Is There Support for the Sticky Information Models in the Michigan Inflation Expectation Data?

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ABSTRACT

In this paper we provide some relevant estimation results on the consumers' inflation expectations formation process. Specifically, we show that the Michigan inflation expectations data support neither Carroll's (2003) epidemiological sticky information model nor the sticky information models of Mankiw and Reis (2002) and Sims (2003). Rather, our empirical results, which are based on a real-time inflation series, indicate that professionals and the general public update their forecasts using the most recently reported statistics. In the case of ordinary people this is annualised monthly inflation, the most commonly reported figure in the news coverage of inflation.

Keywords: public's inflation expectations, Bayesian CVAR, Michigan survey, Survey of Professional Forecasters, real time series

1. Introduction

The inflation expectations of the general public are an important determinant of inflation and other macroeconomic fundaments, 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, pressure firms to raise the prices of their products, and encourage agents to purchase more commodities. In addition, public concern over actual inflation has certainly had an impact on political elections; see Cartwright and Delorme (1985), Parker (1986), Golden and Poterba (1989), Cuzan and Bundrick (1992), Fair (1978 ,1994), and Shiller (1997).

The assumption of rational expectations, which presumes that the agents know the true structure and probability distribution of the economy, is most commonly used line of approach in theoretical and empirical exercises today. However, having encountered problems with this assumption[1], researchers have started to search for alternative models for the expectations formation process. For example, in the models of limited information flows (sticky information models) developed by Mankiw and Reis (2002), Carroll (2003), and Sims (2003) the agents have rational expectations, but the expectations 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.

In a recent empirical paper on inflation expectations formation, Carroll (2003) explores the causality of the Michigan households' mean inflation expectations and the Survey of Professional Forecasters (SPF) mean inflation forecasts. Using the standard Granger causality test, he finds that the professional forecast Granger-causes the household forecast, but that there is no Granger causality in the opposite direction. This evidence of Granger causality plays an essential role in his theory of epidemiological expectations formation. In his epidemiology model, households form their expectations when they randomly come into contact with the relevant information set, which Carroll assumes to consist of news articles on professional forecasters' forecasts. This epidemiology model is closely linked to the sticky information model of Mankiw and Reis (2002), from which Khan and Zhu (2006), Mankiw, Reis and Wolfers (2003), Andres and associates (2005), and Kiley (2007) acquire empirical estimates. All these authors (also Carroll) employ different identification schemes, and estimate that individuals update their expectations roughly once a year. If this is the

[1] See, for example, Zarnowitz (1985), Caskey (1985), Bonham and Cohen (1995), Jeong and Maddala (1996), and Lloyd (1999).

case, a large proportion of the population always use lagged news media forecasts as their information set. Consequently, the inflation expectations of the general public should be modelled as a function of lagged professional expectations.

Branch (2004) developed a promising model of heterogeneous agents, in which the general public form their inflation expectations using a prediction function from a set of costly alternatives. Specifically, he analysed the Michigan households' inflation expectations with the assumption that consumers use three alternative types of forecast functions in their formation process: VAR, adaptive, and naïve type models. His relatively contradictory results have led scientists to think more closely about the process of consumers' inflation expectations formation. We, for example, find the assumption that households have access to VAR estimates to be unrealistic[2], since the ordinary person cannot perceive the causes of inflation. For example, Shiller (1997), in his questionnaire study, asked the respondent to list causes of inflation. The responses to this question were diverse and almost equally represented. Most assumed ‘factors’ of inflation were of a general type, for example ‘greedy’ or ‘government’. This would indicate that identification of any more or less complex econometric or economic models constitutes an overwhelming task for ordinary people. Thus, even if Branch (2005) shows that his model uncertainty approach (Branch, 2004) is a more robust element in the Michigan data than the alternative ‘sticky information’ models of Carroll (2003), Sims (2003) and Mankiw and Reis (2002), his results, in our view, simply indicate that the model uncertainty approach is the more robust of the two alternative implausible models[3].

In the inflation expectations literature there has been almost no work on testing the model fit of sticky information models using actual empirical data on the general public’s inflation expectations. Testing sticky information models is, however, important by reason of the increasing popularity of this approach; see e.g. Easaw and Ghoshray (2003), Andres and colleagues (2005), Kiley (2007), Trabandt (2005), Korenok and Swanson (2004), Coibion (2006), and Reis (2006). In this paper, we show that the Michigan inflation expectations data support neither Carroll’s epidemiological sticky information model nor the sticky information models of Mankiw and Reis (2002) and Sims (2003). Rather, it seems that, when we use so-called real-time series[4], professionals and the general public

[2] One may assume that the VAR forecasts are almost the 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 involved in reading.

[3] We of course agree with Branch (2004) and many others in that the agents are heterogeneous. However, we believe that heterogeneity is mainly a matter of the thought process of individuals and is therefore hardly identifiable. More importantly, it is unclear how important this heterogeneity is in the evolution of aggregate consumer expectations.

[4] Real-time series consist of the figures available to the public and professionals when they formed their beliefs about

update their forecast using the most recently reported statistics. In the case of ordinary people this is annualised monthly inflation, the most commonly reported figure in the news coverage of inflation; see e.g. Shiller (1997), Carroll (2003) and Branch (2004). Thus, our analysis seems to support the view that a significant part of the population form their inflation expectations using the so-called adaptive expectations model.

Our report is organised as follows. In Section 2, we take a close look at Carroll's (2003) estimation results. In Section 3, we explore the empirical relationship between the professionals' and consumers' forecasts and actual real-time inflation using a cointegrated vector autoregressive (CVAR) model. In Section 4, we test sticky information models in general, and finally, in Section 5, we conclude the paper.

2. Looking at the Empirical Results of Carroll

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

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

where CPI is the seasonally adjusted Consumer Price Index for all urban consumers. However, annual inflation figures are asked in the Michigan survey. The Survey Research Center at the University of Michigan asks every month 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 prices will change during the next 12 months, then he is simply asked to supply a twelve-month forecast for annual inflation

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

This provides us with a well-defined absolute numerical scale for responses; hence, we may expect that respondents understand what the survey questions mean and interpret them similarly. Thus,

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future inflation.

modelling the Michigan households' responses may be well-founded; 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 (SPF) conducted by the Federal Reserve Bank of Philadelphia[5]. Moreover, we use here only so-called real-time series, i.e. series consisting of figures which were available to the public when they formed their beliefs regarding future inflation. Our main source of data is the Federal Reserve Bank of Philadelphia[6]; see Croushore and Stark (2001). Missing values in the CPI data were acquired from Norman R. Swanson's home pages[7].

To explore the relationship between the professionals' and households' forecasts and monthly inflation, we start our analysis by estimating the fundamental equation of Carroll (2003). According to Carroll's epidemiological sticky information model, mean measured inflation expectations for the next year should be a weighted average between the current newspaper forecast and the foregoing period's mean measured inflation expectations, i.e.

$$M_t\left[\Pi_{t+4}\right] = \gamma_1 S_t\left[\Pi_{t+4}\right] + \gamma_2 M_{t-1}\left[\Pi_{t+3}\right] + \nu_t\,. \tag{3}$$

where M_t and S_t are operators yielding the population means of the Michigan and SPF inflation expectations at time t, respectively, and ν_t is an error term. The estimate of γ_1 (when $\gamma_2 = 1 - \gamma_1$) should approximate the fraction of the population who will have absorbed the current-period news forecast for the next period.

In our view, the major problem in the analysis of Carroll (2003) lies in the long tails of the Michigan expectation series which are not particularly informative; see e.g. Curtin (1996) and Mankiw, Reis and Wolfers (2003). We control this by estimating Equation (3) using also the population median of the Michigan series.

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[5] Data available at http://www.phil.frb.org/econ

[6] Data available at http://www.phil.frb.org/econ/forecast/readow.html

[7] Data available at http://econweb.rutgers.edu/nswanson/realtime.htm

The estimates of Equation (3) obtained using the mean and median series are presented in Table 1 below[8]. The first result line gives the estimates when no restrictions are set to the parameters. We find that the estimates are very close to those in Carroll's study (γ_1 = 0.36 and γ_2 = 0.66). The point estimates of γ_1 and γ_2 based on median data are also markedly similar.

TABLE 1: Estimation Results for Equations 3 and 4

Model

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

Equation (mean series)	γ_0	γ_1	γ_2	γ_3	$\overline{R}^2$	AIC
(3)		0.37**	0.65**		0.78	-140
		(0.11)	(0.10)			
(3)		0.27**	0.73**			-139
		(0.07)	(0.07)			
(4)	1.177**	0.51**	0.23*	0.04*	0.85	-172
	(0.18)	(0.08)	(0.09)	(0.02		
Equation (median series)	γ_0	γ_1	γ_2	γ_3	$\overline{R}^2$	AIC
(3)		0.35**	0.59**		0.64	-150
		(0.10)	(0.124)			
(3)		0.20**	0.80**			-135
		(0.07)	(0.07)			
(4)	1.29**	0.40**	0.08	0.07**	0.80	-199
	(0.15)	(0.07)	(0.12)	(0.02)		

Newey-West standard errors in parentheses. The results are not sensitive to the choice of lags (5 lags are used). When comparing fitted objects, the smaller the Akaike information criterion (AIC), the better the fit. In the restricted version of Equation (3) AIC is based on the following regression ($M_t[\Pi_{t+4}]$ - $M_{t-1}[\Pi_{t+3}]$) = γ_1($S_t[\Pi_{t+4}]$ - $M_{t-1}[\Pi_{t+3}]$) + v_t. The signs **, * and • denote statistical significance at the 1%, 5% and 10% levels, respectively. Equations are estimated over the period 1981q3 to 2004q1.

The next line in the table gives the estimates when the theoretical restriction $\gamma_2 = 1 - \gamma_1$ is imposed. The point estimate of γ_1 (0.27) is equal to the corresponding estimate of Carroll (2003) and strikingly close to the value (0.25) estimated by Khan and Zhu (2006), Mankiw, Reis and Wolfers (2003), Andres and associates (2005), and Kiley (2007). Given that sticky information models can approximate the true process of public inflation expectations formation, this may indicate that individuals update their expectations about once a year. Regression based on the median series gives a similar message, since we can accept the hypothesis that γ_1 is 0.25. However, when we compare the values of the Akaike Information Criterion (AIC), we find that the fit of the unrestricted version of the model is better, especially when the median series are used.

[8] We will use the standard frequentist approach in order to maintain comparability with previous literature, especially with Carroll (2003).

Carroll also suggests that we may test whether there is a better representation for the public's inflation expectations than Equation (3) by allowing for a constant term and the possibility that some people update their expectations to the most recent past inflation statistics rather than to the SPF forecast. This regression has the form

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

where we use the recently-published annualised monthly inflation Π_t^m, not annual inflation as does Carroll (2003), since most news coverage of inflation is prompted by the release of past annualised monthly inflation statistics.

The estimates of γ_3 in the mean and median cases are positive and statistically significant at the 5% and 1% levels, respectively. This suggests that at least some fraction of the population form their inflation expectation using annualised monthly inflation figures. Our estimates are in disagreement with Carroll's (2003) finding that inflation has no influence on an individual's expectation formation process. In our opinion, his finding stems, first, from the high correlation (≈0.87) between recent annual inflation and the lagged value of the Michigan series, and second, from using the annual inflation series instead of the monthly annualised real-time inflation series.

Surprisingly, the estimate of γ_2 is statistically insignificant in the median case. This bodes ill for Carroll's sticky information model, since it may indicate that the lagged expectation series is merely proxying the missing past inflation rate. Moreover, comparing the AIC values of the theoretical model (Equation 3) with those of the alternative approach (Equation 4), we find that adding a constant term and the past inflation series markedly improves the model fit. Thus, the above findings strongly suggest that we should take a closer look at the underlying phenomenon.

3. The CVAR Analysis

Since the long tails of the Michigan expectation series are not particularly informative, we will henceforth use the Michigan median series. The results with the mean series look quite similar. If the expectations series move together in the long run, which seems to be a reasonable assumption, they can be modelled using co-integrated vector autoregression (CVAR). Let $y_t = (M_t[\Pi_{t+4}]\ S_t[\Pi_{t+4}]\ \Pi_t^m)'$ be a vector of SPF median inflation forecast, Michigan households' median inflation expectation and annualised monthly inflation. Then the CVAR model with p lags can be parameterised in the error correction form

$$\Delta y_t = \psi + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \alpha\beta' y_{t-1} + \varepsilon_t \,, \qquad (5)$$

where $\psi(m \times n)$ is a matrix of exogenous parameters, $\alpha(m \times r)$ a matrix of adjustment coefficients, $\beta(m \times r)$ a cointegrating matrix, n the number of exogenous variables, m the number of endogenous variables, r the number of cointegrating linear relations and Γ_i:s parameter matrices. The error vectors ε_t are assumed to be independent over time and normally distributed with zero mean and covariance matrix Ω[9].

The major problem in the analysis of Equation (5) lies in the interpretation of cointegrating vectors, since the coefficients in β are not necessarily long-run elasticities; see Johansen (2005) for further discussion. Note also that Equation (5) is not a structural form model, which complicates the interpretation of the adjustment coefficients in α. However, we will not enter into an extensive discussion of the estimates of these coefficients, since our main interest is to analyse the cointegrating vectors of β. Despite the existing problems attending CVAR models, the analysis based on them is still a promising alternative when one explores complicated endogenous systems of equations. Finally, we will use the Bayesian approach and posterior density simulations to draw precise inferences on the parameters in β; see an introduction to this approach in Bauwens and Lubrano (1996).

We start our CVAR analysis by studying whether the series can be modelled as unit root processes. We use the classical augmented Dickey-Fuller test (ADF test) in the preliminary data analysis, since this test is readily available and does not demand extra programming effort. The results are shown in Table 2 below. Since the null hypothesis of a unit root is not rejected in either case of an expectation series and only slightly rejected in the case of the annualised inflation series, we will model them as I(1) processes.

[9] Note that we do not assume either the SPF or the 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 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 high inflation expectations of the general public to cause consumer inflation to rise.

TABLE 2: Augmented Dickey-Fuller Tests

Augmented Dickey-Fuller Tests for Michigan Median Inflation Expectations Series, Professional Forecasters' Inflation Forecast Series and annualised monthly inflation series.

Variable	t-adf
Michigan mean series	-1.99
Michigan median series	-1.53
Survey of Professional Forecasters mean series	-0.56
Survey of Professional Forecasters median series	-0.77
Annualised monthly inflation (real- time)	-3.20*

* indicates statistical significance at the 5% level. Equations are estimated over the period 1981q3 to 2004q1.

To see whether the data confirm the existence of a cointegrating relationship between the Michigan, professional and actual inflation series and to find the proper lag length for the model in Equation (5), we follow Corander and Villani (2004) and compute approximate fractional marginal likelihoods (FML)[10]. The FML results (not reported here in order to save space) indicate that the proper lag length is 1 and the cointegration rank is 2.

However, we restrict our model to include only one cointegrating vector (at first) and write the long-run relationship in an informative form

$$M_t[\Pi_{t+4}] = \beta_1 S_t[\Pi_{t+4}] + \beta_2 \Pi_t^m + \mathrm{z_t}\,, \qquad (6)$$

where z_t is a stationary term; that is, we use the parameterisation $\beta = (-1\ \beta_1\ \beta_2)'$. From the estimates of β_1 and β_2 we can see which of the series, $S_t[\Pi_{t+4}]\,\text{or}\,\Pi_t^m$, is more closely related to the Michigan series.

In order to generate conditional and marginal posteriors, we use normal likelihood and an improper prior $p(\Psi,\alpha,\beta,\Gamma_1,...,\Gamma_{p-1},\Omega) \propto |\Omega|^{-0.5(m+1)}$ in our Bayesian analysis. With this choice of prior, the joint posterior distribution of β_1 and β_2 has a 1-1 poly-t density (see Bauwens and Lubrano (1996),

[10] The use of improper priors causes marginal likelihoods to be indeterminate, since the unknown normalising constant of the prior is not the same for different *p*. Thus, these constants will not cancel out in the posterior distribution of *p*. To confront this problem one may use a certain fraction (typically chosen to be minimal) of the data to 'train' the improper prior into a proper posterior which is subsequently used as a prior for the remaining observations; see Villani (2001). This is the idea behind the partial marginal likelihood discussed in O'Hagan (1995). A related approach is to use the fractional likelihood (FML), also discussed in O'Hagan (1995), in which the likelihood of the training sample is approximated by L^b, where L is the likelihood of the whole sample and b the fraction of the training sample. An approximate formula for the FML, in the case of CVAR models, is provided by Corander and Villani (2004).

Corollary 3.1) and we can use the algorithms of Richard and Tompa (1980) to generate random numbers from it. See Bauwens and Lubrano (1996) for further details about analytical integration and for motivation to use this prior.

TABLE 3: Estimation Results for Equation 5 with $r = 1$

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	β_1	β_2	A_1	α_2	α_3
(5)	0.19*	0.38**	-0.06	-0.14*	-0.29**
	(0.08)	(0.07)	(0.10)	(0.06)	(0.05)

The posterior median and standard deviation (in parenthesis) are shown in the table. The signs ** and * denote that zero is not included in the 95% or 99% posterior interval, respectively. Equations are estimated over the period 1981q4 to 2004q1.

The estimates of the CVAR model are presented in Table 3. The high CVAR estimate for the coefficient $\beta_2 = 0.38$ confirms our earlier finding that annualised monthly inflation is an important factor in the public's inflation expectations formation process. On the other hand, the point estimate of $\beta_1 = 0.19$ is relatively low compared to the corresponding OLS result above. One can interpret the estimated cointegrating relation to mean that the expectations of the public are more closely connected to annualised monthly inflation figures than the professionals' forecasts. Note also that professional forecasters' forecasts and Michigan households' expectations have the same forecasting horizon. This may cause the effect of the SPF series on the Michigan households' expectations to be spurious, in the sense that there may be some other factors which both groups use to update their expectations, for example past realisation of inflation.

From Table 3 we can also see that the adjustment speed of annualised monthly inflation[11] and professionals' forecast is relatively rapid, while the public do not adjust their expectations. However, we should regard this result with suspicion, since some relevant information on model dynamics may be lost when the number of cointegrating relations is restricted to one.

Furthermore, one may claim that the estimated rank 2 of the CVAR model picks up the inflation series, which may be stationary, and the cointegration between the Michigan survey and SPF series.

[11] We have divided the actual parameter by 12, since the inflation series captures monthly changes while the expectations series captures annual changes.

This would tender the above results non-meaningful. To control this we estimate two different CVAR models (5) with two different orderings of variables and with $r = 2$. In the first specification we set $y_t = (M_t[\Pi_{t+4}]\ \Pi_t^m\ S_t[\Pi_{t+4}])'$ and use the following identification restriction

$$\beta = \begin{pmatrix} -I_r \\ \beta^* \end{pmatrix}, \tag{7}$$

where $\beta^* = (\beta_1\ \beta_2)$. In this setup, β_1 picks up the relationship between the Michigan survey and SPF series and β_2 the relationship between the SPF and annualised monthly inflation series. Then, if $\beta_1 \neq 0$ and $\beta_2 = 0$, the model picks up the inflation series and cointegration between the two expectations series.

Table 4 shows the results of the CVAR model with a diffuse prior $|\Omega|^{-0.5(m+1)}$ for parameters Ψ, α, and Γ_i, and a flat prior, $p(\beta) \propto 1$, for β; see Bauwens and Lubrano (1996) for more detail on analytical integration and for motivation to use these priors[12]. From the table we can see that the data give support for the parameter β_2 being unity. This result is not surprising if we assume that professionals' forecasts are unbiased. It is also not so surprising that β_1 is positive, since this indicates that the general public's opinion follows actual inflation or the SPF forecast to some extent.

Next, we use the following ordering of variables $y_t = (M_t[\Pi_{t+4}]\ S_t[\Pi_{t+4}]\ \Pi_t^m)'$, with the same identification restriction on β as above (Equation 7) to show that the results remain similar when the parameter β_1 picks up the relationship between the Michigan expectations and annualised monthly inflation and β_2 the relationship between the SPF forecast and annualised monthly inflation.

From the results set out in Table 4 we can see that the estimates of the long-run parameters β_1 and β_2 are almost identical with both orderings of variables. The point estimate of β_1 (0.51) and the

[12] To generate a Monte Carlo sample from the posterior of β^* we used a version of the random walk Metropolis algorithm for Markov Chain Monte Carlo (MMCMC). The algorithm uses the multivariate normal distribution for the jumping distribution on changes in β^*. Our simulation procedure was as follows. We first simulated 20,000 draws using a diagonal covariance matrix with diagonal entries 0.00001 for the jumping distribution. We then used the last 10,000 draws to estimate the posterior covariance matrix of β^* and scaled it by the factor $(2.4)^2/2$ to obtain an optimal covariance matrix for the jumping distribution; see e.g. Gelman and associates (2004). Finally, we ran 100,000 draws and picked up every 100^{th} draw. The values of Geweke's (1992) Z-scores are -0.5669 and -1.080 in the first identification scheme (ordering of variables) and 0.9193 and 1.280 in the second, suggesting that the chains converged. The proportion of accepted jumps was about 0.48 in both cases.

corresponding result in Table 3 suggest that the general public form their inflation expectations using annualised monthly inflation.

TABLE 4: Estimation Results for CVAR model 4 with rank two

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 = ($M_t[\Pi_{t+4}]$ Π_t^m $S_t[\Pi_{t+4}]$)’ and the cointegrating relation is $\begin{pmatrix} -I_r \\ \beta * \end{pmatrix} y_{t-1}$,

Equation	β_1	β_2	α_{11}	A_{21}	α_{31}
(5) with r = 2	0.50**	0.99**	0.61**	-0.22**	0.07
	(0.07)	(0.21)	(0.15)	(0.05)	(0.13)
	α_{12}	α_{22}	α_{32}	ln FML	-
	0.04	0.11**	0.05*	882	-
	(0.03)	(0.01)	(0.03)		

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 = ($M_t[\Pi_{t+4}]$ $S_t[\Pi_{t+4}]$ Π_t^m)’ and the cointegrating relation is $\begin{pmatrix} -I_r \\ \beta * \end{pmatrix} y_{t-1}$,

Equation	β_1	β_2	α_{11}	A_{21}	α_{31}
(5) with r = 2	0.51**	1.03**	0.61**	0.07	-0.22**
	(0.08)	(0.29)	(0.15)	(0.12)	(0.04)
	α_{12}	α_{22}	α_{32}	ln FML	-
	-0.34*	-0.080	0.018	882	-
	(0.08)	(0.06)	(0.31)		

The posterior medians and standard deviations (in parenthesis) are shown in the table. The signs ** and * denote that zero is not included in the 95% or 99% posterior interval, respectively. Equations are estimated over the period 1981q3 to 2004q1.

The point estimates of the adjustment parameter α_1 (≈ 0.6) indicate that the general public adjust their inflation expectations towards long-run equilibrium. Based on the results as represented in Table 4, we may however expect that households do not necessarily adjust their expectations toward the professionals’ forecast. Rather, it is possible that both groups adjust their expectations toward the fully rational outcome. This outcome would probably be annualised monthly inflation for the general public and annual inflation for professional forecasters.

To take a closer look at this, we estimated two other CVAR specifications of Equation 5, namely one with $y_t = (M_t[\Pi_{t+4}]\,\Pi_{t+4}^m)'$ (for the public) and another with $y_t = (S_t[\Pi_{t+4}]\,\Pi_{t+4})'$ (for professionals). The cointegration vector is parameterised as $(-1 \quad \beta_1)'$. In both models we use priors similar to those given above and algorithms of Richard and Tompa (1980) to generate random numbers from the marginal posterior of *β*. The FML results (not reported here in order to save space) indicate that the proper lag lengths are 4 and 2 for the general public and the professionals, respectively.

TABLE 5: Estimation Results for the public's and professionals' CVAR model

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 $y_t = (M_t[\Pi_{t+4}]\ \ \Pi^m_{t+4})'$ and

the cointegrating relation is $M_t[\Pi_{t+4}] = \beta_1 \Pi^m_{t+4} + z_t$

Equation	β_1	α_1	α_2
(5)	0.58**	0.52**	-0.06*
	(0.07)	(0.07)	(0.03)

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 $y_t = (S_t[\Pi_{t+4}]\ \Pi_{t+4})'$ and

the cointegrating relation is $S_t[\Pi_{t+4}] = \beta_1 \Pi_{t+4} + z_t$

Equation	β_1	α_1	α_2
(5)	1.11*	0.14**	-0.13*
	(0.40)	(0.05)	(0.07)

The posterior medians and standard deviations (in the parenthesis) are shown in the table. The signs ** and * denote that zero is not included in the 95% or 99% posterior interval, respectively. Equations are estimated over the period 1981q3 to 2004q1.

From the results of Table 5 we can see that the adjustment coefficients α_1 are positive with high probability. This indicates that both groups adjust their expectations toward a fully rational outcome. However, the general public obviously do not reach fully rational equilibrium, since the long-run parameter β_1 lies below one. If they were rational they would not make systematic errors in forming their expectations. That is, the long-run relation between actual inflation and the public's expectations should be $M_t[\Pi_{t+4}] = \Pi^m_{t+4}$; see for discussion e.g. Berk (1999). We are, of course, aware that using observed monthly inflation rather than annual may influence the chances of the public forming fully rational expectations. Note, however, that the above result is in line with those in previous studies; see e.g. Evans and Gulamani (1984), Frankel and Froot (1987), Souleles (2004), and Mankiw, Reis and Wolfers (2003), among others.

On the other hand, the data support the hypothesis that the long-run parameter of the professionals is one. This means that their forecasts are rational and are adjusted toward the fully rational outcome. Note also that in both cases $\alpha_2 \neq 0$ with high probability, which may support the existence of the New Phillips curve.

Based on the analyses in this and the previous section, we conclude that at least a substantial fraction of the population update their expectations to the most recent past inflation rate rather than to the SPF forecast for the future inflation rate. Moreover, it seems that the general public and professional forecasters adjust their expectations towards a fully rational outcome.

4. How About the Sticky Information Models in General?

Khan and Zhu (2006), Mankiw, Reis and Wolfers (2003), Carroll (2003), Andres and colleagues (2005), and Kiley (2007) acquire empirical estimates for sticky information models which indicate that individuals on average update their information sets once a year. If this is the case, the resulting median forecast of the Michigan survey should be closely related to the geometrically weighted averages of past professional inflation forecasts, and the cross coefficients of the lagged SPF series and their sum $\Sigma\gamma_{12,i}$ should be different from zero.

To explore this we estimated the CVAR model (5) with data $y_t = (M_t[\Pi_{t+4}]\ S_t[\Pi_{t+4}])'$ and cointegrating relationship

$$M_t\left[\Pi_{t+4}\right] = \beta_1 S_t\left[\Pi_{t+4}\right] + z_t\,. \qquad (8)$$

The FML values support this rank restriction ($r = 1$) and the estimated lag length (p) is 1. However, since we are interested in the cross coefficients of the lagged SPF series and their sum, we estimate the CVAR model using 5 lags.

The estimates of this model are shown in Table 6. We see that the data support the hypothesis that the sum $\Sigma\gamma_{12,i}$ is zero. This suggests that the cumulative effect of the lagged SPF series is not a crucial factor in the Michigan series[13]. The data would thus seem not to support Carroll's (2003) epidemiology model or Mankiw's and Reis's (2002) sticky information model.

[13] Note also that results were similar when we used mean series. We also estimated the error correction model with the assumption that the SPF series is exogenous and the results looked similar.

TABLE 6: Estimation Results for Equation 5 (inflation excluded)

Model (VECM)

$$\Delta y_t = \psi + \sum_{i=1}^{p-1} \begin{pmatrix} \gamma_{11,i} & \gamma_{12,i} \\ \gamma_{21,i} & \gamma_{22,i} \end{pmatrix} \Delta y_{t-i} + \alpha\beta' y_{t-1} + \varepsilon_t$$

, 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	$\Sigma\gamma_{12,i}$	B_1	α_1	α_2	ln FML
(5)	0.03	0.41*	0.55**	0.26	682
	(0.43)	(0.31)	(0.21)	(0.14)	

The posterior medians and standard deviations (in parenthesis) are shown in the table. The signs ** and * denote that zero is not included in the 95% or 99% posterior interval, respectively. Equations are estimated over the period 1981q4 to 2004q1.

To confirm this result, we report, in Table 7 below, the medians and standard deviations of the cross coefficients $b_{12,i}$ (i = 1,…,p) and their sums in the following standard Bayesian vector autoregressive (BVAR) model (with a noninformative Jeffreys prior)

$$y_t = b_0 + \sum_{i=1}^{p} B_i y_{t-i} + \varepsilon_t = b_0 + \sum_{i=1}^{p} \begin{pmatrix} b_{11,i} & b_{12,i} \\ b_{21,i} & b_{22,i} \end{pmatrix} y_{t-i} + \varepsilon_t ,$$

where $y_t = (M_t[\Pi_{t+4}]\ S_t[\Pi_{t+4}])'$, b_0 is a vector of constants, B_i:s are parameter matrices and ε_t is a normally distributed error vector with zero mean and Σ covariance.

We can see from the table that the cumulative effect of the SPF forecast on the Michigan series is positive with relatively high probabilities. This seems to be the consequence of the cross coefficient $b_{12,1}$ being positive. This is most obvious in the case of the model with one lag, which is the best approximation to the true data-generating process according to the log FML values. When the lag length is larger, there is posterior correlation between the cross coefficients $b_{12,i}$, and the result is not so obvious, but it is most probable that $b_{12,1}$ is positive and the other cross coefficients ($b_{12,i}$, $i > 1$) are around zero.

We consider this as a consequence of the cointegrating relation between the SPF forecast and the median Michigan expectation, since the parameter matrices B_i are related to the corresponding CVAR matrices according to $B_1 = I + \Gamma_1 + \alpha\beta'$, $B_i = \Gamma_i - \Gamma_{i-1}$, $i = 2,..., p-1$, and $B_p = -\Gamma_p$, where, on the basis of the FML values and parameter estimates of the CVAR models, the elements of Γ_i are close to zero. Thus, Carroll's (2003) finding that the professional forecast Granger-causes the household forecast while there is no Granger-causality in the opposite direction is probably based on the long-run co-movement of professionals' and the general public's forecasts in which the latter group adjust their expectations. However, as already suggested, households do not necessarily adjust their expectations toward the forecasts of professionals. Rather, both professionals and the general public adjust their expectations toward a fully rational outcome, indicating that the fully rational $S_t[\Pi_{t+4}]$ series may simple be proxying the actual observed inflation series Π^m_{t+4}.

TABLE 7: Point Estimates of BVAR Models

Model

$$y_t = \sum_{i=1}^{p} \begin{pmatrix} b_{11,i} & b_{12,i} \\ b_{21,i} & b_{22,i} \end{pmatrix} y_{t-i} + \varepsilon_t$$

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

number of lags	parameter(lag)	Median
1	$b_{12,1}$	0.31 (0.07)**
	ln FML	64.14
	$b_{12,1}$	0.29 (0.23)
2	$b_{12,2}$	-0.03 (0.21)
	$\Sigma\ b_{12,i}$	0.25 (0.09)*
	ln FML	61.39
	$b_{12,1}$	0.31 (0.24)
	$b_{12,2}$	0.06 (0.33)
3	$b_{12,3}$	-0.11 (0.21)
	$\Sigma\ b_{12,i}$	0.27 (0.10)*
	ln FML	57.68
	$b_{12,1}$	0.27 (0.25)
	$b_{12,2}$	0.12 (0.35)
4	$b_{12,3}$	-0.11 (0.34)
	$b_{12,4}$	-0.03 (0.23)
	$\Sigma\ b_{12,i}$	0.25 (0.10)*
	ln FML	53.77

Standard deviations in parentheses. The signs ** and * denote that zero is not included in the 95% or 99% posterior interval, respectively. Equations are estimated over the period 1981q3 to 2004q1.

5. Conclusion

In this paper we have presented new estimation results on Carroll's (2003) epidemiological model of expectations formation process. After controlling for the quality of inflation expectations data by using both the means and medians of the Michigan consumer inflation expectations, we find that a significant proportion of the population update their inflation expectations using the most recently reported inflation statistics. This result is in contrast to Carroll's (2003) finding that inflation has no influence on an individual's expectation formation process. We suggest that his finding may arise from using the annual inflation series instead of the monthly annualised *real-time* inflation series, although annualised monthly inflation is the statistics which households observe in the news media.

We have also used Bayesian CVAR models to explore the relationship between the public's and professionals' inflation expectations and actual inflation. On the basis of our CVAR results we may state that the Michigan Survey data do not support the sticky information models suggested by Mankiw and Reis (2002), Sims (2003) and Carroll (2003). Rather, it seems that a significant portion of the population form their inflation expectations according to so-called adaptive expectations models. There is thus a marked need for further development of a theory for the general public's inflation expectations formation.

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