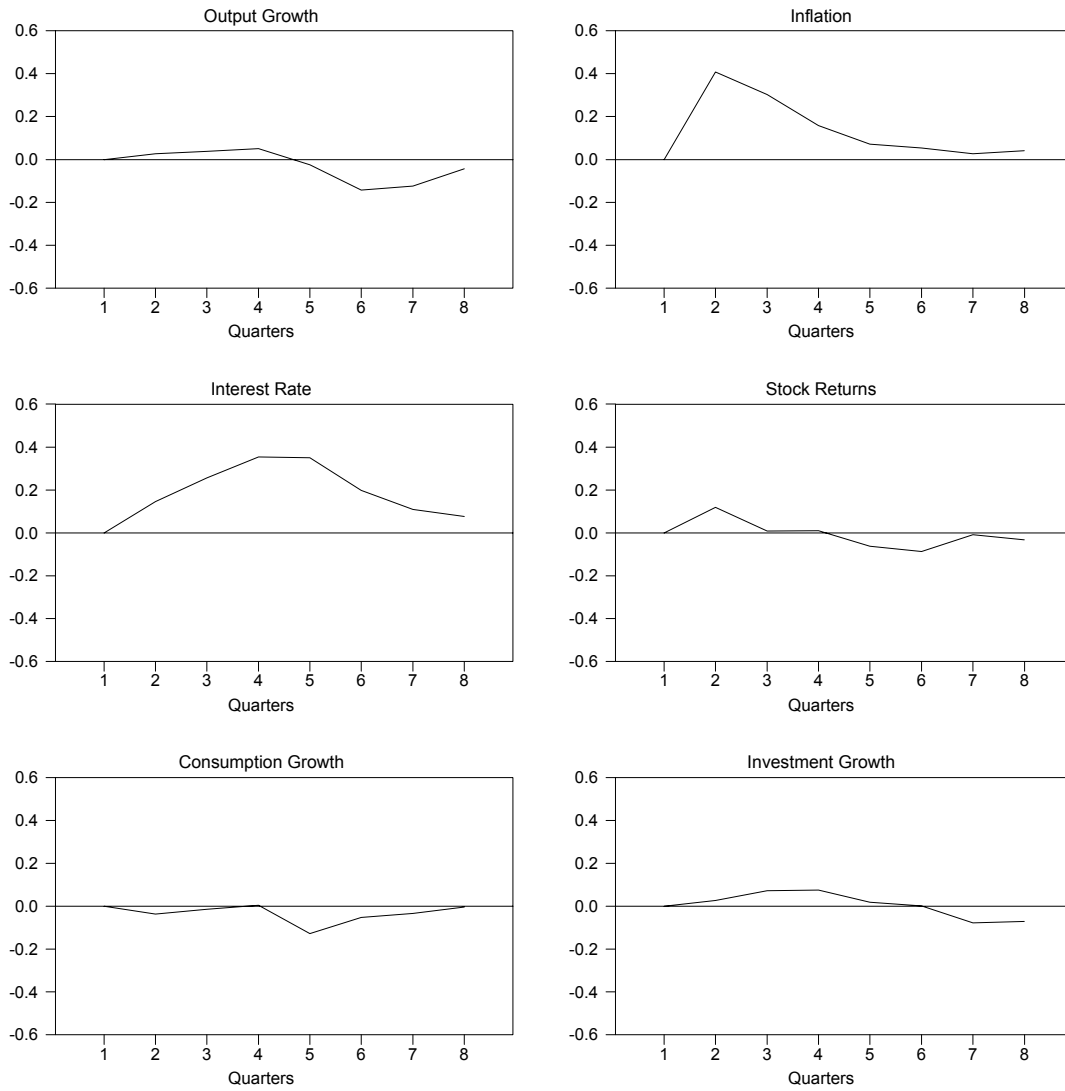**Standardized Impulse Responses of Inflation Forecast Shocks**

Table 1
Summary Statistics of Non-Fundamental Expectations Shocks: 1974Q4 − 2002Q2

	Shock			
	Output		Inflation	
Std. Deviation	0.268		0.102	
Maximum	0.810		0.246	
Minimum	− 0.759		− 0.249	
Autocorrelation at				
lag 1	0.502		0.314	
lag 2	0.203		− 0.038	
lag 3	0.165		0.022	
lag 4	0.265		0.061	
Correlation with	Real Output Growth	Inflation	Real Output Growth	Inflation
at lead/lag				
+2	0.130	− 0.063	0.229*	0.088
+1	0.159	− 0.045	0.113	0.198*
0	0.279*	0.033	0.114	0.140
−1	− 0.003	0.038	0.061	0.047
−2	− 0.038	0.068	− 0.085	0.037

Notes: Non-fundamental expectations shocks refer to the components of mean one-step ahead forecasts that are not explained by real-time observations on fundamentals. Denoting a variable by y_t and the expectations shock in the forecast $y^f_{t+1|t}$ by u_{2t}, the correlation between the shock and the variable at lead j is $Corr(u_{2t}, y_{t+j})$. * denotes significance at 5%.

Table 2
Contributions of Forecast Shocks

Percentage Contribution of Forecast Shocks to *h*-period ahead MSFE of

	Real Output Growth			Inflation	
Shock	Output	Inflation		Output	Inflation
2-step	0.528	0.069		2.582	11.94**
4-step	1.934	0.321		4.498	16.41**
8-step	5.146**	2.327		4.178	14.50**
	Interest Rates			Stock Returns	
Shock	Output	Inflation		Output	Inflation
2-step	2.772	0.806		1.983	1.255
4-step	7.463	3.981		1.847	1.154
8-step	7.342	4.515		1.992	1.976
	Real Consumption Growth			Real Investment Growth	
Shock	Output	Inflation		Output	Inflation
2-step	2.256	0.113		0.828	0.058
4-step	4.464	0.107		1.297	0.814
8-step	7.791**	1.324		3.480	1.369

Note: ** denotes significance at 1%.

Table 3
Variance Decompositions for Real Output Growth and Inflation

Percentage Contribution to *h*-period ahead MSFE of Real Output Growth of Shocks to

h	Real Output Growth	Inflation	Interest Rates	Stock Returns	Real Consumption Growth	Real Investment Growth	Output Forecast	Inflation Forecast
2-step	81.39**	0.218	12.15**	2.489	1.820	1.336	0.528	0.069
4-step	59.41**	1.996	16.13**	11.93*	1.700	6.583	1.934	0.321
8-step	50.36**	5.800*	13.91**	11.23*	1.854	6.373	5.146*	2.327

Contribution to *h*-period ahead MSFE of Inflation of Shocks to

h	Real Output Growth	Inflation	Interest Rates	Stock Returns	Real Consumption Growth	Real Investment Growth	Output Forecast	Inflation Forecast
2-step	0.450	72.81**	6.402	1.128	1.136	3.550	2.582	11.94**
4-step	5.822	58.88**	7.286	2.326	1.133	3.640	4.498	16.41**
8-step	8.471*	50.78**	10.77**	5.663*	1.254	4.378	4.178	14.50**

Note: * and ** denote significance at 5% and 1% respectively.

Table 4
Contributions of Forecast Shocks (Model with Leading Index)

Percentage Contribution of Forecast Shocks to *h*-period ahead MSFE of

	Real Output Growth		Inflation	
Shock	Output	Inflation	Output	Inflation
2-step	0.428	0.064	2.796	11.189**
4-step	1.553	0.250	5.036	15.945**
8-step	4.056*	2.283	4.615	14.161**

	Interest Rates		Stock Returns	
Shock	Output	Inflation	Output	Inflation
2-step	2.772	0.753	1.844	1.171
4-step	7.463	4.301	1.715	1.096
8-step	7.342	5.239	1.925	1.915

	Real Consumption Growth		Real Investment Growth	
Shock	Output	Inflation	Output	Inflation
2-step	1.964	0.105	0.679	0.054
4-step	3.885	0.125	1.001	0.654
8-step	6.366**	1.474	2.465	1.129

Note: * and ** denote significance at 5% and 1% respectively.