Real-time Prediction with UK Monetary Aggregates in the Presence of Model Uncertainty

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- Popular account of UK monetary targeting demise blames predictive content of broad money
- We investigate predictive relationships from money to inflation and real output
- Consider large range of recursively estimated VAR and VECM models, vary number of lags and long-run terms

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- Faced with considerable model uncertainty, we contrast Bayesian Model Averaging (BMA) with selection of single "best" model in each period
- To deal with data uncertainty, we estimate models and generate forecasts with real-time (vintage) data, and contrast results with final vintage data

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Money Matters for Real-time Prediction

- In-sample predictive content fluctuates in real time for broad money, amplified by selection of single "best" model
- Particularly with M3 (policymakers preferred aggregate) for inflation through the 1980s
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- Overall, no evidence that predictive content of broad money diminished in revised data
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- M3 UK monetary target from June 1979, after monitoring period and informal targeting
- Forecast ranges for M3 published and commonly missed (eg 1984/85 to 86/87)
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Governor Pointed to Financial Innovations

- Big Bang 1986 opened London stock exchange to international competition
- Automatic teller machines (late 1970s), abolition of fixed reserve requirements for banks (1981), introduction of debit cards (1987)
- Periodic reclassification of monetary sector; Topping and Bishop (1989)

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Other Disturbances

- Micro reforms throughout the period: industrial relations laws, privatization, changes in social security benefit, taxation

- Statistical reforms early 1990s: see Egginton, Pick, Vahey (2002), Garratt and Vahey (2006), Garratt, Koop and Vahey (2007)

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Bayesian Model Averaging

- We use approximate Bayesian methods to evaluate the terms in

$$p\left(z|Data\right)=\sum_{i=1}^{q}p\left(z|Data,M_i\right)p\left(M_i|Data\right)$$

where z are our probabilities of interest involves taking a weighted average across all models, with weights being the posterior model probabilities

Bayesian Model Averaging (cont)

- We evaluate:

$$p\left(M_i \middle| Data\right) \propto p\left(Data \middle| M_i\right) p\left(M_i\right),$$

where $p\left(Data \middle| M_i\right)$ is the marginal likelihood and $p\left(M_i\right)$ the prior weight attached to this model—the prior model probability

Bayesian Model Averaging (cont)

- Given the controversy attached to prior elicitation, $p(M_i)$ we adopt the noninformative choice where, *a priori*, each model receives equal weight
- The Bayesian literature has proposed many benchmark or reference prior approximations to $p(Data|M_i)$ which do not require the researcher to subjectively elicit a prior (see, e.g., Fernandez, Ley and Steel, 2001)

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Bayesian Model Averaging (cont)

- Here we use the Schwarz or Bayesian Information Criterion (BIC):

$$\ln p\left(Data|M_i\right) \approx l - \frac{K \ln\left(T\right)}{2}$$

- The BMA weights are proportional to the BIC scores —we use the standard noninformative prior familiar to non-Bayesians

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Model Space

- Output equation in VAR:

$$\Delta y_t = \mu + \sum_{i=1}^{p} a_{1i}\Delta y_{t-i} + \sum_{i=1}^{p} a_{2i}\Delta p_{t-i} + \sum_{i=1}^{p} a_{3i}\Delta i_{t-i} + \sum_{i=1}^{p} a_{4i}\Delta e_{t-i} + \sum_{i=1}^{p} a_{5i}\Delta m_{t-i} + \varepsilon_t$$

- Money has no (in-sample) predictive content if:

$$a_{51} = \ldots = a_{5p} = 0$$

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Probabilities

- Probability that money has no predictive content for output:

$$p\left(a_{51} = \ldots = a_{5p} = 0 \middle| Data, M_{var}\right)$$
$$= \frac{\exp\left(BIC_R\right)}{\exp\left(BIC_R\right) + \exp\left(BIC_U\right)}$$

Model Space

- Analogous VECM:

$$\Delta y_t = \nu + \sum_{i=1}^{p} b_{1i}\Delta y_{t-i} + \sum_{i=1}^{p} b_{2i}\Delta p_{t-i} + \sum_{i=1}^{p} b_{3i}\Delta i_{t-i} + \sum_{i=1}^{p} b_{4i}\Delta e_{t-i} + \sum_{i=1}^{p} b_{5i}\Delta m_{t-i} + \sum_{j=1}^{r} \alpha_j \xi_{j,t-1} + \epsilon_t$$

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Probabilities

- Searching across many likely misspecified models
- Use BMA to allow for model uncertainty
- Probability for each of the models given by:

$$p(M_i|Data) = \frac{\exp(BIC_{uM_i})}{\sum_{i=1}^{q} \exp(BIC_{uM_i})}$$

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Extending Amato and Swanson (2001)

- Model space fairly conventional and similar to Amato-Swanson
- BMA allows an assessment of whether "money matters" using evidence from all models considered
- In-sample probabilities indicate that money has predictive content in the 1980s, but with real-time reversals

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Using Data Observations Seen By Policymakers

- Real time data for y, p, m; no revisions for e and r
- Each time series starts 1963Q1
- Here just present results for $M3$; paper contains results for longer samples of $M0$ and $M4$ (start dates differ from $M3$)

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Using Real-time Data

- Analyze successive vintages of data to mimic common practice of applied econometricians in real-time e.g Amato and Swanson (2001)
- We standardize the "publication lag" to two quarters—a vintage dated time t includes time series observations up to date $t-2$

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- Model uncertainty focussed on r and p
- $n = 5$, Max $p = 8$, Max $r = 4 \Longrightarrow 40$ models
- Recursive estimation of models for each variable, 1965Q4 through $\tau = 1978Q4, \ldots, 1989Q2$ (43 recursions)

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Graphical Presentation of In-sample Results

- All models for each vintage use real time data to compute BMA and single best (BIC max) probabilities of interest
- All models using final vintage data to compute BMA probabilities

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Figure 3: Probability M3 Predicts Output Growth

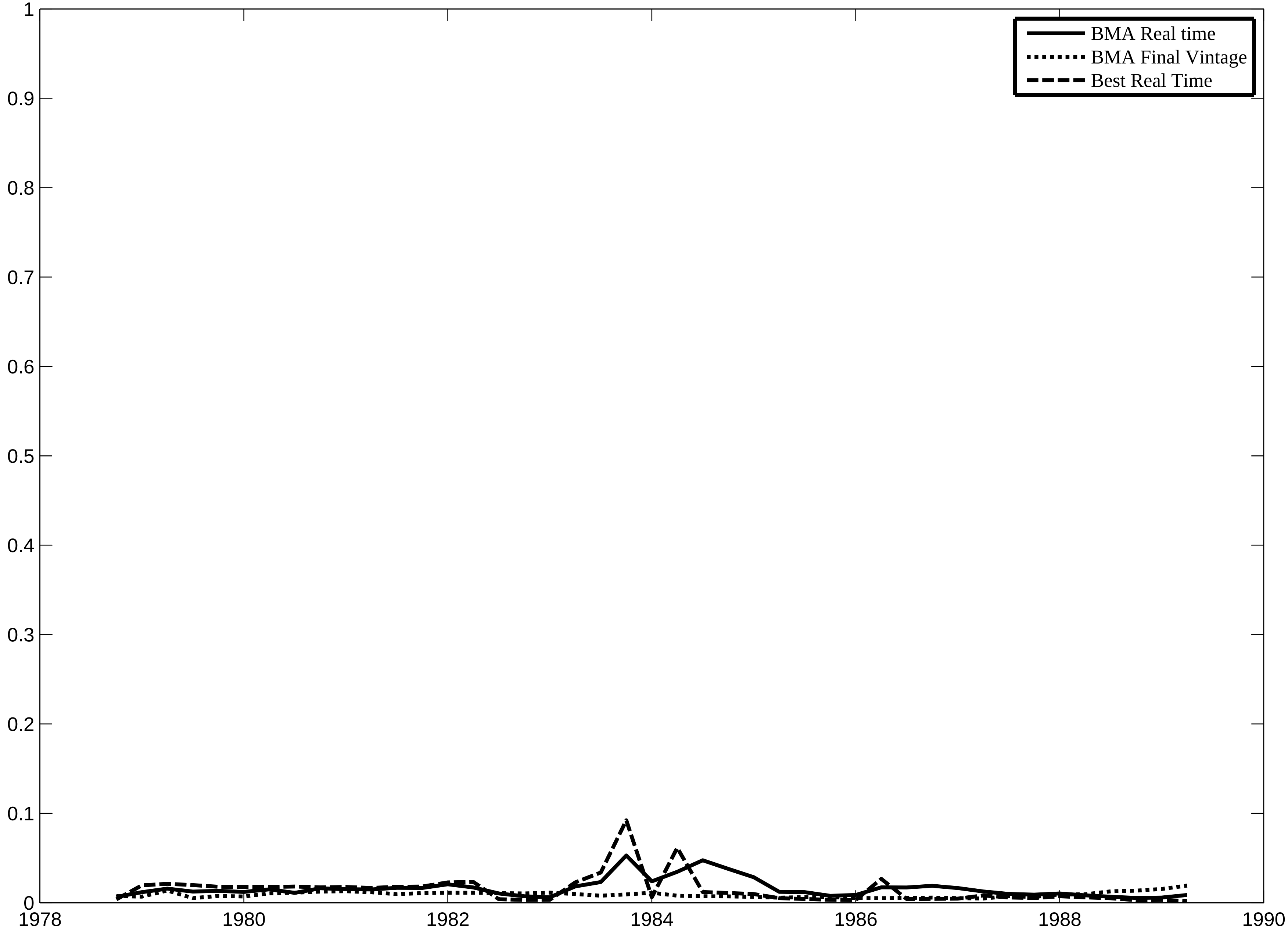


Figure 4: Probability M3 Predicts Inflation

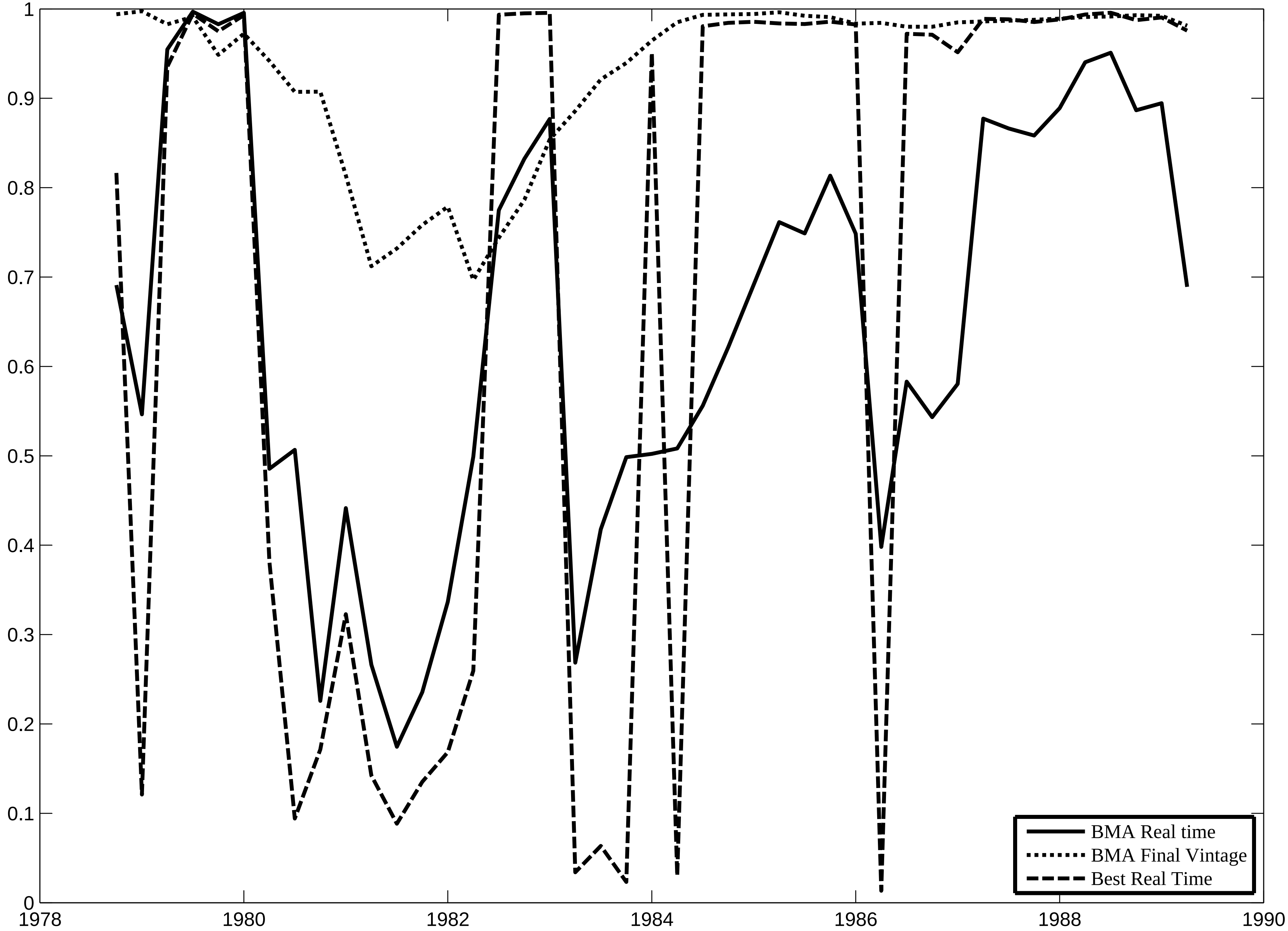


Figure 5: Probability of Inflation > 5 percent, h=8, Net Contribution of M3

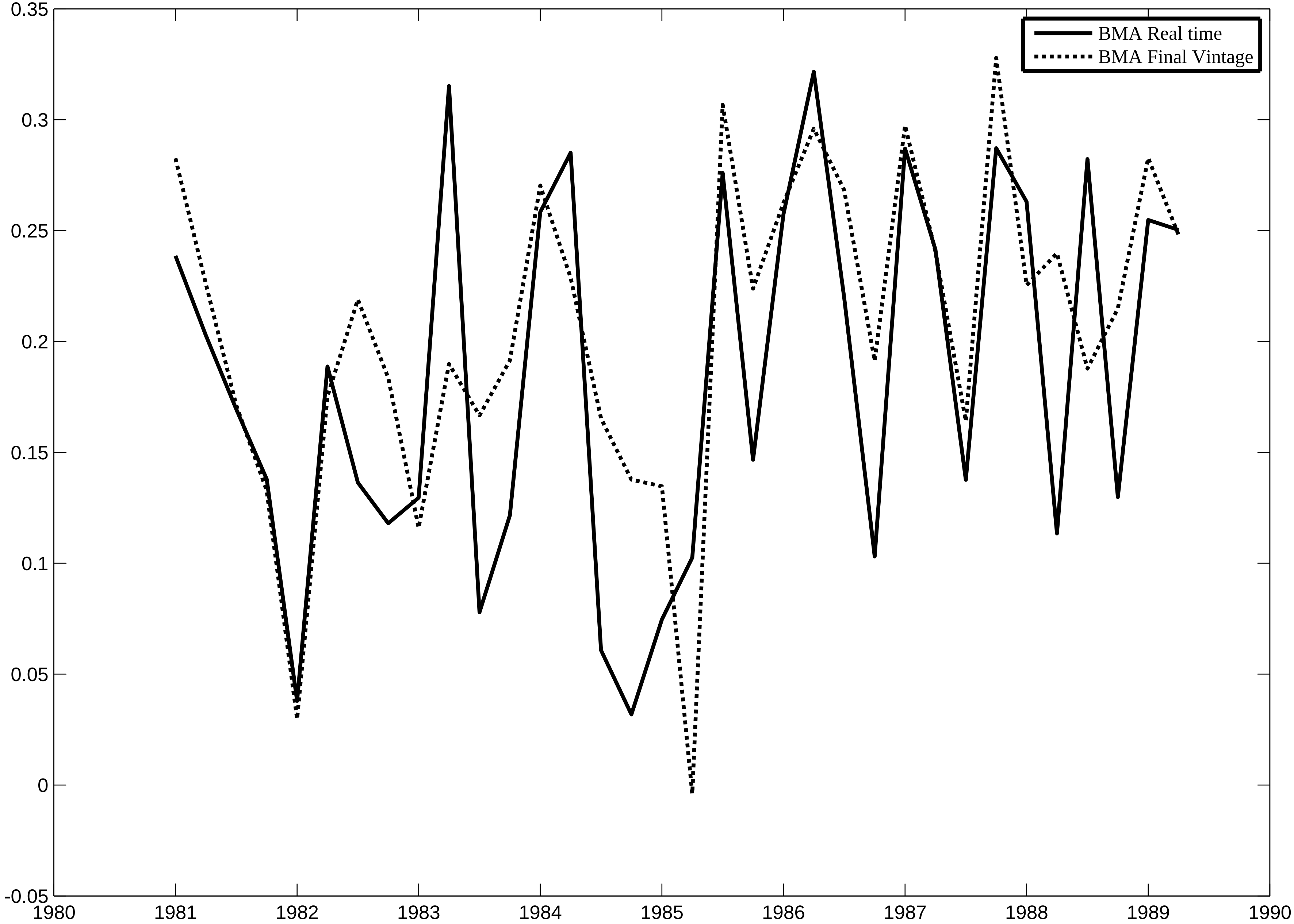


Figure 6: Probability of Output Growth > 2.3 percent, h=8, Net Contribution of M3

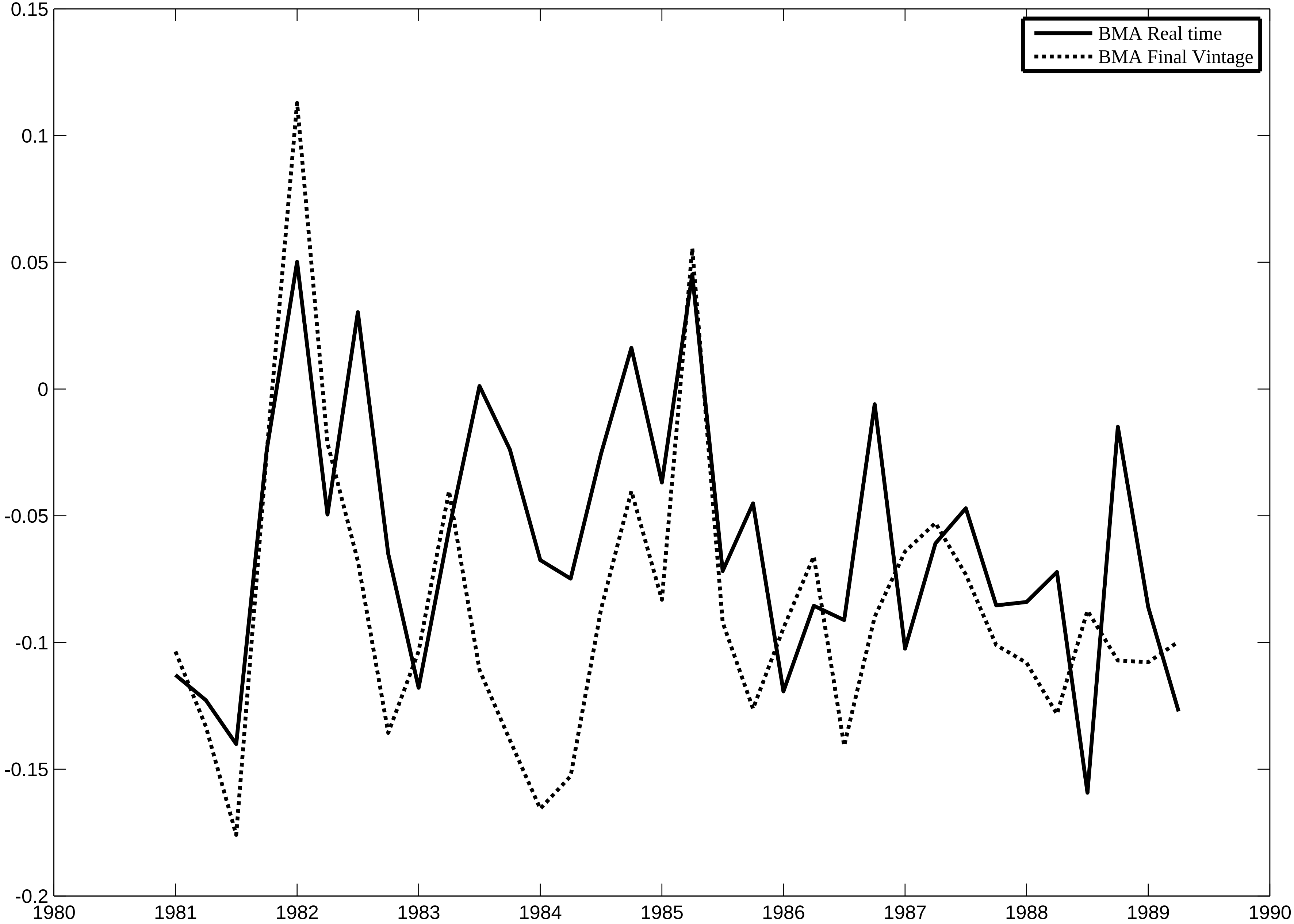


Figure 7: Probability M0 Predicts Output Growth

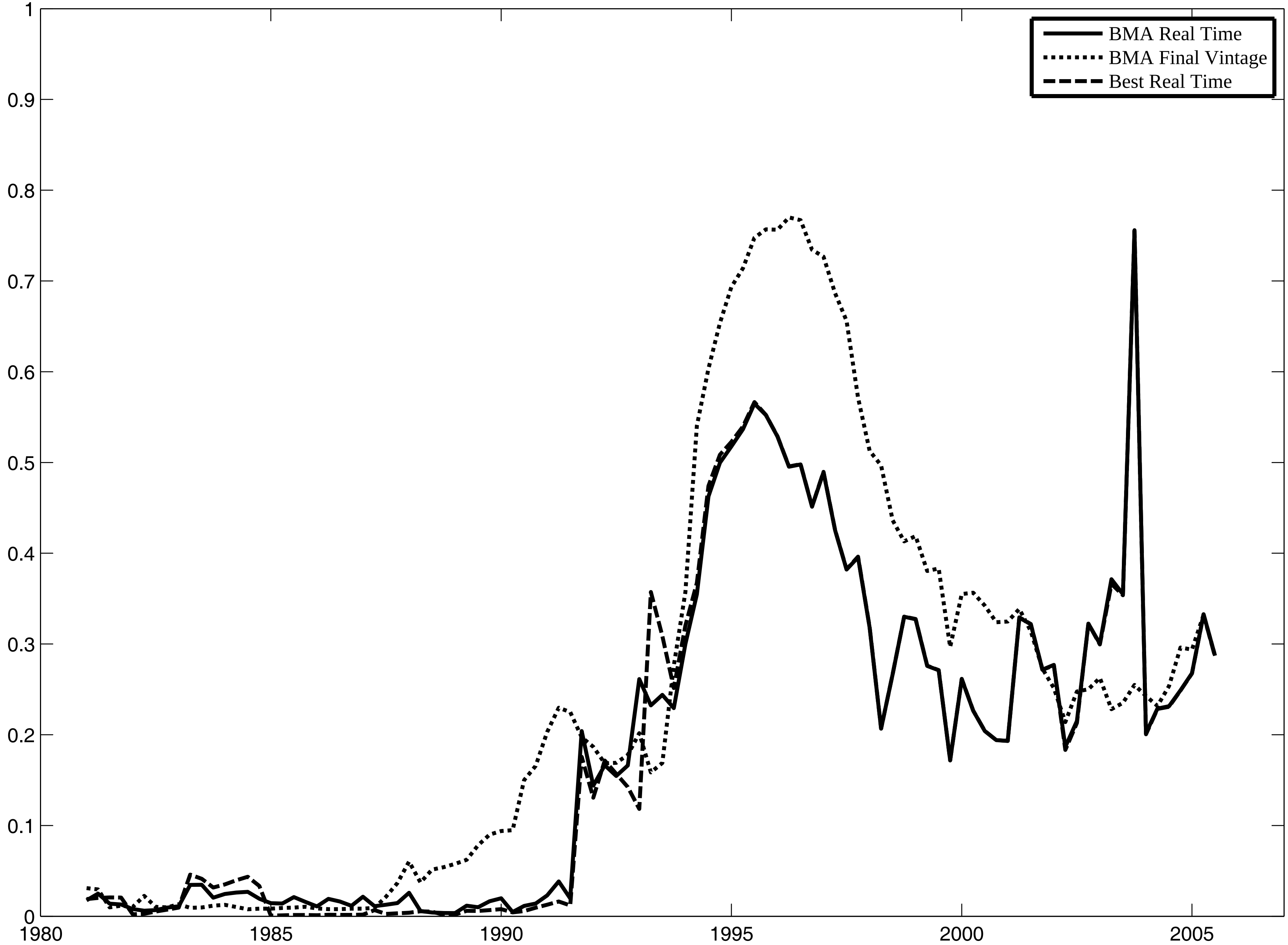


Figure 8: Probability M0 Predicts Inflation

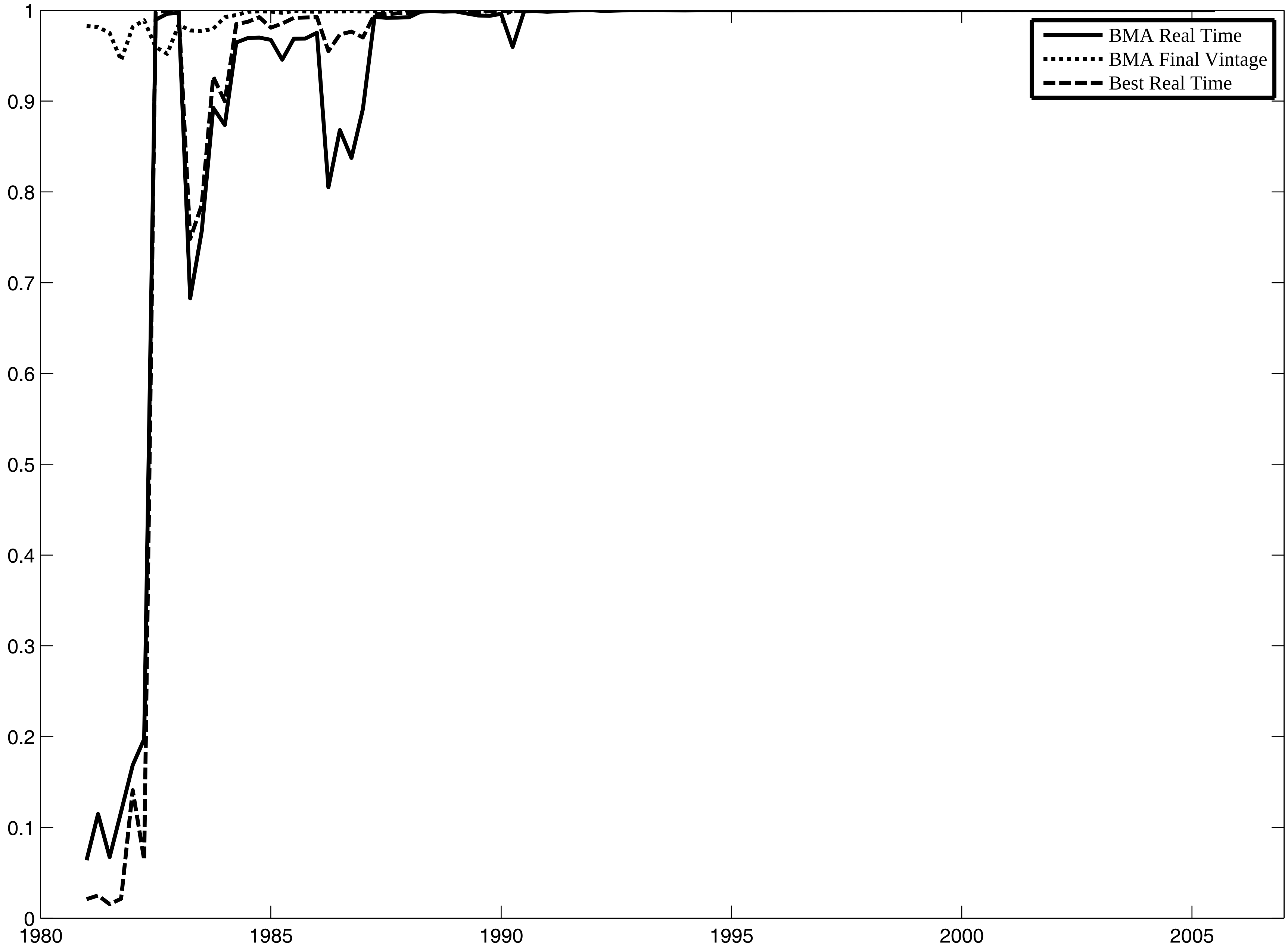


Figure 9: Probability M4 Predicts Output Growth

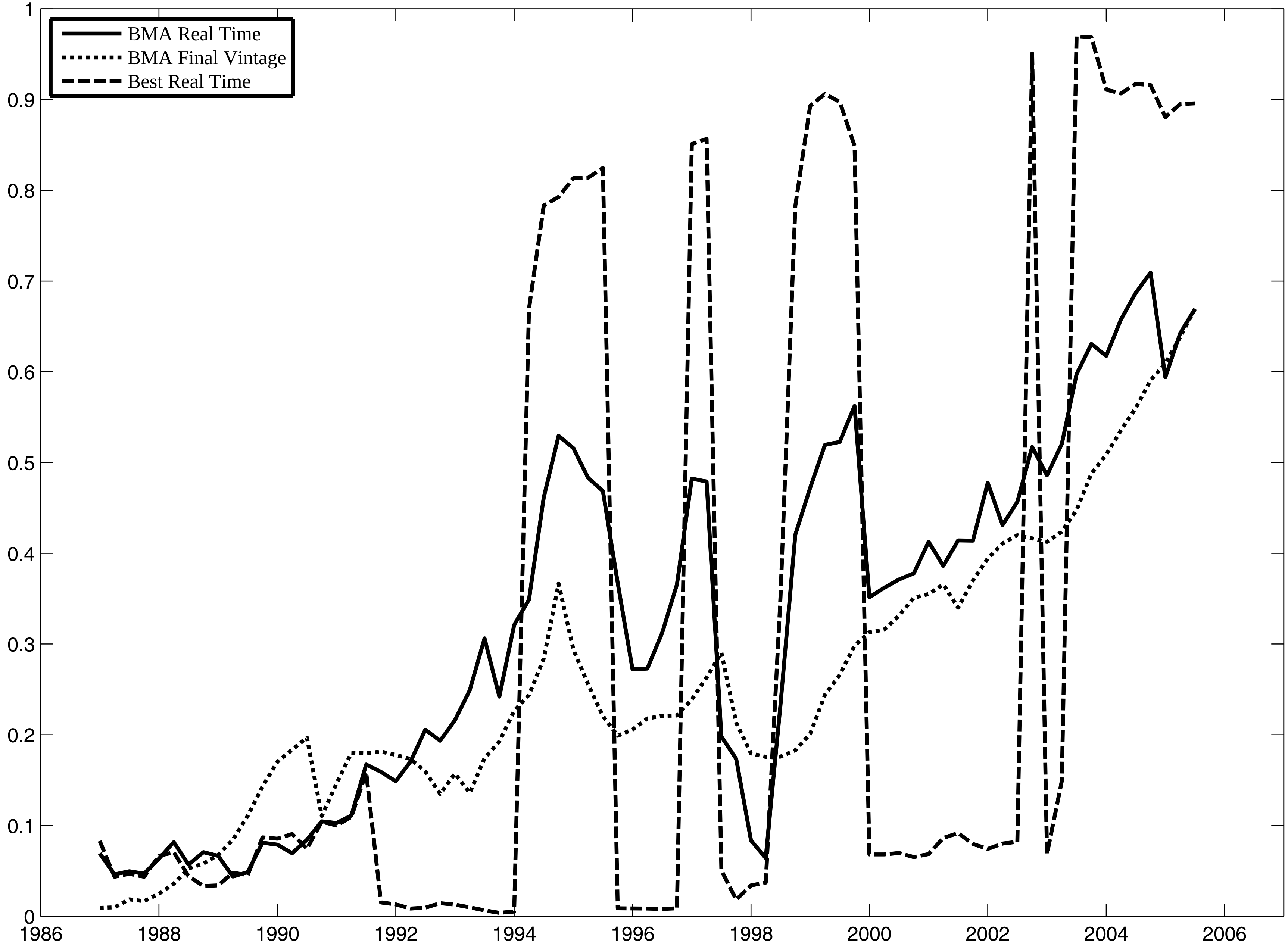
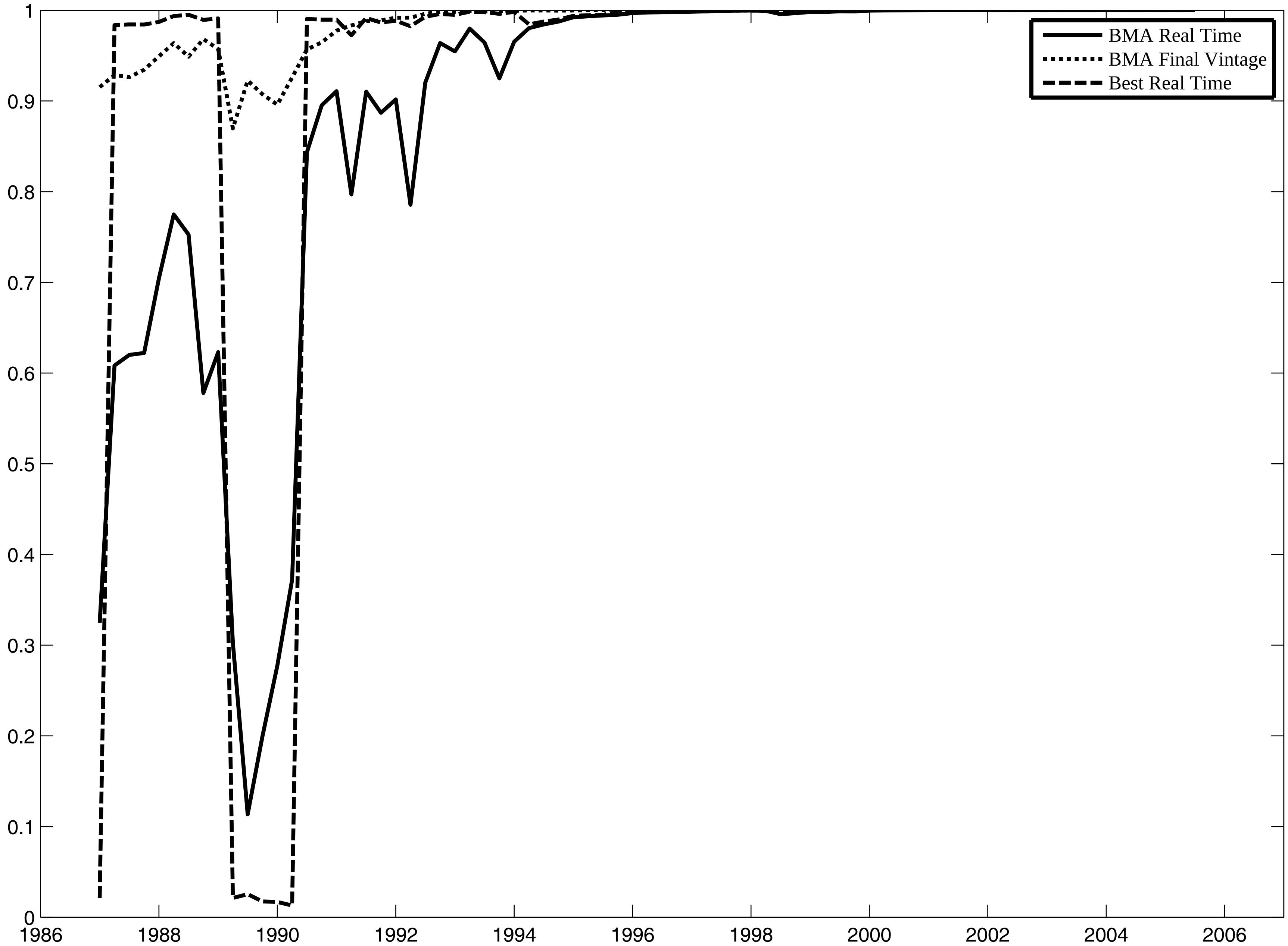


Figure 10: Probability M4 Predicts Inflation



Money and Data Uncertainty Matter

- Real-time data problems masked the predictive power of UK money for 1980s inflation
- Real-time analysis with Best model generated substantial reversals, mitigated by BMA
- UK monetary targeting demise shows that real-time data matter for policy; see Bernanke and Boivin (2003), Orphanides (2001) and Rudebusch (2001)

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Table 1: Evaluation of BMA Out of Sample Central and Probability Forecasts with $M3$, 1981Q1-1989Q2

	Without Money			With Money		
	h=1	*h=4*	*h=8*	*h=1*	*h=4*	*h=8*
(a) Inflation Real Time						
RMSE	1.00	1.00	1.00	1.19	1.40	1.50
DM	·	·	·	-1.93	-4.52	-4.10
$\Pr(d_{t+h} > 0)$	·	·	·	0.51	0.50	0.45
Hit Rate, $\Pr(\Delta p_{t+h} < 5.0\%)$	0.68	0.53	0.65	0.74	0.65	0.65
PT, $\Pr(\Delta p_{t+h} < 5.0\%)$	1.38	-1.60	·	2.33	·	·
(b) Inflation Final Vintage						
RMSE	1.00	1.00	1.00	1.14	1.43	1.78
DM	·	·	·	-2.84	-2.77	-6.34
$\Pr(d_{t+h} > 0)$	·	·	·	0.51	0.50	0.40
Hit Rate, $\Pr(\Delta p_{t+h} < 5.0\%)$	0.68	0.62	0.65	0.56	0.65	0.65
PT, $\Pr(\Delta p_{t+h} < 5.0\%)$	1.27	-0.76	·	-0.79	·	·
(c) Output Growth Real Time						
RMSE	1.00	1.00	1.00	1.06	1.09	1.12
DM	·	·	·	-0.63	-2.24	-0.90
$\Pr(d_{t+h} > 0)$	·	·	·	0.51	0.51	0.51
Hit Rate, $\Pr(\Delta y_{t+h} < 2.3\%)$	0.41	0.68	0.38	0.35	0.68	0.47
PT, $\Pr(\Delta y_{t+h} < 2.3\%)$	-1.69	1.81	-1.42	-1.97	1.71	0.44
(d) Output Growth Final Vintage						
RMSE	1.00	1.00	1.00	1.08	1.10	1.25
DM	·	·	·	-2.77	-1.61	-2.10
$\Pr(d_{t+h} > 0)$	·	·	·	0.51	0.52	0.50
Hit Rate, $\Pr(\Delta y_{t+h} < 2.3\%)$	0.47	0.71	0.38	0.53	0.65	0.47
PT, $\Pr(\Delta y_{t+h} < 2.3\%)$	-0.72	2.14	-1.20	-0.16	1.50	1.24

Notes: RMSE denotes Root Mean Square Error, defined as a ratio relative to the benchmark no money case. DM denotes the Diebold-Mariano (1995) statistic, where the loss function, d_t, is defined using the difference in squared forecast errors of the with and without money models. The probability $\Pr(d_{t+h} > 0)$, is a bootstrapped test statistic described in Appendix B and the text, computed using 5000 replications. The Hit Rate defines the proportion of correctly forecast events, where we assume that the event can be correctly forecast if the associated probability forecast exceeds 0.5. PT is the Pesaran Timmerman (1992) (PT) statistic described in the text.

Table 2: Evaluation of BMA Out of Sample Central and Probability Forecasts with $M0$, 1987Q1-2003Q3

	Without Money			With Money		
	h=1	*h=4*	*h=8*	*h=1*	*h=4*	*h=8*
(a) Inflation Real Time						
RMSE	1.00	1.00	1.00	1.03	1.08	1.12
DM	.	.	.	-0.29	-0.89	-1.48
$\Pr(d_{t+h} > 0)$	.	.	.	0.55	0.55	0.53
Hit Rate, $\Pr(\Delta p_{t+h} < 5.0\%)$	0.72	0.66	0.45	0.78	0.69	0.51
PT, $\Pr(\Delta p_{t+h} < 5.0\%)$	2.40	3.26	2.34	4.18	3.84	2.69
(b) Inflation Final Vintage						
RMSE	1.00	1.00	1.00	1.00	1.04	1.16
DM	.	.	.	-0.03	-0.55	-1.49
$\Pr(d_{t+h} > 0)$	.	.	.	0.56	0.57	0.52
Hit Rate, $\Pr(\Delta p_{t+h} < 5.0\%)$	0.75	0.55	0.34	0.81	0.67	0.48
PT, $\Pr(\Delta p_{t+h} < 5.0\%)$	4.04	2.73	1.71	4.95	3.40	2.01
(c) Output Growth Real Time						
RMSE	1.00	1.00	1.00	0.94	0.96	1.18
DM	.	.	.	0.80	0.34	-2.15
$\Pr(d_{t+h} > 0)$	.	.	.	0.52	0.52	0.52
Hit Rate, $\Pr(\Delta y_{t+h} < 2.3\%)$	0.54	0.46	0.46	0.51	0.57	0.54
PT, $\Pr(\Delta y_{t+h} < 2.3\%)$	-0.23	-1.15	-0.61	-0.35	0.98	0.64
(d) Output Growth Final Vintage						
RMSE	1.00	1.00	1.00	0.93	0.98	1.26
DM	.	.	.	0.78	0.44	-1.80
$\Pr(d_{t+h} > 0)$	.	.	.	0.52	0.52	0.52
Hit Rate, $\Pr(\Delta y_{t+h} < 2.3\%)$	0.49	0.52	0.49	0.55	0.52	0.61
PT, $\Pr(\Delta y_{t+h} < 2.3\%)$	-0.87	0.11	-0.06	0.53	0.08	1.92

Notes: See Notes to Table 1.

Table 3: Evaluation of BMA Out of Sample Central and Probability Forecasts with $M4$, 1987Q1-2003Q3

	Without Money			With Money		
	h=1	h=4	h=8	h=1	h=4	h=8
(a) Inflation Real Time						
RMSE	1.00	1.00	1.00	0.93	0.79	0.81
DM	.	.	.	2.16	2.38	1.41
$\Pr(d_{t+h} > 0)$	.	.	.	0.54	0.56	0.55
Hit Rate, $\Pr(\Delta p_{t+h} < 5.0\%)$	0.72	0.66	0.45	0.81	0.88	0.81
PT, $\Pr(\Delta p_{t+h} < 5.0\%)$	2.40	3.26	2.34	3.98	5.67	4.30
(b) Inflation Final Vintage						
RMSE	1.00	1.00	1.00	0.93	0.90	0.97
DM	.	.	.	0.79	0.71	0.13
$\Pr(d_{t+h} > 0)$	.	.	.	0.55	0.56	0.55
Hit Rate, $\Pr(\Delta p_{t+h} < 5.0\%)$	0.75	0.55	0.34	0.87	0.88	0.78
PT, $\Pr(\Delta p_{t+h} < 5.0\%)$	4.04	2.73	1.71	5.48	5.67	3.63
(c) Output Growth Real Time						
RMSE	1.00	1.00	1.00	1.00	1.12	0.92
DM				0.10	-2.14	0.58
$\Pr(d_{t+h} > 0)$	.	.	.	0.51	0.51	0.51
Hit Rate, $\Pr(\Delta y_{t+h} < 2.3\%)$	0.54	0.46	0.46	0.51	0.60	0.60
PT, $\Pr(\Delta y_{t+h} < 2.3\%)$	-0.23	-1.15	-0.61	-0.62	1.75	2.12
(d) Output Growth Final Vintage						
RMSE	1.00	1.00	1.00	1.00	1.02	0.85
DM	.	.	.	-0.08	-0.58	0.95
$\Pr(d_{t+h} > 0)$	.	.	.	0.51	0.51	0.51
Hit Rate, $\Pr(\Delta y_{t+h} < 2.3\%)$	0.49	0.52	0.49	0.51	0.51	0.63
PT, $\Pr(\Delta y_{t+h} < 2.3\%)$	-0.89	0.11	-0.06	-0.43	-0.36	2.74

Notes: See notes to Table 1.

Figure 1a: Output Growth (annualized percent, final vintage)

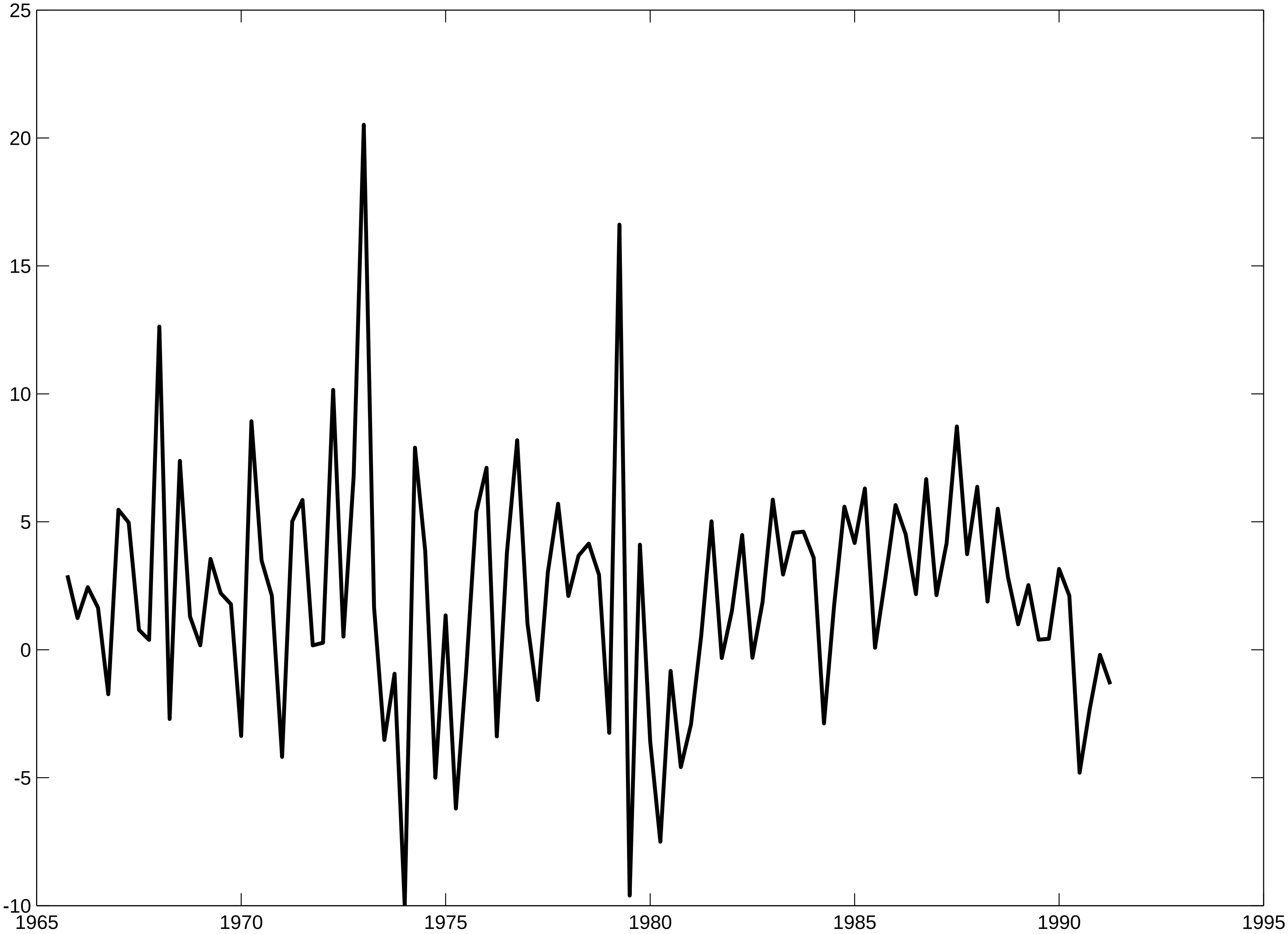

Figure 1b: Inflation (annualized percent, final vintage)

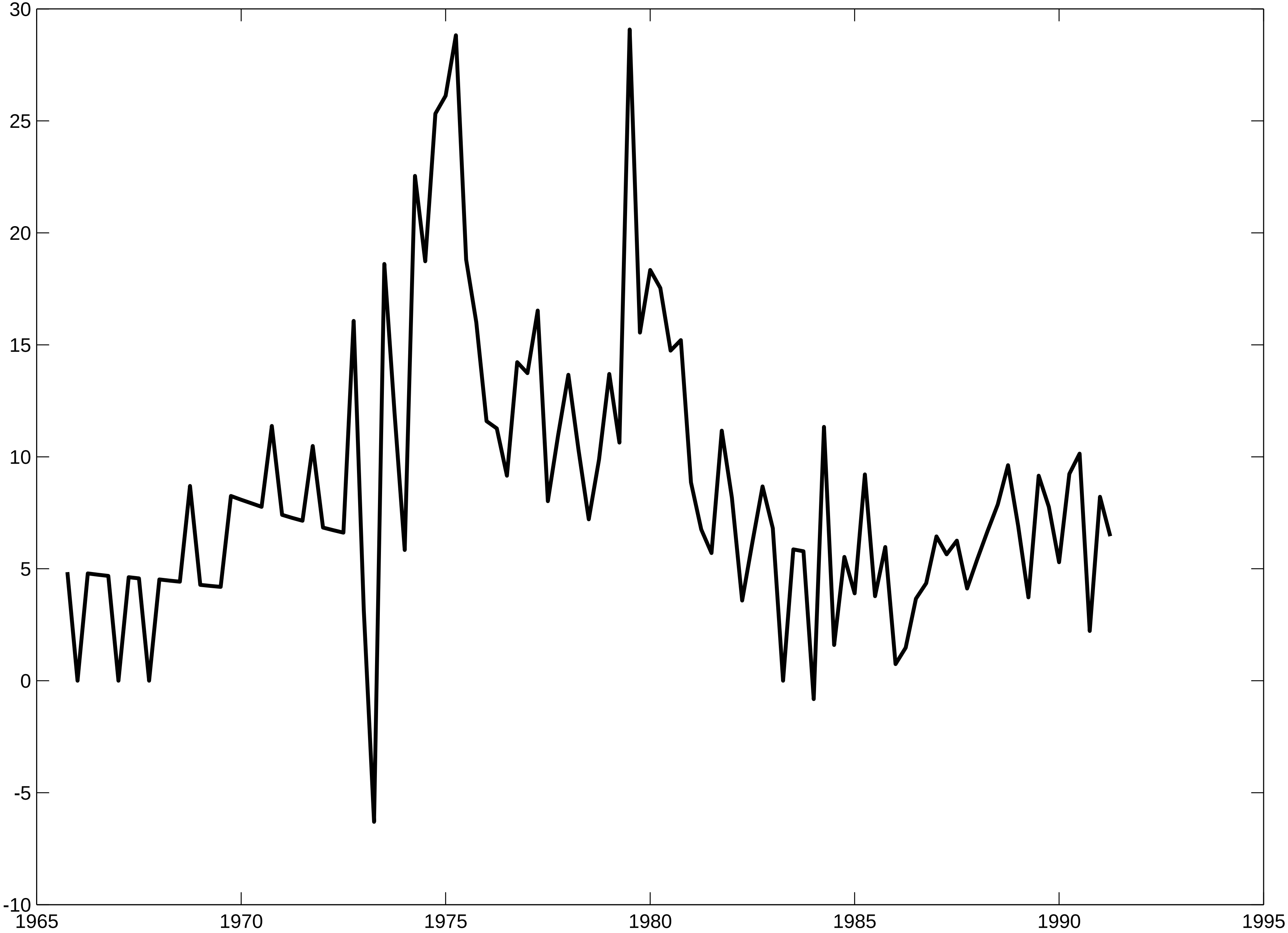

Figure 1c: M3 Growth (annualized percent, final vintage)

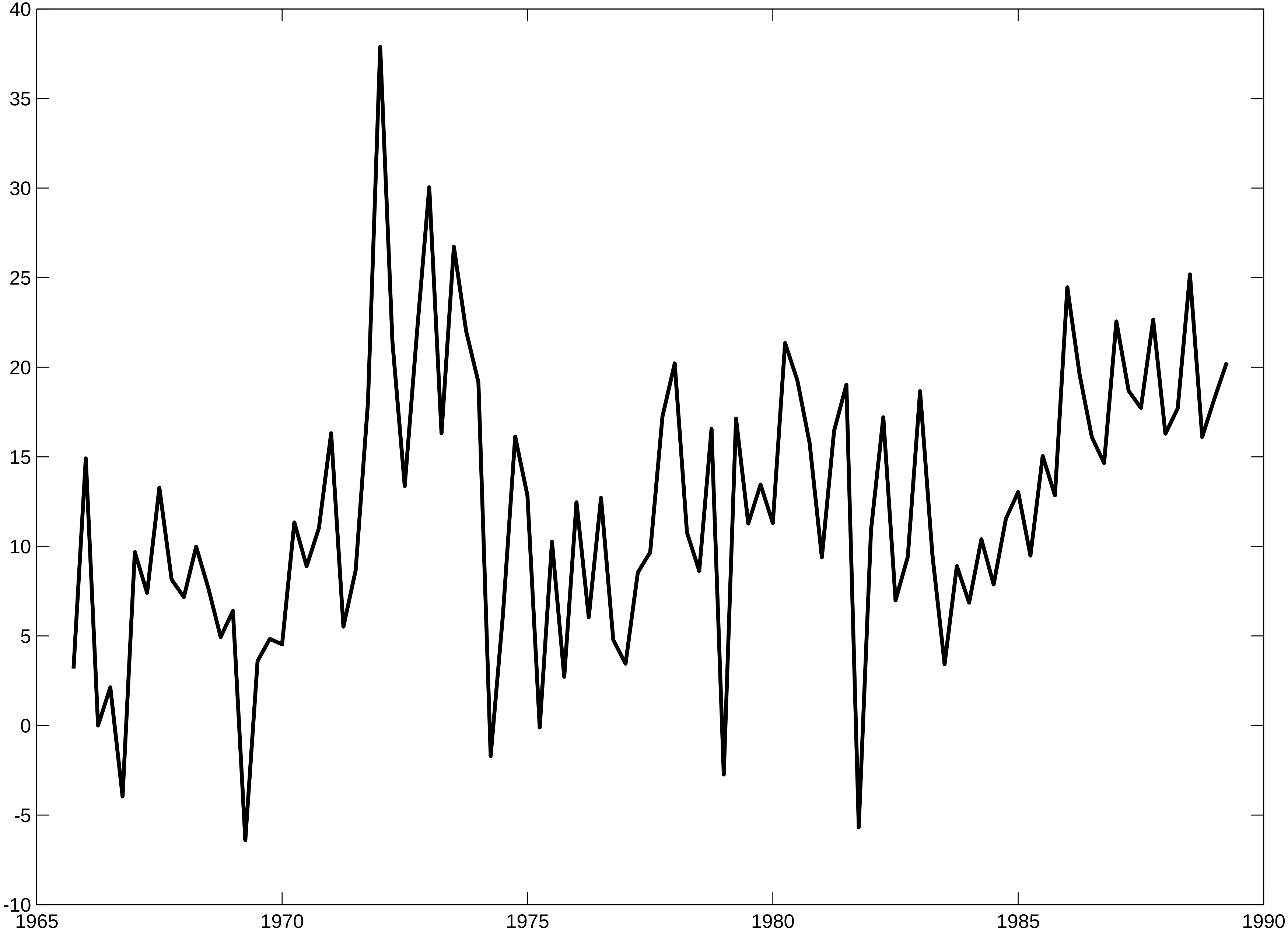

Figure 1d: Change in Effective Exchange Rate (annualized percent)

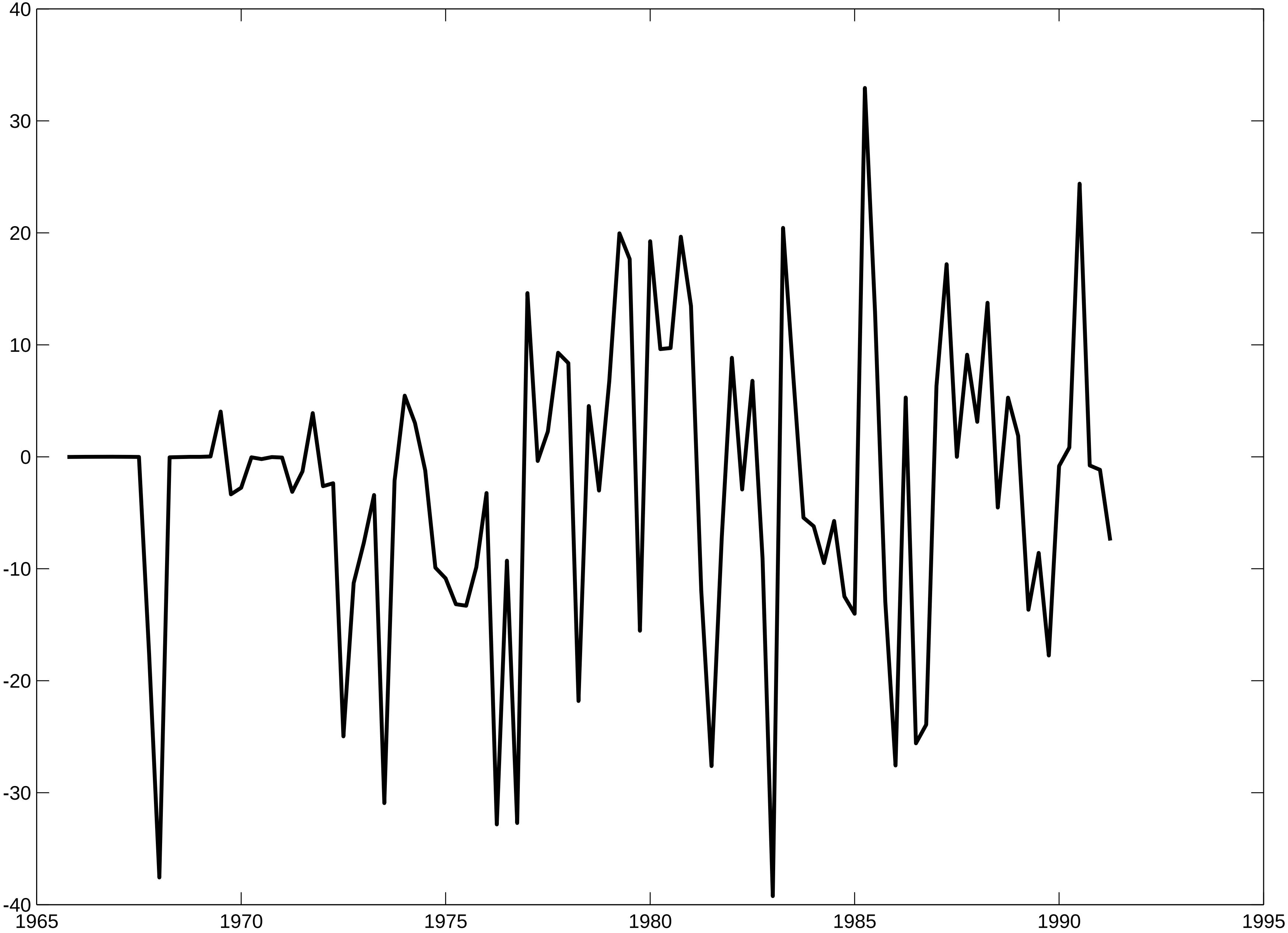

Figure 1e: Interest Rate (percent)

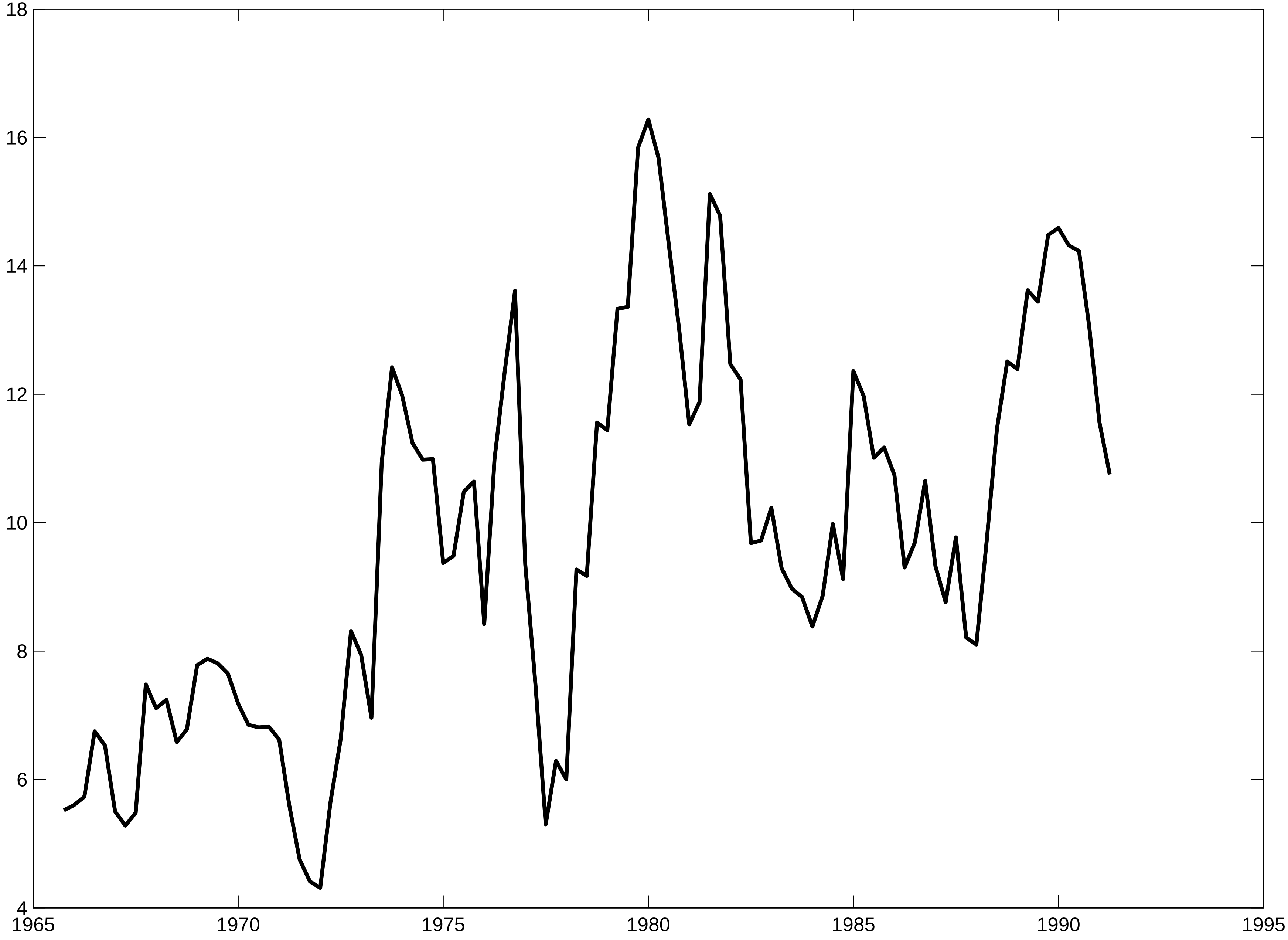

Figure 2: Probability of Various Models with M3