Estimating Firm's Attentiveness in a Sticky Information Phillips Curve

My Contribution

- I estimate a representative firm model in which the lone friction in price setting is the availability of current macroeconomic data.
- A nonlinear sticky information Phillips Curve with drift in the attentiveness rate has not been estimated before.

Importance

- Identifying changes in the attentiveness rate is important because the attention level affects the economy's sensitivity to exogenous shocks.

Need

- Researchers have explored a sticky information Phillips Curve with a fixed attentiveness rate. See Coibion (2010).
- We may expect to see the rate of attention change over time. Branch et al. (2009) created a model in which the attention rate is an equilibrium value given the current state of the economy.

Outline of the remaining section

1. Sticky information Phillips Curve with a fixed attentiveness rate.
2. Sticky information Phillips Curve with drift in the attentiveness rate.
3. Empirical Approach
4. Results

Fixed Attention

- The assumption developed by Mankiw and Reis 2002 is used to model inflation.
- Firms use outdated information until they are randomly "selected" to receive new information.
- The parameter that measures firms' attention is (1-λ), the probability of being selected.

Aggregate Price

Aggregate price is the weighted average over firms' expectation of the optimal price:

$$p_t = \sum_{j=0}^{J-1} (1-\lambda) * \lambda^j E_{t-1-j}(p_t^*) + \varepsilon_t.$$

SIPC with Fixed Model Parameters

Algebra done by previous authors gives us the sticky information Phillips curve.

$$\pi_t = \frac{(1-\lambda)}{\lambda}\alpha x_t + \sum_{j=0}^{J-1}(1-\lambda) * \lambda^j E_{t-1-j}(\pi_t + \alpha \Delta x_t) + \nu_t.$$

SIPC with Drift in Model Parameter

A time-varying version of this model changes how the weights are calculated.

$$\pi_t = \frac{(1-\lambda_t)}{\lambda_t}\alpha x_t + \sum_{j=0}^{J-1} a_{t,j+1} E_{t-1-j}(\pi_t + \alpha \Delta x_t) + \nu_t,$$

Weighting System

$$
\begin{aligned}
a_{t,1} &= (1 - \lambda_t) \\
a_{t,2} &= \lambda_t * (1 - \lambda_{t-1}) \\
a_{t,3} &= \lambda_t * \lambda_{t-1} * (1 - \lambda_{t-2}) \\
a_{t,4} &= \lambda_t * \lambda_{t-1} * \lambda_{t-2} * (1 - \lambda_{t-3}) \\
a_{t,5} &= \lambda_t * \lambda_{t-1} * \lambda_{t-2} * \lambda_{t-3} * (1 - \lambda_{t-4}).
\end{aligned}
$$

Empirical Approach: Data

1. Realized times series data on inflation, output and the natural rate of output
2. Expectation data of firms will be proxied using expectation data from the survey of professional forecasters on output and inflation.

Empirical Approach: Estimation

An extended particle filter will be used to evaluate the likelihood of the model, and the Metropolis-Hastings algorithm used to simulate from the posterior.

Endogeniety

- We expect endogeniety in this type of a model because output and prices are simultaneously determined.
- The instruments used include a constant, three lags of the output gap and the time t-1 forecast of time t+1 inflation.
- In the previous version of this model with a fixed attention rate, Coibion (2010), he preforms the Stock and Yogo (2004) test and rejects the null of weak instruments.

Empirical Approach: Estimation

- The sampler drew 2000 samples of our parameters.
- For each sample of the static parameters, a sample path of λ was created.
- Using a time-wise mean, I have merged the sample paths into one graph.
- The final acceptance rate of the draws stood at 0.44, surpassing the recommended threshold in the literature, yet remaining within an acceptable range.

TVP Estimation

Estimating the SIPC with variation in the rate of attention gives us parameter estimates and a time series of firms' attentiveness to information relevant to price setting.

TVP Estimation

The results of modeling time-varying attention to macroeconomic information are as follows. The estimated values for α and $1 - \lambda_0$ are 0.06 and 0.46, respectively. The ensuing figure shows the time wise mean of the paths and a 95% confidence bound.

TVP Estimation

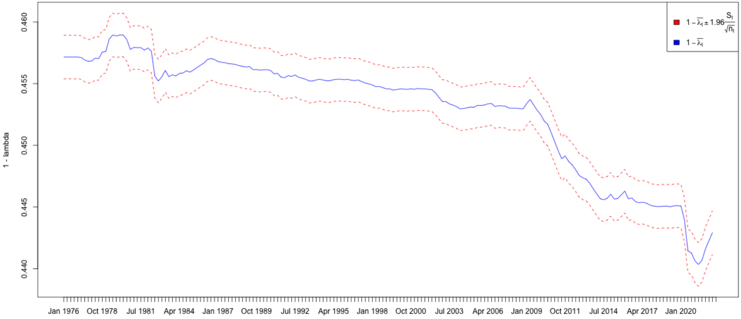

Figure: Proportion of firms using the newest information over time.

TVP Estimation

The time-varying parameter estimation reveals a consistent trend of declining attention over the analyzed period. Commencing from January 1976, the estimated value of $1 - \lambda$ stands at 0.457, progressively decreasing to 0.443 by April 2022.

TVP Estimation

To analyze the economic impact of the identified shifts in the rate of attention, I use the model by [Ball et al., 2003].

$$\sigma_p^2 = Var(\varepsilon_t) \sum_{j=0}^{\infty} \phi_j^2$$

$$\phi_j = \frac{\rho^j}{\alpha^2 \omega + \frac{(1-\lambda)^{j+1}}{1-(1-\lambda)^{j+1}}}$$

TVP Estimation

Using the parameterization in [Branch et al., 2009] , the initial volatility registers at 1.66, tapering down to 1.57 at the end of the analyzed period. A discernible shift in volatility is observed, a decrease of 5.5% in the variance of price. An alternative parameterization found in [Ball et al., 2003] increases the magnitude of the shift to -12.7%.

Fixed Parameter Estimation

Fixed estimation is done using a Metropolis Hasting Sampler and a joint likelihood function equivalent to the particle filter with zero variation.

Fixed Parameter Estimation

Comparing the results for the two model types using the values $1 - \lambda$, I find that the mean value of the TVP estimate is 0.45, similar to the fixed estimate. The fixed estimate is significantly different to the value found by [Coibion, 2010], but similar to that found by [Reis, 2009]. A Bayesian model comparison will shed some light on which estimate is best.

Bayesian Model Comparison

Bayesian model comparison can provide the relative plausibility of two models given our data. The marginal likelihood of each model will form the backone for comparison:

$$p(Y|M_i) = \frac{p(Y|\theta)p(\theta)}{p(\theta|Y)}$$

Bayesian Model Comparison

[Chib and Jeliazkov, 2001] provide the framework for estimating the marginal likelihood when implementing a Markov chain Monte Carlo estimation.

Bayesian Model Comparison

The Metropolis-Hasting Sampler is used to sample from the posterior distribution, creating N samples. I calculate the likelihood function and the prior density at the median of the samples. Then to estimate the posterior ordinate we use the following equation:

$$\widehat{p(\tilde{\theta}|Y)} = \frac{\frac{1}{g}\sum_{g=1}^{G} \alpha(\theta^{[g]}, \tilde{\theta}) q(\tilde{\theta}|\theta^{[g]})}{\frac{1}{J}\sum_{j=1}^{J} \alpha(\tilde{\theta}, \theta^{[g]})},$$

Bayesian Model Comparison

- $\alpha(\theta^{[g]}, \tilde{\theta})$ is the probability of accepting the median value instead of sample g and
- $q(\tilde{\theta}|\theta^{[g]})$ is the likelihood of the variation between the median and the sample.
- J draws are taken by random variation from the median, then
- $\alpha(\tilde{\theta}, \theta^{[g]})$ is the probability of accepting that draw instead of the median. The probabilities are then averaged to get the numerator and denominator to get an estimate of the ordinate.

Bayesian Model Comparison

To calculate the probability of a time-varying attention model, I find the ratio between the marginal likelihood of the TVP model and the total marginal likelihood of both the TVP model and the fixed parameter model.

Bayesian Model Comparison

A Bayesian model comparison between the fixed model and the TVP model favors the fixed parameter model. The probability placed on the fixed parameter model is 0.84. This analysis favors a model that excludes a time-varying parameter for attention but it cannot be ruled out statistically.

Conclusion

The results from modeling time-varying attention reveal a declining trend in attention over the analyzed period. A enriched model allows us to see the economic implications for aggregate price volatility.