

## Modelling the General Public's Inflation Expectations Using the Michigan Survey Data

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Postprint / Postprint

Zeitschriftenartikel / journal article

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### Empfohlene Zitierung / Suggested Citation:

Luoma, A., & Luoto, J. (2009). Modelling the General Public's Inflation Expectations Using the Michigan Survey Data. *Applied Economics*, 41(10), 1311-1320. <https://doi.org/10.1080/00036840701604339>

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## Modelling the General Public's Inflation Expectations Using the Michigan Survey Data

Journal:	<i>Applied Economics</i>
Manuscript ID:	APE-05-0717
Journal Selection:	Applied Economics
Date Submitted by the Author:	23-Dec-2005
Complete List of Authors:	Luoma, Arto; University of Tampere, Department of Mathematics, Statistics and Philosophy Luoto, Jani; University of Jyväskylä, School of Business and Economics
JEL Code:	C11 - Bayesian Analysis < C1 - Econometric and Statistical Methods: General < C - Mathematical and Quantitative Methods, C22 - Time-Series Models < C2 - Econometric Methods: Single Equation Models < C - Mathematical and Quantitative Methods, D83 - Search Learning Information and Knowledge < D8 - Information and Uncertainty < D - Microeconomics, D84 - Expectations Speculations < D8 - Information and Uncertainty < D - Microeconomics
Keywords:	learning models, inflation expectations, survey data

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23 Running title: Modelling the General Public's Inflation Expectations  
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51 Abstract:

52 In this paper we discuss a few models developed to explain the general public's  
53 inflation expectations formation and provide some relevant estimation results.  
54 Furthermore, we suggest a simple Bayesian learning model which could explain the  
55 expectations formation process on the individual level. When the model is aggregated  
56 to the population level it could explain not only the mean values, but also the variance  
57 of the public's inflation expectations. The estimation results of the mean and variance  
58 equations seem to be consistent with the results of the questionnaire studies in which  
59 the respondents were asked to report their thoughts and opinions about inflation.  
60

Keywords: learning models, inflation expectations, survey data

## I Introduction

The inflation expectations of the general public are an important determinant of inflation and other macroeconomics fundamentals, since they at least influence the process of wage bargaining, price setting and speculative buying. For example, higher inflation expectations may lead employees to demand higher wage settlements, push firms to a rise the prices of their products, and encourage agents to purchase more commodities. In addition, public concern about actual inflation has even certainly had an impact on political elections - see Cartwright and Delorme (1985), Parker (1986), Golden and Poterba (1989), Cuzan and Bundrick (1992), Fair (1994) and Shiller (1997). Thus, the inflation expectations of the general public play an essential role in modern market economies.

The assumption of rational expectations, which presumes that the agents know the true structure and probability distribution of the economy, is most commonly used in theoretical and empirical exercises today. However, having observed problems with this assumption,<sup>1</sup> researchers have started to search alternative models for the expectations formation process. For example, in the models of limited information flows, developed by Mankiw and Reis (2002) and Sims (2003), the agents have rational expectations but are not based on complete information, while in the boundedly rational learning models they behave as professional scientists and use methods of scientific inference (see Sargent (1993) and Evans and Honkapohja (2001) for surveys). The reader should note that when these models are used, it is important to distinguish between the expectations

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<sup>1</sup> see for example Zarnowitz (1985), Bonham and Cohen (1995), Jeong, Jinook, and G. S. Maddala (1996) and Lloyd (1999)

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3 of ordinary people and professionals, because these two groups use different methods  
4 and resources to form their expectations (for example, see results of Schiller, 1997).  
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10 In recent empirical literature of inflation expectations formations, Branch (2004 a)  
11 developed a promising model of heterogeneous agents, in which the general public  
12 forms its inflation expectations using a prediction function from a set of costly  
13 alternatives. Specifically, he assumes that consumers use three alternative types of  
14 forecast functions in their formation process: VAR, adaptive and naïve type models. His  
15 relatively contradictory results have lead scientists to think more closely about the  
16 process of consumers' inflation expectations formation. We, for example, find the  
17 assumption that households have access to VAR estimates to be unrealistic<sup>2</sup>. This is  
18 because the ordinary person cannot perceive the causes of inflation. Shiller (1997) in his  
19 questionnaire study, asks the respondents to list causes of inflation. The responses to  
20 this question were diverse and almost equally represented. Most assumed 'factors' of  
21 inflation were of a general type, such as 'greedy' or 'government'. Thus, identification  
22 of any more or less complex econometric or economic models seems to be an  
23 overwhelming task for ordinary people. In addition, we of course agree with Branch  
24 (2004 a) and many others in that the agents are heterogeneous. However, we believe  
25 that heterogeneity is mainly concerned with the thought process of individuals and is  
26 therefore hardly identifiable. More importantly, it is unclear how important this  
27 heterogeneity is in the evolution of aggregate consumer expectations.  
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55 Carroll (2003) explores the causality of the Michigan households' mean inflation  
56 expectations and the Survey of Professional Forecasters (SPF) mean inflation forecasts.  
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60 <sup>2</sup> One may assume that the VAR forecasts are almost same as the forecasts of professionals made available to the public through news articles, but they cannot be directly compared since there is no cost to read those news articles.

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3 Using the standard Granger causality test he finds that the professional forecast  
4  
5 Granger-causes the household forecast, but that there is no Granger causality in the  
6  
7 opposite direction. This evidence of Granger causality plays an essential role in his  
8  
9 theory of epidemiological expectations formation. In his epidemiology model,  
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11 households form their expectations when they randomly come into contact with the  
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13 relevant information set which Carroll assumed to consist of news articles about  
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15 professional forecasters' forecasts. This epidemiology model is closely linked to the  
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17 sticky information model of Mankiw and Reis (2002), for which Khan and Zhu (2002)  
18  
19 and Mankiw, Reis and Wolfers (2003) acquire empirical estimates. All these authors  
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21 employ different identification schemes, and estimate that individuals update their  
22  
23 information sets on average every 12 months. If this is the case, a large proportion of  
24  
25 the population always uses lagged news media forecasts as their information set.  
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27 Consequently, inflation expectations of the general public should be modelled as a  
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29 function of lagged professional expectations. Finally, Branch (2004 b) compares these  
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31 'sticky information' models to the model uncertainty approach of Branch (2004 a) and  
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33 states that model uncertainty is a more robust element of the Michigan data.  
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44 In this paper, we show that the Michigan inflation expectations data support neither  
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46 Carroll's epidemiological model nor the sticky information model of Mankiw and Reis  
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48 (2002). Moreover, we suggest a simple Bayesian learning model for the formation  
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50 process of inflation expectations and show that by using this type of a boundedly  
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52 rational model we can describe individuals' opinions and their uncertainty about them.  
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54 When the model is aggregated from the individual to national level and certain  
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56 assumptions are made it can explain not only the mean values, but also the variance of  
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58 the public's inflation expectations. The estimation results of the mean and variance  
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3 equations seem to be consistent with the results of the questionnaire studies in which the  
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5 respondents were asked to report their thoughts and opinions about inflation.  
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10 In the inflation expectations literature, there has been almost no work testing learning  
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12 models using actual empirical data. An important exception is Caskey (1985), who in  
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14 his excellent paper uses a learning model, similar to ours, for professional forecasters'  
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16 views about future inflation. However, formation of inflation expectations requires  
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18 these professionals to assimilate media reports, personal observations, macroeconomic  
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20 data, and other forms of information that might be generated in obscure ways.  
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22 Therefore, the use of an econometric model or some simple alternative behaviour model  
23  
24 to explain their expectation formation might be problematic (see Manski, 2004).  
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26 However, the expectation formation of the general public is likely more straightforward.  
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28 A typical individual observes inflation through news media reports, which are mainly  
29  
30 based on annualized monthly inflation figures, and perceives the process of inflation on  
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32 a very superficial level. Thus, modelling inflation expectations using a simple, well-  
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34 defined random process might be ideal in this case.  
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43 Our report is organized as follows. In Section II, we explore the empirical relationship  
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45 between the professionals' and consumers' forecasts. In Section III, we discuss the  
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47 formation process of the general public's inflation expectations and present a Bayesian  
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49 learning model. In Section IV, we test how well the outcomes of this model can explain  
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51 the mean and variance of inflation expectations. Finally, in Section V we conclude the  
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53 paper.  
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## II Exploring the Relationship Between the Professionals' and Households' Forecasts and Monthly Inflation

The most commonly published economic news articles for the general public likely concern the annualized monthly inflation figures

$$\Pi_t^m = 1200 \times \ln\left(\frac{CPI_t}{CPI_{t-1}}\right), \quad (1)$$

where CPI is the seasonally adjusted Consumer Price Index for all urban consumers. However, every month, the Survey Research Center at the University of Michigan asks a random sample of at least 500 households the following question: 'During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?'. If a respondent expects that the prices will change during the next 12 months then he is simply asked to supply a twelve months ahead forecast for annual inflation

$$\Pi_t = 100 \times \ln\left(\frac{CPI_t}{CPI_{t-12}}\right). \quad (2)$$

This provides us with a well-defined absolute numerical scale for responses; hence, the respondents understand what the survey questions mean and interpret them similarly. Thus, modelling the Michigan households' responses is sensible; see Manski (2004) for further discussion on the topic.

We use the quarterly means of the above series, since the only relevant candidate series for the views of professional forecasters which has the same forecasting horizon as the Michigan series is the four-quarter inflation forecast from the Survey of Professional Forecasters conducted by the Federal Reserve Bank of Philadelphia<sup>3</sup>. Moreover, we use here only so-called real-time series, i.e. series which were available to the public when they formed their beliefs about future inflation. Our main source of data is the Federal Reserve Bank of Philadelphia<sup>4</sup> (see Croushore and Stark, 2001). The missing values of the CPI data were acquired from Norman R. Swanson's home pages<sup>5</sup>.

To explore the relationship between the professionals' and households' forecasts and monthly inflation we start our analysis by estimating Carroll's (2003) equation (12) with constant term and recently published annualized monthly inflation  $\Pi_t^m$  (not annual inflation as in Carroll),

$$M_t[\Pi_{t+4}] = \gamma_0 + \gamma_1 S_t[\Pi_{t+4}] + \gamma_2 M_{t-1}[\Pi_{t+3}] + \gamma_3 \Pi_t^m + v_t, \quad (3)$$

where  $M_t$  and  $S_t$  are operators that yield the population means (or medians) of the Michigan and SPF inflation expectations at time  $t$ , respectively, and  $v_t$  is an error term.

The estimates obtained using the mean and median series are presented in Table 1.

The estimates of  $\gamma_3$  in the mean and median cases are positive and significant at the 5% and 1% levels, respectively. This suggests that annualized monthly inflation, which is the most commonly reported inflation figure in the news media, is an important factor to

<sup>3</sup> data are available at <http://www.phil.frb.org/econ>

<sup>4</sup> data are available at <http://www.phil.frb.org/econ/forecast/readow.html>

<sup>5</sup> data are available at <http://econweb.rutgers.edu/nswanson/realtime.htm>

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3 explain the Michigan mean and median series. Our estimates are in disagreement with  
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5 Carroll's (2003) finding that inflation has no influence on an individual's expectation  
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7 formation process. In our opinion, his finding arises, first, from the high correlation  
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9 (0.865) between recent annual inflation and the lagged value of the Michigan series, and  
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11 second, from using the annual inflation series instead of the monthly annualized  
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13 inflation series.  
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20 Surprisingly, when we look at the estimate of  $\gamma_2$  in the median case, its estimate is not  
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22 statistically significant. Therefore, we could possibly exclude the lagged value of the  
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24 Michigan series from the regression equation (3). This empirical finding causes a real  
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26 problem to Carroll's epidemiology model. Moreover, the reader should note that as  
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28 Curtin (1996) and Mankiw, Reis and Wolfers (2003) argue, the long tails of the  
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30 Michigan expectation series are not particularly informative and, therefore, the results  
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32 acquired using median values might be more sensible. Therefore, in the following we  
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34 will focus on the median values of the Michigan series.  
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41 Carroll (2003) argues that the constant term in equation 3 is spuriously significant  
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43 because it implies, for example, that if both actual inflation and the professional's  
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45 expectations were to go to zero forever, people would continue to expect a positive  
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47 inflation rate forever i.e. they wouldn't eventually learn. However, this is only true  
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49 when we expect that individuals form their expectations as Carroll assumes. For  
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51 example, if individuals form their expectations using learning models, the presence of a  
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53 positive constant in regression poses no problem.  
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3 Unfortunately, the results presented above are not very reliable, because using non-  
4 stationary time series in regression analysis may yield spurious regression and  
5 inconsistent parameter estimates (see, for example, Hamilton, 1994). On the other hand,  
6 if the series are cointegrated, the ordinary least squares (OLS) estimates might be biased  
7 due to endogeneity and serial autocorrelation (see Banerjee *et al*, 1993, Chapter 7).  
8 Therefore, we studied whether the series are unit root processes. The results of the  
9 augmented Dickey-Fuller test are shown in Table 2. Since the null hypothesis of a unit  
10 root is not rejected in either case of an expectation series and only slightly rejected in  
11 the case of the annualized inflation series, we model them as I(1) processes.  
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27 If the expectations series move together in the long-run, which seems to be a reasonable  
28 assumption, they can be modelled using co-integrated vector autoregression (CVAR).  
29 Let therefore  $y_t = (M_t[\Pi_{t+4}] S_t[\Pi_{t+4}] \Pi_t^m)'$  be the vector of the SPF median inflation  
30 forecast, the Michigan household median inflation expectation and annualized monthly  
31 inflation, respectively. Then the CVAR model can be parameterized in the error  
32 correction form  
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$$\Delta y_t = \psi + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \alpha \beta' y_{t-1} + \varepsilon_t, \quad (4)$$

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50 where  $\psi$  is a vector of parameters,  $\alpha$  a matrix/vector of adjustment coefficients,  $\beta$  a co-  
51 integrating matrix/vector and  $\Gamma_i$ 's parameter matrices. The error vectors  $\varepsilon_t$  are assumed  
52 to be independent over time and normally distributed with zero mean and covariance  
53 matrix  $\Omega^6$ .  
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<sup>6</sup> Note that we do not assume the SPF nor inflation series to be exogenous. For example, even if the lagged values of the Michigan series do not help forecast the future SPF values, one should not take this

We will use the Bayesian approach and posterior density simulations to make exact inference on the parameters. To see whether the data confirm the existence of a co-integrating relation between the Michigan, professional and actual inflation series and to find proper lag length for the model (4) we follow Corander and Villani (2004) and compute approximate fractional marginal likelihoods (FML). The FML results (not reported here in order to save space) indicate that the proper lag length is 1 and cointegration rank 2.

However, we restrict our model to include only one co-integrating vector and write the long-run relationship in an informative form

$$M_t[\Pi_{t+4}] = \beta_1 S_t[\Pi_{t+4}] + \beta_2 \Pi_t^m + z_t, \quad (5)$$

where  $z_t$  is a stationary term; that is, we use the parametrisation  $\beta = (-1 \ \beta_1 \ \beta_2)'$ . From the estimates of  $\beta_1$  and  $\beta_2$  we can see which of the series  $S_t[\Pi_{t+4}]$  or  $\Pi_t^m$  is more closely related to the Michigan series.

In order to generate conditional and marginal posteriors, we use normal likelihood and an improper prior  $p(\Psi, \alpha, \beta, \Gamma_1, \dots, \Gamma_{p-1}, \Omega) \propto |\Omega|^{-0.5(m+1)}$  in our Bayesian analysis. With this choice of prior the joint posterior distribution of  $\beta_1$  and  $\beta_2$  has a 1-1 poly-t density (see Corollary 3.1 in Bauwens and Lubrano, 1996) and we can use the algorithms of Richard and Tompa (1980) to generate random numbers from it.

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as a sign of noncausality, since professional forecasters should use the information offered by consumer expectations when they form their forecasts. For example, they might expect that the high inflation expectations of the general public cause consumer inflation to rise.

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The estimates of the CVAR model are presented in Table 1. Since more than 4% of the probability mass of  $\beta_1$  lies below zero, one must be careful when stating that the general public uses professional forecasters' forecasts when they form their expectations. On the other hand, the high CVAR estimate  $\beta_2 = 0.349$  confirms our earlier results that annualized monthly inflation is an important factor in the public's inflation expectations formation process. One can also interpret the estimated cointegrating relation so that the expectations of the public are more closely connected to annualized monthly inflation figures than the professionals' forecasts, since professionals also use other information in their forecasts, such as unemployment rates and lagged inflation estimates. See also the estimates of equation (6) in Table 1, where annualized inflation is excluded from regression. The link between the Michigan and SPF expectations does not seem strong here either, since the 95 % posterior interval of  $\beta_1$  includes zero.

Khan and Zhu (2002), Mankiw, Reis and Wolfers (2003) and Carroll (2003) acquire empirical estimates which indicate that in sticky information models, individuals update their information sets on average every 12 months. If this is the case, the resulting median forecast of the Michigan survey should be closely related to the median of geometrically-weighted averages of past professional inflation forecasts and the cross coefficients of the lagged SPF series and their sum  $\sum \gamma_{21}^{(i)}$  should be different from zero. Therefore, we estimated the CVAR model of equation (4) with data  $y_t = (M_t[\Pi_{t+4}] S_t[\Pi_{t+4}])$  and cointegrating relationship

$$M_t[\Pi_{t+4}] = \beta_1 S_t[\Pi_{t+4}] + z_t. \quad (6)$$

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3 The FML based estimates for rank support this restriction (rank = 1) and the estimated  
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5 lag length is 1. However, because we are interested in the coefficients of the lagged SPF  
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7 series and their sum ( $\sum \gamma_{21}^{(i)}$ ) we estimate the CVAR model using four lags.  
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12 The estimates of this model are shown in Table 1 (equation (6)). As the lag length  
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14 estimate indicates, the posterior density of  $\sum \gamma_{21}^{(i)}$  has a lot of its probability mass close  
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16 to zero. Thus, the cumulative effect of the lagged SPF series on the Michigan series is  
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18 not economically or statistically significant<sup>7</sup>. It seems that the data do not support  
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20 Carroll's (2003) epidemiology model nor Mankiw's and Reis's (2002) sticky  
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22 information model.  
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30 Finally, Table 3 shows the medians and standard errors of the cross coefficients  $\gamma_{21}(i)$  ( $i$   
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32 = 1, ..., p) and their sums when standard Bayesian vector autoregressive (BVAR) models  
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34 with a noninformative Jeffrey's prior distribution and different lag lengths<sup>8</sup> are used.  
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36 We can see from the table that the parameters  $\gamma_{21}(i)$  are not significantly different from  
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38 zero except in the model with one lag. However, as Carroll's Granger causality test  
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40 indicates, the cumulative effect of the SPF forecast on the Michigan series is positive  
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42 with high probability. Thus, there seems to be a relation between the professional's and  
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44 the general public's forecasts, but this relation is probably a kind of long-run co-  
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46 movement in which the general public adjusts its expectations as the significant  
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48 estimate for the adjustment parameter  $\alpha_1 = 0.487$  indicates (see Equation 6 in Table 1).  
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51 However, households do not necessarily adjust their expectations toward the forecasts  
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57 <sup>7</sup> Note also that no one of the parameters  $\gamma_{21}^{(i)}$  had a posterior distribution deviating significantly from  
58 zero (results were similar when we use mean series). We also estimated the error correction model with  
59 the assumption that the SPF series is exogenous and the results looked similar.

60 <sup>8</sup> The model is of the form  $y_t = \sum_{i=1}^p \Gamma_i y_{t-i} + \varepsilon_t$ , where  $\Gamma_i$ 's are parameter matrices and  $\varepsilon_t$  is the normally distributed error term with zero mean and  $\Sigma$  covariance.

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3 of professionals. Rather, both professionals and the general public adjust their  
4 expectations toward actual annual inflation i.e. both groups correct their expectations  
5 toward the fully rational outcome.  
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12 In summary, we do not find that the data support Carroll's (2003) epidemiology model  
13 or Mankiw's and Reis's (2002) sticky information model. Therefore, there is a need for  
14 some alternative theory for the general public's inflation expectations.  
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### 19 20 21 III Modelling the Consumers' Formation of Inflation Expectations 22 23 24 25

26 In our candidate theory, which offers an alternative explanation for the general public's  
27 inflation expectations formation process, we assume that each individual has his own  
28 personal beliefs about the process of inflation. They update this prior knowledge  
29 regularly using annualized monthly inflation figures and possibly some other variables  
30 offered by the news media and use the updated information to form their expectations.  
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32 We find several reasons why inflation expectations of the general public should  
33 modelled using a well-defined random process with personal probabilities about the  
34 parameter values of the process. Firstly, individuals cannot observe inflation directly but  
35 through the news media, since in everyday life they observe the prices not the inflation.  
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37 Secondly, it is well known that typical individuals' views about the inflation process are  
38 relatively poor. They may not have any clear idea about the causes of inflation. It is very  
39 descriptive that the most common answer was 'greed' or 'greedy', when Shiller (1997),  
40 in his questionnaire study, asked people to list the causes of inflation. Thirdly, we,  
41 unlike Mankiw and Reis (2002) or Carroll (2003), expect that most people follow  
42 economic news daily or at least regularly. We agree with Shiller (1997) who argues:  
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44 'Because the word "inflation" is so much a part of everyday lives, it has many  
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3 associations and connotations to ordinary people. Moreover, because shopping, and  
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5 thereby noticing prices, is an everyday activity for ordinary people, thinking about  
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7 prices is also a major part of people's thinking, and the subject "inflation" is one of  
8  
9 great personal interest for most people'. Furthermore, when Shiller (1997) asked people  
10  
11 if they find news stories about inflation interesting, 89% reported that inflation news  
12  
13 reports are very or somewhat interesting (see more discussion on individuals'  
14  
15 expectation behaviour: Kahneman and Tverky, 1979, Nisbett and Ross, 1980, Gleitman,  
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17 1996, Mahmoud, El-Gamal and Grether, 1995, Shiller, 1997, Akerlof, Dickens and  
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19 Perry, 2000, and Manski, 2004). Therefore, we assume that a typical individual believes  
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21 that the process of inflation is captured by the model  
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$$\Pi_t = X_{t-4}B + \varepsilon_t, \quad (7)$$

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34 where  $\varepsilon_t$  is a normally distributed error term with zero mean and  $\sigma^2$  variance and  $X_{t-4}$  is  
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36 a row vector which includes annualized monthly inflation and other possible  
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38 explanatory variables. We believe that a simple univariate process describes the public's  
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40 views about the process of inflation better than a multivariate process, since ordinary  
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42 people seem to fail to understand the concept of general equilibrium (see Shiller, 1997).  
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49 However, the opinions about the parameter values of the above process may vary  
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51 strongly among individuals. To allow for this kind of disagreement, we further assume  
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53 that every individual has his own personal beliefs about the parameters of the model (7).  
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55 Moreover, we assume that the personal prior distribution of the  $i$ th individual for the  
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57 parameter vector  $B^i$  is multivariate normal:  
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$$B^i \sim N\left(B_0^i, \sigma^2 (V_0^{-1})^i\right), \quad (8)$$

where  $B_0$  is the individual's prior estimate of  $B$  and matrix  $(V_0^{-1})^i$  is a measure of his uncertainty, relative to  $\sigma^2$ . If, for example, the  $i$ th individual believed that inflation follows a random walk process, the parameter of recent inflation in  $B_0$  would be equal to 1 and the corresponding diagonal entry in  $V_0^{-1}$  very small. The parameters of other variables in  $B_0$  would be zero and the corresponding variances in  $V_0^{-1}$  very small. Thus we have a very flexible behavioural model which covers the observed disagreement about the causes of inflation and explains the variance of inflation expectations among households (see Shiller, 1997, and Mankiw, Reis and Wolfers, 2003).

We further assume that the  $i$ th individual forecasts inflation on the basis of his evolving beliefs about  $B$  (confer Caskey, 1985). Each period he obtains new information on annualized monthly inflation and other possible explanatory variables from news articles he uses it to update his beliefs about the parameter vector  $B$ . This updating process can be best described using the following recursive equations of the Kalman filter:

$$\hat{B}_t^i = \hat{B}_{t-1}^i + K_t (\Pi_t - X_{t-4} \hat{B}_{t-1}^i) \quad (9)$$

$$(\hat{V}_t^{-1})^i = (\hat{V}_{t-1}^{-1})^i - K_t^i X_{t-4} (\hat{V}_{t-1}^{-1})^i \quad (10)$$

$$K_t^i = (\hat{V}_{t-1}^{-1})^i X_{t-4}' \left( X_{t-4} (\hat{V}_{t-1}^{-1})^i X_{t-4}' + 1 \right)^{-1} \quad (11)$$

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5 where vector  $K_t$  is the so-called Kalman gain. We do not expect that individuals fully  
6 remember the observations of possible explanatory variables, presented in past news  
7 articles; however, our point is that this kind of a recursive system might be the best  
8 description of their learning process. The model also covers the possibility that some  
9 people have such strong prior beliefs that they do not change them.  
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20 Finally, assuming that the  $i$ th individual uses a quadratic loss function in his forecasts  
21 and taking into consideration that his thought processes cannot be fully replicated, we  
22 model his inflation expectations as  
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$$29 \quad E_t^i(\Pi_{t+4}) = X_t \hat{B}_t^i + u_t^i, \quad (12)$$

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34 where the operator  $E_t^j$  denotes the  $i$ th individual's expectation at time  $t$  and  $u_t$  a  
35 normally distributed error with zero mean and  $\sigma_u^2$  variance. Unfortunately, because of  
36 the nature of consumer surveys, such as the Michigan survey data, we cannot test the  
37 Bayesian learning model directly. The reason is that consumer surveys use random  
38 samples of respondents and the respondents are different every month. Therefore, it is  
39 not possible to track individual learning processes using the data. However, the  
40 Bayesian learning model has a couple of consequences which we can test empirically.  
41 Firstly, the model implies that the mean of the expectations can be calculated as  
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$$57 \quad m\{E_t^i[\Pi_{t+4}]\} = X_t m\{\hat{B}_t^i\} + m\{u_t^i\} \quad (13)$$

where  $m\{\}$  denotes mean over all individuals in the population. Secondly, the variance of expectations is given by

$$\text{Var}(E_t^i[\Pi_{t+4}]) = X_t \text{cov}(\hat{B}_t^i) X_t' + \text{var}(u_t^i), \quad (14)$$

where  $\text{cov}(\hat{B}_t^i)$  is the covariance matrix measuring the dispersion of opinions among the general public.

Equation (13) implies that the population variance of inflation expectations is a function of annualized monthly inflation and possibly some other variables reported in the news media and of the variances and covariances of the individuals' parameter estimates.

#### IV Empirical test of the Bayesian Learning Model

The respondents of the monthly Michigan surveys have learning paths with different lengths and starting points. Therefore, it seems reasonable to assume that the mean vector  $m\{\hat{B}_t^i\}$  and dispersion matrix  $\text{cov}(\hat{B}_t^i)$  in equations (13) and (14) stay constant over time. Then we can estimate them using OLS. However, the reader should note that we can not trust the standard t-statistics related to these parameters, since the time series involved in these models are unit root or nearly unit-root processes. However, our main objective is to investigate how well the outcomes of the Bayesian learning model can predict the mean and variance series of the actual Michigan inflation expectations. We

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3 suggest that the key things here are the correct signs of the variance estimates and the  
4 prediction power of the estimated models. To proceed further, we set<sup>9</sup>  
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$$10 \text{ var}(M_t[\Pi_{t+4}]) = \text{var}(E_t^i[\Pi_{t+4}]) + \text{error} = X_t' \text{cov}(\hat{B}_t^i) X_t + \text{var}(u_t^i) + \text{error}, \quad (15)$$

$$11$$

$$12$$

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$$16 M_t[\Pi_{t+4}] = m\{E_t^i[\Pi_{t+4}]\} + \text{error} = X_t m\{\hat{B}_t^i\} + m\{u_t^i\} + \text{error}. \quad (16)$$

$$17$$

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$$20$$

21 Moreover, we assume that the most probable components of  $X_t$  are annualized monthly  
22 inflation  $\Pi_t^m$  and the 3-month T-bill rate, since most commonly published economic  
23 news articles on the subject concern these figures and since the public seems to perceive  
24 the relation between inflation and the interest rate (Shiller, 1997). Our alternative  
25 candidate series, which may compensate for the T-bill series, are those which are most  
26 probably regularly reported by all major media in the US:  
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- 37 a) SPF forecast
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- 39 b) Unemployment rate
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- 42 c) Annualized quarterly growth of GDP
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- 45 d) Annualized monthly growth of M1
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49 The results for the variance and mean equations are summarized in Table 4. We can see  
50 that the variance model based on inflation and the 3-month T-bill rate and the variance  
51 model based on inflation alone give similar correlations between the predicted variance  
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56 <sup>9</sup> To analyze the predicted variance of the learning model we need a longer sample period than the period  
57 1981/3-2004/1 for which the professionals' CPI inflation forecast series is available. To obtain a longer  
58 forecast period 1970/1-2004/1 we used SPF's GDP deflator forecast series. We regressed the CPI  
59 inflation forecast series on the GDP deflator inflation forecast series and a constant and predicted the CPI  
60 inflation forecast series for the period 1970/1-1981/2 using the estimated regression model. The  
parameter estimates were 0.68 and 0.89 for the constant and the GDP deflator forecast series,  
respectively).

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3 series and the actual Michigan variance. However, the actual mean series has a  
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5 remarkably higher correlation with the predicted mean series based on inflation and the  
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7 T-bill rate than with the predicted series based on inflation alone. These results suggest  
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9 that a part of the population always believes the process of inflation to be random walk,  
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11 which causes the variance of the Michigan survey to be high, while another part of them  
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13 is aware of the relationship between inflation and the interest rate (confer Shiller, 1997).  
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20 The model based on monthly inflation and the 3-month T-bill rate gives relatively high  
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22 correlation coefficients between the predicted and actual Michigan mean series,  
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24 compared to the models based on inflation and unemployment, inflation and the  
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26 quarterly growth rate of GDP or inflation and the monthly growth rate of M1. The drop  
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28 of the correlation coefficient from the mean model based on inflation and the T-bill rate  
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30 to the mean model based on inflation and the unemployment rate is quite large, about  
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32 11%. Moreover, the correlation between the predicted mean series based on annualized  
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34 monthly inflation and the actual Michigan mean series is 0.645, which suggests that the  
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36 growth of money, growth of GDP or unemployment series add practically nothing to the  
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38 learning model expectations based on monthly inflation (compare correlations reported  
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40 in Table 4). These findings are in line with Shiller's (1997) questionnaire study, in  
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42 which he observes that most people seem to fail to think of economic models; people do  
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44 not tend to see any connection between inflation and unemployment, i.e. the Phillips  
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46 curve, or between inflation and money growth, i.e. the quantity theory of money.  
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55 The variance model based on inflation and unemployment and the model based on  
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57 inflation and the SPF series give us the highest correlations between the predicted and  
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59 actual variance series (0.88 and 0.9). However, if we take a closer look at the parameter  
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3 estimates of these models, we find that in both these models the estimates of  
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5  $\text{var}(u)+\text{var}(b_0)$  are negative, which of course does not make sense. One plausible  
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7 explanation for the high correlation between the professionals' forecast series and the  
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9 Michigan variance series ( $\text{cov}(b_2, b_0) = 14.7$ ) is that there is a higher probability for  
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11 individuals who believe inflation to be random walk to give lousy forecasts when  
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13 inflation is rationally expected to increase rapidly than during a stable low inflation  
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15 period.  
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22 In summary, based on the weak relation between the SPF and Michigan median series,  
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24 as found when estimating equations (5) and (6) in Section 2, and the results presented in  
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26 the current section, we conclude that a Bayesian learning model based on annualized  
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28 monthly inflation series and the 3-month T-bill rate offers us a more plausible  
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30 explanation for the general public's inflation expectations than the limited information  
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32 flows models based on rational or nearly rational forecast series.  
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## 40 VI Conclusion

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45 In this paper, we have empirically shown that a simple Bayesian learning model is a  
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47 feasible explanation for the general public's inflation expectations formation. We have  
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49 also shown that the Michigan Survey data do not support models of limited information  
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51 flows, discussed the theoretical basis of the Bayesian model and come to the conclusion  
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53 that it gives a more realistic picture of individuals' expectation behaviour in the case of  
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55 inflation than some new models presented in the literature, such as models of limited  
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57 information flows or models with uncertainty approach. Learning models have, of  
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59 course, many variants, but the advantage of Bayesian models is that by using personal  
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3 probabilities, one can describe individuals' opinions and their willingness to update  
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5 them. From our point of view, Bayesian learning models are worth further development  
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8 in the context of the *public's* inflation expectations.  
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Table 1: Estimation Results for Equations 3, 5 and 6

Equation	$\gamma_0$	$\gamma_1$	$\gamma_2$	$\gamma_3$	$R^2$
(3) with mean series	1.176*** (0.181)	0.510*** (0.080)	0.233** (0.090)	0.042** (0.019)	0.849
(3) with median series	1.324*** (0.145)	0.386*** (0.059)	0.074 (0.112)	0.079*** (0.020)	0.794

Model (VECM)

$$\Delta y_t = \psi + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \alpha \beta' y_{t-1} + \varepsilon_t$$
, where  $y_t = (M_t[\Pi_{t+4}] \ S_t[\Pi_{t+4}] \ \Pi_t^m)'$  and the cointegrating relation is  $M_t[\Pi_{t+4}] = \beta_1 S_t[\Pi_{t+4}] + \beta_2 \Pi_t^m + z_t$ 

Equation	$\beta_1$	$\beta_2$	-	-	-
(5)	0.149 95.2%	<b>0.349</b> 100%	-	-	-

Model (VECM)

$$\Delta y_t = \psi + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \alpha \beta' y_{t-1} + \varepsilon_t$$
, where  $y_t = (M_t[\Pi_{t+4}] \ S_t[\Pi_{t+4}])'$  and the cointegrating relation is  $M_t[\Pi_{t+4}] = \beta_1 S_t[\Pi_{t+4}] + z_t$ 

Equation	$\sum \gamma_{21}^{(i)}$	$\beta_1$	$\alpha_1$	$\alpha_2$	-
(6)	-0.500 84.0%	0.418 96.9%	<b>0.487</b> 98.7%	0.223 95.5%	-

Newey-West standard errors in parentheses. The results are not sensitive to the choice of lags (4 lags are used). The signs \*\*, \* and • denote statistical significance at the 1%, 5% and 10% levels, respectively. In the Bayesian analysis part we report the posterior median and the share of posterior mass which lies above (below) zero when the median is positive (negative). The median is given in bold face when zero is not included in the 95% posterior interval).

Sample 1981/Q3 – 2004/Q1

Table 2: Augmented Dickey-Fuller Tests

Variable	t-ADF
Michigan mean series	-1.993
Michigan median series	-1.529
Survey of Professional Forecasters mean series	-0.5551
Survey of Professional Forecasters median series	-0.7668
Annualized monthly inflation (Realtime)	-3.201*

Sample 1981/Q3 – 2004/Q1

\* indicates statistical significance at the level of 5%

Table 3: Point Estimates of BVAR Models

Model

$$y_t = \sum_{i=1}^p \Gamma_i y_{t-i} + \varepsilon_t$$

with Jeffrey's Prior and Different Lag Lengths ( $p=1, \dots, 4$ )  
 where  $y_t = (M_t[\pi_{t+4}] \ S_t[\pi_{t+4}])'$

number of lags	parameter(lag)	median
1	$\gamma_{21}(1)$	0.31 (0.07)
	$\gamma_{21}(1)$	0.29 (0.23)
2	$\gamma_{21}(2)$	-0.03 (0.21)
	sum $\gamma_{21}(i)$	0.25 (0.09)
3	$\gamma_{21}(1)$	0.31 (0.24)
	$\gamma_{21}(2)$	0.06 (0.33)
	$\gamma_{21}(3)$	-0.11 (0.21)
	sum $\gamma_{21}(i)$	0.27 (0.10)
4	$\gamma_{21}(1)$	0.27 (0.25)
	$\gamma_{21}(2)$	0.12 (0.35)
	$\gamma_{21}(3)$	-0.11 (0.34)
	$\gamma_{21}(4)$	-0.03 (0.23)
	sum $\gamma_{21}(i)$	0.25 (0.10)

standard deviations in parentheses

Table 4: Estimation Results for Variance and Mean Equations

## Variance Model

$$\text{var}(M_t[\Pi_{t+4}]) = X_t' \text{cov}(\hat{B}_t^i) X_t + \text{var}(u_t^i) + \text{error}$$

Variables	var(u)+var(b <sub>0</sub> )	var(b <sub>1</sub> )	cov(b <sub>1</sub> ,b <sub>0</sub> )	var(b <sub>2</sub> )	cov(b <sub>2</sub> ,b <sub>0</sub> )	cov(b <sub>1</sub> , b <sub>2</sub> )	correlation between predicted and actual variance series
monthly inflation	21.617 (1.698)	0.591 (0.082)	-0.272 (0.110)	-	-	-	0.842
monthly inflation and T-bill	3.178 (5.034)	0.292 (0.110)	3.836 (1.318)	0.116 (0.136)	3.278 (1.473)	-0.406 (0.214)	0.842
monthly inflation and SPF forecasts	-20.636 (6.530)	0.573 (0.148)	1.994 (1.380)	0.216 (0.534)	14.679 (3.504)	-1.351 (0.493)	0.908
monthly inflation and unemployment	-69.320 (19.495)	0.131 (0.072)	12.172 (1.999)	-0.498 (0.382)	17.485 (5.497)	-1.302 (0.267)	0.875
monthly inflation and growth of GDP	24.828 (3.956)	0.162 (0.091)	3.281 (1.290)	0.028 (0.065)	-2.669 (0.930)	0.318 (0.123)	0.809
monthly inflation and growth of M1	14.348 (3.638)	0.143 (0.087)	4.036 (1.235)	-0.161 (0.403)	3.625 (1.875)	0.053 (0.306)	0.818

Sample 1970/Q1 – 2004/Q1

## Mean Model

$$M_t[\Pi_{t+4}] = X_t m\{\hat{B}_t^i\} + m\{u_t^i\} + \text{error}$$

Variables	b <sub>0</sub>	b <sub>1</sub>	b <sub>2</sub>	correlation between predicted and actual mean series
monthly inflation (b <sub>1</sub> )	3.176 (0.142)	0.295 (0.037)	-	0.645
monthly inflation (b <sub>1</sub> ) and T-bill (b <sub>2</sub> )	2.341 (0.129)	0.149 (0.023)	0.228 (0.023)	0.852
monthly inflation and SPF forecasts	1.516 (0.130)	0.054 (0.025)	0.678 (0.044)	0.918
monthly inflation and unemployment	1.658 (0.293)	0.270 (0.032)	0.257 (0.045)	0.757
monthly inflation and growth of GDP	3.369 (0.165)	0.291 (0.036)	-0.070 (0.032)	0.668
monthly inflation and growth of M1	3.101 (0.158)	0.298 (0.037)	0.053 (0.048)	0.651

Sample 1981/Q3 – 2004/Q1

## References:

Akerlof, G. A., Dickens, W. T. and Perry, G. L. (2000) Near-Rational Wage and Price Setting and the Optimal Rates of Inflation and Unemployment, *Brookings Papers on Economic Activity*.

Andrews, D. W. K. (1991) Heteroskedasticity and autocorrelation consistent covariance matrix estimation, *Econometrica*, **59**, pp. 817—858.

Banerjee, A., J.J. Dolado, J.W. Galbraith, and D.F. Hendry (1993) *Cointegration, Error Correction, and the Econometric Analysis of Non-Stationary Data*, Oxford University Press

Berk, J. M. (1999) Measuring inflation expectations: a survey data approach, *Applied Economics*, **31**, 1467-1480.

Branch, W. A. (2004a) The Theory of Rationally Heterogeneous Expectations: Evidence from Survey Data on Inflation Expectations, *Economic Journal*, **114**, 592-621.

Branch, W. A. (2004b) Sticky Information and Model Uncertainty in Survey Data on Inflation Expectations, Working paper, College of William and Mary.

Bonham, C. and Cohen, R. H. (1995) Testing the Rationality of Price Forecasts: Comment, *American Economic Review* **85**, 284—89.

Carlson, J. A. (1975) Are Price Expectations Normally Distributed? *Journal of the American Statistical Association*, **70**, 749-754.

Carroll, C. D. (2003) Macroeconomic Expectations of Households and Professional Forecasters, *Quarterly Journal of Economics*, 269-298.

Caskey, J., (1985) Modeling the Formation of Price Expectations: A Bayesian Approach, *The American Economic Review*, **75**, 768-776.

1  
2  
3  
4  
5 Cartwright, P. A. and DeLorme, C. D. Jr. (1985) The Unemployment-Inflation Voter  
6 Utility Relationship in the Business Cycle: Some Evidence, *Southern Economic*  
7 *Journal*, **51**, 898-905.  
8  
9

10  
11  
12 Croushore, D. and Stark, T. (2001) A Real-Time Data Set for Macroeconomists,  
13 *Journal of Econometrics* **105**, 111-130.  
14  
15

16  
17 Curtin, R. (1996) Procedure to Estimate Price Expectations, mineo, University of  
18 Michigan Survey Research Center.  
19

20  
21  
22 Cuzan, A. G. and Bunderick, C. M. (1992) Selected Fiscal and Economic Effects on  
23 Presidential Elections, *Presidential Studied Quarterly*, **22**, 127-134.  
24  
25

26  
27  
28 Corander, J. and Villani, M. (2004) Bayesian Assessment of Dimensionality in Reduced  
29 Rank Regression, *Statistica Neerlandica*, **58**, 255-270.  
30  
31

32  
33 Fair, R. C. (1978) The Effect of Economic Events on Votes for President, *The Review of*  
34 *Economics and Statistics*, **60**, 159-173.  
35  
36

37  
38 Fair, R. C. (1994) The Effect of Economic Events on Votes for President: 1992 Update,  
39 Cowles Foundation Discussion Paper No. 1084.  
40  
41

42  
43 Forsells, M. and Kenny, G. (2002) The Rationality of Consumer's Inflation  
44 Expectations: Survey-Based Evidence for the Euro Area, European Central Bank  
45 Working Paper Series, No. 163.  
46  
47  
48

49  
50  
51 Gleitman, Henry (1996) *Basic Psychology*, New York: Norton.  
52  
53

54  
55 Golden, D. G. and Poterba, J. M. (1980) The Price of Popularity: The Political Business  
56 Cycle Reconsidered, *American Journal of Political Science*, 696-714.  
57  
58

59  
60 El-Gamal, M. A. and Grether, D. M. (1995) Are People Bayesian? Uncovering  
Behavioral Strategies, *Journal of the American Statistical Association*, **90**, 1137-1145.

1  
2  
3  
4  
5 Hamilton, D. James (1994) *Time series analysis*, Princeton university press.  
6  
7

8  
9 Evans, G. W. and Honkapohja S. (2001). *Learning and Expectations in*  
10 *Macroeconomics*, Princeton University Press.  
11

12  
13 Jeong, J. and Maddala G. S. (1996) Testing the Rationality of Survey Data Using the  
14 Weighted Double-Bootstrapped Method of Moments, *Review of Economics and*  
15 *Statistics* **78**, 296-302.  
16  
17

18  
19 Kahneman, D. and Tversky, A. (1979), Prospect Theory: An Analysis of Decision under  
20 Risk, *Econometrica* **47**, 263-92  
21  
22

23  
24 Khan, H. and Zhu Z. (2002) Estimates of the Sticky-Information Phillips Curve for the  
25 United States, Canada and the United Kingdom, Bank of Canada Working paper 2002-  
26 19, forthcoming Journal of Money, Credit and Banking.  
27  
28

29  
30 Lloyd B. T. Jr. (1999) Survey Measures of Expected U.S. Inflation, *Journal of*  
31 *Economic Perspective*, **13**, 125-144.  
32  
33

34  
35 Manski C. F. (2004) Measuring Expectations, *Econometrica*, **72**, 1329 -  
36  
37

38  
39 Mankiw, N. G. and Reis R. (2002) Sticky Information Versus Sticky Prices: A Proposal  
40 to Replace the New Keynesian Phillips Curve, *Quarterly Journal of Economics*, **117**,  
41 1295-1328.  
42  
43

44  
45 Mankiw, G. N. Reis R and Wolfers J. (2003) Disagreement About Inflation  
46 Expectations, *NBER Macroeconomics Annual 2003*.  
47  
48

49  
50 Nisbett, R. and Ross L. (1980) *Human Inference: Strategies and Shortcomings of Social*  
51 *Judgment*, Englewood Cliffs, NJ: Prentice-Hall.  
52  
53

54  
55 O'Hagan, A. (1995) Fractional Bayes factors for model comparison (with discussion),  
56 Journal of the Royal Statist. Society, Ser. B, **57**, 99-138.  
57  
58  
59  
60

1  
2  
3  
4  
5 Parker, G. R., (1978) Economic Partisan Advantages in Congressional Contests: 1938-  
6 1978, *Public Opinion Quarterly*, **50**, 387-401.  
7  
8  
9

10  
11  
12  
13  
14 Richark, J. F. and Tompa, H (1980). On the Evaluation of Poly-t Density Functions,  
15 *Journal of Econometrics*, 12, 335-351.  
16  
17

18  
19 Sargent, T. J., (1993) *Bounded Rationality in Macroeconomics*, Oxford University  
20 Press, Oxford.  
21  
22

23  
24  
25 Sims, C. A. (2003) Implications of Rational Inattention, *Journal of Monetary*  
26 *Economics*, **50**, 665-690.  
27  
28

29  
30 Shiller, R. J. (1997) Why Do People Dislike Inflation, in *Reducing Inflation: Motivation*  
31 *and Strategy*, edited by Christina D. Romer and David H. Romer. Chicago: University  
32 of Chicago press.  
33  
34

35  
36  
37 Stock, J. H. and Watson, M. W. (1999) Forecasting inflation, *Journal of Monetary*  
38 *Economics*, **44**, 293-335.  
39  
40

41  
42 Zarnowitz, V. (1985) Rational Expectations and Macroeconomic Forecasts, *Journal of*  
43 *Business & Economic Statistics*, **3**, 293-311.  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60