Household inflation expectations- exploiting the cross-sectional dimension

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Motivation: main questions

• Can sticky information models capture some of the dynamics of UK inflation expectations better than the full information models?

• Is the proportion of agents updating information sets each period constant or time varying - which specification fits UK surveys better?

• Can we find any evidence of the sticky information model in the micro data?
Rational expectations
- agents share information sets and form expectations conditional on that information
- everybody has the same expectations

Expectations formation is heterogeneous across agents
- agents have different information sets (Mankiw and Reis (2002), Mankiw et al. (2003), Carroll (2003))
- agents use different models to form expectations (Gramlich (1983), Branch and Evans (2005), Branch (2007), Molnar and Reppa (2010))
- agents have different processing capabilities - learning models (Orphanides and Williams (2003))
1. Methodology

2. Data description

3. Results- macro analysis
   - Similar exercise to Mankiw, Reis and Wolfers (2003) on UK data (Part 1)
   - Fit the full distribution of the model forecasts to that of the Barclays Basix survey (Part 2)

4. Results- micro analysis

5. Conclusion
Methodology

There are two dimensions to our exercise:

• The time when the information set was updated - information types
• The way the new information is incorporated - forecasting process

Recursive forecasting process:

1) equal weight on all information available (constant coefficient)
2) variable weight on new information (TVP with stochastic volatility)
3) most weight on new data (constant gain least square)
Information set

- Inflation (RPIX)
- Real time GDP growth
- Bank Rate

Sample: 1967 Q1 to 2010 Q2

Start forecast: 1987 Q1 for Basix and 2000 Q1 for NOP

Surveys of inflation expectations

- Barclays Basix
  - asks about inflation rate
  - 1987Q1 to 2010Q3
  - 1 and 2 years ahead expectations; from 2008, also 5 years ahead expectations

- Bank NOP
  - asks about prices in general
  - 2000Q1 to 2010Q3
  - 1 year ahead expectations & perceptions; from 2008, also 2 and 5 years ahead expectations
1) Constant coefficient BVAR

\[ Y_t = \beta_t \ast Y_{t-1} + \varepsilon_t \]

Type 1
\[ Y_{t+1|t} = \beta_t \ast Y_t \]
Most informed

Type 2
\[ Y_{t+1|t-1} = \beta^2_{t-1} \ast Y_{t-1} \]

Type 3
\[ Y_{t+1|t-3} = \beta^3_{t-3} \ast Y_{t-3} \]

Least informed

1987 Q1
Start of Barclays Basix survey

2010 Q1 2010 Q2 2010 Q3 2011 Q3
Latest observation

2010 Q1 2010 Q2 2010 Q3 2011 Q3
Latest observation
Results: Mankiw, Reis and Wolfers (2003) on UK data

Part 1

- Assume that the same fraction $\theta$ of households updates its information set every period
  - estimate $\theta$ s.t. weighted mean of BVAR estimates is closest to survey mean
  - analyse dispersion

- Add parameter uncertainty
  - estimate $\theta$ s.t. weighted mean of BVAR estimates is closest to survey mean
  - analyse dispersion

- Compare with full information model with parameter uncertainty
Results: Mankiw, Reis and Wolfers (2003) on UK data

Population shares are geometrically distributed…

![Graphs showing mean, disagreement, and age distribution of information sets](image-url)
Results: Mankiw, Reis and Wolfers (2003) on UK data

...add parameter uncertainty
...full information model

Results: Mankiw, Reis and Wolfers (2003) on UK data
Part 2

1) Estimate the Barclays Basix survey’s density and that of the model based forecasts using a normal Kernel.

2) Use the Kullback-Leibler (Klic) distance measure to assess how ‘close’ the model based densities are to that of the survey.

\[ Klic(p, p^*) = \int \log \left( \frac{p^*(x)}{p(x)} \right) p^*(x) dx \]

- Forecast density of the model
- Density of survey
Results: models generating density forecasts

Models:

- Full information model

- Sticky information model:
  - static weights: min Klic over entire sample
  - time varying weights: min Klic for every quarter in the sample

$Beta(\alpha, \beta) = \text{beta distribution parameterised by two shape parameters}$
Results: Klic- distance measure between model based and survey density
Results: estimated PDFs

- 1990 Q3
- 2000 Q1
- 2008 Q1
- 2009 Q1

- Blue: Basix survey
- Red: Full information model
- Green: Static weights
- Black: Time varying weights
Results: estimated weights in the time varying sticky information model

Share of those who updated in latest quarter

Share of those who updated 2 years ago

Share of those who updated 4 years ago
Results- micro analysis

**Aim**: match characteristics of NOP respondents to BVAR forecasts

- **frequent updaters**: those who last updated within the last year
- **infrequent updaters**: those who last updated between 6 and 15 quarters ago
- **rare updaters**: those who last updated between 16 and 20 quarters earlier
- **don’t knows**: those who do not form expectations

**Method**: run a probit regression for these 4 ‘types’ on individual characteristics
Results - micro analysis

- **13% do not formulate expectations** - likely to be women, not have a degree, not to own a house or have a mortgage
- **87% form expectations** - likely to be male, have a degree, own a house and/or have a mortgage
- **47% have a match** in the model based forecasts - use those that have only one match (cc. 17%)

  - **Frequent updaters**
    - 8% more likely to be educated than rare updaters
    - More likely to have a mortgage, not to own or rent
  - **Infrequent updaters**
    - Likely to have a mortgage as well as own their own house
    - Lower probability of a degree than frequent updaters
### Results- micro analysis

<table>
<thead>
<tr>
<th>Pers char</th>
<th>Depvar</th>
<th>Frequent updaters</th>
<th>Infrequent updaters</th>
<th>Rare updaters</th>
<th>Don’t know</th>
</tr>
</thead>
<tbody>
<tr>
<td>Edu: degree</td>
<td>0.085***</td>
<td>0.023***</td>
<td>-0.017</td>
<td>-0.029***</td>
<td></td>
</tr>
<tr>
<td>Edu: secondary</td>
<td>0.044***</td>
<td>0.014</td>
<td>-0.002</td>
<td>-0.019***</td>
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</tr>
<tr>
<td>Own house outright</td>
<td>0.018</td>
<td>0.025**</td>
<td>0.033**</td>
<td>-0.023***</td>
<td></td>
</tr>
<tr>
<td>Has mortgage</td>
<td>0.027**</td>
<td>0.024**</td>
<td>0.021*</td>
<td>-0.025***</td>
<td></td>
</tr>
<tr>
<td>Rents</td>
<td>-0.062***</td>
<td>0.012</td>
<td>0.039***</td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td>Obs</td>
<td>12,832</td>
<td>12,832</td>
<td>12,832</td>
<td>45,655</td>
<td></td>
</tr>
</tbody>
</table>

***: 1%, **: 5%, *: 10% significance level
Conclusion

- Full information model fits less well than sticky information models

- Sticky information model with t.v. weights fits the Basix survey best—although more free parameters!

- Around high inflation in 1990s, we estimate households to have updated their information on average just under once a year

- During the great stability, this increased to every other year.

- Micro-analysis suggests frequent updaters are more likely to be highly educated than the rest
To do next...

- Add several models of expectations formations for comparison such as: TVP and a constant gain parameter model
- Re-do the analysis for these
- Analyse perceptions and 2 years ahead expectations in more detail
- Entire exercise using different price indexes such as CPI and RPI
- Explore how to incorporate the news on inflation as a factor in affecting the frequency of data updates.
- Add other sources of prediction heterogeneity- different consumption baskets for example