

Professional Survey Forecasts and Expectations in DSGE Models

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Motivation

- Evaluate alternative hypothesis about the way expectations are specified in our DSGE models.
- Use the Survey of Professional Forecasters as observables for the expectations in the model in order to discipline the various belief models.
- Exploit optimally the information in the surveys to improve the model forecasts for the realized real-time data and for the survey forecasts.

Main Insights

- The integration of survey forecasts/nowcasts in the structural DSGE model solves an important information filtering problem: observing the nowcasts identifies the persistent nature of the fundamental shocks. It allows us to classify shocks as persistent or temporary.
- With this model re-specification, we can explain jointly the survey and realized real-time macro data without ‘exogenous’ sentiment shocks.
- The observation of the survey forecasts for the very short horizon, the so-called nowcasts, is crucial for improving the macro-model forecast: there is no additional gain from observing longer horizon surveys.
- By relaxing the constraint that expectations are formed consistently with the actual law of motion, we avoid that the ALM-process inherits the inefficiencies that are present in the forecasting performance of the survey nowcasts.
- The belief models on which the expectations are based must contain sufficient information in order to explain the survey forecasts.
- Updating of the beliefs by Bayesian learning and/or updating of the weights of heterogeneous belief models play an important role in explaining:
 - time varying trends in the perceived trend growth rate, inflation target and markups;
 - time-variation in the transmission of shocks and macro-economic volatility.

Related literature

- Testing FIRE hypothesis in survey expectations (Mankiw et al 2003, Coibion Gorodnichenko 2015, Bordalo et al 2018, Angeletos et al 2020)
- Role of sentiment and beliefs in finance (Greenwood Schleifer 2013, Adam Marcet , Bhandari et al 2019, Krishnamurthy Li 2020, Maxted 2020, Sufi Taylor 2021), housing (Adam et al 2011, Piazzesi et al 2021, Chodorow-Reich et al 2021) and macro (Angeletos et al 2013-2018, Milani et al 2012-2018, Adam Merkel 2019)
- Excellent forecasting performance of survey data (Ang et al 2007) and integration of survey forecasts in forecasting with reduced form (Ghysels Wright 2006, Clark et al 2017, Tallman 2018, Giannone et al 2009) and structural models (Milani 2011, Del Negro et al 2013, Carvalho et al 2019)
- Adaptive learning in macro-models (Evans Honkapohja 2009, Woodford 2013, Milani 2007-2011, Eusepi Preston 2011, Hommes 2020, Molavi 2019)

Overview of the presentation

- Motivation for the use of SPF-nowcasts as proxy variables for expectations
- Details on observed data and model specification
- Estimation results under the RE hypothesis and remaining issues
- Alternative belief specification and the updating approach:
 - MSV-beliefs and flexible constant updating
 - Restricted Beliefs
 - Heterogeneous Beliefs
- Estimation results with alternative belief setups

Why SPF expectations ?

- SPF forecasts are generally considered as precise and timely forecasts for macro-economic aggregates. Professional Forecasters have an interest to process large information sets and to adjust their forecast flexibly to account for changes in the dynamics of the macro-economy.
- Macro-economic models process only a limited set of macro-economic aggregates that are measured in real-time with considerable uncertainty and measurement error.
- Survey expectations of households and firms behave different than SPF forecasts and might contain other/additional information relevant for the actual decisions of these agents, but this fact does not necessary invalidate the use of SPF surveys as proxies for the expectations in the model.

=> test information content of SPF survey for forecasting our dataset

=> test predictability of forecast error of SPF

Why SPF expectations ?

- In a reduced-form VAR decomposition exercise, the innovations in the survey nowcasts explain a substantial fraction of the forecast error variance of our real-time 7-variable SW dataset (nowcast ordered last in Cholesky, 5 year horizon):

	Innovation in the SPF-nowcast for			
Fraction of the variance explained in real-time data for:	output	consumption	investment	inflation
output	0.29	0.21	0.17	0.04
consumption	0.11	0.33	0.12	0.09
investment	0.19	0.24	0.33	0.02
inflation	0.06	0.03	0.07	0.19
short rate	0.19	0.13	0.33	0.01
nowcast	0.50	0.71	0.57	0.44

Why SPF expectations ?

- **Predictability test** for the survey nowcast error shows an important underestimation problem but only in the investment data: forecast error is significantly positive related to the revision in the forecasts (see also Bordalo et al 2018, CG 2015)

$$y_{t+1} - y_{t+1|t} = a + \mathbf{b} * (y_{t+1|t} - y_{t+1|t-1})$$

	output	consumption	investment	Inflation
b-coefficient	0.17	0.17	0.49	-0.12
st.error	<i>0.10</i>	<i>0.17</i>	<i>0.16</i>	<i>0.16</i>
R2	0.02	0.01	0.05	0.00

Dataset and Model specification

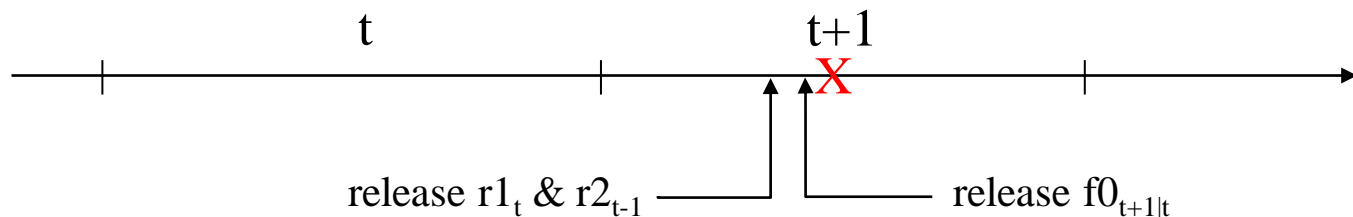
- Extended list of real-time data and SPF-nowcasts as observables: 17 observables for 1981Q2-2019Q2
- Standard 7-variable dataset of SW(2007) but now with real-time data: first and second release for real growth in GDP, consumption, investment, hours, wage, and GDP-inflation (+ FF-rate).
- 4 SPF-nowcasts for real GDP, consumption, investment and inflation.
- Measurement equations:

$$\Delta(\log(\text{GDP}_{\text{first release}})) = dy_{r1}_t = (y_t - y_{t-1}) + ctrend + e_t^{y-r1}$$

$$\Delta(\log(\text{GDP}_{\text{second release}})) = dy_{r2}_t = (y_{t-1} - y_{t-2}) + ctrend$$

$$\Delta(\log(\text{SPF}_{\text{GDP nowcast}})) = dy_{f0}_t = (y_{t+1} - y_t) + ctrend_{y_{f0}} + e_t^{y-f0}$$

- Measurement errors (6+4) are modelled as i.i.d. processes.
- Timing assumptions: KF state vector $a_{t|t}$ is updated at point **X** after publication of first release for t (and second release for $t-1$) and SPF-survey forecast for $t+1$:



Dataset and Model specification: fundamental shocks

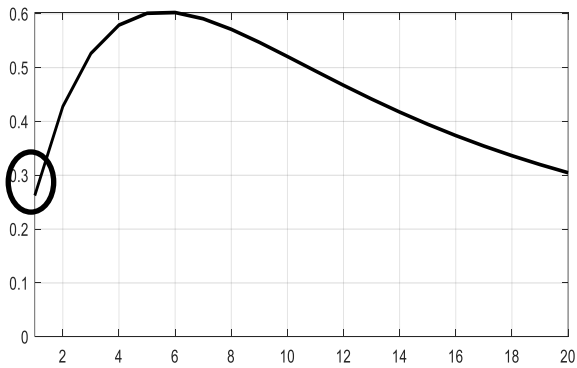
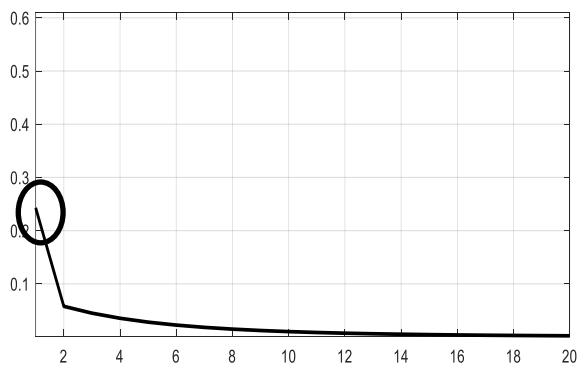
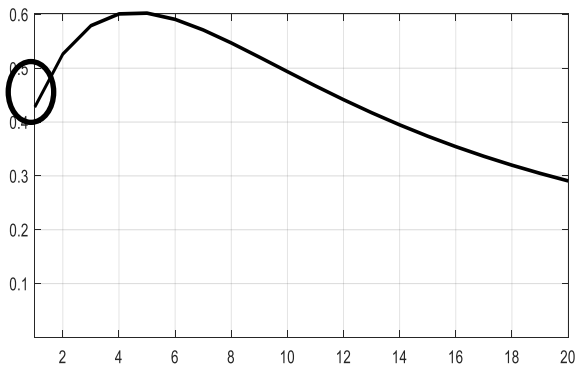
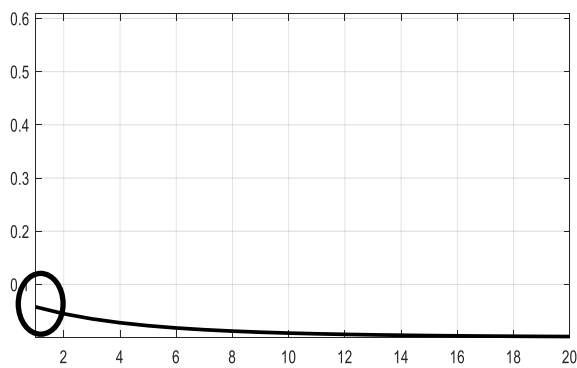
- Observing the 4 SPF-nowcasts provides the necessary and timely information to identify the persistent or transitory nature of the fundamental shocks that are realized in period t .
- The shock process for risk premium, investment specific technology, exogenous spending, price and wage markup is specified as:

$$b_t = b_t^{ar} + b_t^{iid} \quad \text{with} \quad b_t^{ar} = \rho_b b_{t-1}^{ar} + \varepsilon_t^{b-ar} \quad \text{and} \quad b_t^{iid} = \varepsilon_t^{b-iid}$$

where ε_t^{b-ar} and ε_t^{b-iid} are two i.i.d. innovations.

- These two shock components are identified only through the observation of the nowcasts (see figure).
- Together with the TFP and monetary policy shocks, we have in total 12 structural innovations in the model. Compared to the original SW that was estimated on final data, the use of real-time data up to the second release results in different estimates for shocks (later revisions have an important impact) (see also Jacobs-Van Norden 2011, Bognanni 2016).
- Agents in the model are assumed to have the same information as the SPF-participants: instead of using the published real-time and survey data, higher-frequency interpolations could be used instead.

IRFs for persistent/ temporary shocks

	Persistent risk premium shock	Temporary risk premium shock
<p>Impact on</p> <p style="text-align: center;">c_t</p>	 <p>The graph shows the impulse response function for a persistent risk premium shock on consumption at time t. The y-axis ranges from 0 to 0.6, and the x-axis from 0 to 20. The curve starts at approximately 0.3 at time 0, rises to a peak of 0.6 at time 6, and then gradually declines towards 0.35 at time 20. A circle highlights the initial value of 0.3.</p>	 <p>The graph shows the impulse response function for a temporary risk premium shock on consumption at time t. The y-axis ranges from 0 to 0.6, and the x-axis from 0 to 20. The curve starts at approximately 0.25 at time 0, drops sharply to about 0.05 by time 2, and remains near zero thereafter. A circle highlights the initial value of 0.25.</p>
<p style="text-align: center;">$E_t c_{t+1}$</p>	 <p>The graph shows the impulse response function for a persistent risk premium shock on the expected consumption at time t+1. The y-axis ranges from 0 to 0.6, and the x-axis from 0 to 20. The curve starts at approximately 0.4 at time 0, rises to a peak of 0.6 at time 6, and then gradually declines towards 0.3 at time 20. A circle highlights the initial value of 0.4.</p>	 <p>The graph shows the impulse response function for a temporary risk premium shock on the expected consumption at time t+1. The y-axis ranges from 0 to 0.6, and the x-axis from 0 to 20. The curve starts at approximately 0.05 at time 0 and remains very close to zero throughout the 20 periods. A circle highlights the initial value of 0.05.</p>

Results under the RE-hypothesis

- Compare forecasting performance of RE-model with and without observing nowcasts, and with and without shock respecification:

Comparing RE-models based on RMSE-performance				
	Without nowcasts	With nowcasts Without respecification	With nowcast With respecification	SPF nowcast
output	0.44	0.42	0.35	0.35
consumption	0.52	0.51	0.42	0.43
investment	1.78	1.73	1.50	1.49
inflation	0.21	0.21	0.21	0.23
short rate	0.12	0.12	0.11	-

Results under the RE-hypothesis

- Diebold-Mariano tests show that the model forecasts are not significantly different from the SPF-forecasts also for longer horizons: using information from the nowcasts is sufficient to capture the information from the surveys.
- The measurement error on observed nowcast variables is minimal and has no longer any predictive information in our Reduced-Form Variance Decomposition exercise.

=> The SPF-surveys can be integrated within the model-consistent FIRE setup: the information from surveys helps to identify the persistence of the fundamental shocks which is not possible based on realized data only.

=> There is no need for additional exogenous sentiment shocks to fit the survey data in combination with the actual realized macro data.

Remaining issues with RE-hypothesis

- RE models can extract useful information from the surveys but they also inherit the inefficiencies due to the model-consistent expectation restriction: $ALM=PLM$.
- Forecasts from RE model augmented with survey data underestimate investment realizations just like the SPF-nowcasts (see Table).

Remaining issues with RE-hypothesis: predictability test

$$y_{t+1} - y_{t+1|t} = a + \mathbf{b} * (y_{t+1|t} - y_{t+1|t-1})$$

SPF-nowcast	Output	Consumption	Investment	Inflation
b-coefficient	0.17	0.17	0.49	-0.12
St-error	<i>0.10</i>	<i>0.17</i>	<i>0.16</i>	<i>0.16</i>
R2	0.02	0.01	0.05	0.00
RE-model predictions				
b-coefficient	0.15	0.22	0.73	0.07
St-error	<i>0.11</i>	<i>0.14</i>	<i>0.17</i>	<i>0.22</i>
R2	0.01	0.01	0.11	0.00

Remaining issues with RE-hypothesis: time-variation

- RE models also fail to produce any time-variation in the transmission mechanism of shocks due to changes in beliefs.
- Lindé-Smets-Wouters 2016 documented the non-Gaussian nature and the heteroscedasticity/garch dynamics in forecast errors and structural innovations of estimated DSGE models.
- Compared to the original SW-model that was estimated on final data, the use of real-time data substantially worsens all these test-statistics on the residuals: later revisions in the data have an important and systematic impact (see also Orphanides 2001, Jacobs-Van Norden 2011, Bognanni 2016).

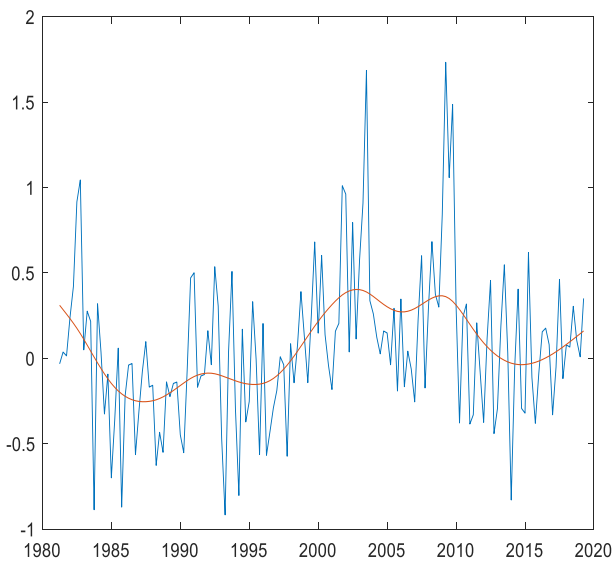
=> A large literature in finance and macro suggests that at least part of this time-varying volatility and under/over-reaction to shocks can be explained by changes in beliefs and/or sentiment.

Remaining issues with RE-hypothesis: long run stochastic trends

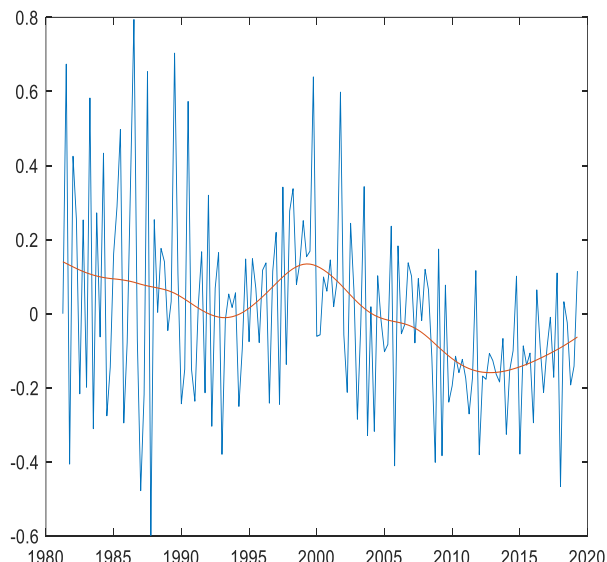
- RE models imply stabilizing expectations around a constant steady state.
- In contrast, macro-data display stochastic trends and breaks in equilibrium rates and long run relations: trend growth rate, long run inflation expectation, markups, risk-free and natural rates (see figure).

Remaining issues with RE-hypothesis: long run stochastic trends

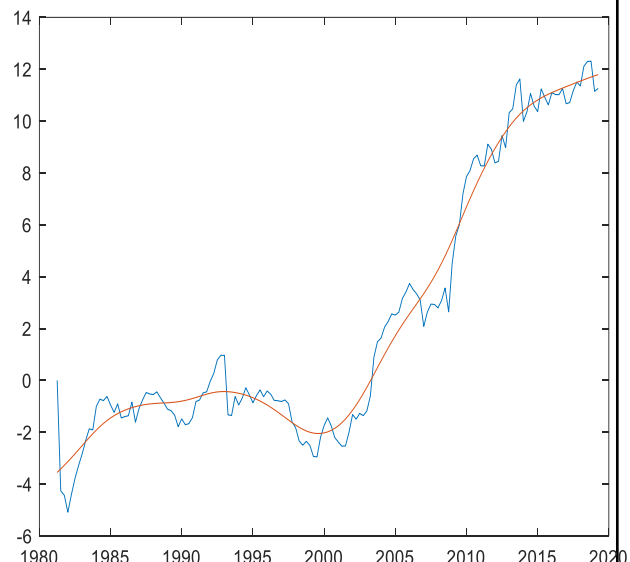
Tfp innovations



Risk premium



Price markup



Alternative models for expectations

- All forward variables in the decision rules are substituted by their belief model.
- Agents update these beliefs using Bayesian (Adaptive) Learning.
- Observing Survey Nowcasts adds discipline on the belief specification and the updating process.

- Four alternative specifications of the belief models (PLMs) are considered:
 1. MSV beliefs: use complete information set equivalent to the RE setup
 2. MSV beliefs with flexible constant updating
 3. Restricted belief models specified as AR processes augmented with shock innovations
 4. Heterogeneous beliefs that combine (2) and (3) based on recent relative forecasting performance

Implementation of Bayesian updating of the beliefs

- Starting from the linearized structural model representation:

$$A^+ E_t y_{t+1}^f + A^0 y_t + A^- y_{t-1} + B \varepsilon_t = 0$$

- Agents use belief models (PLM) to form expectations:

$$y_t^f = X'_{t-1} \beta_{t-1} + u_t$$

$$\beta_t = \bar{\beta} + \rho(\beta_{t-1} - \bar{\beta}) + e_t$$

- The belief coefficients are updated with the Kalman Filter:

$$\beta_{t|t} = \beta_{t|t-1} + P_{t|t-1} X_{t-1} (X'_{t-1} P_{t|t-1} X_{t-1} + \Sigma_u)^{-1} (y_t^f - X'_{t-1} \beta_{t|t-1})$$

$$\beta_{t+1|t} = \bar{\beta} + \rho(\beta_{t|t} - \bar{\beta})$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1} X_{t-1} (X'_{t-1} P_{t|t-1} X_{t-1} + \Sigma_u)^{-1} X'_{t-1} P_{t|t-1}$$

$$P_{t+1|t} = \rho P_{t|t} \rho + \Sigma_e$$

Implementation of Bayesian updating of the beliefs

- KF is initialized as:

$$\beta_0 = \bar{\beta} = E(XX')E(y^f X')$$

$$P_0 = \gamma(X'\Sigma_u^{-1}X)^{-1}$$

- With moment matrixes ($E(XX')$ and $E(y^f X')$) and the prior on the covariance matrix Σ_u for the SUR model based on the REE-dynamics:

$$\Sigma_u = E(y^f - X\bar{\beta})(y^f - X\bar{\beta})'$$

- and prior on Σ_e for parameter uncertainty also proportional to the GLS-covariance:

$$\Sigma_e = \sigma(X'\Sigma_u^{-1}X)^{-1}$$

- Parameters ρ , γ and σ determine the updating sensitivity: sufficient to estimate ρ .
- Beliefs are assumed to fluctuate around the REE-implied solution. This avoids the need to solve for Restricted Equilibrium dynamics and stabilizes the updating process (See Hommes et al 2020, and Molavi 2019 for alternative approaches).

Alternative models for expectations

- Four alternative specifications of the belief models are considered:
 1. MSV beliefs
 2. MSV beliefs with flexible constant updating
 3. Restricted belief models
 4. Heterogeneous beliefs combining (2) and (3)

- Model comparison results

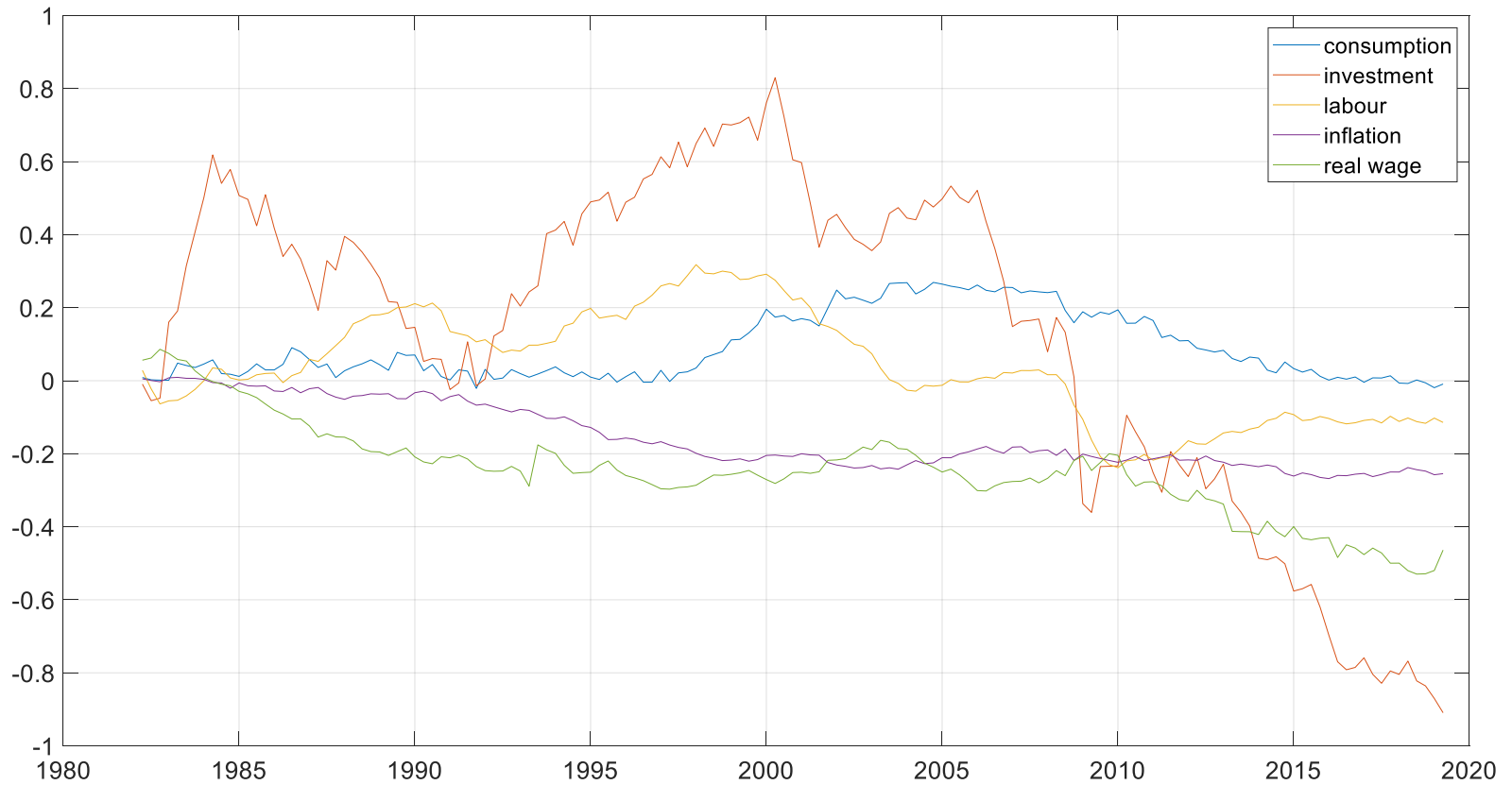
MSV beliefs

- Estimated models with MSV-beliefs deviate only marginally from the RE version: beliefs are based on the same information and initialized around the REE-solution.
- Updating in beliefs is limited and restricted to a few belief coefficients that generate little time-variation in the transmission mechanism of shocks.
- Each belief equation has 15 parameters and several variables in the Minimal State Vector are highly correlated which induces a multicollinearity problem in the updating process (problem comparable to large TVP-models e.g. Primiceri 2005, Koop et al 2013, Chan et al 2020)
- Kalman filter updating works efficiently for state variables fluctuating around their steady-state consistent with the REE-dynamics but becomes unstable if some states follow a non-stationary process. Such behaviour results in low estimates for ρ (or σ).
- ⇔ MSV-learning applications in the literature usually applied on small models.

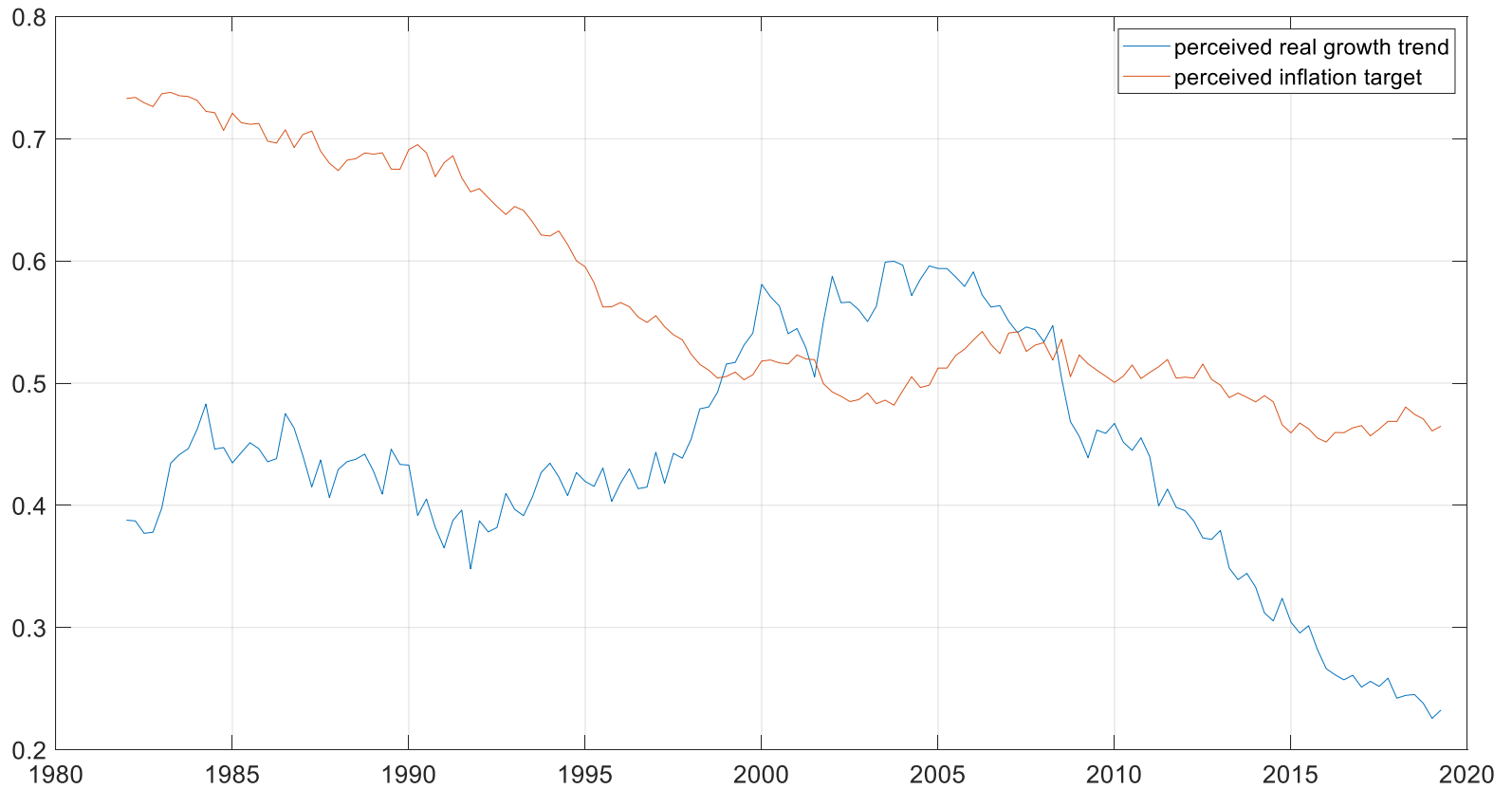
MSV beliefs with flexible updating of constants

- Non-stationary trends in endogenous and exogenous variables are potentially driven by breaks in steady state concepts: productivity trend growth, markup, risk free rate, perceived inflation target etc.
- One way to capture these breaks in our approach is to adjust the constant terms in the belief model. But our standard priors on the belief coefficients are based on the assumptions that the data fluctuate around the unique steady state and according to the stationary REE-dynamics.
- By introducing specific priors on the persistence ($\rho_{cte} > \rho$) and the variance of the belief constants ($\sigma_{cte} > \sigma$), the updating process for constants becomes more response to the systematic forecast errors and the structural breaks.

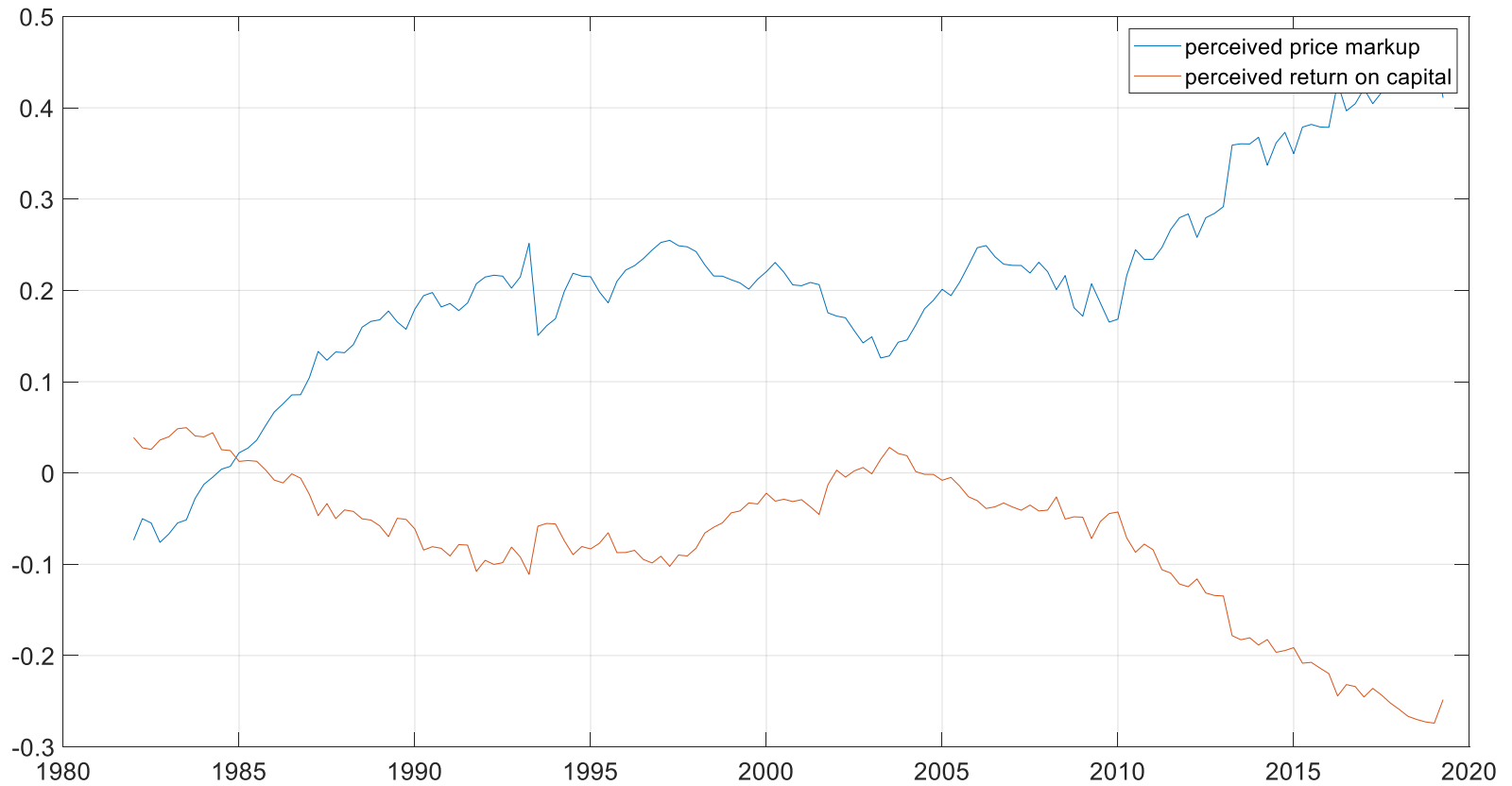
MSV beliefs with flexible updating of constants



MSV beliefs with flexible updating of constants



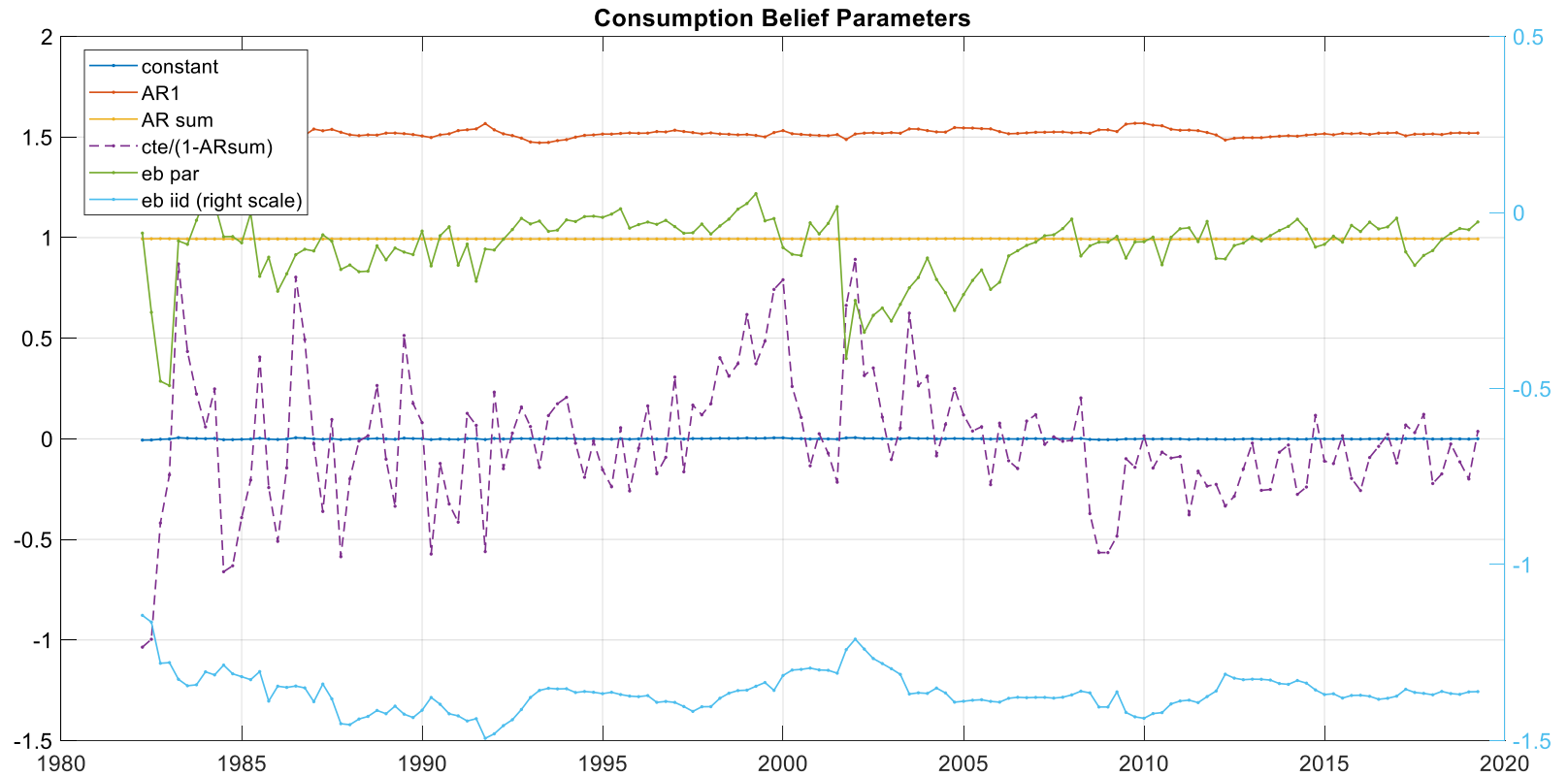
MSV beliefs with flexible updating of constants



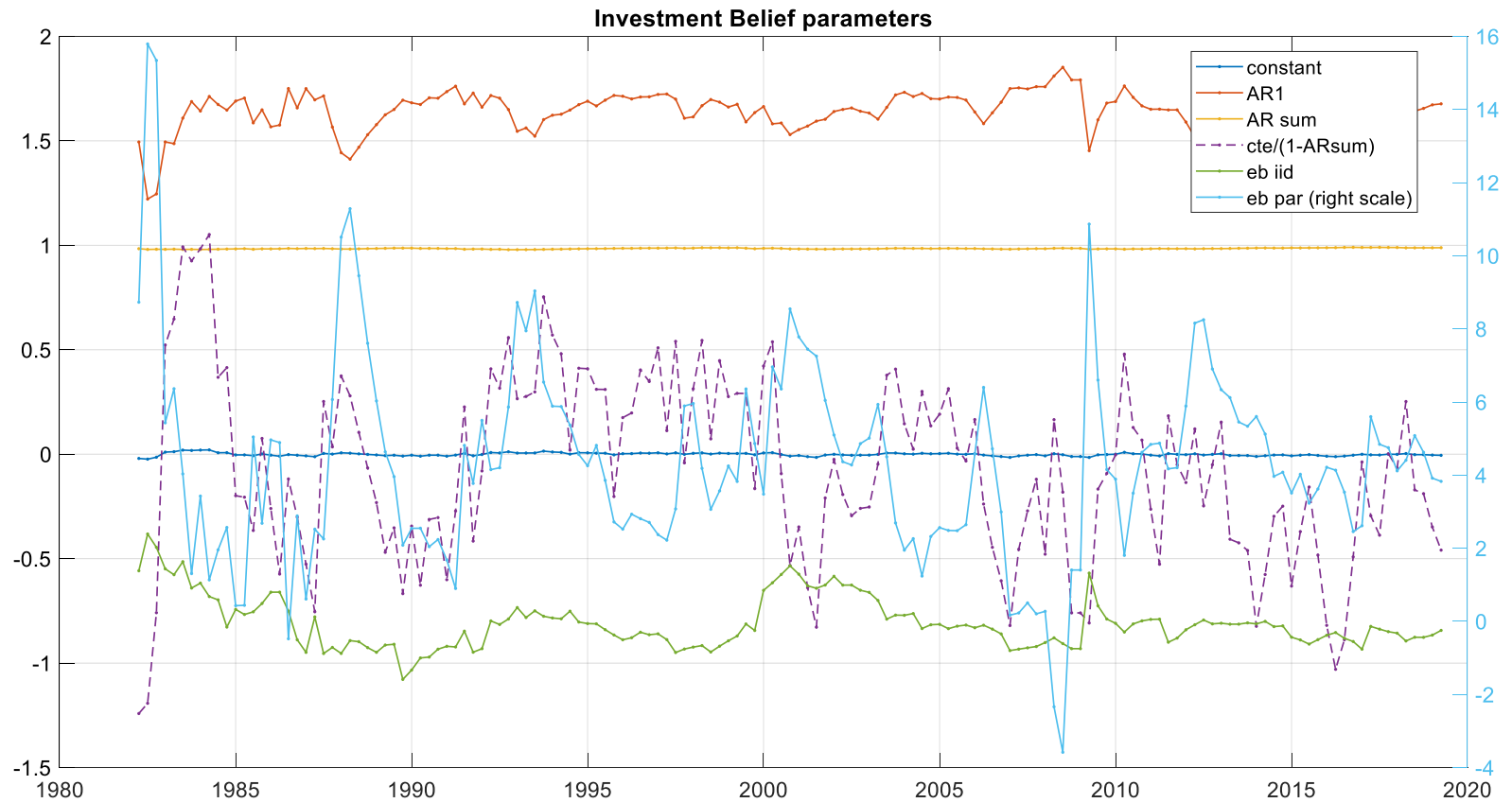
Restricted Belief models

- Our Restricted Belief (RB) models (PLMs) are specified as reduced form time-series models: AR(3) process augmented with innovations in the structural shocks.
- AR(3) process allows for maximum flexibility in the updating of the dynamics (first and second lag) while keeping the overall persistence close to one for the levels.
- Innovations in the structural shocks are necessary in the belief models to allow expectations to react to shocks instantaneously. This information in the beliefs is also necessary to capture the rich information of the SPF-nowcasts and to compete with these surveys in terms of forecasting performance.
- Simple AR belief specifications (like in Hommes Zhu 2014, Slobodyan Wouters 2012, or factor models as in Molavi 2019) produce variation in the overall persistence of the beliefs but can not compete with the rich information content and precision of the SPF-nowcasts.
- The initialisation of these Restricted Beliefs is still based on the implied parameters for these processes under REE-dynamics.
- This RB-setup implies a flexible updating process for constants and dynamics: persistence and shock elasticities.

Restricted Belief models: consumption beliefs



Restricted Belief models: investment beliefs



Heterogenous Beliefs with Updating and Regime Switching

- Instead of assuming homogenous expectations and gradual updating of belief models (PLM), we also consider a setup in which agents have heterogeneous beliefs and switch between belief models based on the past forecasting performance of these belief models:

$$E_t^A y_{t+1}^f = \omega_t^{MSV} E_t^{MSV} y_{t+1}^f + \omega_t^{RB} E_t^{RB} E_t y_{t+1}^f$$

with ω_t^i evolving as a function of the past belief forecast errors $\varepsilon_{j,t}^i$ (model i, variable j):

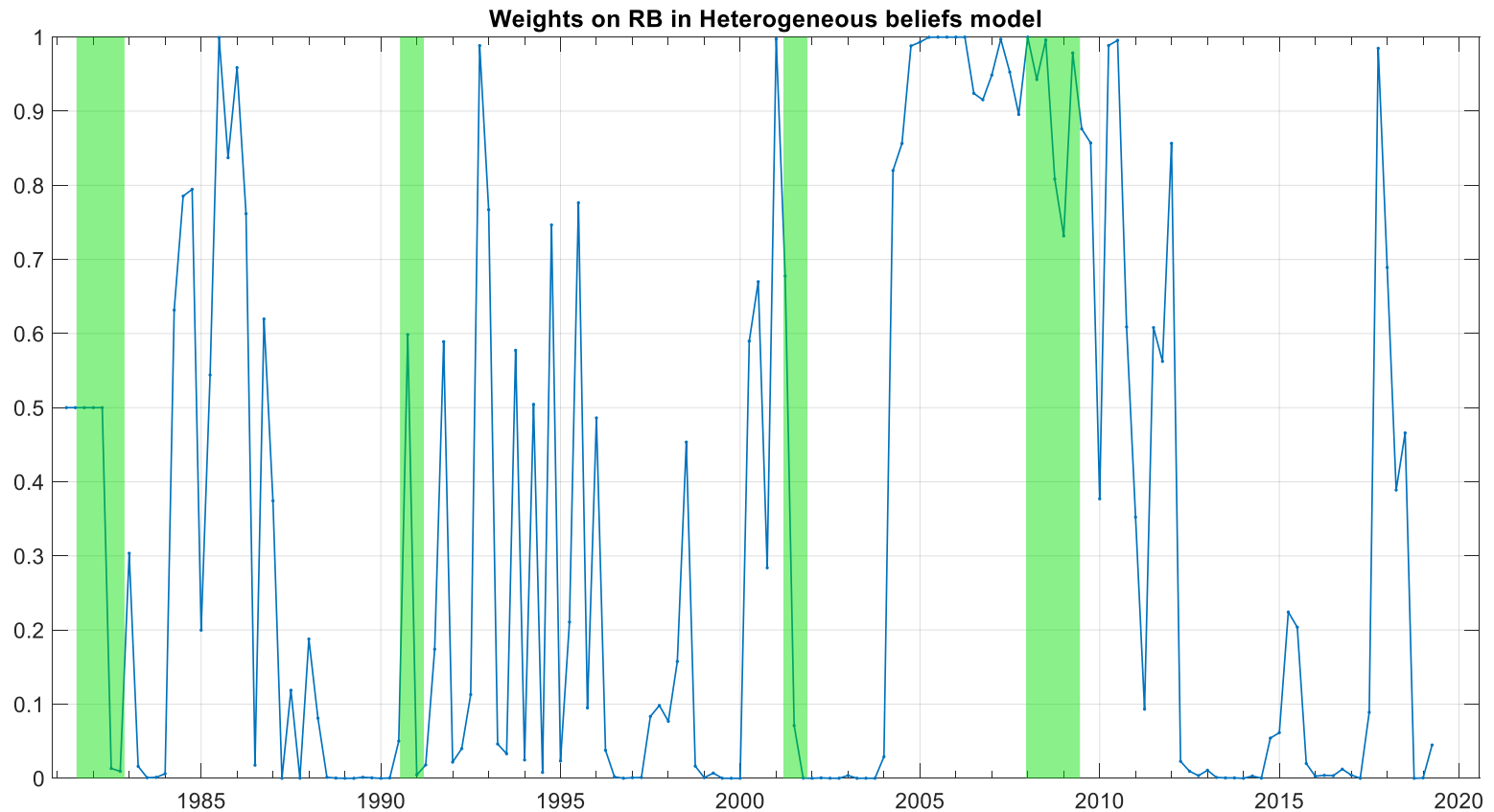
$$\omega_t^i = \frac{\exp(-\xi m_t^i)}{\sum_i \exp(-\xi m_t^i)} \quad \text{with} \quad m_t^i = \log(\Pi_j \text{wsfe}_{j,t}^i)$$

$$\text{wsfe}_{j,t}^i = \theta \text{wsfe}_{j,t}^i + (1 - \theta)(\varepsilon_{j,t}^i)^2$$

with θ determining the memory length and ξ the sensitivity of the weight to the forecast errors (see Brock Hommes (1997) and De Grauwe (2011) for similar discrete choice model setups)

- These different expectation models are evaluated in the same model with one set of structural parameters: these parameters must be robust to produce competitive forecasts with potentially different transmission mechanisms of the shocks.

Heterogenous Beliefs with Updating and Regime Switching: weights figure



- Average weight for Restricted Belief model is 0.34: this fraction is very stable also in simulation experiments. RB gets more weight after big shocks or repeated innovations in the same direction.

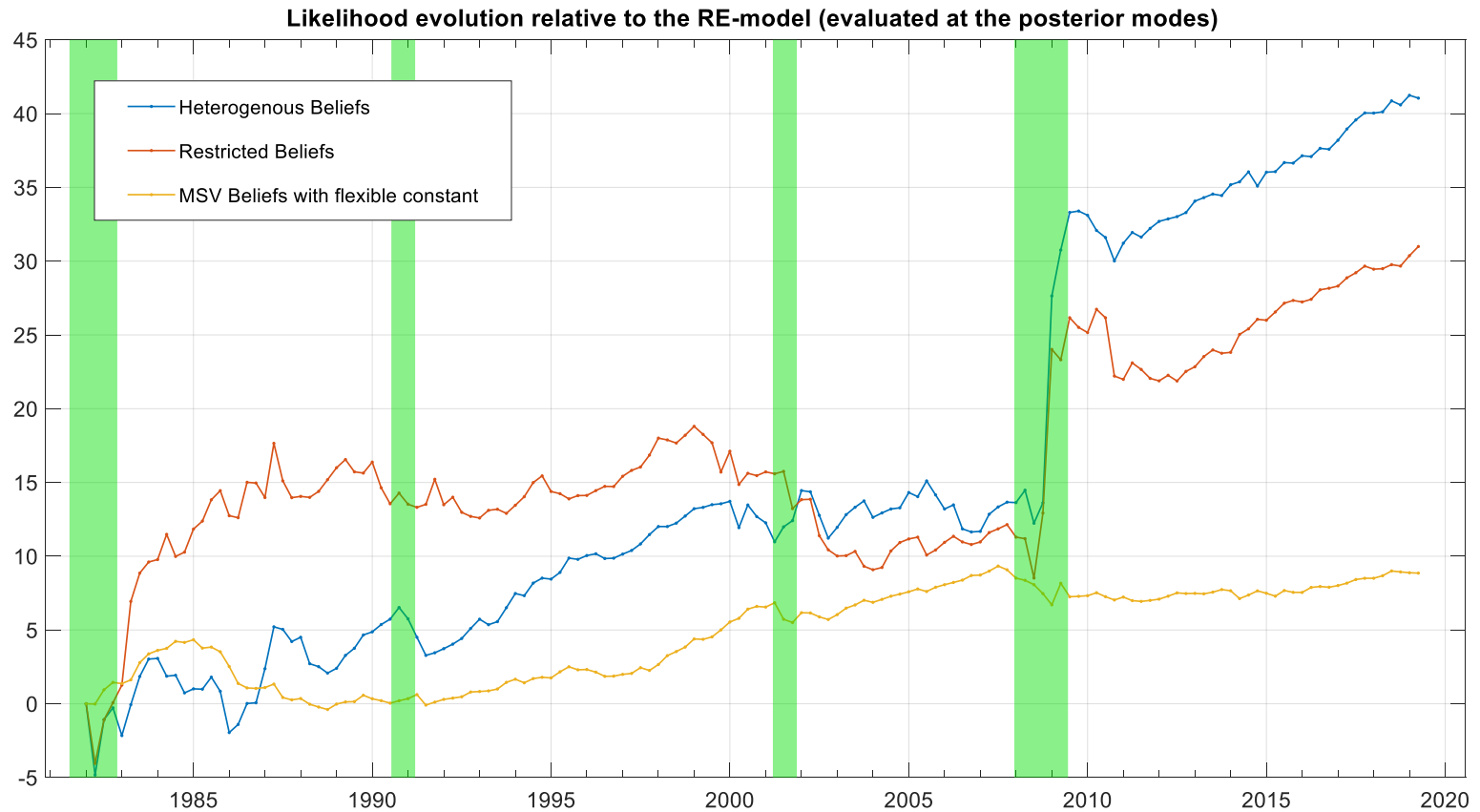
Model comparison results

- The relative model likelihood provides a measure for the overall performance of the different expectation hypothesis in the SW-model with an augmented dataset of real-time data and SPF-nowcasts:

	Marg. Lik
RE-model	-217.7
MSV Beliefs with flexible cte	-209.1
Restricted Beliefs	-176.4
Heterogeneous Beliefs	-173.9

- MSV Beliefs with flexible updating mainly improve the model performance by producing more precise point forecasts that reduce the systematic forecast errors.
- Restricted and Heterogeneous Belief models with Bayesian Learning improve the precision of the forecasts but also generate a realistic time-varying predictive density distribution.

Model comparison: relative likelihood over time



- The gain from flexible constants is realized gradually over time.
- RB performs better during periods of increased volatility.
- HB combines the benefits from the two setups.

Model comparison: rmse forecasts for realized data and nowcasts

π_{r1}	dy_r1	dc_r1	di_r1	ff rate	π_{f0}	dy_f0	dc_f0	di_f0
RE-model with nowcast observation								
0.21	0.35	0.42	1.50	0.12	0.10	0.29	0.27	0.67
MSV Beliefs with flexible constant (relative to RE-model)								
1.00	1.02	1.00	1.00	0.99	0.98	1.00	0.98	1.00
Restricted Beliefs								
1.01	1.03	1.00	0.94	0.97	1.03	1.03	1.04	0.95
Heterogeneous Beliefs								
1.00	0.98	1.00	0.89	0.99	0.98	0.96	1.00	0.81

- RE-model is performing already well relative to SPF nowcasts.
- Model forecast performance is good both in terms of realized real-time data and SPF-nowcast.
- Additional gains in terms of point forecasts are modest and mainly concentrated in investment.

Model comparison: further results

- DM-test for longer horizon forecasts illustrate that the model forecasts are not statistically significant different from the SPF surveys up to 5-quarters ahead.

5-quarter ahead	MSV	MSVflexcte	RB	HB
Output	-0.51	-0.59	-0.25	-0.82
Consumption	0.15	-0.67	0.10	-0.18
Investment	-0.44	-0.67	-0.90	-1.20
Inflation	-1.80	-1.91	-1.86	-1.25

- There is no further gain from observing longer term forecasts.
- Measurement errors on nowcasts remain small and have no predictive information.

Do Belief Models relax the limitations of the RE-Model ?

- Predictability of forecast errors
- Time variation in beliefs and volatility / under-overreaction in shocks
- Non stationary trends and breaks: see above

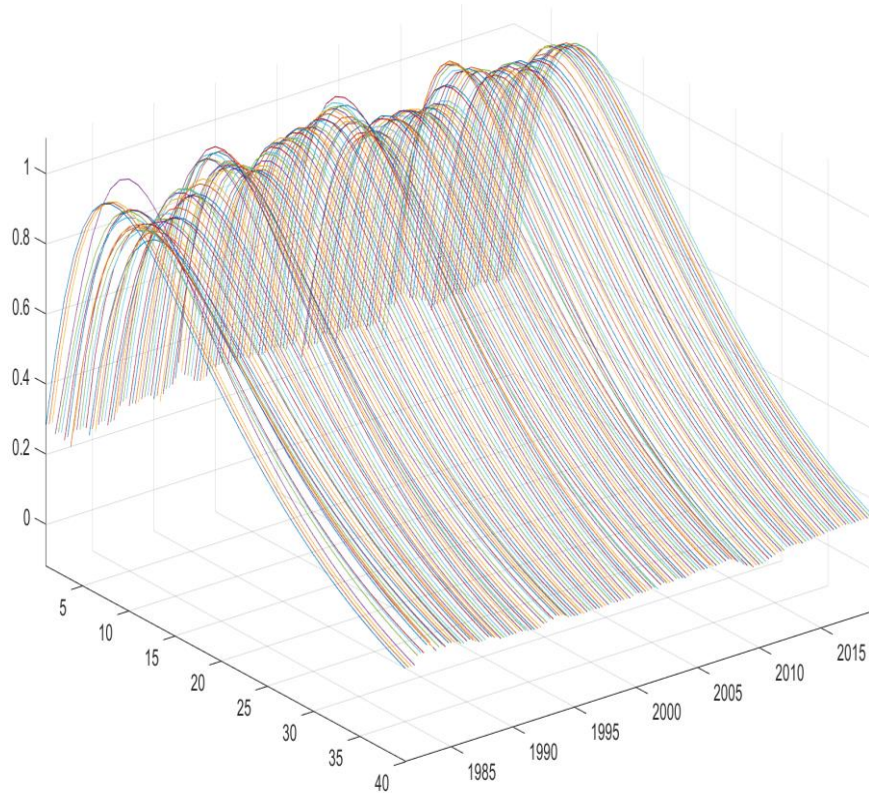
Do Belief Models relax the limitations of the RE-Model: predictability test

$$y_{t+1} - y_{t+1|t} = a + \mathbf{b} * (y_{t+1|t} - y_{t+1|t-1})$$

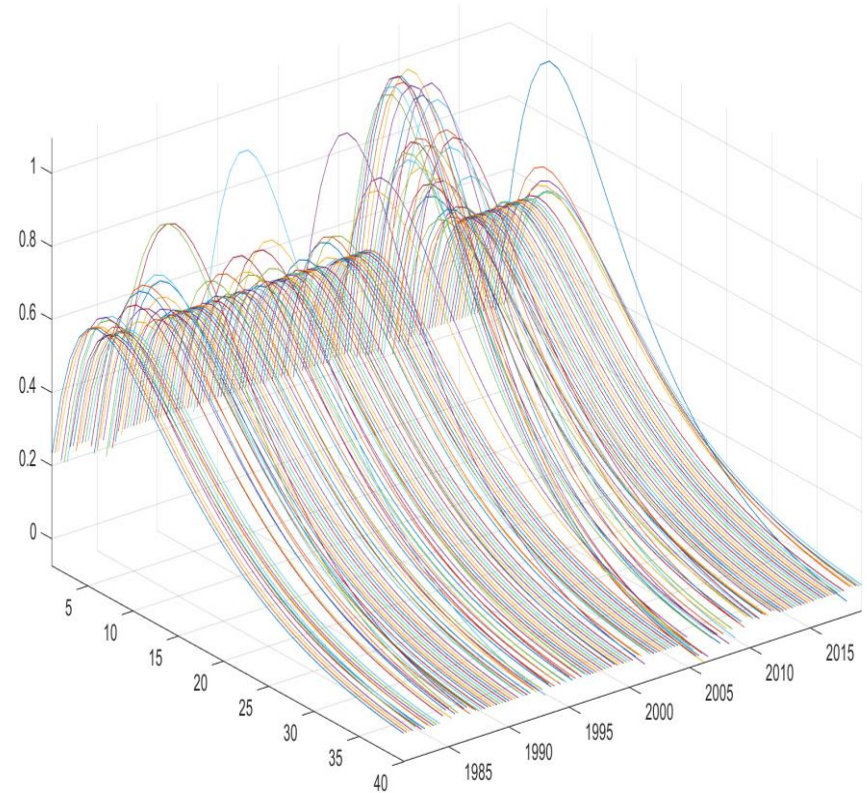
	Output		Consumption		Investment		Inflation	
SPF-Nowcast								
b	0.17		0.17		0.49		-0.12	
RE-model: ALM=PLM								
b	0.15		0.22		0.73		0.07	
Restricted Beliefs								
	ALM	PLM	ALM	PLM	ALM	PLM	ALM	PLM
b	-0.14	0.11	0.12	0.40	0.17	0.49	0.24	0.17
Heterogenous Beliefs								
b	0.00	0.15	0.29	0.48	0.34	0.82	-0.07	0.10

Do Belief Models relax the limitations of the RE-Model: time variation and extrapolation ?

Response of y to persistent risk premium shock in RB-model

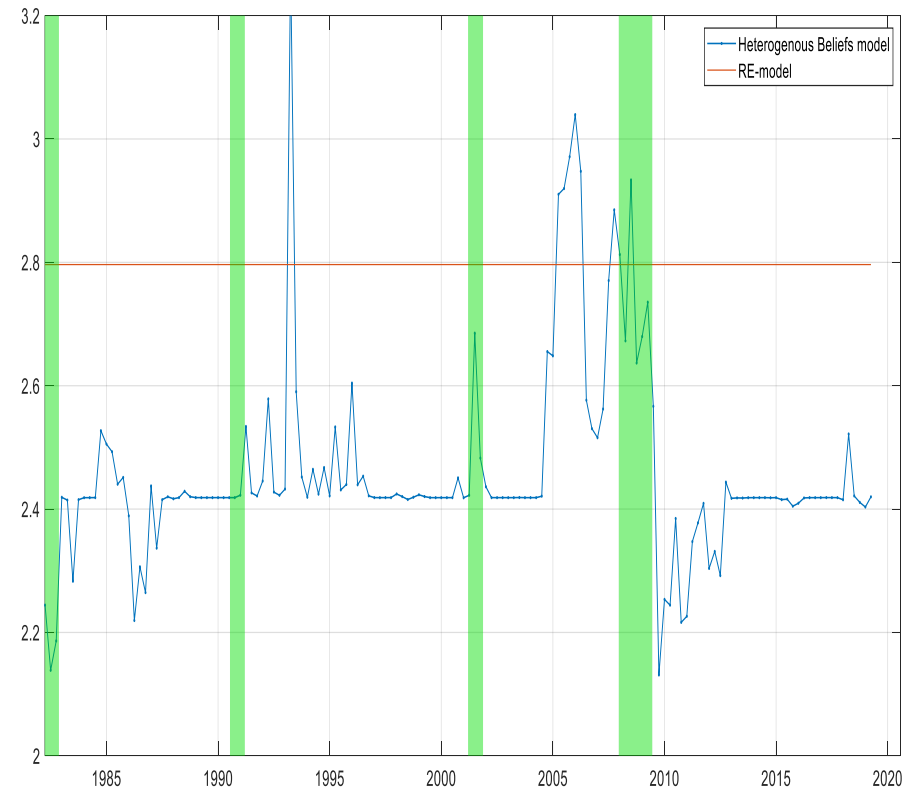
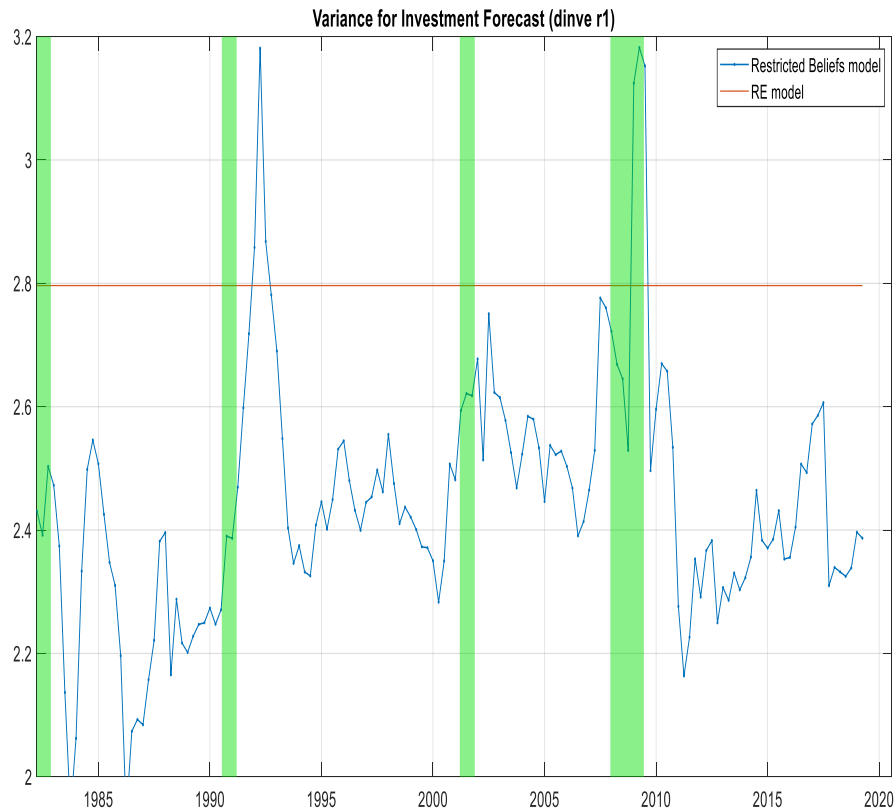


Response of y to persistent risk premium shock in HB-model



- Updating in beliefs and variation in the weight of heterogeneous belief models produce time-variation in the transmission of shocks.

Do Belief Models relax the limitations of the RE-Model: time variation and extrapolation ?



- This time-variation in the variance of the predictive distribution explains a large fraction of the improvement of the model likelihood.

Concluding remarks

- The paper provides an efficient procedure for incorporating and explaining survey forecasts in DSGE-models. The procedure can also be used to include higher-frequency nowcasts from large-data real-time models.
- This model-setup of expectations based on belief models and updating should be compared with alternative explanations for beliefs and sentiment models.
- Survey expectations from less-informed households and firms can also be incorporated and their additional/alternative relevance for explaining the macro-aggregates can be tested.
- Implications of the ZLB, Forward Guidance or QE can be integrated explicitly in this setup by adding the implied anticipated monetary policy shocks of these constraints and interventions to the information set in the belief models (Stevens-Wouters) or by introducing a ZLB-regime for the policy and/or expectations (Ozden).

