

Real-time Prediction with UK Monetary Aggregates in the Presence of Model Uncertainty¹

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ABSTRACT: A popular account for the demise of UK monetary targeting regime blames the weak predictive relationships from broad money to inflation and real output growth. In this paper, we investigate these relationships using a variety of monetary aggregates, which were used as intermediate UK policy targets during this period. We consider a large set of recursively estimated Vector Autoregressive (VAR) and Vector Error Correction models (VECM) which differ in terms of lag length and the number of cointegrating terms. Faced with this model uncertainty, we utilize Bayesian model averaging (BMA) and contrast it with a strategy of selecting a single best model. Conditional on the real-time data available to UK policymakers, we demonstrate that the in-sample predictive content of broad money fluctuates throughout the 1980s for both strategies. However, the strategy of choosing a single best model amplifies these fluctuations. Out-of-sample predictive evaluations rarely suggest that money matters for either inflation or economic growth, regardless of the model selection strategy. The view that the predictive content of UK broad money diminished during the 1980s receives little support for the revised data.

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1 Introduction

The demise of UK monetary targeting is generally argued to have taken place in 1985-86; see for example Cobham (2002, p61). A landmark speech by the Governor of the Bank of England in October 1986 indicated that the unpredictability of the relationships between broad monetary aggregates and inflation and output undermined monetary targeting (Leigh-Pemberton, 1986). UK policymakers turned to exchange rate targeting for the remainder of the decade (see, Cobham, 2002, chapters 3 and 4, and Batini and Nelson, 2005, section 4). By the time of the Governor's 1986 speech, the most monetarist Government in the UK's post-WWII history had ceased to base policy on monetary aggregates.

In this paper, we investigate the predictability of UK inflation and output using the monetary aggregates $M0$, $M3$ and $M4$. We carry out a recursive analysis to investigate whether the predictive content of money varies over time. Results are presented using both final vintage data and the real-time data which would have been available to a UK policymaker at each point in time. In terms of our set of models, we adopt the same Vector Error Correction Model (VECM) framework as Amato and Swanson (2001). By using Bayesian model averaging (BMA), we allow for model uncertainty with respect to the lag length and the number of cointegrating terms. We report probabilistic assessments of whether "money matters" by taking weighted averages across all models considered. The weights are the posterior model probabilities derived by approximate Bayesian methods based on the Schwarz Bayesian Information Criterion (BIC).

Our application uses a core set of variables comprising money, real output, prices, the short-term interest rate and the exchange rate. We find that, using both BMA and the best model in each period, predictability for output and inflation fluctuates somewhat in real time. These results are consistent with the US findings of Amato and Swanson (2001). However, the single best model selection strategy gives typically greater instability in the predictive relationships than BMA.

The view that the predictive content of broad money diminished during the 1980s receives little support for the revised data. Despite the emphasis given to it by policymakers in the 1980s, the broad monetary aggregate $M3$ displays little in-sample predictability for output, with either real-time or revised data. In contrast, using in-sample evidence, the probability that broad money predicts inflation exceeds 70 percent for most of the 1980s. This result requires the benefit of hindsight about data revisions however. With real-time data, the probability of prediction for inflation exhibits large fluctuations, which are mitigated considerably by BMA. Of particular macroeconomic significance is the sharp decline in in-sample predictability for inflation immediately preceding the Bank of England's 1986 assessment which marked the end of the UK's monetary targeting experiment. Out-of-sample forecast densities for inflation conditional on models including $M3$ indicate substantially higher inflationary pressures from 1986 onwards (although the out-of-sample forecasts are rather imprecise). Ignoring $M3$ as a predictor of inflation masks the real-time evidence of the UK's late 1980s inflationary boom.

Although $M3$ was the monetary target preferred by UK policymakers for much of the

1980s, the government also published targets for $M0$ and $M4$ at times. We find that the narrower measure exhibits greater in-sample real-time predictability for inflation, and smaller fluctuations in predictability than with $M3$. We find little support for in-sample predictability of economic growth with $M0$. Nevertheless revised data suggest stranger support than is apparent with real-time data. Turning to the broader money measure, $M4$, we find strong support for predictability of inflation. The real-time fluctuations are much larger for real output growth than for inflation, and as with $M3$, these are mitigated considerably by BMA. Hence, we conclude that impact of data revisions on in-sample predictability is not restricted to a particular monetary aggregate. With the benefit of longer samples of real-time data for $M0$ and $M4$, the out-of-sample performance of the predictive densities improves with money.

The predictive properties of money for inflation and output are perennial macroeconomic issues. Numerous studies have assessed whether money predicts output and/or inflation, conditional on other macroeconomic variables. Nevertheless, the evidence on the extent of the marginal predictive content of money remains mixed. For example, (among others) Feldstein and Stock (1994), Stock and Watson (1989), Swanson (1998) and Armah and Swanson (2006) argued that US money matters for output; and Friedman and Kuttner (1992), and Roberds and Whiteman (1992) argued that it does not. Stock and Watson (1999, 2003) and Leeper and Roush (2002, 2004) apparently confirmed the earlier claim by Roberds and Whiteman (1992) that money has little predictive content for inflation; Bachmeier and Swanson (2006) claimed that it does. These studies used substantially revised US data, also known as final vintage data. Amato and Swanson (2001) argue that using the evidence available to US policymakers in real time, the evidence is weaker for the money-output relationship.

With the exception of Roberds and Whiteman (1992), the existing US literature does not allow formally for model uncertainty.² Implementation of the classical approach traditionally adopted in the literature requires the researcher to select one preferred model from a broad set of models by a sequential testing procedure. The process requires decisions about the number of cointegrating relationships, the sign and size of the long-run parameters, the number of lags and any restrictions on the short-run dynamics. After selecting the preferred specification at each point in time, the econometrician unconcerned about model uncertainty, discards the other models regardless of the probability that those specifications are appropriate. In real-time analysis, the researcher typically selects a single “best” model in each period, and ignores completely models that may have been preferred in previous periods. Any probabilistic statements about the objects of economic importance, such as the marginal predictive content of money, are conditioned on the researcher’s best model specification.

Whether model uncertainty compounds the real-time difficulties of assessing the predictive properties of money has not previously been studied. Egginton, Pick and Vahey (2003), Faust, Rogers and Wright (2006), Garratt and Vahey (2006) and Garratt, Koop

²UK studies adopting a Bayesian limited information approach to modeling money demand include Lubrano, Piers and Richard (1986), and Steel and Richard (1991). The US study by Amato and Swanson (2001) discusses model robustness.

and Vahey (2007) have shown that initial measurements to UK macroeconomic variables have at times been subject to large revisions. The phenomenon was particularly severe during the late 1980s. But these papers do not discuss the predictability of money for output or inflation.

The remainder of the paper is organized as follows. Section 2 provides a summary of the UK's monetary targeting experience. Section 3 discusses the econometric methods. Section 4 describes the UK data. Section 5 presents some results and section 6 concludes.

2 The UK's Monetary Targeting Experience

Although UK monetary targeting is often perceived as a 1980s phenomenon, attention to the behaviour of monetary aggregates was a feature of UK macroeconomic policy in the 1960s and 1970s; see Bank of England (1978). The monetary regime became formalized as a target for $M3$ in July 1973, but was revised in late 1976 to refer to $\mathcal{L}M3$, which excludes private-sector foreign currency deposits.³

Uncertainty surrounds the end date for monetary targeting. The announcement by the Chancellor of the Exchequer, Nigel Lawson, to suspend the target for $\mathcal{L}M3$ in October 1985 clarifies the policymaker's dissatisfaction with monetary targeting (see Cobham, 2002, p46). However, the target for $\mathcal{L}M3$ is revived in the 1986 Budget the following spring. The remarks in October 1986 by the Governor of the (dependent) Bank of England (Leigh-Pemberton, 1986, p507) question again the predictability for output and inflation of broad money. Since the Governor draws attention to the discussions with Chancellor about the future of monetary targeting, some central bank watchers argue that the attention shifts towards exchange rate issues before October; see, for example Cobham (2002, chapters 3 and 4), and Nelson and Batini (2005, section 4). Policymakers set target or monitoring ranges for the growth of the monetary aggregates $M0$ and $M4$ from 1987; see Cobham (2002, p51, table 3A.5). This year also saw $\mathcal{L}M3$ relabeled $M3$ and the series previously known as $M3$ became $M3c$. (In our empirical analysis, we refer to the appropriate broad money aggregate as $M3$ regardless of whether the real-time label was $M3$ or $\mathcal{L}M3$.)

Leigh-Pemberton (1986) identifies financial innovation as distorting the underlying relationships between broad money and other macro aggregates. He also argues that these unanticipated events are responsible for the forecast failures for broad money. For example, the Government had missed its published forecast ranges for $\mathcal{L}M3$ growth for three successive years between 1984/5 and 1986/7; see Leigh-Pemberton (1986, p500, chart 3).⁴ Many financial innovations stem from the financial deregulation taking place throughout the 1980s, including the Big Bang of 1986 which opened the London Stock Market to international competition (Bank of England, 1986, p71-73). Cobham (2002, p38, table 3.3) classifies the financial innovations by main area of impact: banks, building

³Cobham (2002, p27) noted that a measure of narrow money, $M1$, was monitored during the years of informal monetary targeting between 1974 and 1976.

⁴Cobham (2002, p28) has argued that difficulties in meeting the broad money target led to temporary targets for $M1$ and $PSL2$. The latter aggregate referred to the components of $\mathcal{L}M3$ plus selected liquid assets and was subsequently relabeled $M5$.

societies, money market, and capital markets. The first two categories probably had the largest direct impact on measures of money. Examples involving banks include: the move to automatic teller machines (from the late 1970s), the abolition of fixed reserve requirements for banks (1981), and the introduction of debit cards (1987).

The most notable disturbances to broad money come from periodic reclassification of the monetary sector. Narrow measures of money, such as $M0$, are largely unaffected.⁵ Topping and Bishop (1989) describe the impacts of the inclusion of trustee savings banks in the monetary sector during 1981, and the conversion of the Abbey National building society into a limited liability bank in 1989. Both caused substantial shocks to the level of broad money. They estimate that the trustee savings banks adds approximately 10 percent to the $\pounds M3$ stock. Subsequently, the conversion by Abbey National caused the Bank of England to suspend publication of $M3$. Cobham (2002, p39) notes that the merging of the bank and building society sectors and the increased provision of retail financial services are facilitated by developments in the money and capital markets, which become more competitive through the 1970s and 1980s. As a result of these many reforms, private and public companies hold increasing amounts of assets (and liabilities), including broad money.

Accompanying these financial innovations, policymakers introduce many microeconomic reforms including: industrial relations laws; privatization of public companies; changes in social security benefits; and personal and corporate tax changes.⁶ Nigel Lawson argues that the financial innovations are perceived as part of the government's policy of supply-side reforms which raises trend economic growth, although the size of this response is subject to uncertainty (Lawson, 1992, p804-5).

The wave of economic reforms, which starts in the 1970s and affects the UK economy over the subsequent decades, also extends to the provision of UK statistics. Egginton, Pick and Vahey (2003), Garratt and Vahey (2006) and Garratt, Koop and Vahey (2007) show that the Central Statistical Office (CSO) make substantial revisions to preliminary measurement of economic growth during the late 1980s. Policymakers at both HM Treasury and the Bank of England partly blame data inaccuracies for the inflationary boom at the end of the decade; see, Hibberd (1990) and Leigh-Pemberton (1990). In 1989, Nigel Lawson, Chancellor of the Exchequer 1983-1989, took responsibility for the CSO (later renamed the Office for National Statistics, ONS) and a number of major reforms that were introduced between 1989 and 1993, are described in detail by Wroe (1993).⁷ Patterson and Heravi (1991) and Patterson (2001) show that pre-1990 UK data errors are very persistent, and contribute to the uncertainty around the order of integration of UK

⁵Target ranges for narrow money (but not $M4$) were set from 1984; see Cobham (2002, p51, table 3A.4).

⁶Although many of the more notable microeconomic reforms take place in the 1980s, the process is ongoing. See (among others) Blanchflower and Freeman (1994) and Card and Freeman (2004) for discussions.

⁷As a result of these and more minor recent reforms (see Robinson, 2005), the magnitude of data revisions and volatility moderates after the late 1980s (see Garratt and Vahey, 2006, and Garratt, Koop and Vahey, 2007).

national account variables.⁸

In the empirical analysis that follows, we assess whether the predictive content of broad monetary fluctuated through the period of monetary targeting using UK real-time data. Our econometric methodology is motivated by the considerable model uncertainty generated by the many financial innovations, the microeconomic reforms, and the persistent data inaccuracies throughout our sample period. In the subsequent section, we show how we incorporate uncertainty over the rank of the cointegrating vector and lag structure in our empirical analysis by utilizing Bayesian methods.

3 Econometric Methods

3.1 Bayesian Model Averaging

Bayesian methods use the rules of conditional probability to make inferences about unknowns (for example, parameters, models) given knowns (for example, data). For instance, if $Data$ is the data and there are q competing models, M_1, \dots, M_q , then the posterior model probability, $p(M_i|Data)$ where $i = 1, 2, \dots, q$, summarizes the information about which model generated the data. If z is an unknown feature of interest common across all models (for example, a data point to be forecast, an impulse response or, as in our case, the probability that money has predictive content for output), then the Bayesian is interested in $p(z|Data)$. The rules of conditional probability imply:

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

Thus, overall inference about z involves taking a weighted average across all models, with weights being the posterior model probabilities. This is Bayesian model averaging (BMA). In this paper, we use approximate Bayesian methods to evaluate the terms in (1).

For each model, note that BMA requires the evaluation of $p(M_i|Data)$ (that is, the probability that model M_i generated the data) and $p(z|Data, M_i)$ (which summarizes what is known about our feature of interest in a particular model). We will discuss each of these in turn. Using Bayes rule, the posterior model probability can be written as:

$$p(M_i|Data) \propto p(Data|M_i) p(M_i), \quad (2)$$

where $p(Data|M_i)$ is referred to as the marginal likelihood and $p(M_i)$ the prior weight attached to this model—the prior model probability. Both of these quantities require prior information. Given the controversy attached to prior elicitation, $p(M_i)$ is often simply set to the noninformative choice where, *a priori*, each model receives equal weight. We will adopt this choice in our empirical work. Similarly, 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).

⁸Siklos (1996, 2006) discusses persistence in US data revisions.

Here we use the Schwarz or Bayesian Information Criterion (BIC). Formally, Schwarz (1978) presents an asymptotic approximation to the marginal likelihood of the form:

$$\ln p(\text{Data}|M_i) \approx l - \frac{K \ln(T)}{2}. \quad (3)$$

where l denotes the log of the likelihood function evaluated at the MLE, K denotes the number of parameters in the model and T is sample size. The previous equation is proportional to the BIC commonly used for model selection. Hence, it selects the same model as BIC. The exponential of the previous equation provides weights proportional to the posterior model probabilities used in BMA. This means that we do not have to elicit an informative prior and is familiar to non-Bayesians. It yields results which are closely related to those obtained using many of the benchmark priors used by Bayesians (see Fernandez, Ley and Steel, 2001).

With regards to $p(z|\text{Data}, M_i)$, we avoid the use of subjective prior information and use the standard noninformative prior. Thus, the posterior is proportional to the likelihood function and maximum likelihood estimates (MLEs) are used as point estimates. Two of our features of interest, z , are the probability that money has no predictive content for (i) output, and (ii) inflation.

3.2 The Models

The models we examine are VECMs (and without error correction terms, Vector Autoregressions (VARs)). Let \mathbf{x}_t be an $n \times 1$ vector of the variables of interest, then a VECM can be written as:

$$\Delta \mathbf{x}_t = \boldsymbol{\alpha} \boldsymbol{\beta}' \mathbf{x}_{t-1} + \mathbf{d}_t \boldsymbol{\mu} + \boldsymbol{\Gamma}(L) \Delta \mathbf{x}_{t-1} + \boldsymbol{\varepsilon}_t, \quad (4)$$

where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $n \times r$ matrices with $0 \leq r \leq n$ being the number of cointegrating relationships. $\boldsymbol{\Gamma}(L)$ is a matrix polynomial of degree p in the lag operator and \mathbf{d}_t is the deterministic term. In models of this type there is considerable uncertainty regarding the correct multivariate empirical representation of the data. In particular there can be uncertainty over the lag order and the number of cointegrating vectors (or the rank of $\boldsymbol{\beta}$). Hence this framework defines a set of models which differ in the number of cointegrating vectors (r), lag length (p) and the specification of deterministic terms. Note that the VAR in differences occurs when $r = 0$. If $r = n$ then $\boldsymbol{\alpha} = I_n$ and all the series do not have unit roots (i.e. this usually means they are stationary to begin with). In this version of the paper, we simply set \mathbf{d}_t so as to imply an intercept in (1) and an intercept in the cointegrating relationship.

The next step is to calculate the “feature of interest” in every model. In all that follows we consider a VECM (or VAR) which contains the five ($n = 5$) quarterly variables used in this study; real output (y_t), the price level (p_t), a short-term nominal interest rate (i_t), exchange rate (e_t), and as a fifth variable a monetary aggregate referred to as m_t . In our subsequent analysis, we use three different measures of money: $M0$, $M3$, and $M4$. (See section 4 for detailed descriptions of the data.) Hence, $\mathbf{x}_t = (y_t, p_t, i_t, e_t, m_t)'$ (where

lower case denotes the natural logarithm of the variables). Where cointegration does not occur, the key equation in the VAR (which we refer to generically as M_{var}), is:

$$\begin{aligned} \Delta y_t = & \mu + \sum_{i=1}^p a_{1i} \Delta y_{t-i} + \sum_{i=1}^p a_{2i} \Delta p_{t-i} + \sum_{i=1}^p a_{3i} \Delta i_{t-i} \\ & + \sum_{i=1}^p a_{4i} \Delta e_{t-i} + \sum_{i=1}^p a_{5i} \Delta m_{t-i} + \varepsilon_t \end{aligned} \quad (5)$$

and money has no predictive content for output if $a_{51} = \dots = a_{5p} = 0$. From a Bayesian viewpoint, we want to calculate $p(a_{51} = \dots = a_{5p} = 0 | Data, M_{var})$.

Using the same type of logic relating to BICs described above (that is, BICs can be used to create approximations to Bayesian posterior model probabilities), we calculate the BICs for M_{var} (the unrestricted VAR) and the restricted VAR (that is, the VAR with $a_{51} = \dots = a_{5p} = 0$). Call these BIC_U and BIC_R , respectively. Some basic manipulations of the results noted in the previous section says that:

$$p(a_{51} = \dots = a_{5p} = 0 | Data, M_{var}) = \frac{\exp(BIC_R)}{\exp(BIC_R) + \exp(BIC_U)}. \quad (6)$$

This is, the ‘‘probability that money has no predictive content for output’’ for one model, M_{var} .

Note that we also consider the probability that money has no predictive content for inflation, in which case the equation of interest would be the price equation, where everything is identical.

Where cointegration does occur, the analogous VECM case adds the additional Granger causality restriction on the error correction term (see the discussion in Amato and Swanson, 2001, after their equation 2). The model would take the form (referred to generically as M_{vec}) :

$$\begin{aligned} \Delta y_t = & \mu + \sum_{i=1}^p b_{1i} \Delta y_{t-i} + \sum_{i=1}^p b_{2i} \Delta p_{t-i} + \sum_{i=1}^p b_{3i} \Delta i_{t-i} \\ & + \sum_{i=1}^p b_{4i} \Delta e_{t-i} + \sum_{i=1}^p b_{5i} \Delta m_{t-i} + \sum_{i=1}^r \alpha_i \xi_{r,t-1} + \varepsilon_t \end{aligned} \quad (7)$$

where the $\xi_{i,t}$ ($i = 1, \dots, r$) are the error-correction variables constructed using the maximum likelihood approach of Johansen (1988, 1991). The restricted VECM would impose $b_{51} = \dots = b_{5p} = 0$ and $\alpha_1 = \dots = \alpha_r = 0$ and the probability would be:

$$p(b_{51} = \dots = b_{5p} = 0 \text{ and } \alpha_1 = \dots = \alpha_r = 0 | Data, M_{vec}). \quad (8)$$

Imposing the additional restriction with respect to the loading coefficient for the ECM terms enables an assessment of whether money is long-run forcing for output and inflation (see Granger and Lin, 1995).

We calculate the probability that money has no predictive content for output using, as appropriate, (6) or (8) for every single model, M_1, \dots, M_q . Having done this we construct probabilities for each of the models using:

$$p(M_i|Data) = \frac{\exp(BIC_{uM_i})}{\sum_{i=1}^q \exp(BIC_{uM_i})}. \quad (9)$$

where (BIC_{uM_i}) is the BIC value of the q^{th} unrestricted model (either VAR or VECM). These are the weights used in the BMA procedure.

Hence, our econometric methodology allows for the model uncertainty apparent in any assessment of the predictive content of money, and discussed in detail by Amato and Swanson (2001). We retain the well-understood classical approach to the estimation of each model in the model space; but we take BMA of the classical estimates in order to take model uncertainty into consideration formally. Our approach can be interpreted as an approximate Bayesian method (both approximating within each model – e.g. plugging in classical estimates for VECM and approximating the weights across the models using BIC). By using this methodology, we are able to assess the predictive content of money for other macro variables (and other objects of interest) using evidence from all the models considered.

4 The Data

In our recursive analysis of the predictive content of money, we consider two distinct data sets. The first uses final vintage data. That is the set of measurements taken in 2006Q1. The second uses the vintage of real-time data which would have been available to a policymaker at each vintage date. For example, the real-time data set for the vintage date 1989Q4 contains the historical observations which were available to forecasters at the end of 1989Q4. In our application, we work with a “publication lag” of two quarters—a vintage dated time t includes time series observations up to date $t - 2$. The differences between these observations at given vintage date and the final vintage measurements are often substantial; see Garratt and Vahey (2006).⁹ The real-time data set comprises one vintage per quarter, starting with the 1979Q2 vintage and ending with 2006Q1. For each vintage, the time series observations start with the 1965Q4. All real-time measurements were published initially by the CSO and its successor, the ONS, in *Economic Trends* and *Economic Trends: Annual Supplement*. Since *Economic Trends* is published monthly, there could be as many as three measurements published for each quarter. We standardized the time interval between vintages by selecting the last monthly release for each quarter.

By analyzing successive vintages of data in our real-time data set, we mimic the common practice followed by applied econometricians in real-time. This approach is

⁹We adopt the standard terminology used in the more recent literature where a vintage of data refers to a set of measurements published at a given vintage date. See, for example, Diebold and Rudebusch (1991) and Croushore and Stark (2001).

common in the real-time literature; see for example Amato and Swanson (2001). In contrast, others including Howrey (1978), Koenig et al (2003) and Koop, Garratt and Vahey (2006) consider measurements that have been revised the same number of times within the regression model.¹⁰

The (seasonally-adjusted) real-time GDP(E) data were taken from the Bank of England’s on-line real-time database.¹¹ Garratt and Vahey (2006) describe and compare the various sources of UK real-time data, including the Bank of England’s data set. This paper is also the source of the real-time implicit price deflator data used in our study, extended to the 2006Q1 vintage.

For the monetary aggregates, we compiled real-time data for the measures of money for which policymakers set targets for approximately 10 years during our sample.¹² The CSO and ONS did not report all three series between 1977Q4 and 2006Q1. As a result, our analyses of $M0$, $M3$ and $M4$ use different evaluation periods. $M0$ was initially labeled the “wide monetary base” when it was introduced for the 1981Q2 vintage.¹³ The monetary aggregate (usually) referred to as $\mathcal{L}M3$ was introduced for the 1977Q4 vintage and was phased out in the vintage dated 1989Q4. The broad money measure $M4$ was introduced for the vintage date 1987Q3. With the exception of $M3$, the last vintage date is 2006Q1. Revisions to the UK monetary aggregates occurred mainly as a result of changes to the seasonal adjustment by the CSO and ONS.¹⁴ (Unfortunately, real-time seasonally unadjusted figures were not published in *Economic Trends*.) The money series have also been affected by periodic re-classifications. As discussed in detail in section 2, many of these resulted from financial innovation.¹⁵

Since the interest rate and the exchange rate are unaffected by revisions, the real-time measurements are exactly the same as those in the final vintage. The interest rate is the 90 day Treasury bill average discount rate; the exchange rate is the sterling effective exchange rate.¹⁶

In our empirical work, we take the natural logarithms of the raw data published by the ONS and CSO. All quarterly growth rates are defined as the first difference of the log variables. For the interest rate, we use $r_t = 0.25 \times \log(1 + (R_t/100))$.

Figures 1a through 1e plot the final vintage (2006Q1) measurements. Figure 1a shows that the UK experienced stronger economic growth and less volatility in the 1980s, relative to the 1970s. The inflationary pressures build from 1986, with inflation reaching roughly

¹⁰Alternatively, Aruoba (2005) and Croushore (2005) compare preliminary measurements with those taken just before a “benchmark” revision. Croushore and Evans (2006) discuss the econometric issues related to the choice of revision definitions.

¹¹The Bank of England provided the real GDP data up to the latest vintage on request. Vintages to 2002 can be downloaded from Bank of England website.

¹²The $M0$ and $M4$ series were originally collected and described by Garratt and Vahey (2006).

¹³Since the ONS does not publish estimates for $M0$ before 1969Q2, we used notes and coins prior to this date.

¹⁴Mills (1987) analyzes the revision properties of pre-1987 $M3$ data; see also Topping and Bishop (1989).

¹⁵The real-time data used in our empirical analysis are based on the actual measurements released by the ONS. Post-1981 $M3$ data have been scaled to remove the impact of the trustee savings banks.

¹⁶Both series are published by the ONS in *Financial Statistics*.

10 percent in the first half of 1990 as shown in Figure 1b. The strong economic growth and associated build up of inflation is sometimes referred to as the “Lawson Boom”. Figure 1c shows that $M3$ growth begins to ratchet up from mid 1983, and fluctuates in a band between 14 and 26 percent from 1986. Money growth gives a preliminary indication of the late 1980s inflationary boom. Nelson and Batini (2005, p69-70) argue that this monetary base expansion reflects a change in policy priorities. In particular, they argue that Chancellor Nigel Lawson preferred to target exchange rates rather than monetary aggregates. Cobham (2002, p58) notes the importance of Deutschmark shadowing prior to the UK’s entry in to the Exchange Rate Mechanism. Figure 1d shows that about the time of the Governor’s 1986 speech—which many commentators think indicated the demise of formal UK monetary targeting—the effective exchange rate dips sharply, and then recovers until 1989. Like the exchange rate, the interest rate plotted in Figure 1e display considerable volatility throughout the period. During the the 1980s, interest rate volatility drops somewhat as the Government moves away from monetary targeting. But at the end of the Lawson Boom, interest rates rise sharply back to the levels seen in the 1970s and remain high during the slump of the early 1990s.

We emphasize that the Figures 1a through 1e show the revised data. In real-time a policymaker would not observe these measurements.

5 Empirical Results

Our empirical analysis assesses the predictive content of money for real output and inflation, both in and out of sample, taking into account model uncertainty, as outlined in Section 3. The models are defined by the cointegrating rank, r , and the lag length, p . We consider $r = 0, \dots, 4$ and $p = 1, \dots, 8$ (see text below motivating this choice). With five variables, $n = 5$, we consider $5 \times 8 = 40$ models, $q = 40$. In every period of our recursive exercise, we estimate all of the models for each vintage date using the real-time data set. We also recursively estimate the same models using final vintage data. We compute the probability of predictability for real output growth and inflation for each monetary aggregate by BMA in each case and contrast this with the probability derived from the best model, defined as the model with highest BIC.

A preliminary analysis of the $M3$ final vintage time series observations for 1965Q4 to 1989Q2 illustrates the considerable uncertainty encountered by an empiricist in the selection of p and r . Using likelihood ratio (LR) tests, the Akaike Information Criteria (AIC) and the BIC to select the lag length, the lags are 3, 1 or 0. This lag choice has implications for the cointegrating rank. For example, if we choose $p = 3$, the trace and maximum eigenvalue tests indicate a rank of 0, whilst if we choose $p = 1$, the trace test indicates a rank of 1 and the maximum eigenvalue test a rank of 2. Many of these issues have been discussed by Doornik, Hendry and Nielsen (1998).

We present our empirical results in four sections. Since the $M3$ aggregate is of particular macroeconomic significance, in the first three sections we restrict our attention to this measure of money. The first section examines the in-sample behaviour of the various models. The second section evaluates in-sample Granger causality from money to inflation

and output. The third section examines out-of-sample prediction. Results in all sections are recursively generated using data for 1965Q4 through to 1989Q2 (43 recursions). Remember that $M3$ was phased out in the 1989Q4 vintage—the last recursion uses data up to 1989Q2 given the publication lag). The fourth section describes the in-sample and out-of-sample analysis for the other monetary aggregates. For $M0$, the analysis uses the $t = 1981Q1, \dots, 2005Q3$ (a total of 99 recursions), and for $M4$, $t = 1987Q1, \dots, 2005Q3$ (75 recursions).

5.1 Model Comparison with $M3$ Systems

In this section, we describe the probabilities attached to each model in our recursive BMA exercise based on the real-time data and using $M3$ as the monetary aggregate.

For each time period, the same three models almost always receive the vast majority of the posterior probability. These three preferred models all have the same lag length, $p = 1$, and hence, we focus on the uncertainty about the number of cointegrating relationships.

Figure 2 plots the probability of $r = 1, 2$ and 3 cointegrating relationships.¹⁷ Since the sample includes many financial innovations, microeconomic reforms, and persistent data inaccuracies, we do not attempt an economic interpretation of the number of cointegrating relationships.

The overall impression one gets from looking at Figure 2 is that the number of cointegrating vectors varies over time and we cannot ignore model uncertainty. It is rare for a single model to dominate (for example, to get more than 95% of the posterior model probability), and the model with highest probability does tend to vary over time. There is almost no evidence for three cointegrating relationships. Models with two cointegrating relationships tend to receive increasing probability as time goes by. However, prior to 1982, there is more evidence for $r = 1$. During the critical period in which monetary targeting was abandoned, the $r = 2$ and $r = 1$ models are roughly equally likely, with several switches in the identity of the preferred model.

5.2 In-sample Prediction with $M3$ Systems

In this section, we examine the in-sample ability of the $M3$ monetary aggregate to predict inflation and real output in our recursive real-time data exercise. Figure 3 shows the probabilities of predicting real output; and Figure 4 shows the corresponding plot for predicting inflation.¹⁸ All probabilities are calculated using the approach described in equation (8) and the subsequent text. Each figure contains three lines. Two of these use the real time data to plot, for each period in the recursive real-time evaluation period, the probability of predictability calculated using BMA and using the single model with highest probability—the best model. The third line presents the recursive BMA results based on the last (2006Q1) vintage of data. Hence, two of the lines use real-time data, the third line has the advantage of hindsight. The dates shown on the x -axis refer to the

¹⁷The probability of $r = 0$ is approximately zero for all money definitions.

¹⁸This is one minus the probabilities defined in Section 3.

last observation for each vintage; these differ from the vintage date by the publication lag. So, for example, the 1986Q4 vintage has 1986Q2 as the last time series observation.

Figure 3 shows that $M3$ has no predictive power for real output for the period of interest, regardless of the model selection strategy or the type of data. Remember that $M3$, the preferred monetary target of UK policymakers in this period, was phased out in 1989 where Figure 3 ends.

Figure 4 presents the probability that money has predictive power for inflation. The lines in this figure are very erratic. For instance, using real-time data and selecting a single model, the probability that money can predict inflation swings rapidly from near zero to near one several times in the 1980s. A researcher using a traditional approach which selects a single model could conclude that money mattered in some periods, but then next quarter did not matter all. These switches between times when money matters and when it does not occur with embarrassing frequency. On the other hand, model averaging yields a much less volatile pattern. It is worth noting that for the last vintage in 1986, when the Governor claimed predictability was causing difficulties with the monetary targeting regime, the probability that money could predict inflation, using BMA and real-time data, is around 0.4 (plotted as 1986Q2). If we use the strategy of selecting a single model, this probability jumps from roughly one for 1986Q1, to less than 0.05 for 1986Q2, and back to nearly one again the following quarter. The BMA approach indicates some volatility too, but to a much lower degree. With final vintage data, the BMA approach reveals no marked deterioration in causation during the mid 1980s. Instead, following a fall to around 0.7 in the early 1980s, the probability of causation for inflation rises back to approximately one by mid 1984. We conclude that for $M3$, data revisions played a substantial part in the periodically weak evidence that money causes inflation.¹⁹

Figures 3 and 4 show reveal no evidence that the in-sample predictive power of $M3$ deteriorated during the mid 1980s based on final vintage data and using BMA to calculate the probabilities. It appears that $M3$ never had much predictive content for real output. Deterioration becomes visible when real-time data are considered for prediction of inflation.

5.3 Out-of-Sample Prediction with $M3$ Systems

Amato and Swanson (2001) argue that out-of-sample forecast performance should be used to judge the predictive content of money in real-time. Although this approach is appealing in principle, small sample problems can make inference based on out-of-sample performance difficult in practice; see Clark and McCracken (2007) and the references therein.

To illustrate the practical issues involved in real-time evaluation of out-of-sample prediction, consider a monetary policymaker evaluating the forecasting performance of our many models during 1986Q4. Publication lags for real-time data mean that the policymaker has time series observations up to 1986Q2. The lags between monetary policy

¹⁹The papers by Orphanides (2001, 2003), Bernanke and Boivin (2003) and Rudebusch (2001) debate the contribution of data revisions to US monetary policy from the perspective of policy rules.

implementation and other macroeconomic variables implies that monetary policymakers are typically concerned with projections between one and two years ahead. If the out-of-sample horizon of interest is 8 quarters from the last available observation, i.e. 6 quarters ahead from the vintage date, the forecast of interest is for 1988Q4. Preliminary real-time outturns for this observation will only be released in the 1989Q2 vintage. Any changes in monetary policy at that date will have impacts roughly one to two years later—and by then, the UK business cycle has entered a different phase (see Figure 1a). A further complication is that the initial outturns of macroeconomics data may not be reliable for forecast evaluations. Amato and Swanson (2001) argue that real-time forecasters should evaluate models using a number of vintages of outturns in real-time out-of-sample prediction evaluation, although this introduces further lags in any real-time evaluation process to allow for data revisions.

With these issues in mind, and given the short sample of UK data available with the *M3* definition of money—recall that we have just 43 recursions in total—we limit our formal out-of-sample prediction analysis to using the final vintage for outturns. We emphasize that these tests are not timely indicators of model performance—only a forecaster with the 2006Q1 vintage (and the real-time data set) could reproduce the result tables reported in this section. Nevertheless, the analysis provides some insight into the out-of-sample performance of our models.

As in the previous section, we discuss the forecasting performance of different models, methodologies and data sets. To be precise, we compare:

1. Classes of VARs and VECMs with and without *M3*.
2. Model averaging and model selection procedures.
3. Results using real-time data and final vintage data.

Technical details about how the forecasting is done are provided in an appendix. Suffice it to note here that, if Δp_{t+h} is our variable of interest (i.e. inflation in this instance or output growth, h periods in the future), then we forecast using information available at time t (denoted as $Data_t$), then BMA provides us with a predictive density $p(\Delta y_{t+h}|Data_t)$. Our model selection provides us with $p(\Delta p_{t+h}|Data_t, M_{Best})$ where M_{Best} is the model with the highest value for BIC. All of the features of interest in the table below are functions of these predictive densities (i.e. point forecasts are the means of these densities, etc.).

Tables 1a and 1b presents results relating to the predictability of inflation and output growth, respectively. The upper panels of each present results using real time data; the bottom panels use final vintage data.

Let us first look at the point forecasts. The rows labeled “RMSE” are the root mean squared forecast errors (where the forecast error is the actual realization minus the mean of the predictive distribution). All results are presented relative to the RMSE produced by BMA using the models without money. A number less than one indicates an improved forecast performance relative to this case. The general picture presented is that including

money does not improve forecasting performance. It is interesting to note that these conclusions hold regardless of whether we do BMA or select the best model. Thus, our results are robust to this important aspect of statistical methodology.²⁰

The Diebold-Mariano(DM) (1995) statistics also relate to the point forecasts where the loss function is defined using the difference in squared forecast errors of each model relative to the benchmark real time BMA model with no money. The null hypothesis of equal predictive ability is then tested where the p-values reported in parentheses assume a standard normal distribution. Note in the limiting case such statistic follows a non-standard distribution. An examination of the p-values for the DM-statistics allows us to formalize the statements made in the previous paragraph. That is, inclusion of *M3* causes point forecast performance for inflation to deteriorate in a manner which a frequentist statistician would say was statistically significant.

The previous discussion related to point forecasts and which utilizes only the mean of the predictive distribution. The remaining information in the tables relate to other features of the predictive distribution. Using the BMA predictive density, $p(\Delta p_{t+h}|Data_t)$, we can calculate predictive probabilities such as $p(\Delta p_{t+h} < a|Data_t)$ for any value of a . Following Egginton, Pick and Vahey (2002), we assume that the inflation rate prevailing when Nigel Lawson started as Chancellor in July 1983 is the threshold of interest.²¹ Hence, for inflation we set $a = 5$ percent. We define a “correct forecast” as one where $p(\Delta p_{t+h} < a|Data_t) > 0.5$ and the observed revision is less than a . The proportion of correct forecasts is referred to as the “hit rate” and is presented in the tables.

An examination of Table 1(a) indicates that inclusion of money does improve some of the hit rates with real-time data, often by a substantial amount, at shorter horizons. For instance, the hit rate at $h=4$ with real-time data is about 52 percent when money is excluded. However, when money is included the hit rate rises to approximately 64 percent. In contrast, with final vintage data, the inclusion of money causes no change in the hit rates for $h = 8$, a small change for $h=4$ but is larger for horizon $h = 1$ where it deteriorates from 64 percent to 48 percent. In general, the hit rates are identical with best or Bayesian model selection. The inclusion of money has a bigger role in getting the shape and dispersion of the predictive distribution correct than in getting its location correct since the RMSE results provided little evidence that including money improves point forecasts.

Finally, the rows labeled “P-T” present a frequentist measure of absolute forecast performance from Pesaran and Timmermann (1992). This is the directional market timing statistic and the hypothesis test based on this statistic uses the same information as the Kuipers score (i.e. it measures the proportion growth rates greater than the threshold a that were correctly forecast minus the proportion of below mean growth rates that were

²⁰In practice, doing BMA using the restricted models (i.e. those with money excluded) yields results which are virtually identical as using the single best restricted model. This occurs since these models restrict the error correct term to be zero in equation being forecast (and most of the model uncertainty relates to the number of cointegrating relationships). For this reason, we do not present results for model selection among the restricted models.

²¹Nigel Lawson suggested that ‘(t)he acid test of monetary policy is its record in reducing inflation . . . The inflation rate is judge and jury’ (Lawson, 1992, p.481).

incorrectly forecast). Under the null hypothesis that the forecasts and realizations are independently distributed the P-T statistic has a standard normal distribution. There is only one of these which is greater than the 10 percent critical value of 1.64.²²

In panel (b) of Tables 1, we report the same set of evaluation statistics for central and probability forecasts for output growth. We consider the probability event $p(\Delta y_{t+h} < a | Data_t)$ where we set $a = 2.3\%$, the average annualized growth rate for the 1980Q1-2005Q4 period. The general conclusion is broadly similar to the inflation case. The RMSE does not improve when money is included, and the DM statistics suggest that a majority of the differences are insignificantly different from zero. The final vintage RMSEs are typically marginally lower than the real-time data equivalents (the exception is for $h = 8$, with and without money). There is a strong similarity of the RMSE results for BMA and Best models, just as there was the case for the inflation numbers.

The same inference, that the inclusion of money makes relatively small differences, can be drawn from the BMA predictive probabilities for output growth. Depending on the horizon we see a worsening through to an improvement. For example, including money with the real time data worsens an already poor hit rate from 44% to 32% at $h = 1$, stays the same at 64% for $h = 4$ and improves from 44% to 56% for $h = 8$. Using final vintage data and excluding money, the hit rates improve in two cases, but not for $h = 8$. Including money has mixed impacts on final vintage hit rates: both $h = 1$ and $h = 8$ have higher hit rates with money, but the $h = 4$ case deteriorates. The P-T statistics indicate that the differences in market timing are insignificant typically. Selecting the best model for each recursion produces results very similar to the BMA strategy.

The overall impression from our out-of-sample prediction analysis with the *M3* monetary aggregate is that the BMA strategy with no money provides a benchmark that is difficult to beat. For our short sample, there is little evidence that including money in the system makes substantial differences to out-of-sample prediction, either with real-time or final vintage data.

Since the in-sample evidence reported in the previous section provides a strong case for the inclusion of money in our VAR and VECM systems with BMA and real-time data, we provide plots of net contribution of *M3* to the assessment of inflationary pressures and above-trend economic growth. Figure 5 plots the difference in the real-time BMA probability of inflation greater than five percent, with and without money at $h = 8$.²³ Although the differential fluctuates through the recursions, the net contribution of *M3* is to increase the proportion of the predictive density above the five percent threshold—the inclusion of money gives a stronger indication of inflationary pressures. For example, the 1986Q4 vintage (plotted as 1986Q2) raises the posterior probability of the high inflation event by nearly 40 percent, and the difference fluctuates between 30 and 10 percent thereafter. With final vintage data, the fluctuations are generally smaller about a slightly higher mean, but the message is similar: the exclusion of the monetary aggregates implies

²²Note that some of the P-T statistics are undefined. This is due to the denominator of the P-T statistic being zero which arises due to the small sample size we have for *M3*.

²³The dates shown refer to the last observation in each vintage. Other horizons give broadly similar plots for Figures 5 and 6.

a much more benign inflation outlook.

Turning to Figure 6, which plots the difference of output growth greater than 2.3 percent with and without money, we see adding monetary aggregates to our systems causes the probability of above-trend economic growth to fall. The volatility is somewhat lower than for the inflation event shown in Figure 5; and the use of real-time data, rather than final vintage data, adds to the volatility. Although the plots for the two data sets differ at times, the general story is that real-time data leads to a similar—but slightly noisier—assessment of the net contribution of M3 to the probability of strong economic growth.

5.4 *M0* and *M4* Results

Since *M3*, the monetary target preferred by UK policymakers for much of the 1980s, was phased out in 1989, the evaluation of our systems with *M3* is based on small samples. The government also published targets for *M0* and *M4* at times during the 1980s, and for these monetary aggregates we have real-time data up to the vintage 2006Q1.

We focus initially on the in-sample evidence of prediction from money to real output growth and inflation.²⁴ Figure 7 shows that the case for believing that *M0* causes economic growth is weak throughout the 1980s, regardless of whether we use BMA or select the best model. The real-time probability only rises above 0.1 in the early 1990s. Note however, that using final vintage data yields substantially more evidence that money has predictive power for real output growth. For instance, suppose we were to adopt a rule of thumb where probabilities greater than 0.5 lead us to conclude that money has predictive power for output. Using real-time data we would almost never conclude that money has predictive power for output. However, using final vintage data, we would conclude money does have predictive power for output for the recursions ending 1994Q2 through to 1998Q1, although more recent observations suggest weaker predictability.

Figure 8 shows that there is generally stronger predictability of *M0* for inflation, particularly from 1983 onwards, regardless of whether we use real-time or final-vintage data, or we adopt BMA or select a single model. However, there are times when the real-time data indicate sharp declines in predictability for both model selection strategies. For example, the probability of money predicting inflation using BMA falls approximately 30 percentage points in 1983Q2, and 17 percentage points in 1986Q2—which may have influenced the Bank of England’s assessment of predictability at the end of 1986. After 1987, the probability of prediction for inflation is nearly one.

Figure 9, which uses *M4*, shows stronger evidence of predictability for real output growth than for either *M0* or *M3*, but only after 1990 and rarely is the evidence extremely strong. All three of the lines in this figure indicate that the probability of predictability generally rises through time, reaching 0.65 or more by the end of the evaluation period. However, there are important and interesting differences between the three lines. Using real-time data, the strategy of selecting a single best model yields a much more volatile line. The differences between BMA results using real-time and last-vintage data are not

²⁴The in-sample analysis of the models for *M0* and *M4* can be obtained from the authors on request.

so pronounced. However it is interesting to note that, in contrast to $M0$, the real-time evidence that $M4$ predicts output is slightly but consistently higher than with final vintage data.

Figure 10 shows the in-sample probability that $M4$ predicts inflation. Using real-time data, the late 1980s do seem to be a volatile time. As with many other cases, BMA results are much smoother than those produced using the strategy of selecting a single model. However, as of 1990 the probability that money can predict inflation reaches 0.8 or more, and settles down to approximately one by the mid 1990s, comfortably before Bank of England independence in 1997. Using final vintage data, the probability that money can predict inflation is almost one throughout the entire time period.

A story consistent with all three monetary aggregates is that there is little evidence in-sample that money can predict real output growth in the 1980s. However, after the early 1990s (at least for monetary aggregates where real-time data is available) there is at least some evidence of predictability. But, with the exceptions noted above, evidence of predictability is almost never extremely strong using either real-time or last-vintage data. For $M4$ the evidence using real-time is obscured by fluctuations in probabilities, which are mitigated to some extent by BMA. The evidence that money predicts inflation in-sample is stronger through the evaluation period. Although both $M0$ and (from 1987) $M4$ posterior probabilities display large fluctuations in real-time, the problem is less severe than with $M3$.

Turning to the out-of-sample evidence, Table 2 uses VARs and VECMs where $M0$ is the money variable (“M0 System”). Table 3 uses $M4$ (“M4 System”). In each case, the upper panel refers to inflation; and the lower panel to real output growth. Remember that these systems are estimated with much more data than the $M3$ system since this monetary aggregate was discontinued in 1989.

Looking first at the point forecasts, the general picture presented is that including $M0$ does not significantly improve forecasting performance in real-time.²⁵ In contrast, with the M4 System the RMSEs are typically less than one and decrease with forecast horizon. It is interesting to note that these conclusions hold regardless of whether we do BMA or select the best model. For the M4 System inclusion of money does improve forecasting performance in a manner which a frequentist statistician would say was statistically significant for inflation at the $h = 1$ and $h = 4$ horizon using BMA.

An examination of Table 3 for the $M4$ Systems indicates that inclusion of money improves many of the hit rates in real-time, often by a substantial amount. This is most noticeable with long horizons ($h = 8$), although even then the P-T statistics indicate statistical insignificance. For the $M0$ Systems shown in Table 2, there is little improvement in the hit rates in real time from the inclusion of the monetary aggregate. These results hold with both the BMA and best model selection strategy.

For both $M0$ and $M4$ systems, the support for the inclusion of money is typically marginally stronger with final vintage data than with real-time data, but any improvement in central forecasts and hit rates remains insignificant. This characterization holds

²⁵Recall that all results are presented relative to the RMSE produced by BMA using the models without money. Thus, a number less than one indicates an improved forecast performance relative to this case.

regardless of the model selection strategy.

To summarize our analysis of the $M0$ and $M4$ systems, We find that narrow money exhibits greater in-sample real-time predictability for inflation, and smaller fluctuations in predictability than for $M3$ systems. We find little support for in-sample predictability of economic growth with $M0$. Nevertheless revised data suggest somewhat more support than with real-time data. For broad money, $M4$, we find strong support for predictability of inflation. The real-time fluctuations are much larger for real output growth than for inflation, and as with $M3$, these are mitigated considerably by BMA. With the benefit of longer sample of real-time data, the out-of-sample performance of the predictive densities for $M4$ systems, and to a lesser extent for $M0$ systems, improves marginally with money.

6 Conclusions

This paper investigates whether money has predictive power for output or inflation in the UK. We carry out a recursive analysis to investigate whether predictability has changed over time. Furthermore, we use real-time data which allows us to examine whether prediction would have been possible in real time (that is, using the data which would have been available at the time the prediction was made) and/or retrospectively (using final vintage data). We consider a large set of Vector Autoregressive (VAR) and Vector Error Correction models (VECM) which differ in terms of lag length and the number of cointegrating terms. Faced with this model uncertainty, we use Bayesian model averaging (BMA) and contrast it to a strategy of selecting a single best model.

Our empirical results are divided into in-sample and out-of-sample sections. With regards to in-sample results, using the real-time data available to UK policymakers, we find that the predictive content of $M3$ fluctuates throughout the sample. However, the strategy of choosing a single best model amplifies these fluctuations relative to BMA.

With BMA and final vintage data, the predictive content of broad money did not diminish substantially during the 1980s. The $M3$ monetary aggregate displays little predictability for output at any point and the probability that broad money predicts inflation rises though the mid 1980s. But this result requires the benefit of hindsight about data revisions. With real-time data, a sharp drop in in-sample predictability about inflation occurs coincident with the abandonment of formal monetary targeting.

Our out-of-sample analysis suggests little support for the hypothesis that $M3$ matters for inflation or output during the 1980s. With the benefit of longer samples, the evidence is marginally stronger with $M0$ and, in particular, $M4$.

UK policymakers have argued that the unpredictability of the relationships between broad monetary aggregates and inflation and output undermined the UK's monetary targeting experiment. The results in this paper show that these features are apparent only when analyzing real-time data. Hence, the inaccuracy of preliminary data measurements contributed to the demise of UK monetary targeting.

Table 1: Evaluation of Central and Probability Forecasts with *M3*:
(a) Inflation

<i>(i) Real Time Data</i>									
	<u>BMA – no money</u>			<u>BMA- money</u>			<u>Best - money</u>		
	<i>(Benchmark)</i>								
	h=1	h=4	h=8	h=1	h=4	h=8	h=1	h=4	h=8
<u>Central</u>									
RMSE	1.00	1.00	1.00	1.08	1.25	1.57	1.12	1.27	1.53
DM Stat	·	·	·	2.71 (0.00)	2.23 (0.01)	3.52 (0.00)	2.63 (0.00)	3.07 (0.00)	3.74 (0.00)
<u>Pr($\Delta p_{t+h} < 5\%$)</u>									
Hit Rate	64%	52%	68%	72%	64%	68%	64%	64%	68%
P-T	1.11	-1.41	·	2.04	-1.41	·	1.04	·	·
<i>(ii) Final Vintage Data</i>									
	<u>BMA- no money</u>			<u>BMA- money</u>			<u>Best - money</u>		
	h=1	h=4	h=8	h=1	h=4	h=8	h=1	h=4	h=8
<u>Central</u>									
RMSE	1.32	1.05	1.03	1.51	1.50	1.82	1.57	1.60	1.82
DM Stat	1.73 (0.04)	0.61 (0.27)	0.81 (0.21)	2.48 (0.01)	2.95 (0.00)	6.16 (0.00)	2.39 (0.01)	2.22 (0.01)	6.05 (0.00)
<u>Pr($\Delta p_{t+h} < 5\%$)</u>									
Hit Rate	64%	60%	68%	48%	64%	68%	48%	64%	68%
P-T	1.04	-0.78	·	-1.54	·	·	-1.54	·	·

(b) Output Growth

<i>(i) Real Time Data</i>									
	<u>BMA – no money</u>			<u>BMA- money</u>			<u>Best - money</u>		
	<i>(Benchmark)</i>								
	h=1	h=4	h=8	h=1	h=4	h=8	h=1	h=4	h=8
<u>Central</u>									
RMSE	1.00	1.00	1.00	1.04	1.04	1.06	1.03	1.06	1.04
DM Stat	.	.	.	1.11 (0.13)	0.78 (0.22)	0.70 (0.24)			
<u>Pr($\Delta y_{t+h} < 2.3\%$)</u>									
Hit Rate	44%	64%	44%	32%	64%	56%	32%	64%	56%
P-T	-1.46	1.34	-0.62	2.22	1.22	1.03	2.22	1.22	1.03
<i>(ii) Final Vintage Data</i>									
	<u>BMA- no money</u>			<u>BMA- money</u>			<u>Best - money</u>		
	h=1	h=4	h=8	h=1	h=4	h=8	h=1	h=4	h=8
<u>Central</u>									
RMSE	1.03	1.05	0.89	1.08	1.04	1.02	1.08	1.07	1.03
DM Stat	0.47 (0.32)	0.87 (0.19)	-1.52 (0.94)	0.79 (0.21)	0.30 (0.38)	0.13 (0.45)	0.85 (0.21)	0.61 (0.27)	0.23 (0.41)
<u>Pr($\Delta y_{t+h} < 2.3\%$)</u>									
Hit Rate	48%	72%	40%	52%	60%	52%	52%	60%	52%
P-T	-0.46	2.18	1.01	-0.52	0.85	1.00	-0.52	0.85	1.00

Notes: RMSE denotes Root Mean Square Error, defined as a ratio relative the benchmark real time BMA case where money is not included. DM denotes the Diebold Mariano (1995) statistic, where the loss function is defined using the difference in squared forecast errors of each model in the above table relative to the benchmark real time BMA model with no money. The null hypothesis of equal predictive ability is then tested where the p-values reported in parentheses assume a standard normal distribution. Note in the limiting case such statistic follows a non-standard distribution. 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. The P-T statistic allows a formal hypothesis of directional forecasting performance.

Table 2: Evaluation of Central and Probability Forecasts with $M0$:
(a) Inflation

<i>(i) Real Time Data</i>									
	<u>BMA – no money</u>			<u>BMA- money</u>			<u>Best - money</u>		
	<i>(Benchmark)</i>								
	h=1	h=4	h=8	h=1	h=4	h=8	h=1	h=4	h=8
<u>Central</u>									
RMSE	1.00	1.00	1.00	0.94	1.01	0.99	0.95	1.02	1.00
DM Stat	.	.	.	-1.06 (0.14)	0.13 (0.44)	-0.14 (0.43)	-0.90 (0.82)	0.37 (0.36)	0.01 (0.49)
$\Pr(\Delta p_{t+h} < 5\%)$									
Hit Rate	85.1%	68.1%	42.6%	80.9%	68.1%	44.7%	80.9%	68.1%	44.7%
P-T	-0.55	0.57	1.15	0.79	1.94	1.20	0.79	1.94	1.20
<i>(ii) Final Vintage Data</i>									
	<u>BMA- no money</u>			<u>BMA- money</u>			<u>Best - money</u>		
	h=1	h=4	h=8	h=1	h=4	h=8	h=1	h=4	h=8
<u>Central</u>									
RMSE	1.11	1.03	1.07	1.05	0.94	1.10	1.04	0.92	1.12
DM Stat	1.20 (0.11)	0.94 (0.17)	3.77 (0.00)	0.42 (0.33)	-0.71 (0.34)	0.84 (0.20)	0.38 (0.35)	-0.86 (0.20)	0.97 (0.17)
$\Pr(\Delta p_{t+h} < 5\%)$									
Hit Rate	78.7%	51.1%	30%	80.9%	66%	46.8%	80.9%	66%	46.8%
P-T	0.65	0.03	0.86	0.79	0.49	1.26	0.79	0.49	1.26

(b) Output Growth

<i>(i) Real Time Data</i>									
	<u>BMA – no money</u>			<u>BMA- money</u>			<u>Best - money</u>		
	<i>(Benchmark)</i>								
	h=1	h=4	h=8	h=1	h=4	h=8	h=1	h=4	h=8
<u>Central</u>									
RMSE	1.00	1.00	1.00	0.98	0.98	1.34	0.97	0.96	1.38
DM Stat	.	.	.	-0.41 (0.66)	-0.25 (0.60)	2.11 (0.02)	-0.52 (0.70)	-0.38 (0.65)	2.27 (0.01)
$\Pr(\Delta y_{t+h} < 2.3\%)$									
Hit Rate	63.8%	53.2%	51.1%	57.4%	51.1%	51.1%	57.4%	51.1%	51.1%
P-T	0.42	-0.98	-0.05	-0.20	-0.71	-0.25	-0.20	-0.71	-0.25
<i>(ii) Final Vintage Data</i>									
	<u>BMA- no money</u>			<u>BMA- money</u>			<u>Best - money</u>		
	h=1	h=4	h=8	h=1	h=4	h=8	h=1	h=4	h=8
<u>Central</u>									
RMSE	0.91	1.07	0.95	0.88	1.04	1.20	0.87	1.06	1.23
DM Stat	-1.69 (0.04)	1.61 (0.05)	-1.28 (0.11)	-1.41 (0.08)	0.67 (0.25)	1.54 (0.06)	-1.42 (0.07)	0.80 (0.21)	1.64 (0.05)
$\Pr(\Delta y_{t+h} < 2.3\%)$									
Hit Rate	61.7%	53.2%	55.3%	55.3%	53.2%	61.7%	55.3%	53.2%	59.6%
P-T	-0.11	-0.71	0.02	-0.73	-0.98	1.33	-0.73	-0.98	0.98

Table 3: Evaluation of Central and Probability Forecasts with *M4*:
(a) Inflation

<i>(i) Real Time Data</i>									
	<u>BMA – no money</u>			<u>BMA- money</u>			<u>Best - money</u>		
	<i>(Benchmark)</i>								
	h=1	h=4	h=8	h=1	h=4	h=8	h=1	h=4	h=8
<u>Central</u>									
RMSE	1.00	1.00	1.00	0.92	0.80	0.81	0.95	0.81	0.82
DM Stat	.	.	.	-2.38 (0.01)	-2.32 (0.01)	-1.43 (0.08)	-1.09 (0.86)	-2.13 (0.98)	-1.38 (0.92)
$\Pr(\Delta p_{t+h} < 5\%)$									
Hit Rate	85.1%	68.1%	42.6%	91.5%	95.7%	89.4%	91.5%	95.7%	87.2%
P-T	-0.55	0.57	1.15	-0.27	0.00	-0.38	-0.27	0.00	-0.45
<i>(ii) Final Vintage Data</i>									
	<u>BMA- no money</u>			<u>BMA- money</u>			<u>Best - money</u>		
	h=1	h=4	h=8	h=1	h=4	h=8	h=1	h=4	h=8
<u>Central</u>									
RMSE	1.01	1.05	1.03	0.94	0.98	1.06	0.95	1.01	1.07
DM Stat	.	.	.	-0.53 (0.30)	-0.12 (0.45)	0.23 (0.41)	-0.41 (0.66)	0.05 (0.48)	0.25 (0.41)
$\Pr(\Delta p_{t+h} < 5\%)$									
Hit Rate	78.7%	51.1%	29.8%	91.5%	95.7%	85.1%	91.5%	95.7%	93.6%
P-T	0.65	0.03	0.86	-0.27	0.00	-0.50	-0.27	0.00	-0.22

(b) Output Growth

<i>(i) Real Time Data</i>									
	<u>BMA – no money</u>			<u>BMA- money</u>			<u>Best - money</u>		
	<i>(Benchmark)</i>								
	h=1	h=4	h=8	h=1	h=4	h=8	h=1	h=4	h=8
<u>Central</u>									
RMSE	1.00	1.00	1.00	0.99	1.12	0.92	1.05	1.19	0.92
DM Stat	.	.	.	-0.12 (0.45)	2.13 (0.02)	-0.58 (0.28)	1.32 (0.09)	3.11 (0.00)	-0.54 (0.29)
$\Pr(\Delta y_{t+h} < 2.3\%)$									
Hit Rate	63.8%	53.2%	51.1%	63.8%	61.7%	57.4%	63.8%	59.6%	57.4%
P-T	-0.42	-0.98	-0.05	0.42	-0.77	0.32	0.42	-1.10	0.32
<i>(ii) Final Vintage Data</i>									
	<u>BMA- no money</u>			<u>BMA- money</u>			<u>Best - money</u>		
	h=1	h=4	h=8	h=1	h=4	h=8	h=1	h=4	h=8
<u>Central</u>									
RMSE	0.93	1.05	0.92	0.93	1.07	0.79	0.95	1.07	0.78
DM Stat	-1.09 (0.14)	1.19 (0.12)	-1.61 (0.95)	-0.78 (0.22)	1.38 (0.08)	-1.15 (0.13)	-0.54 (0.71)	1.29 (0.09)	-1.16 (0.13)
$\Pr(\Delta y_{t+h} < 2.3\%)$									
Hit Rate	61.7%	53.2%	55.3%	57.4%	57.4%	55.3%	57.4%	55.3%	57.4%
P-T	-0.11	-0.71	0.02	-1.36	1.36	-0.88	-0.45	-1.59	.

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Appendix: Predictive Densities for VARs and VECMs

Let the VAR be written as:

$$Y = XB + U \tag{A.1}$$

where Y is a $T \times n$ matrix of observations on the n variables in the VAR. X is an appropriately defined matrix of lags of the dependent variables, deterministic terms, etc.. B are the VAR coefficients and U is the error matrix, characterised by error covariance matrix Σ .

Based on these T observations, Zellner (1971, pages 233-236) derives the predictive distribution (using a common noninformative prior) for out-of-sample observations, W generated according to the same model:

$$W = ZB + V, \tag{A.2}$$

where B is the same B , V has the same distribution U , etc. (see Zellner, 1971, chapter 8 for details of definitions, etc.). Crucially, Z is assumed to be known. In this setup, the predictive distribution is multivariate Student-t (see page 235 of Zellner, 1971).

But the previous material assumed Z is known. How can we handle Z in our case? In the case of one period ahead prediction, $h = 1$, then Z is known. That is, in (A.1), if Y contains information available at time t , then X will contain information dated $t - 1$ or earlier. Hence, in (A.2) if W is a $t + 1$ quantity to be forecast, then Z will contain information dated t or earlier. But what about the case of h period ahead prediction where $h > 1$. Then Z is not known. But, following commn practice, we can simply estimate a different VAR for each h . For $h = 1$ work with a standard VAR as described above. For $h > 1$, still work with a VAR defined as in (A.1), except let Y contain information at time t , but let X only contain information through period $t - h$ (i.e. let X contain lags of explanatory variables lagged at least h periods).

The preceding describes how we derive h step ahead predictive densities for VAR models. The VECM can be written as in (A.1) if we include in X the error correction terms (in addition to all the VAR explanatory variables). We replace the unknown cointegrating vectors which now appear in X by their MLEs. If we do this, analytical results for predictive densities can be obtained exactly as for the VAR. Note that this is an approximate Bayesian strategy and, thus, the resulting predictive densities will not fully reflect parameter uncertainty. We justify this approximate approach through a need to keep the computational burden manageable. Remember that we have 80 models (i.e. 40 VARs and VECMs, each of which has a variant with money and a variant without money) and six different data combinations (e.g. we have real-time and final vintage versions of our variables and use three different monetary aggregates). For each of the six different data combinations we have to do a recursive prediction exercise (involving up to 100 forecast periods). Furthermore, we have to do all this for $h = 1, 4$ and 8 . Our empirical results involve posterior and predictive results for 315,360 VARs or VECMs. Thus, it is important to make modelling choices which yield analytical posterior and predictive results. If

we had to use posterior or predictive simulation, the computational burden would have been overwhelming.

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

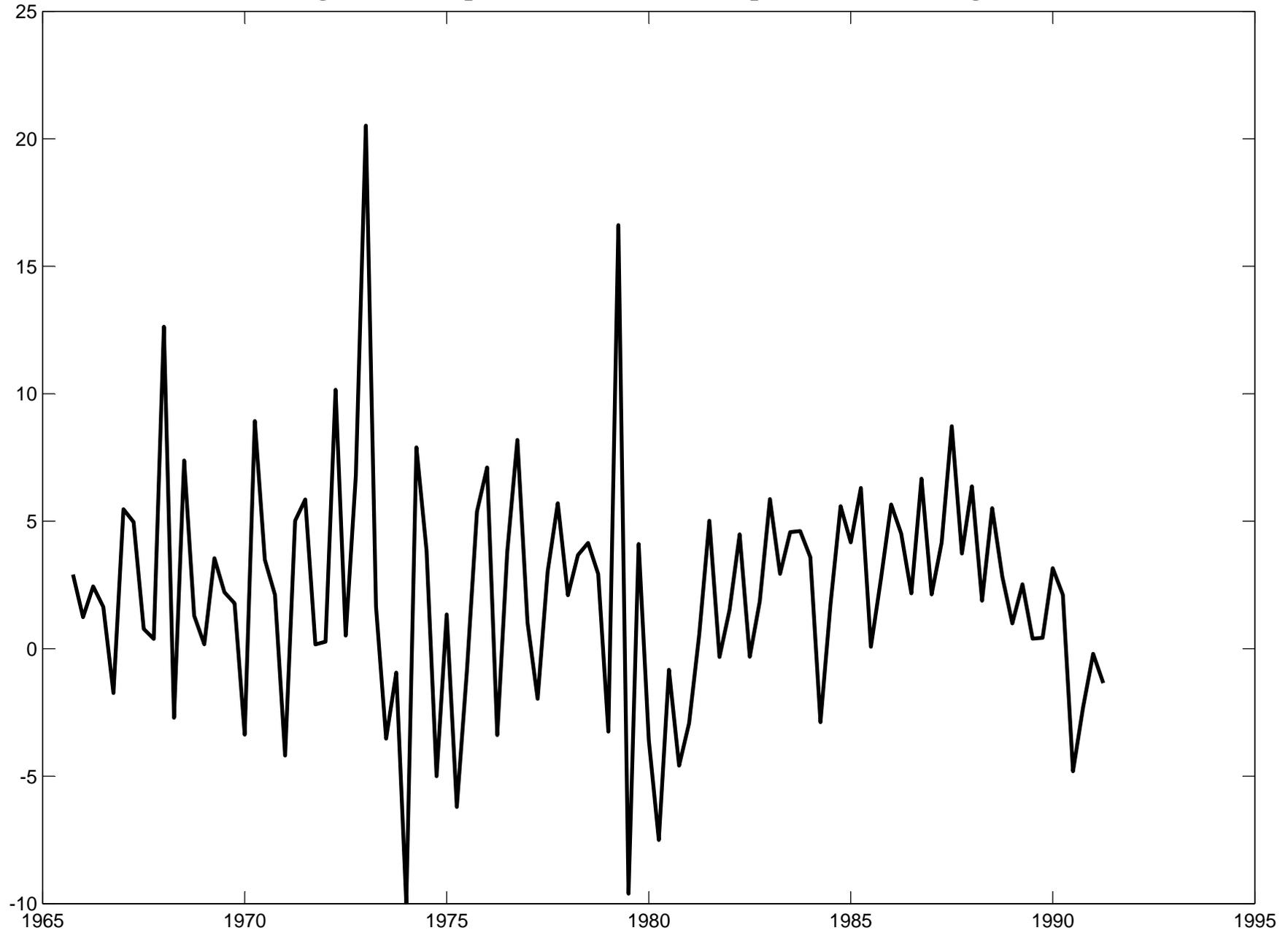


Figure 1b: Inflation (annualized percent, final vintage)

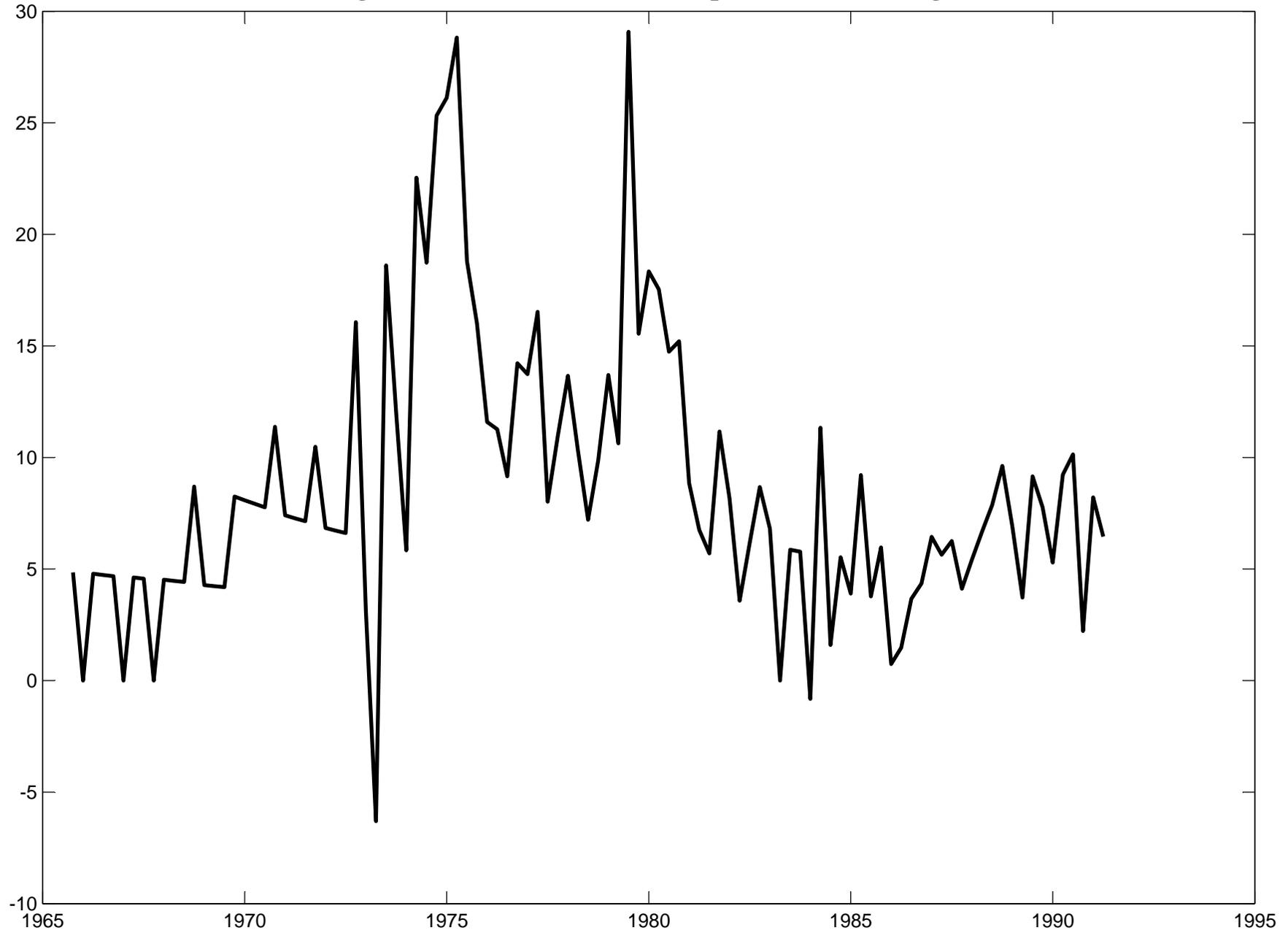


Figure 1c: M3 Growth (annualized percent, final vintage)

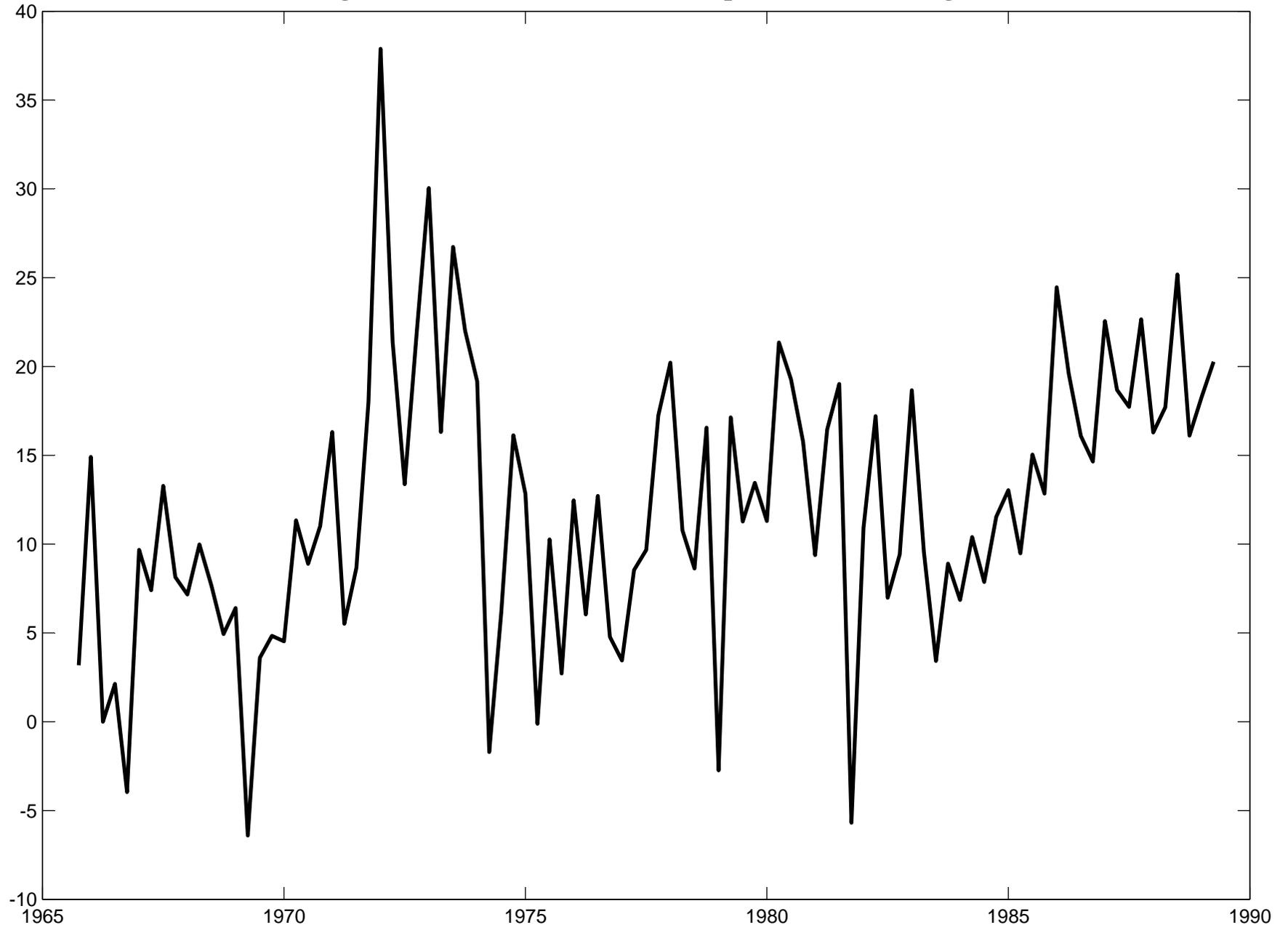


Figure 1d: Change in Effective Exchange Rate (annualized percent)

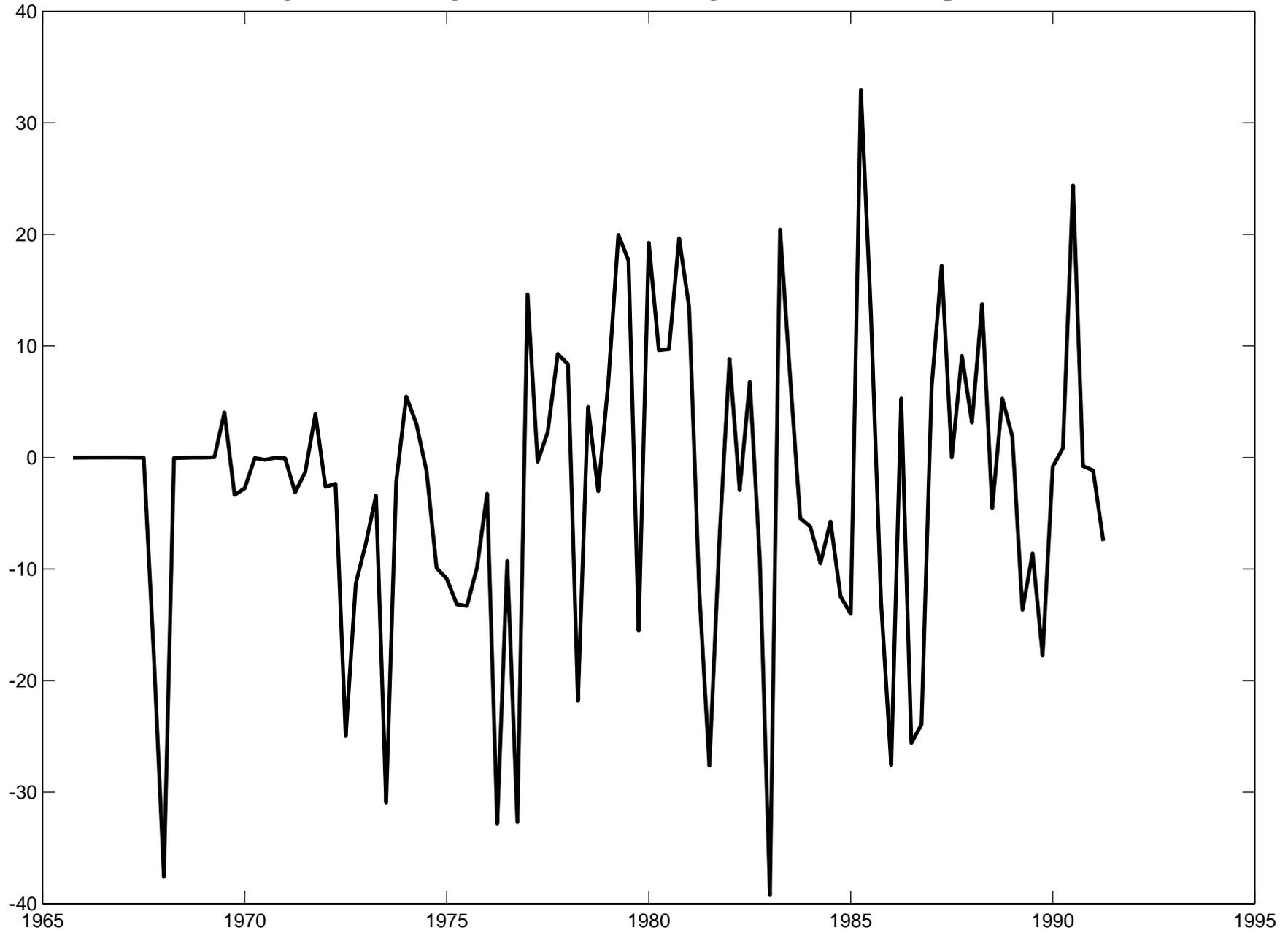


Figure 1e: Interest Rate (percent)

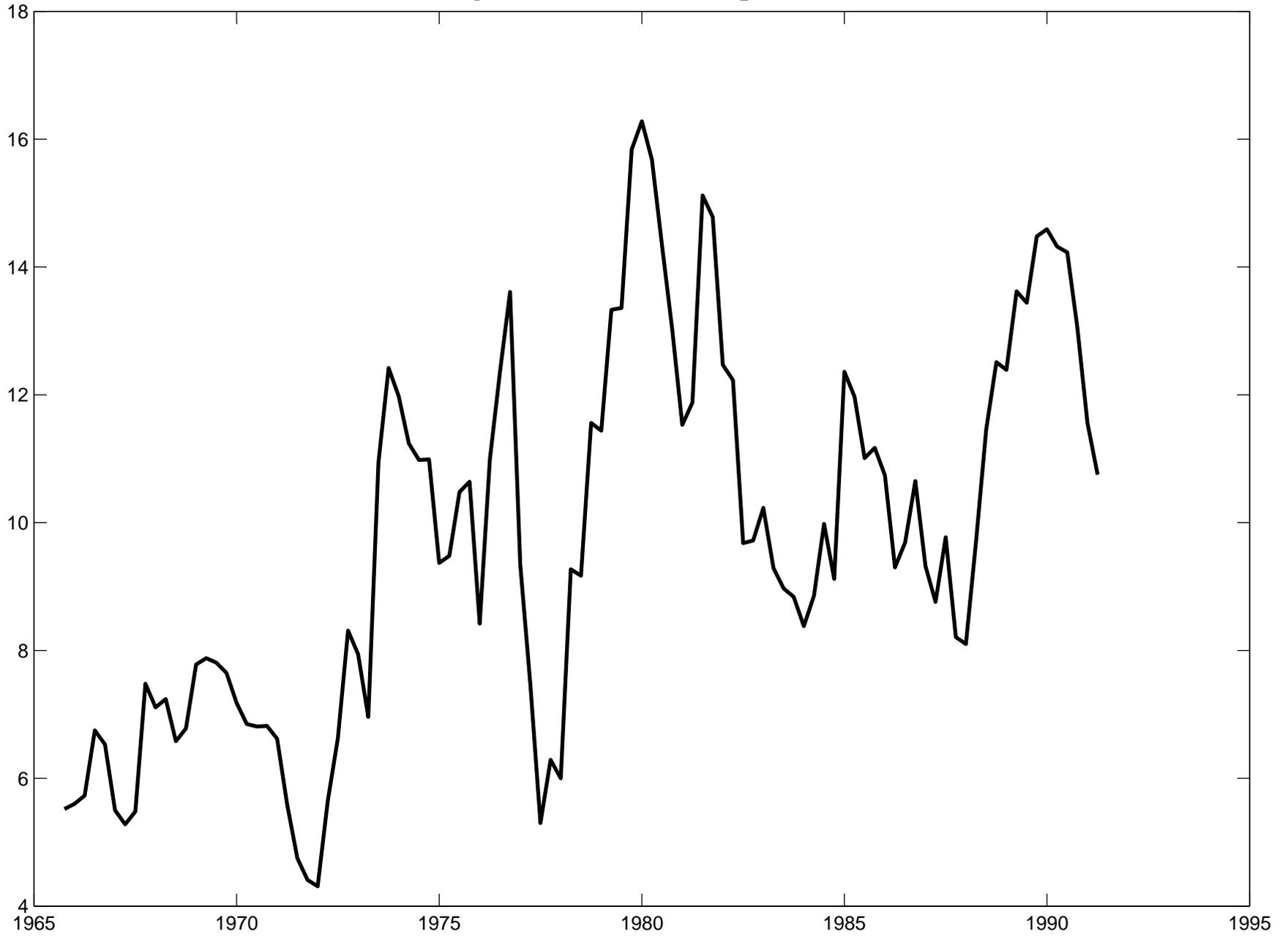


Figure 2: Probability of Various Models with M3

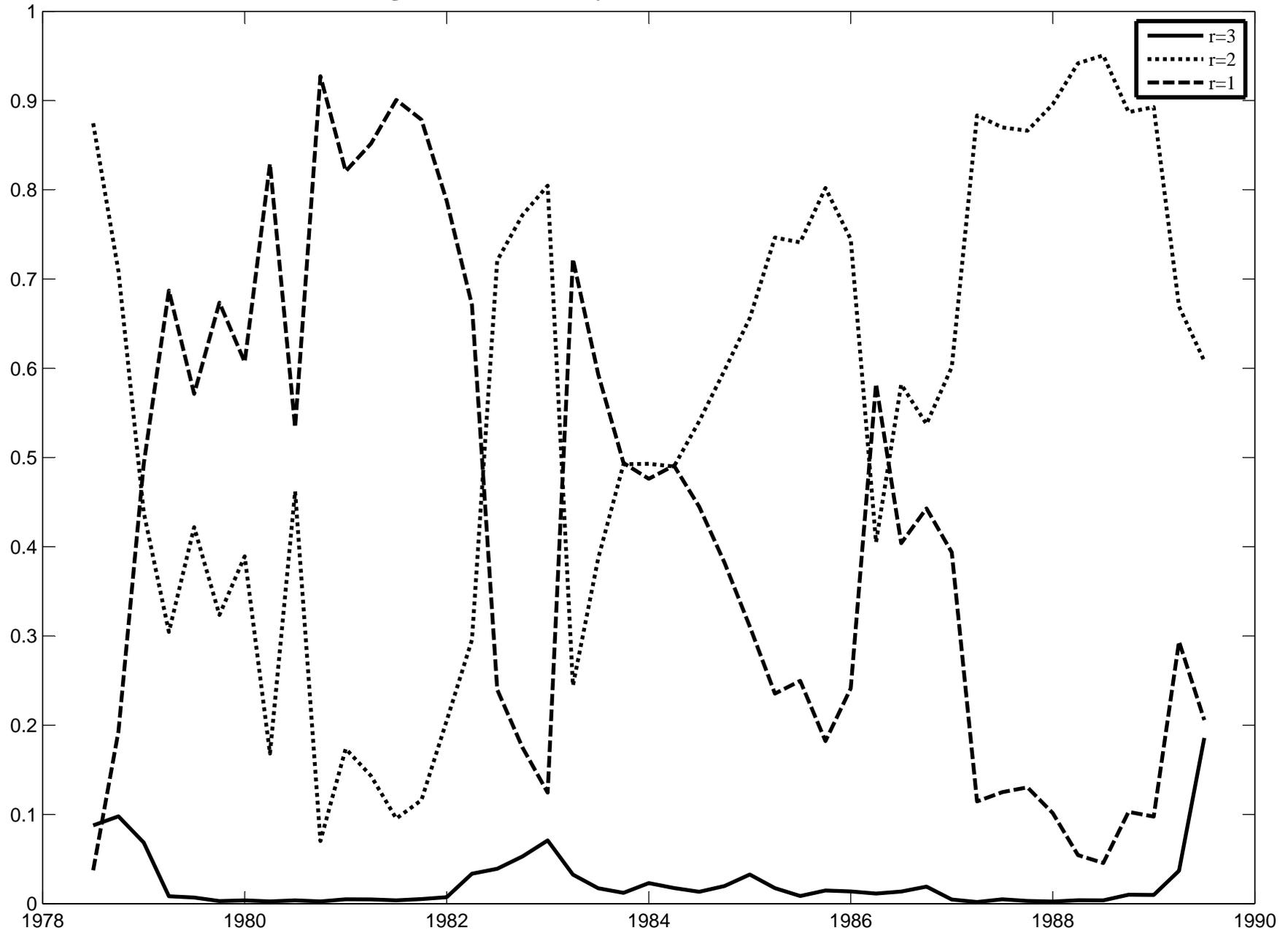


Figure 3: Probability M3 Predicts Output Growth

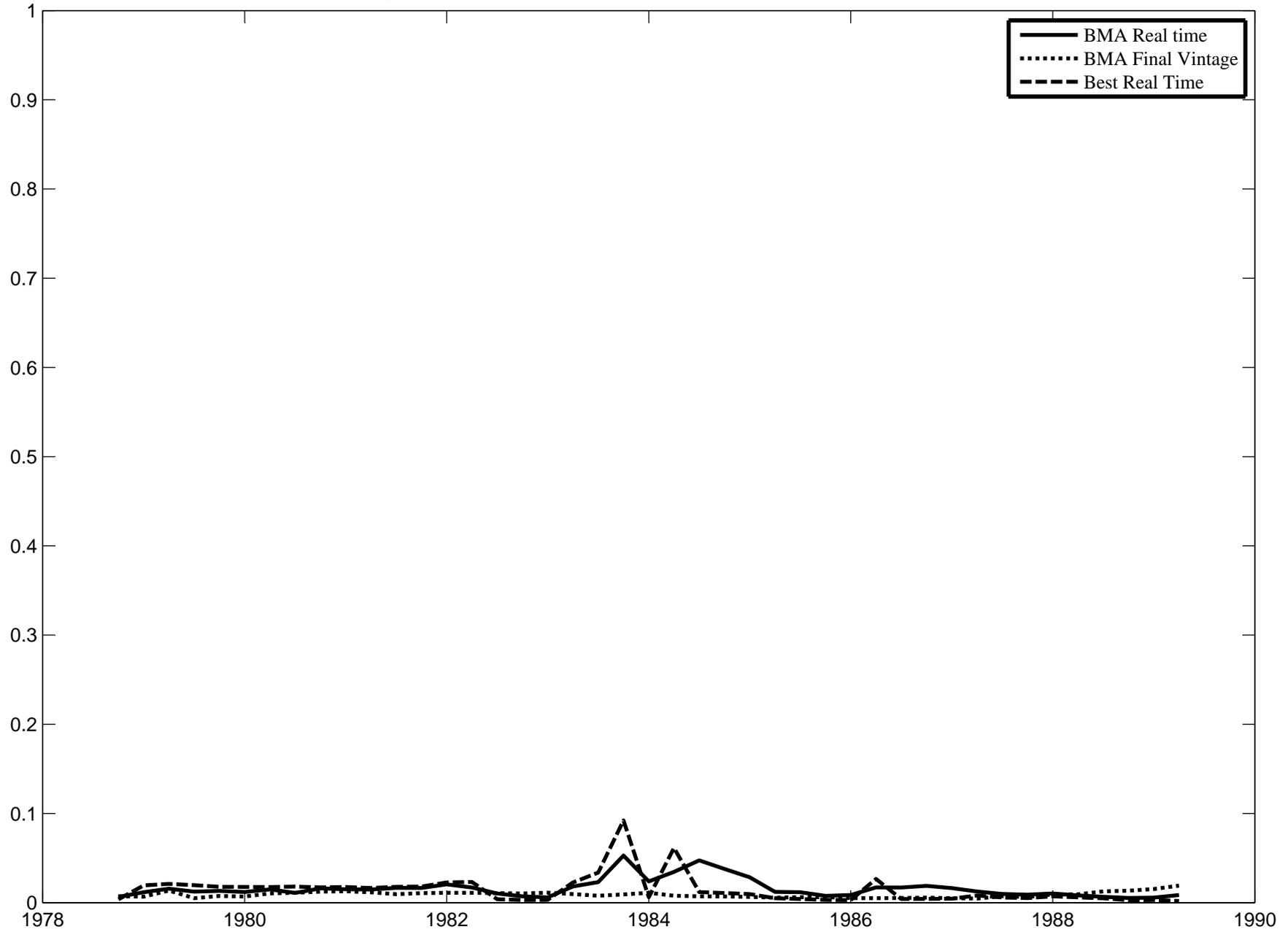


Figure 4: Probability M3 Predicts Inflation

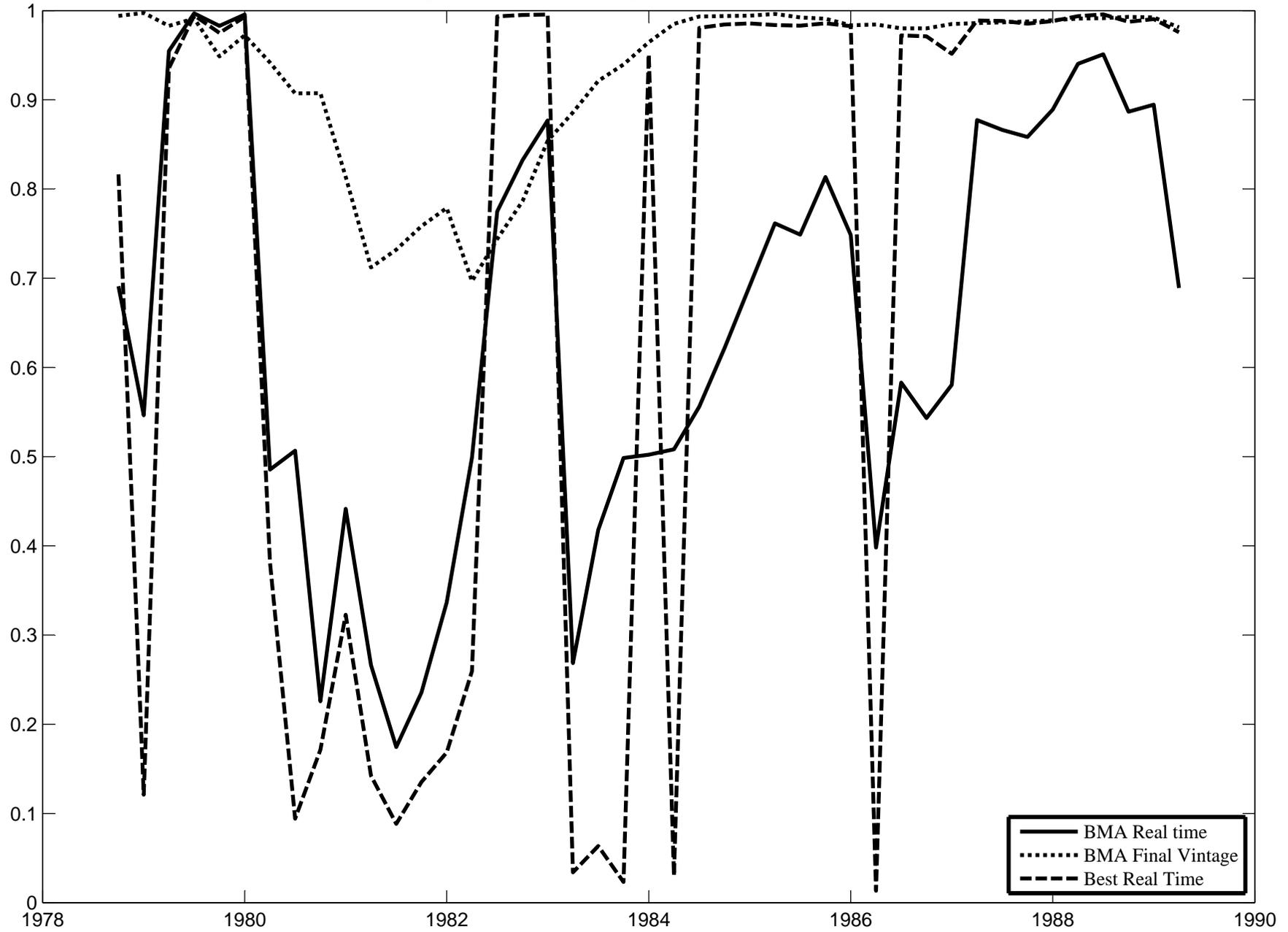


Figure 5: Probability of Inflation > 5 percent, Net Contribution of M3

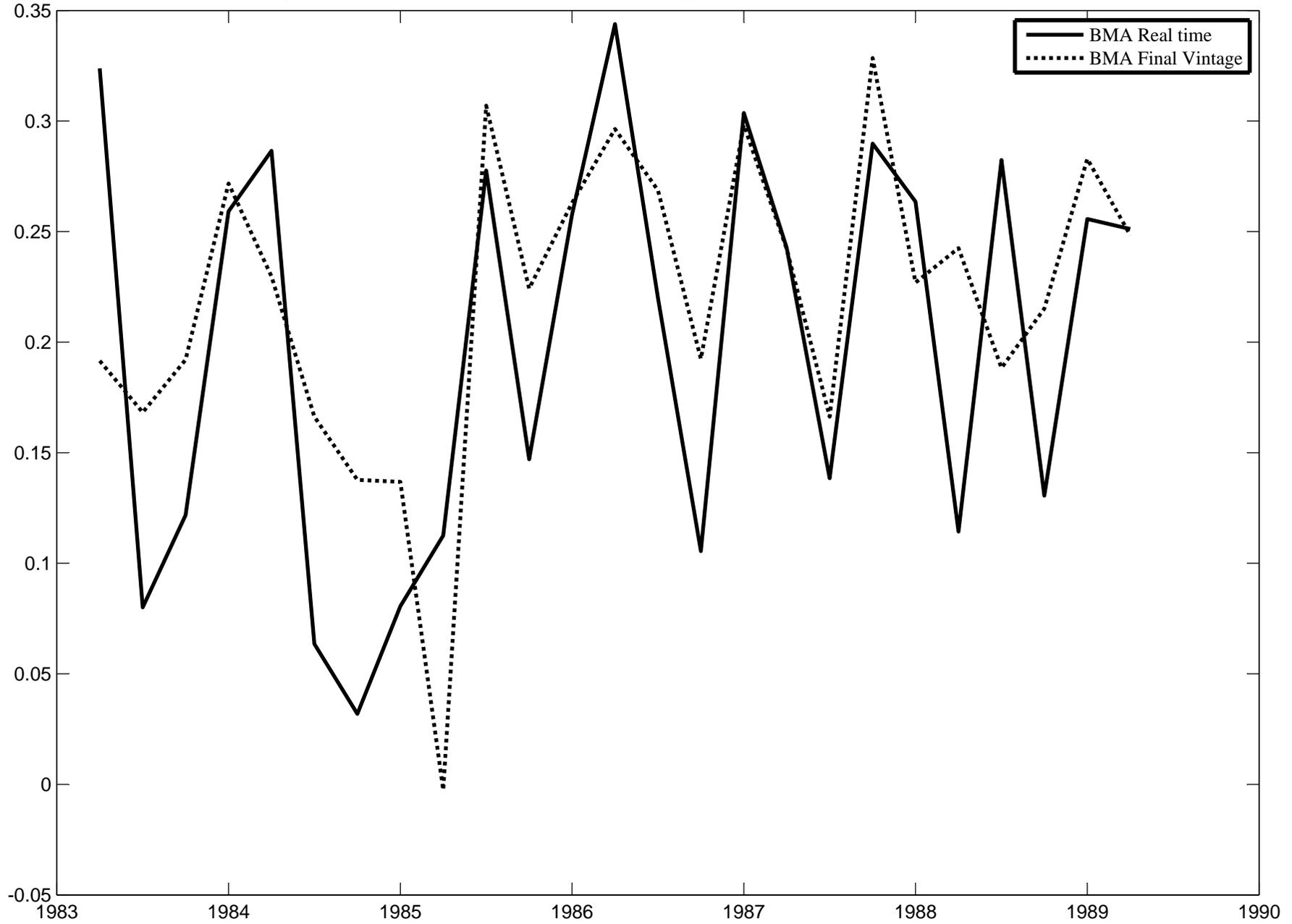


Figure 6: Probability of Output Growth > 2.3 percent, Net Contribution of M3

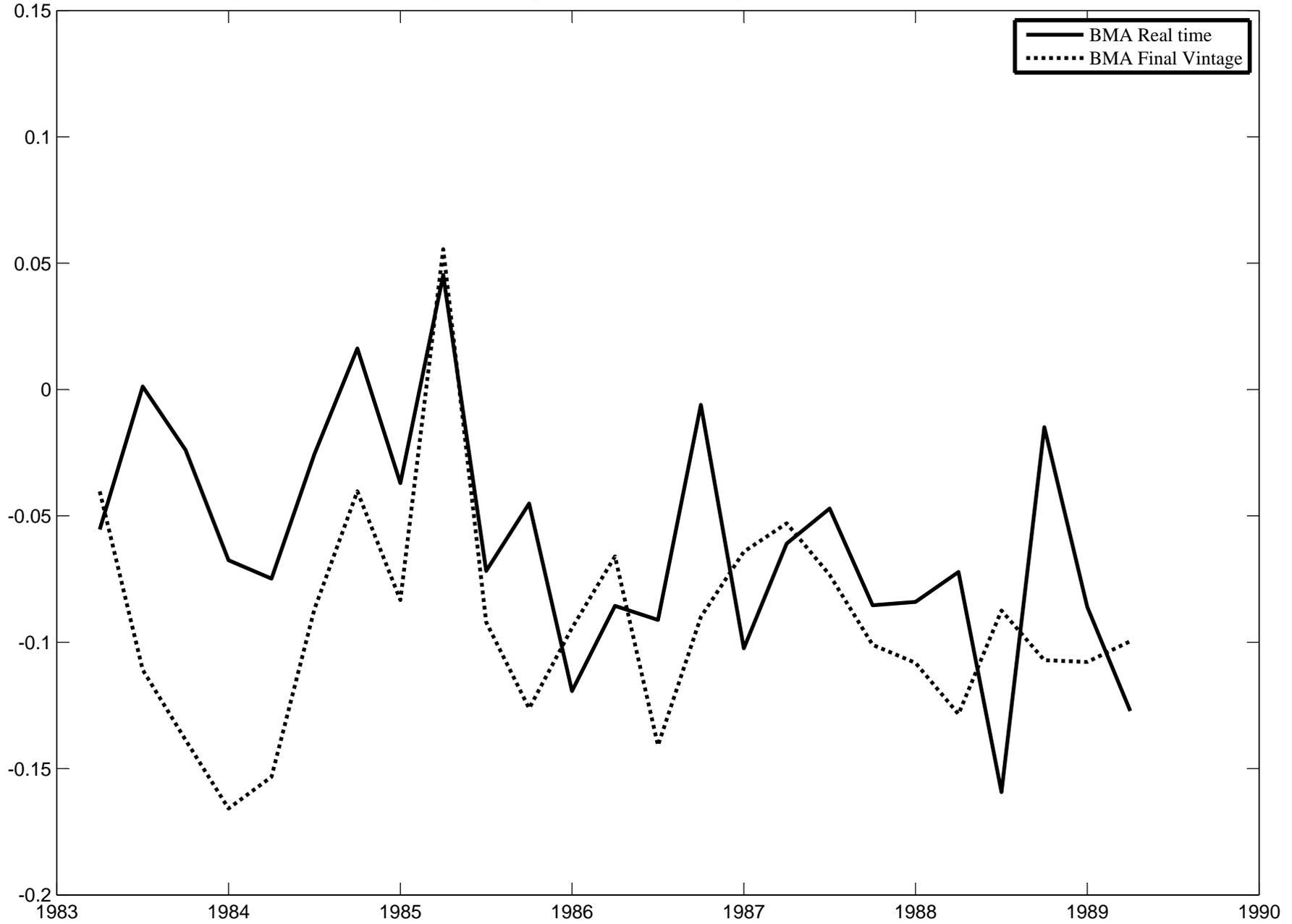


Figure 7: Probability M0 Predicts Output Growth

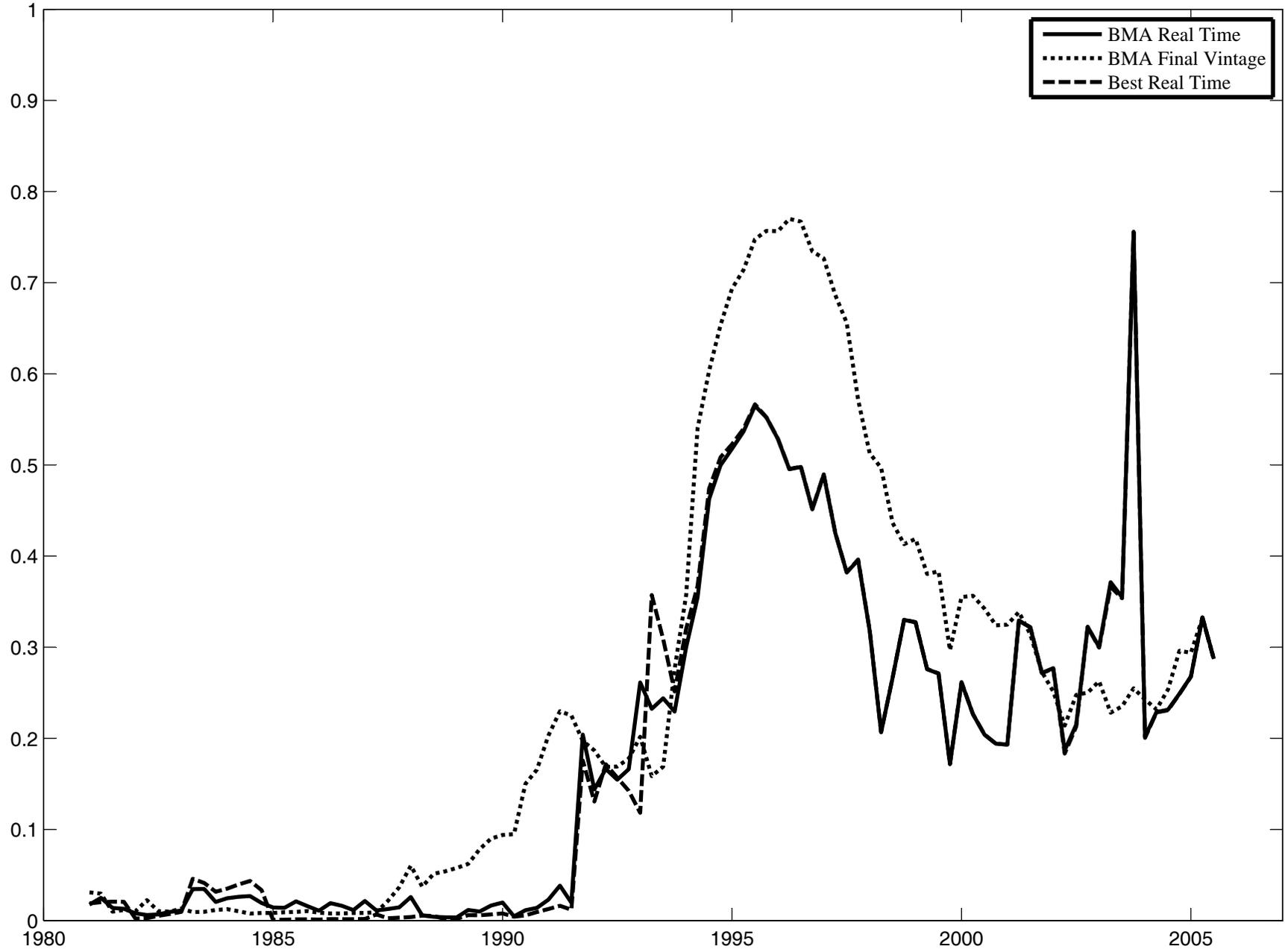


Figure 8: Probability M0 Predicts Inflation

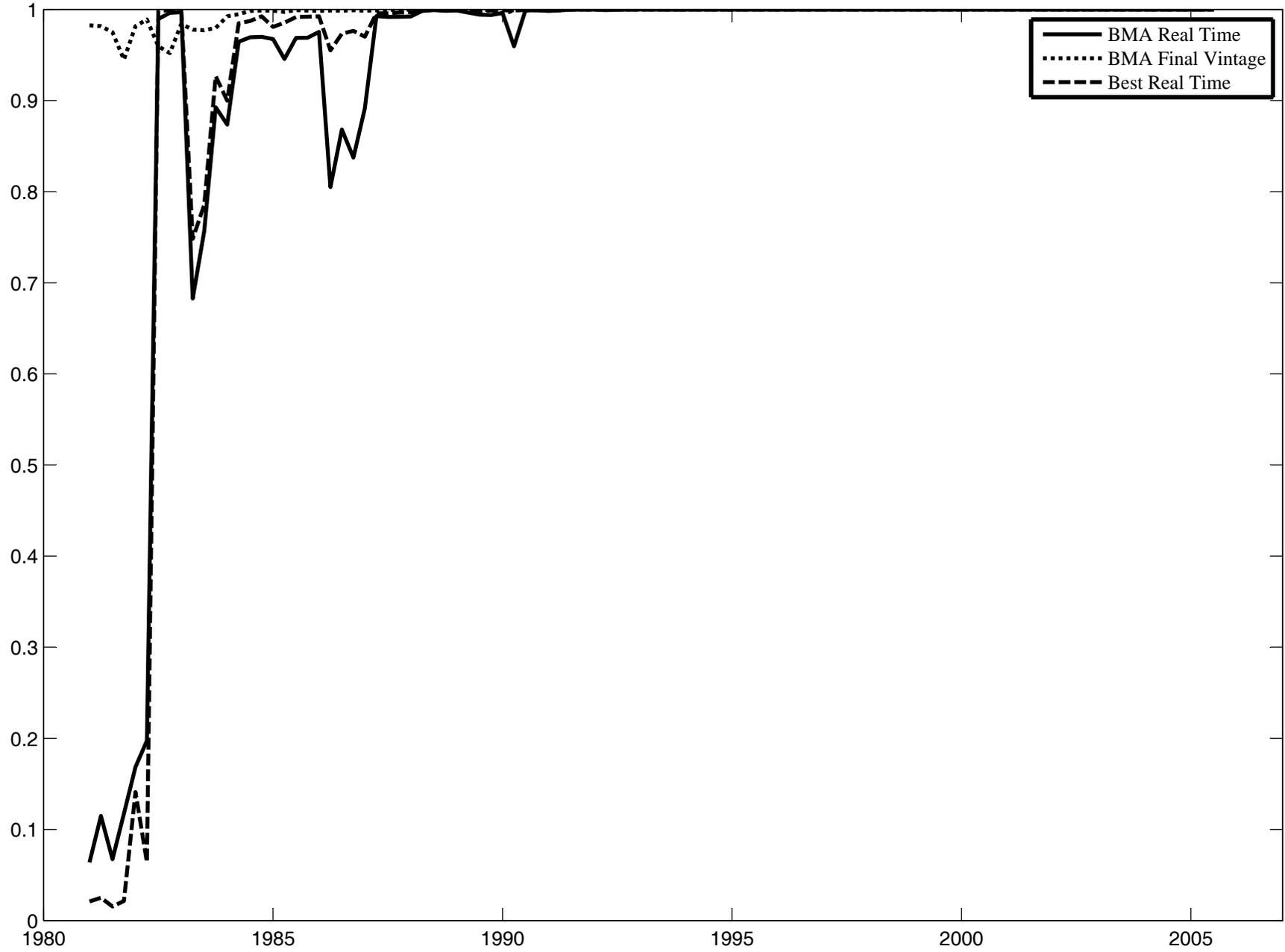


Figure 9: Probability M4 Predicts Output Growth

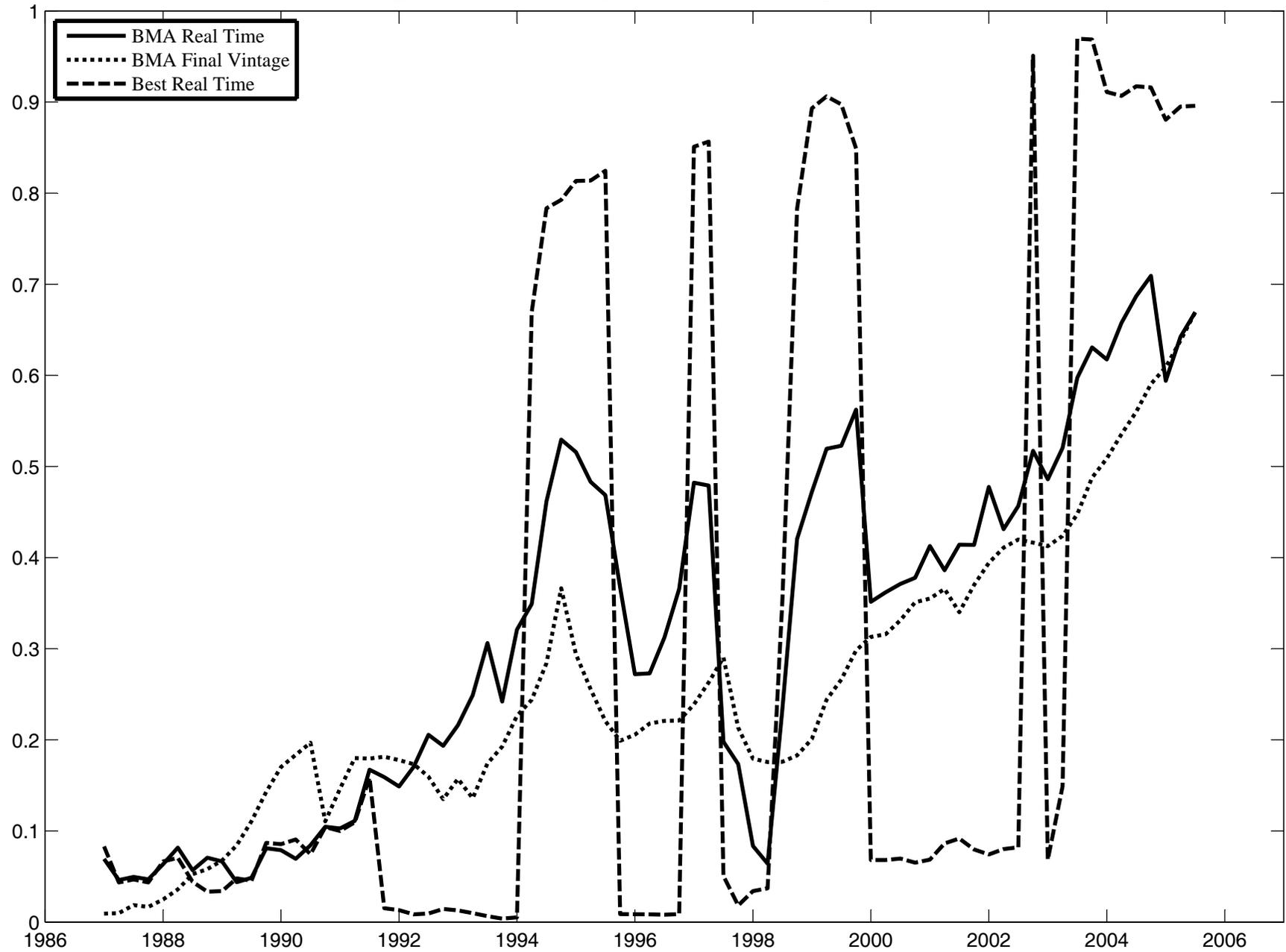


Figure 10: Probability M4 Predicts Inflation

