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# Household inflation expectations- exploiting the cross-sectional dimension

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## Motivation: main questions

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- 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

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

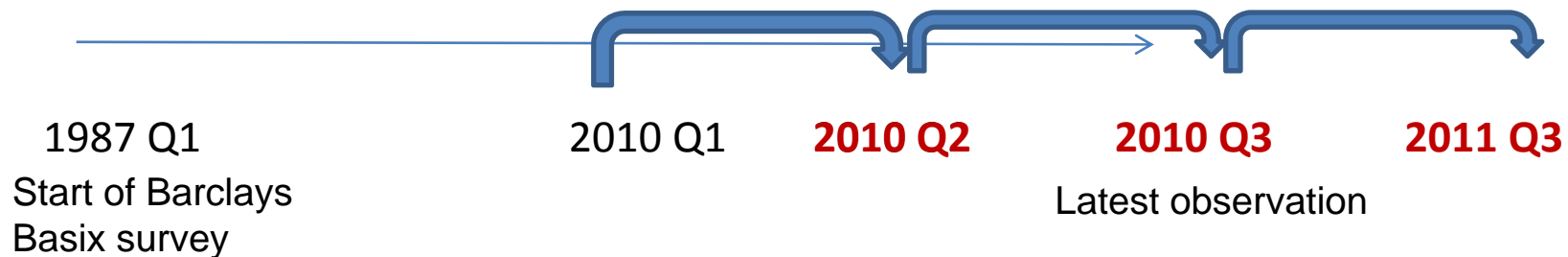
**Sample:** 1967 Q1 to 2010 Q2

**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



$$Y_t = \beta_t * Y_{t-1} + \varepsilon_t$$

Type 1     $Y_{t+1|t} = \beta_t * Y_t$     Most informed

Type 2     $Y_{t+1|t-1} = \beta_{t-1}^2 * Y_{t-1}$

Type 3     $Y_{t+1|t-3} = \beta_{t-3}^3 * Y_{t-3}$

⋮

Type 20     $Y_{t+1|t-20} = \beta_{t-20}^{20} * Y_{t-20}$     Least informed

## Part 1

- Assume that the same fraction  $\theta$  of households updates its

information set every period



add parameter uncertainty

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

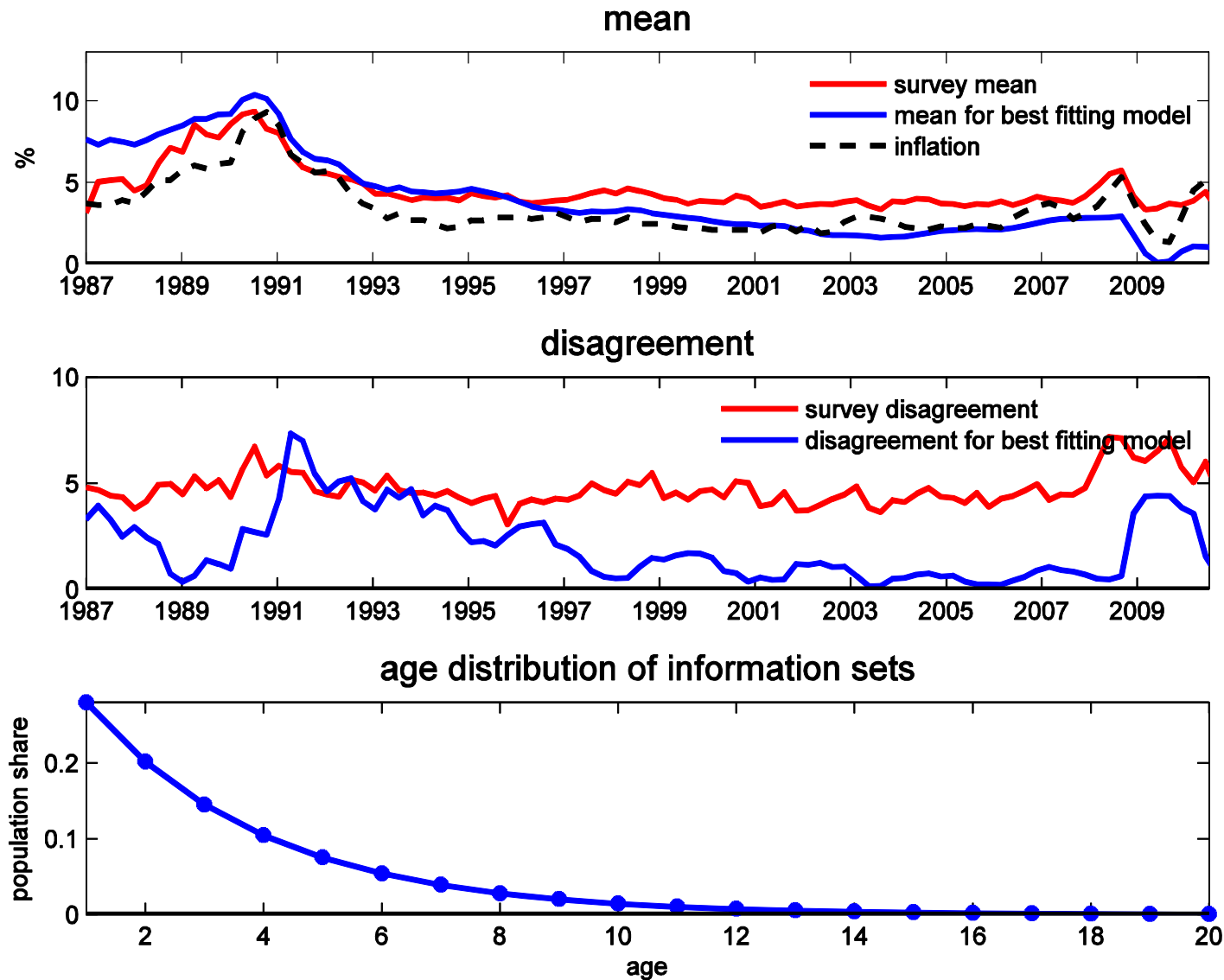
estimate  $\theta$  s.t. weighted mean of BVAR estimates is closest to survey mean  
analyse dispersion

- Compare with full information model with parameter uncertainty



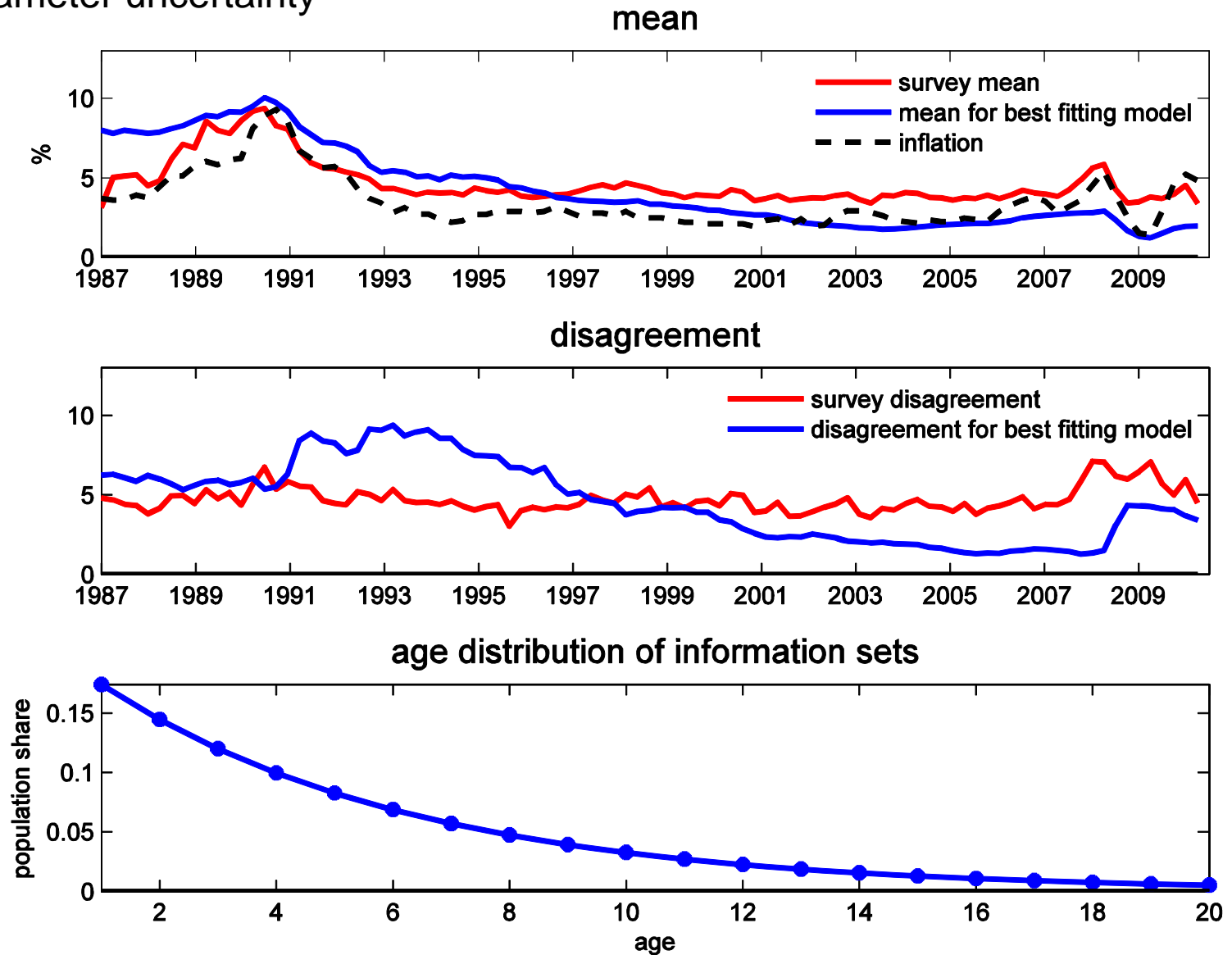
## Results: Mankiw, Reis and Wolfers (2003) on UK data

Population shares are geometrically distributed...



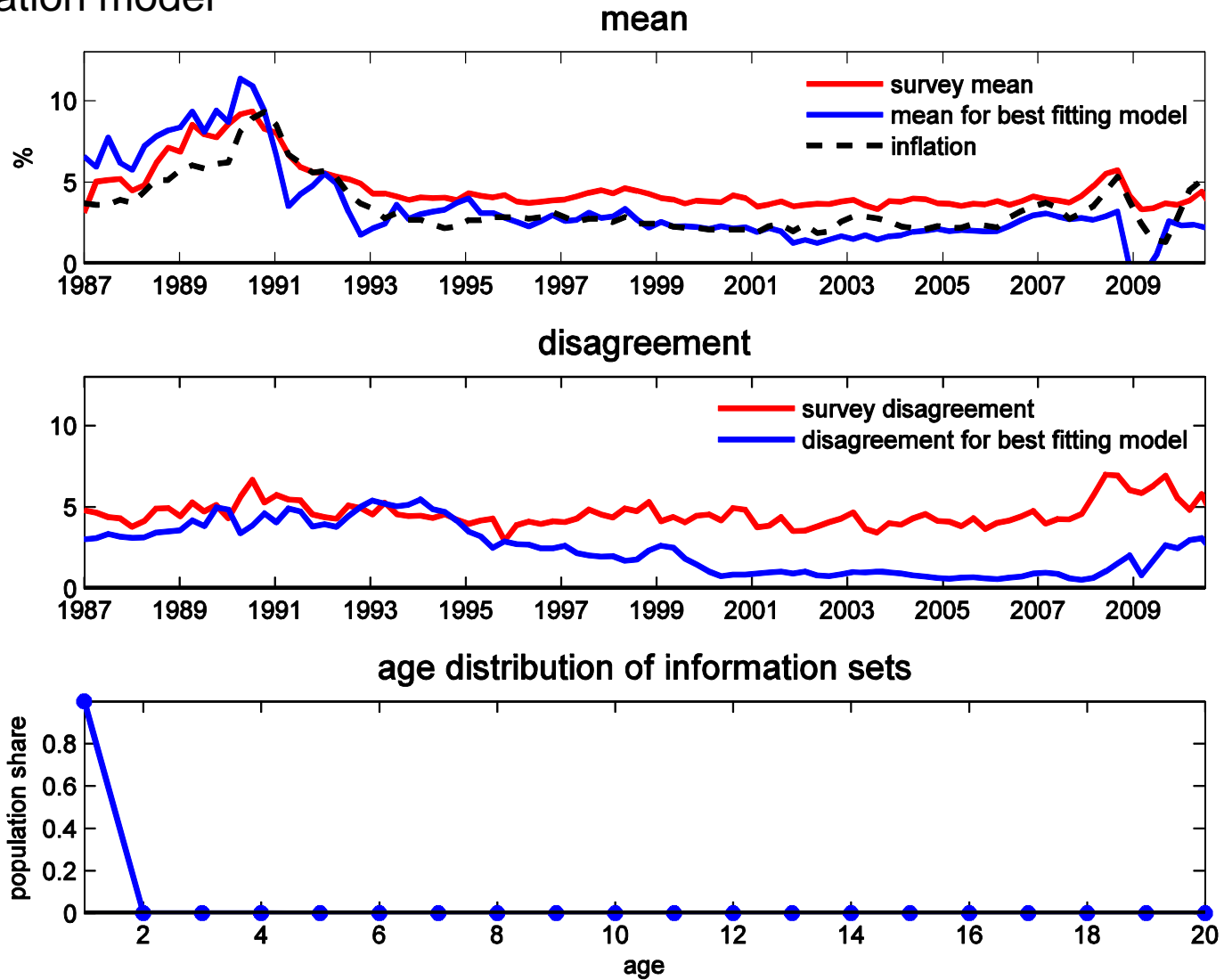
## Results: Mankiw, Reis and Wolfers (2003) on UK data

...add parameter uncertainty



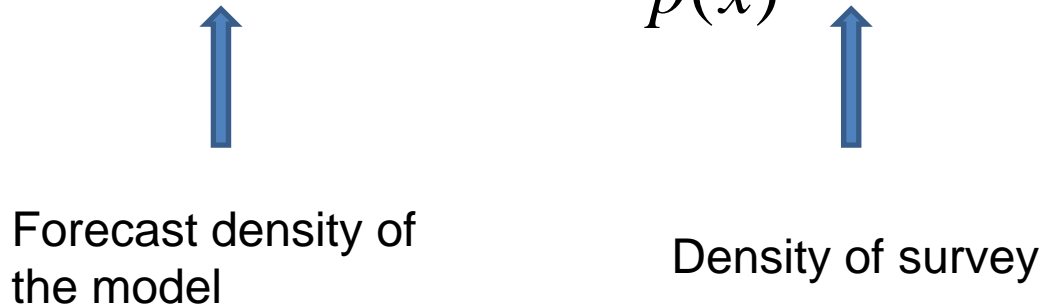
# Results: Mankiw, Reis and Wolfers (2003) on UK data

...full information model



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

$$Klic(p, p^*) = \int \log\left[\frac{p^*(x)}{p(x)}\right] p^*(x) dx$$
The diagram shows the Kullback-Leibler distance formula. Below the formula, there are two blue arrows pointing upwards. The first arrow points from the label 'Forecast density of the model' to the variable 'p' in the denominator of the fraction inside the logarithm. The second arrow points from the label 'Density of survey' to the variable 'p\*' in the numerator of the fraction inside the logarithm and also to the 'p\*' in the integrand outside the logarithm.

Forecast density of  
the model

Density of survey

## Results: models generating density forecasts

### Models:

- Full information model

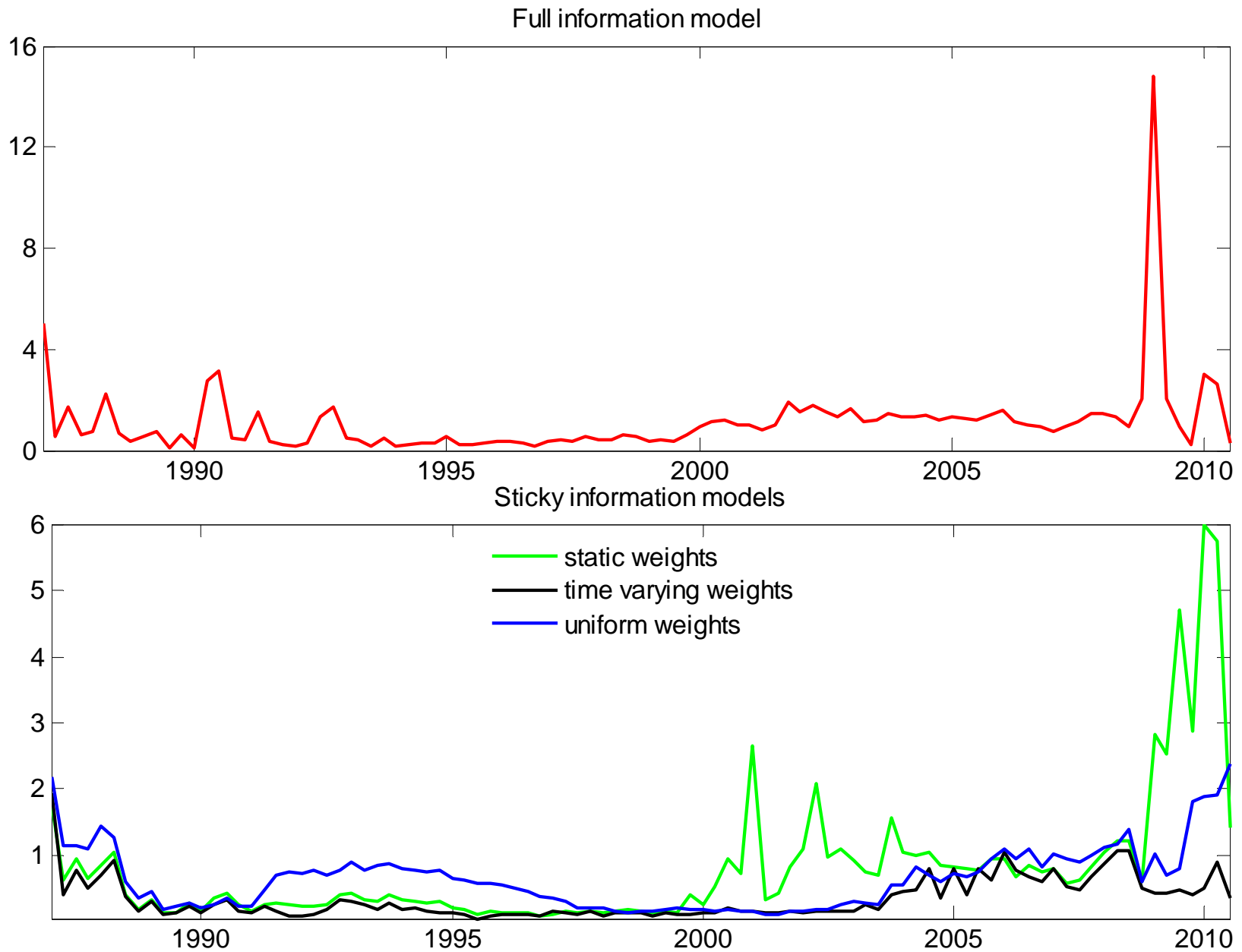
- Sticky information model:

→ static weights- min Klic over entire sample

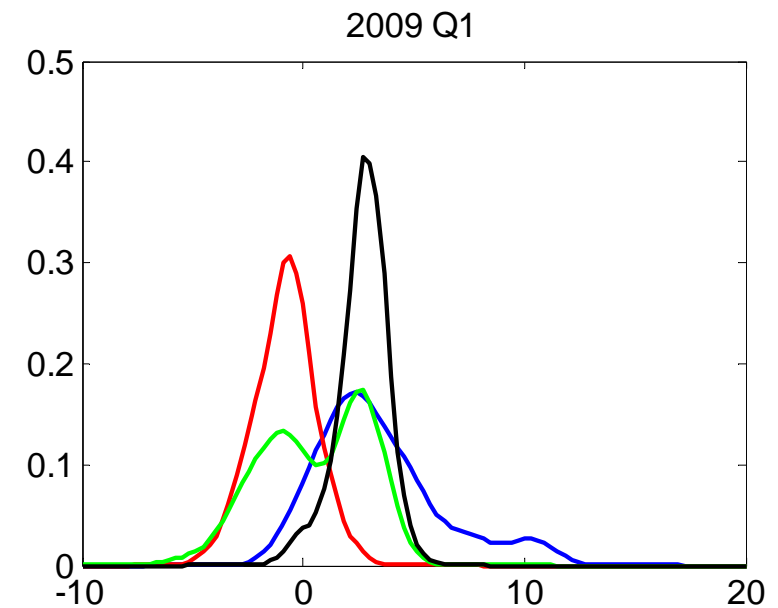
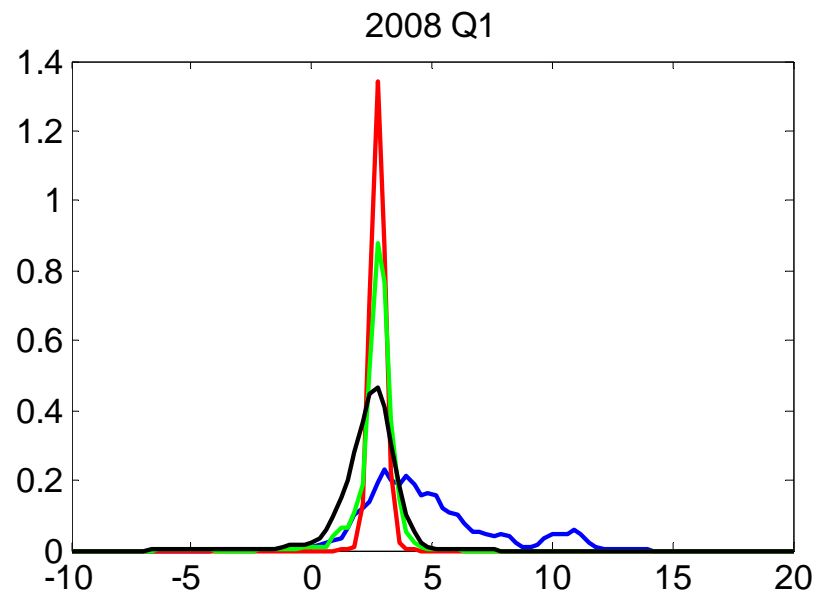
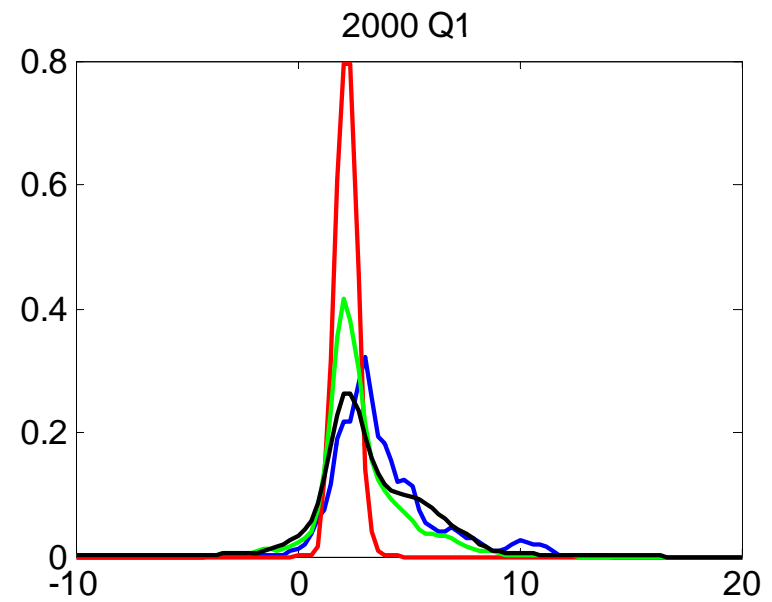
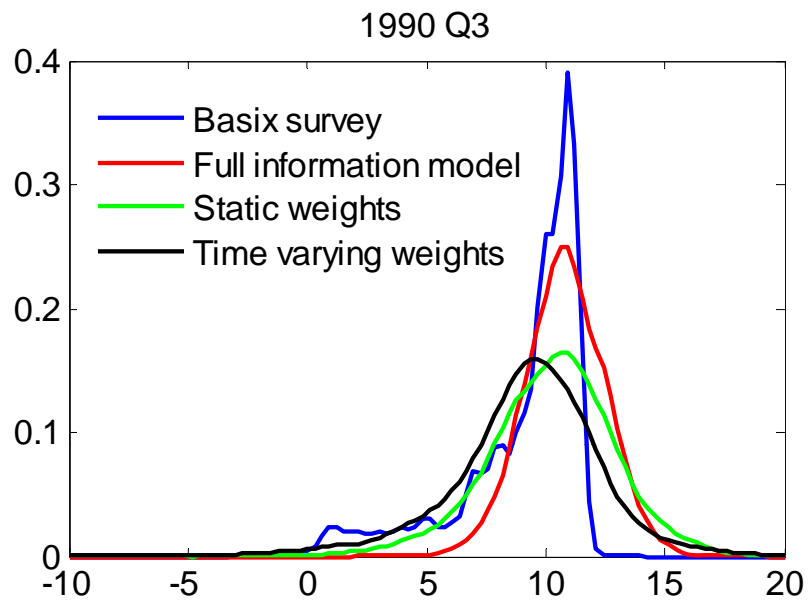
→ time varying weights- min Klic for every quarter in the sample

$Beta(\alpha, \beta)$  = beta distribution parameterised by two shape parameters

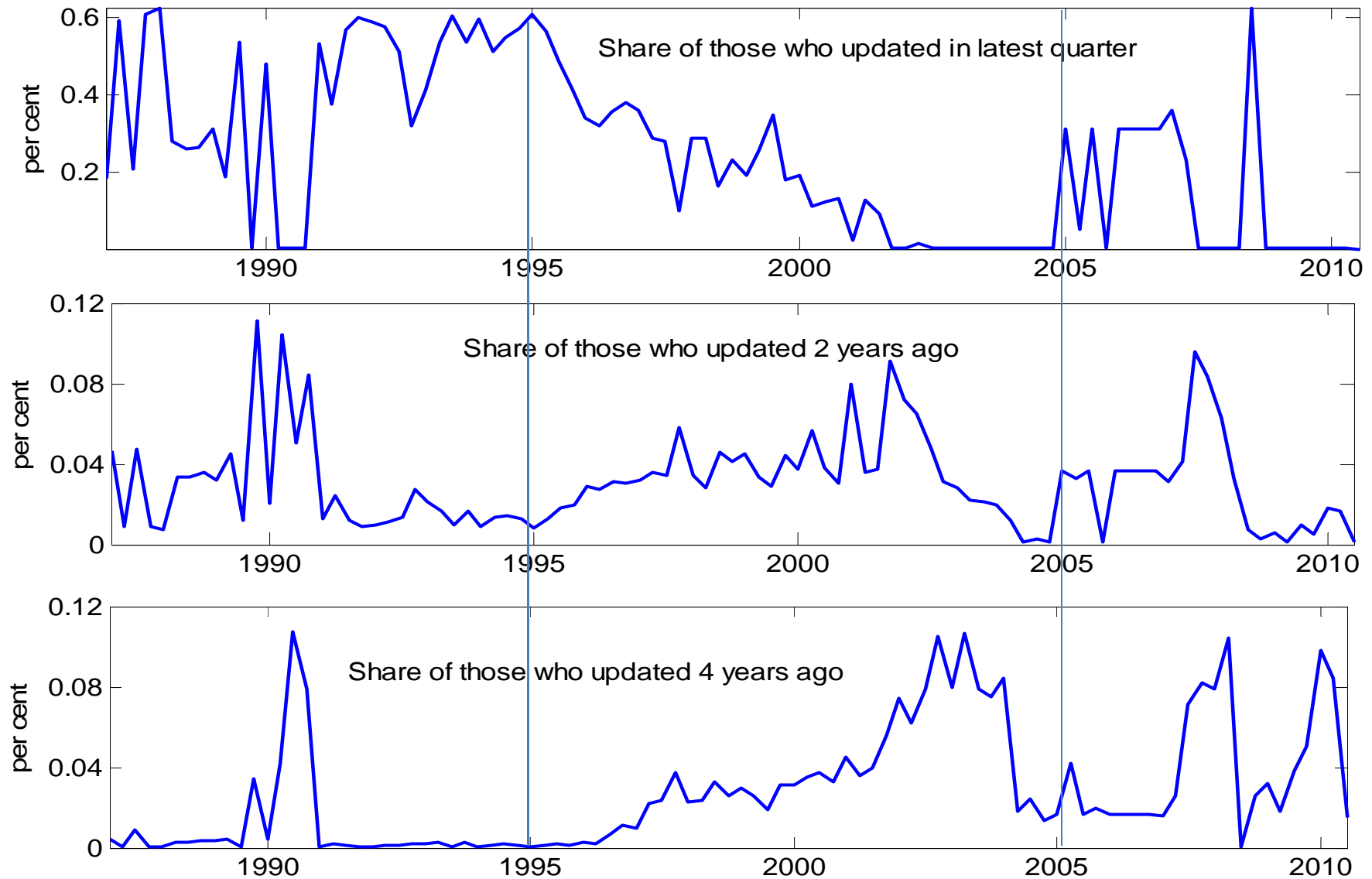
## Results: Klic- distance measure between model based and survey density



## Results: estimated PDFs



## Results: estimated weights in the time varying sticky information model





## Results- micro analysis

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**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

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

\*\*\*: 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