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Searching for the FED's Reaction Function

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Abstract

There is still some doubt about those economic variables that really matter for the FED's decisions. In comparison to other estimations, this study uses the approach of Bayesian Model Averaging (BMA). The estimations show that over the long run inflation, unemployment rates, and long-term interest rates are the crucial variables in explaining the Federal Funds Rate. In the other two estimation samples, also the federal deficit and M2 were of relevance. In addition, we present the best models in more detail. Finally, a model average is constructed via BMA. The model average substantially outperforms a simple Taylor rule.

Keywords: FED, Monetary Policy Reaction Functions, Model Uncertainty, Bayesian Model Averaging
JEL: E43, E52, E58

1. Introduction

In 2013, the Federal Reserve System (FED) will celebrate its 100th birthday. As the central bank of the world's largest economy, it is not only highly influential in its own economy but also for other economies and central banks. Thus, it is of great importance to know which factors significantly explain the FED's behaviour. For this purpose, a huge amount of monetary policy reaction functions was established. The first ones to do so were Dewald and Johnson in 1963. According to them, the American monetary policy between 1952 and 1962 can best be described by growth and unemployment rates. This was just the starting point for further studies that all had the same aim, namely to explain what the FED actually did. One of the most influential papers was that of John B. Taylor in 1993. He introduced the so-called Taylor rule which explains the actual Federal Funds Target Rate as a combination of the inflation rate, the neutral real interest rate, the inflation gap and the output gap. Besides those famous studies, there is an abundance of other works that deal with reaction functions. The only feature, however, that all those studies have in common is their target. The difference in those studies lies mainly in the variables that they use in their reaction functions. Among these are growth rates, inflation rates, unemployment rates, exchange rates, long-term interest rates, debt or deficit, net trade, money aggregates, stock prices, oil prices, and technology or productivity.[1] There is, therefore, still some doubt about those factors that really determine the monetary policy of the FED, even after such a long period of time.

This paper aims to solve this problem with a different approach: whereas most studies use conventional regression analysis or time-series approaches, this study uses the approach of Bayesian Model Averaging (BMA). The advantage of this technique is apparent especially in the case where there is a high degree of model uncertainty. Using BMA in this case has several benefits: first of all, it makes it possible to identify those variables which are of relevance in the FED's behaviour by calculating the probability that a certain variable will be considered in the FED's decisions. Moreover, we can use the BMA framework to compare a large number of different models to find out which of them have the best fit in describing what the FED actually did. Finally, model selection is not the aim of BMA but the averaging of all possible models (weighted by their probability of being the "true" model) in order to receive a kind of "uncertainty model" which does not neglect any information by sorting out less efficient models.

The paper starts with an overview of theoretical arguments on the FED's reactions and of the corresponding literature (section 2). Then the concept of BMA (section 3) and the data used in this study (section 4) will be presented. Section 5 applies BMA to the reaction function of the FED and presents the results of the estimation. Section 6 gives a conclusion.

2. Potential Determinants of the FED's Behaviour

If one thinks about variables that are possibly important for monetary policy, one should first take a look at the legal framework. According to the Federal Reserve Act Section A2, the Federal Reserve Bank *"shall maintain long run growth of the monetary and credit aggregates commensurate with*

[1] Khoury (1993) provides an overview of studies about the FED's reaction function until 1986.

the economy's long run potential to increase production, so as to promote effectively the goals of maximum employment, stable prices, and moderate long-term interest rates".

Thus, low unemployment rates are most important for monetary policy if the order of the goals says something about their relevance. Several studies show the impact of unemployment rates on monetary policy (e. g. Christensen and Nielsen, 2009; Boivin, 2006). An alternative to unemployment is GDP or GDP growth. As a result, most studies use output growth rates (e. g. Vanderhart, 2000) or output gaps as independent variables. Output gaps are routinely included in Taylor rules (e. g. Clarida et al., 2000). Moreover, the FED should promote stable prices. Therefore, it is crucial to establish whether short run output growth was induced by an increase in aggregate demand or in aggregate supply. Hence, a (demand-sided) increase in GDP that is above the potential output could cause inflation risks and may lead the FED to raise interest rates. By contrast, the central bank could lower interest rates if potential output increases. An increase in productivity is a positive supply side shock which usually results in a higher GDP and downward pressure on prices. The central bank is then caught in a dilemma between stabilising output (by contractionary monetary policy) and stabilising prices (by expansionary monetary policy). Therefore, as productivity growth usually results in GDP growth, one cannot predict the direction of the FED's response to an increase in productivity. In order to take into account whether a higher GDP was the outcome of productivity growth or higher demand, output gaps (actual GDP minus potential GDP) or productivity, itself, could be used as explanatory variables. Galí et al. (2003) show that an optimal Taylor rule would require contractionary monetary policy if there is a positive technology shock. During the regimes of Volcker and Greenspan, the FED increased interest rates slightly as productivity increased. In the pre-Volcker period the response of the FED was too contractionary, meaning that growth was over-stabilised at the expense of too low inflation rates (ibid.).

As stable prices are the FED's second goal, inflation measured by consumer price indices is used to be included in reaction functions (e. g. Boivin, 2006). Furthermore, all factors that are crucial to inflation could have an impact on monetary policy. Generally, four different kinds of inflation can be distinguished according to their underlying causes of inflation: demand-pull inflation, cost-push inflation, money growth, and imported inflation. As explained above, a positive output gap indicates excess demand and, thus, can lead to (demand-pull) inflation. There are several variables which might cause cost-push inflation. Raising input or intermediate product prices (i. e. oil[2] and energy prices) boost producers' costs. Therefore, producer price indices are routinely included in reaction functions (Vanderhart, 2000). Furthermore, the quantity theory of money points out the role of money in determining inflation rates. In contrast to Woodford (2008), who states that money is not important for monetary policy, some evidence is found of an impact on money aggregates for actual central bank behaviour (Abrams et al., 1980). The most important factor in the short run is imported inflation. This could either be the result of increasing inflation rates abroad or a depreciation of the domestic currency. However, the main focus nowadays lies on exchange rates (e. g. International Monetary Fund Research Dept., 1996). Another variable which is also associated with inflation is the fiscal deficit or federal debt. Policy makers have an incentive to make use of inflation taxes to reduce debt[3]. This is politically easier to achieve than to cut spending or increase taxes. Subsequently, the central bank should react to an increase in federal debt with contractionary monetary policy to reduce incentives to increase debt. On the other hand, it could accommodate expansionary fiscal policy, especially in economic downturns. It also has to be taken into consideration that politics influences central bankers, too. Grier (1991) shows, for instance, the role of the Senate Banking Committee[4]. Froyen et al. (1997) point out the impact of political pressure on monetary policy decisions.

The third goal of monetary policy in the US is to promote moderate long-term interest rates. This target is very often neglected because it seems to be minor. One has to be careful because long-term interest rates have

[2]The optimal monetary policy in case of an oil price shock depends on the source of the shock (Bodenstein et al., 2012).

[3]Catao and Terrones (2005) show that the effects of fiscal deficits on inflation are most prevalent in developing countries and countries with high inflation rates. On the other hand, there is no significant relationship between government deficits and inflation in developed countries or countries with low inflation rates. However, Sims (2011) points out the role of fiscal deficits during the Great Inflation in the US.

[4]According to Grier (1991), a more liberal Committee is associated with larger increases in the money base. However, Chopin et al. (1996) contradict these findings and show that the opposite is true.

an ambiguous meaning. On the one hand, the central bank is supposed to bring down short-term interest rates in order to provide the goal of moderate long-term interest rates. On the other hand, an increase in long-term interest rates could be the result of increasing inflation expectations. Then the central bank ought to increase their key interest rates so as to prevent rising inflation risks. At the same time, the central bank could lower interest rates if long-term interest rates decrease. This could also thwart the risk of inverse yield curves. According to Christensen and Nielsen (2009), an increase in long-term interest rates leads to contractionary monetary policy, i. e. higher key interest rates.

Besides that, there are other factors which could matter for monetary policy. For instance, stock markets have become more and more important over the last decades. They are also relevant for central banks. After the burst of the dot-com bubble, the FED substantially decreased the Federal Funds Rate. Stock prices are good early indicators for recessions, especially for one to three quarterly periods (Estrella and Mishkin, 1998). Accordingly, the FED reacts at an early stage and cuts interest rates when stock prices go down (Rigobon and Sack, 2003). However, it does not react similarly to increases in stock prices according to Hoffmann (2013). Moreover, it could counteract a boom at an early stage or even try to burst a stock market bubble.

In addition to the goals of maximum employment, stable prices, and moderate long-term interest rates, the FED could also help to achieve the goal of external balance. Thus, it would increase interest rates if the current account surplus rises and vice versa. Higher interest rates lead to higher export prices and lower import prices via the exchange rate channel. The result is a lower surplus if the Marshall-Lerner condition applies. The influence of the balance of payments or net trade is controversial. Studies find both positive (Avery, 1979) and inverse effects (Epstein and Schor, 1986) on monetary policy.

3. Estimation Procedure: Bayesian Model Averaging (BMA)

The motivation for using the approach of Bayesian Model Averaging (BMA) lies in the fact that there is a high degree of model uncertainty concerning the FED's behaviour (for a detailed definition of different kinds of econometric uncertainty see for example Brock et al. (2007)). In looking for an adequate model for the FED's behaviour there is neither a functional form which could be preferred nor do we know what independent variables should be included. Choosing a certain model - even if this model shows the best fit among several possible models - leads to the neglect of all information of other models which may also be valid to a certain degree. Therefore, this approach of model selection would obviously lead to wrong inferences. In frequentist econometrics, model uncertainty can only be taken into account in some ad hoc approach, because frequentist econometrics does not provide a statistical foundation for model averaging. Forms of frequentist econometric model averaging exist as well (see, for instance, Hjort and Claeskens, 2003; Claeskens and Hjort, 2008, pp. 192-195), but it is only a Bayesian econometric approach which offers a solid foundation for model averaging.

Corresponding to the "Bayesian logic", model uncertainty can be considered by computing the probability (pr) of a quantity of interest Δ under the condition of some given data D, i. e. $pr\,(\Delta|D)$. In this way the probability of Δ does not rely on a certain model M with parameters θ_i (summarised in a vector θ). Therefore, the starting point of BMA (which was first considered by Leamer in 1978 but was developed mainly by Raftery et al. (1997) and Hoeting et al. (1999)) is the idea that the required posterior probability $pr\,(\Delta|D)$ can be calculated as follows (according to the rule of total probability):

$$pr\,(\Delta|D) = \sum_{r=1}^{R} pr\,(\Delta|M_r, D)\, pr\,(M_r|D) \tag{1}$$

Here M_r is an element of the model space $\mathcal{M}$, where $\mathcal{M}$ contains R models. To calculate this weighted average in (1), firstly the posterior probability distribution of the models M_r conditioned on the data D is needed. With Bayes' theorem (Bayes, 1763) these posterior probabilities of models M_r can be calculated in the following manner:

$$pr\,(M_r|D) = \frac{pr\,(D|M_r)\, pr\,(M_r)}{\sum_{l=1}^{R} pr\,(D|M_l)\, pr\,(M_l)} \tag{2}$$

In this equation, $pr\,(M_r)$, which is called the prior model probability, can be interpreted as the probability of M_r being the true model. $pr\,(D|M_r)$ is called integrated or marginal likelihood function of the model M_r. The posterior probability of Δ conditioned on the Model M_r and the data D in (1) is just calculated using "usual" Bayesian econometrics, i. e. estimation considering parameter uncertainty. It mainly depends on the specification of Δ.

In the case of identifying determinants of the FED's behaviour, we will work in a linear regression framework, which can be specified in the context of BMA (Koop, 2003, pp. 266-272). It is, therefore, assumed that there are K potential explanatory variables for a linear regression model which can explain the value of the (effective) Federal Funds Rate (represented by the vector y). $\mathcal{M}$ then contains $R = 2^K$ different models M_r, which are defined by their combination of regressors (k_r represents the number of regressors of model M_r). Thus, any model M_r is of the following format:

$$y = \alpha\iota + X_r\beta_r + \epsilon, \tag{3}$$

Here, y is a $N \times 1$ vector with observations of the dependent variable (e. g. the effective Federal Funds Rate), X_r is a $N \times k_r$ matrix with observations of the explanatory variables of the model M_r, α is a scalar, ι is a $N \times 1$ vector of ones, and β_r is a $k_r \times 1$ vector which contains the coefficients of the explanatory variables of the model M_r.

With regard to the prior distributions of the parameters, Koop (2003, pg. 269) recommends choosing $pr\left(\alpha\right) \propto 1$ and $pr\left(\sigma^{-2}\right) \propto \sigma^2$. Moreover, for $pr\left(\beta_r|\sigma^2\right)$, a normal distribution of the form $\mathcal{N}\left(0_{k_n}, \sigma^2\left(g_r X_r' X_r\right)^{-1}\right)$, which represents the most widely used g-prior (according to Zellner (1986)), is chosen. Fernández et al. (2001a) recommend the following values for g_r, which we also make use of in our estimations: $g_r = K^{-2}$ if $N \leq K^2$, and $g_r = N^{-1}$ if $N > K^2$. For the prior probability distribution of the models M_r over the model set $\mathcal{M}$, a uniform distribution is assumed.

Finally, it is worth looking closer at the quantity of interest Δ. In the case considered here, Δ should be some reference number describing the FED's behaviour. Usually, even if one is interested in $pr\left(\Delta|D\right)$ (here $pr\left(\Delta|y\right)$), this complete probability distribution is, on the whole, not calculated but some reference numbers in the form of expected values:

$$E\left(g\left(\Delta\right)|D\right) = \sum_{r=1}^{R} E\left(g\left(\Delta\right)|M_r, D\right) pr\left(M_r|D\right) \tag{4}$$

$g\left(\Delta\right)$ is an optional function depending on Δ and can, thus, take different formats. In our case of the FED's behaviour, $g\left(\Delta\right)$ is equal to the value of any possible regression coefficient β_i. Therefore, equation (4), formulated for every β_i, describes the posterior mean of the possible regression coefficient β_i:

$$E\left(\beta_i|y\right)=\sum_{r=1}^{R}E\left(\beta_i|M_r,y\right)pr\left(M_r|y\right) \tag{5}$$

With (5), one easily receives the fitted values of the model average $\hat{y}$ via $\hat{y}=X\cdot E\left(\beta|y\right)$, where X is the $N\times K$ matrix with observations of the possible explanatory variables, and β is the $K\times 1$ vector of the coefficients β_i of the explanatory variables. Hence, $E\left(\beta|y\right)$ represents the $K\times 1$ vector of the posterior means of all possible regression coefficients (see (5)).

With an increasing number of potential variables the model space $\mathcal{M}$ gets extremely large. Therefore, calculating the posterior model probability (see (2)) for every single model (needed for the summation in (1) or for calculating corresponding reference numbers like in (4)) can get problematic as every single model M_r would have to be evaluated. To manage this numeric problem of exhaustive summation, the concept of Markov Chain Monte Carlo Model Composition (MC^3) was developed to approximate the posterior model distribution. Therefore, instead of using (1) directly, all reference numbers in the form of expected values (see (4) and (5)) are calculated via the following approximation:

$$E\left(g\left(\Delta\right)|D\right)\approx\frac{1}{J-J_0}\sum_{j=J_0+1}^{J}E\left(g\left(\Delta\right)|M^{(j)},D\right) \tag{6}$$

Hence, the average of the J draws of the algorithm is calculated (neglecting a certain number of initial draws J_0). For $J-J_0\rightarrow\infty$ this average converges to $E\left(g\left(\Delta\right)|D\right)$.

BMA in a linear regression framework has previously been applied in other contexts. For instance, Bandiera et al. (2010) examined indicators of sovereign defaults (not in a linear regression but in a logit and probit framework). Fernández et al. (2001b) used BMA in cross country growth regressions. The studies of Wright (2008) and Masih et al. (2010) are methodologically very similar. Wright (2008) analysed influencing factors of exchange rates and Masih et al. (2010) examined determinants of returns on capital. However, central bank behaviour has not been investigated in a BMA framework until now.

4. Data

Before we apply the BMA approach to estimate the policy reaction functions, we have to specify the data set we use. We run three separate estimations. The first one looks at the period between 1960 and 2012. This estimation contains ten different explanatory variables. As in any Taylor rule, inflation ($infcpi$) and monthly output growth (y) are included. Since we want to estimate the FED's behaviour on a monthly basis, we need to use industrial production instead of GDP. To differentiate between different reasons of growth, productivity ($prod$) is also included. It is computed as the productivity in the durable goods sector. Hence, industrial production of durable goods is divided by the number of employees in this sector. Both, industrial production and productivity are computed as monthly percentage growth rates. The inflation rate is defined as the annual percentage change in the consumer price index. Moreover, we include the annual percentage change in the producer price index ($infppi$) and the monthly percentage change in spot oil prices (West Texas Intermediate) (oil) to account for cost-push inflation. Furthermore, the civilian unemployment rate (un) is included as this is one of the target variables of the FED according to the Federal Reserve Act. In addition, we also use the yearly percentage change in broad money ($m3$), the monthly percentage change in net trade of goods (nx), as a proxy for the current account, the monthly percentage change in stock prices ($stock$), and a long-term interest rate (il), as measured by the ten-year government bonds rate. For the stock prices, we use the S&P 500 Stock Price Index. The variable for growth in the stock price index is lagged by six months. The problem is that the stock market reacts immediately after a change in monetary policy. Due to this simultaneous response (Rigobon and Sack, 2003), it is better to use a lagged variable. Furthermore, stock prices are a good leading indicator for GDP especially for one to three quarterly periods (Estrella and Mishkin, 1998).

The second estimation focuses on the post-Bretton Woods period (1973-2012). It also contains variables for the monthly percentage change in the exchange rate (ex) and the federal debt (def). The federal deficit is computed as a moving average of the changes of quarterly deficits. The exchange rate represents a trade-weighted (nominal) US Dollar index versus main trading partners (direct quote).

The third estimation covers the period after the so-called monetarist experiment[5] from 1982 to 2013. A further aim of this estimation is to show estimation results using real time data. Thus, this data set includes vintage data sets for M2 ($m2$, instead of M3), unemployment rates, yearly percentage changes in consumer and producer price indices, and monthly percentage changes in industrial production. Due to the non-availability of real time data for a general producer price index for this period, this estimation uses the producer price index for finished goods. The data for exchange rates, oil prices, stock prices, and long-term interest rates are the same as in the first two estimations as there are no revisions in those time series. Productivity, federal deficits, and net exports are not included in this estimation as there is no real time data available for this period. While it is possible to get real time data for the latter estimation, it is not possible to get vintage data for the longest period of our estimation. Nonetheless, we present all estimations in this article as a further estimation with non-real time data for the 1982-2013 period shows that there are only minor differences between real time and non real time estimations. Furthermore, the differences between vintage and non vintage data are small for all of our estimations. For instance, the correlation coefficient between the industrial production growth rate using real time and non real time data is above 0.8 for the period between 1960 and 2012. The correlation coefficient between the real time and non real time unemployment and inflation rates is in each case around 0.99. Thus, it seems reasonable to present the results of the longer estimation to show the influence of different variables over the long run.

The dependent variable in all estimations is the effective Federal Funds Rate (EFFR). In comparison to the Federal Funds Target Rate, the EFFR has the advantage that it is a continuous variable and our estimation procedure requires a metric measurement level. Furthermore, the FED sometimes used target bands and changed interest rates several times a month in the early years of its history. Finally, the EFFR and the Target Rate are very similar; the correlation coefficient between these two time series is 0.98 from 1971 to 2013. All this justifies the use of the EFFR in our estimation.

All data with the exception of M3, net trade, and long-term interest rates are taken from the Federal Reserve Economic Data (FRED) of the Federal

[5] Goodfriend and King (2005) argue that the FED did not conduct monetary targeting but used increases in interest rates to squeeze out inflation. Thus, it is controversial to call this period the "monetarist experiment".

Reserve Bank of St. Louis. The other three time series are taken from the OECD. We analysed the characteristics of all time series. Whilst most of them seem to be stationary, interest rates and inflation rates might have a unit root for certain time periods. This, however, is not a problem for our analysis as a Bayesian estimation framework does not require time series to be stationary in order to get meaningful results (Sims, 1988). We also tested for causality comparing the correlation between different leads and lags of the EFFR and the explanatory variables. The correlation coefficients are either not significantly different from zero or not significantly different for leads and lags. Hence, we can reject the hypothesis that the effect goes from the EFFR to the explanatory variables and not the other way around. In addition, we know that the transmission of monetary policy comes into effect with a certain time lag. This justifies the use of these data in our study.

5. Results

Using the BMS Toolbox (developed by Feldkircher and Zeugner (2009)), different aspects of the FED's behaviour can be analysed.[6] Our first aim is to identify the variables which are of relevance for reactions of the FED. Hence, for each possible explanatory variable the posterior inclusion probability (PIP) is calculated. It can, in general, be interpreted as the probability that this variable is part of the "true" model. It is calculated as the proportion of models accepted by the MC^3 algorithm which contain this explanatory variable in relation to all models drawn by the MC^3 algorithm. From this figure, one can infer how important the corresponding explanatory variable is for the investigated process. In our case it can therefore be interpreted as the probability that a certain variable will be incorporated in the FED's decisions.

In addition, the posterior means of all possible regression coefficients (Post. Mean) are computed according to (5) (using (6)). Since not every model contains all possible explanatory variables, coefficients of variables which are not part of the corresponding model are set to zero. The posterior standard deviation (Post. SD) of each regression coefficient is computed as:

$$StD\left(\beta_i|D\right) = \sqrt{Var\left(\beta_i|D\right)} = \sqrt{E\left(\beta_i^2|D\right) - \left(E\left(\beta_i|D\right)\right)^2} \qquad (7)$$

[6] General statistics of the estimations run with this toolbox can be found in the Appendix (Table A.5).

Furthermore, the relative frequency with which an estimated parameter enters into a regression model with a positive sign (conditional on inclusion) is derived. This number is called conditional positive sign (Cond. Pos. Sign).

Table 1 shows these figures for the sample January 1960 until September 2012 while Table 2 shows the same for the shorter sample beginning in January 1982.[7]

Variable	PIP	Post. Mean	Post. SD	Cond. Pos. Sign
$infcpi$	1.0	0.3294	0.02225	1.0
un	1.0	-0.5377	0.03027	0
il	1.0	1.025	0.02364	1.0
$m3$	0.1397	0.003833	0.0113	1.0
y	0.09316	-0.008036	0.03162	0
$prod$	0.07149	-0.001931	0.009456	0
$stock$	0.05946	0.000622	0.003606	1.0
oil	0.05283	0.0002423	0.001627	1.0
nx	0.04386	$3.335 \cdot 10^{-6}$	$3.432 \cdot 10^{-5}$	1.0
$infppi$	0.0419	0.00018	0.003557	0.9967

Table 1: MC^3 results (sample 1960:01-2012:09)

Obviously, the inflation rate $infcpi$, the unemployment rate un and long-term interest rates il seem to have crucial influence on the FED's decisions as they always enter into the FED's reaction function. The difference in the PIP between the top three variables and the remaining seven in the long sample is drastic. M3 has a PIP of 0.14, while the other variables do not even reach a PIP of 0.10 (in the long sample). Whilst in the long time-series only those three variables are of major relevance, the other samples include two further variables with relatively high PIPs: the federal deficit and M2. Fiscal deficits are only included in the sample from 1973 to 2012 because there are no data on federal deficits for the long sample. In the 1973-2013 sample, the federal deficit is highly relevant (PIP of 0.93). In the sample from 1982 to 2013, the long-term interest rate, the unemployment rate, and

[7]The MC^3 results of the sample from 1973 to 2012 are reported in the Appendix (Table A.6).

M2 have a PIP of 1. This is a surprising result as the FED declared in 1982 that it does not rely on monetary aggregates any more. Comparing the results of the respective samples reveals that most variables' PIPs only change marginally with respect to different estimation periods. The variable for money growth, however, gets more important the shorter the estimation period is. The impact of both stock prices and industrial production increases in the shorter estimation sets, too. Industrial production is, however, more important in the period between 1973 to 2012 than in the sample from 1982 to 2013.

Variable	**PIP**	**Post. Mean**	**Post. SD**	**Cond. Pos. Sign**
il	1.0	0.986	0.03038	1.0
$m2$	1.0	0.1309	0.01982	1.0
un	1.0	-0.446	0.03216	0
$infcpi$	0.9584	0.2643	0.07521	1.0
$stock$	0.315	0.007438	0.01267	1.0
y	0.1052	-0.01186	0.04524	0
$infppi$	0.09055	0.005243	0.02428	1.0
ex	0.05204	-0.0006777	0.009651	0.008148
oil	0.04947	$3.532 \cdot 10^{-5}$	0.00141	0.9112

Table 2: MC^3 results (sample 1982:01-2013:03)

The Post. Means of all possible regression coefficients and the conditional positive sign give information about the magnitude and the direction of the influence of the variables on the FED's behaviour. We first analyse the longest sample. Rising inflation and long-term interest rates both lead to increasing interest rates as their conditional positive sign is 1.0. The conditional positive sign of unemployment is 0 which means that this variable always has a negative sign in the reaction functions. The Post. Mean can be interpreted as follows: an increase in inflation by one percentage point leads to an increase in the EFFR of 0.3294. The effect for long-term interest rates is even larger. The sign of this coefficient makes sense assuming that the increase in the nominal long-term interest rates is caused by rising inflation expectations. Thus, the FED tries to reduce inflation expectations by increasing short-term interest rates. The mean coefficient of unemployment is -0.5377. To sum up, the FED reacts to increasing inflation and long-term interest rates with contractionary monetary policy while an increase in the unemployment rate leads the FED to react with expansionary monetary policy. This shows that the FED acts exactly in line with the goals mentioned in the Federal Reserve Act.

Furthermore, rising oil prices lead the FED to increase interest rates. However, the mean coefficient is relatively low in the first sample (0.0002). This means that the FED reacts to supply side shocks with contractionary monetary policy albeit to a minor extent. The signs of most of the other coefficients are in line with the arguments mentioned above. In theory, the effect of productivity on the FED's decisions is unclear. The sample shows that productivity has a negative impact on the Federal Funds Rate. This means that the FED seems to put more emphasis on price stability than on output stabilisation.[8] Moreover, the FED seems to balance out the current account because it raises interest rates when net trade increases. However, the Post. Mean of the coefficient is extremely low in the first sample, in which it was almost not important at all according to the PIP. Producer price inflation is the least important variable in the long sample. According to the conditional positive sign, it does not always enter into the reaction functions with a positive sign. There remains one contradictory result (considering the theoretical arguments): the monthly change in industrial production has a negative Post. Mean. However, this puzzle can be solved when the Post. SDs of the coefficients are taken into consideration. The Post. SD for industrial production is larger than the corresponding Post. Mean. Thus, the "true" coefficient could also be zero meaning that this variable does not have any impact on the FED's decisions. This is also evident from the low PIP of this variable.[9] However, it is true for all variables with the exception of the most influential ones that the Post. SD exceeds the Post. Mean. In the first

[8]This result is contrary to the findings of Galí et al. (2003) but in line with Greenspan (2004) who argued that the FED was "able to be much more accommodative to the rise in economic growth than [...] past experiences would have deemed prudent" especially in the nineties.

[9]Another explanation for the unexpected sign of industrial production might be the problem for central bankers to understand the reason for GDP growth: large GDP growth does not necessarily require contractionary monetary policy if it is caused by productivity growth.

sample, the Post. SD is larger than the Post. Mean for all variables except the three variables with a PIP of 1.0 ($infcpi$, un, and il).

The sample from 1973 to 2012 was used in order to get an impression of the impact of federal deficits and exchange rates on the FED's behaviour. Most interestingly, higher federal deficits result in lower interest rates. One percentage point increase in the change of the federal deficit leads to a decrease in the Federal Funds Rate by 0.4977 on average. This shows that the FED does in fact support the federal government in times of increasing deficits. One reason for that could be that the FED wants to prevent a crowding out of private loans. According to the estimation, the FED reacts to a depreciation of the dollar against other currencies with increasing interest rates. This is also what one would expect from the theory.

In addition, we ran two estimations for the period from 1982 to 2013. In order to get an impression of possible differences between real time and non-real time data estimations, one estimation used vintage data, the other one revised data. For the purpose of clarity, only the results of the estimation using real time data are reported here (Table 2) as both estimations are very similar. The most important variables in this estimation all have the right sign with respect to the theoretical assumptions. An increase in the long-term interest rate or in the yearly percentage change of M2 by one percentage point leads the FED to increase the Federal Funds Rate by 0.9860 or 0.1309, respectively. There is one major change with respect to exchange rates. Whilst exchange rates had a positive conditional positive sign in the sample from 1973 to 2012, they now enter into the reaction functions in most cases with a negative sign. Thus, the FED mostly reacts to a depreciation of the dollar with expansionary monetary policy.[10] The variable for changes in the stock market index is more relevant in this short sample. Both the PIP and the Post. Mean are larger than in the longest sample. This can be explained by the fact that there were three major stock market crises after 1982. The coefficients of the other variables change only slightly.

We do not only look at single explanatory variables but we also use the BMA framework to compare all models of our linear regression model space

[10]The negative coefficient of exchange rates might be explained by the fact that they change in expectation of changing interest rates. This is especially true, if the FED gives information about its future behaviour. Since the FED is highly transparent in their decisions, it is reasonable to assume that exchange rates change in advance, too.

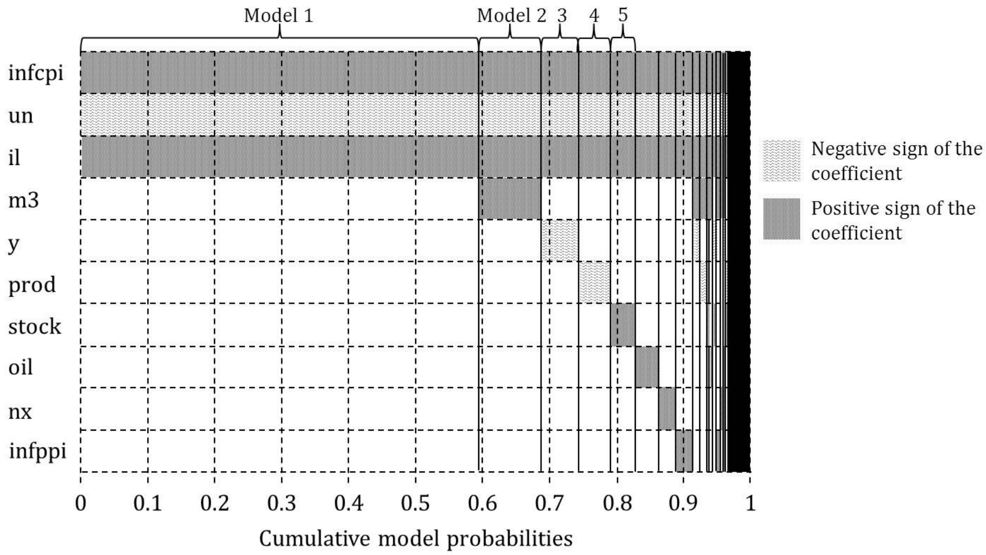

Figure 1: “Model ranking“ (sample 1960:01-2012:09)

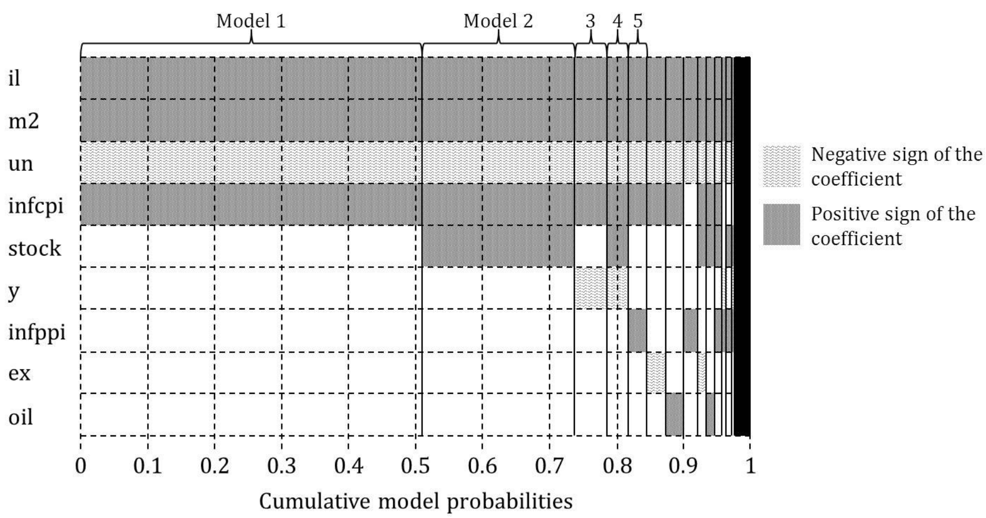

Figure 2: “Model ranking“ (sample 1982:01-2013:03)

to identify those models that achieve the best fit in describing what the FED actually did. Figures 1 and 2 show graphically (for the two different samples) the estimated models ordered by their posterior model probability (see equation 2): the horizontal axes show the cumulative (posterior) model probabilities while one can find the explanatory variables of a specific model on the vertical axes (where the variables are ordered by their PIP). The coloured boxes mark the variables included in a certain model, where variables entering with a positive (negative) coefficient are coloured in dark (light) grey.

The posterior expected model size (i. e. the mean number of regressors included in a model describing the FED's behaviour) for the 1960-2012 sample is 3.5024 whereas it is 4.5706 for the 1982-2013 sample. Looking closer at the most meaningful models (i. e. those models with the highest posterior probabilities), one has to notice that the five most relevant models only cover about 83% (in the 1960-2013 sample) and 85% (in the 1982-2012 sample) of the total posterior model probability. That means that selecting one single model - even if it is the best model according to its Bayesian posterior model probability - implies neglecting a lot of information. This motivates the approach of BMA, whose aim is not to select a single model but to average over all possible models (weighted by their probability of being the true model) to receive a kind of uncertainty model which does not neglect any information by disregarding less efficient models.

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
$infcpi$	0.3309	0.3286	0.3246	0.3272	0.3324
un	-0.5369	-0.544	-0.5387	-0.5335	-0.5367
il	1.025	1.022	1.028	1.026	1.023
$m3$	0	0.02663	0	0	0
y	0	0	-0.08209	0	0
$prod$	0	0	0	-0.02732	0
$stock$	0	0	0	0	0.01026
oil	0	0	0	0	0
nx	0	0	0	0	0
$infppi$	0	0	0	0	0

Table 3: Top-5 models - Posterior mean of the estimated coefficients (sample 1960:01-2012:09)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
il	0.9821	0.9798	0.9864	0.9853	0.9918
$m2$	0.1305	0.1333	0.128	0.1303	0.1306
un	−0.4454	−0.4446	−0.4444	−0.443	−0.4478
$infcpi$	0.2773	0.2796	0.2685	0.268	0.2466
$stock$	0	0.02333	0	0.02594	0
y	0	0	−0.09293	−0.1248	0
$infppi$	0	0	0	0	0.01555
ex	0	0	0	0	0
oil	0	0	0	0	0

Table 4: Top-5 Models - Posterior mean of the estimated coefficients (sample 1982:01-2013:03)

Tables 3 and 4 show in detail which variables are included in the five most relevant models and what their estimated coefficients (i. e. the Post. Means of the coefficients) are in these models. The variables are ordered by their posterior inclusion probabilities. The best model for the longer sample includes inflation, unemployment, and long-term interest rates. Since they all have a PIP of 1.0, they appear in any reaction function. The coefficients of these three variables in the best (i. e. most likely) model are relatively similar to the average Post. Means presented in Table 1. The Posterior Model Probability (PMP) of that model is 0.5961. Accordingly, around 60% of the FED's behaviour can be explained by this specific model. This is also evident from Figure 1 (looking at the cumulative model probability). The estimated Post. Means of the coefficients of the three most relevant variables are relatively stable. The main difference between the 1960-2012 and the 1973-2012 estimation is that in the latter case each of the best five models consists of consumer price inflation, unemployment rates, long-term interest rates, and federal deficits.[11] A different picture is shown in the 1982-2013 sample. The best model contains four variables: inflation, unemployment rates, long-term interest rates, and M2. In comparison to the longer sample, the best model can explain about 51% of the FED's behaviour. There are again only minor differences in the Post. Means of the coefficients between

[11] The top-5 models of this sample are reported in the Appendix (Table A.7).

the five best models. Finally, it has to be emphasised that we only could find the best fitting models looking at the posterior model probabilities computed by the BMA approach.

The final step is to construct the Bayesian model average for the two samples. Figures 3 and 4 show the fitted values of the two estimated model averages. The grey lines show the actual values of the EFFR. The dashed line shows the respective Bayesian model average. Furthermore, we ran a separate OLS regression to get estimates for a Taylor rule. For this purpose, we took consumer price inflation and industrial production growth rates as independent variables. The dotted line shows the fitted values of the Taylor rule.

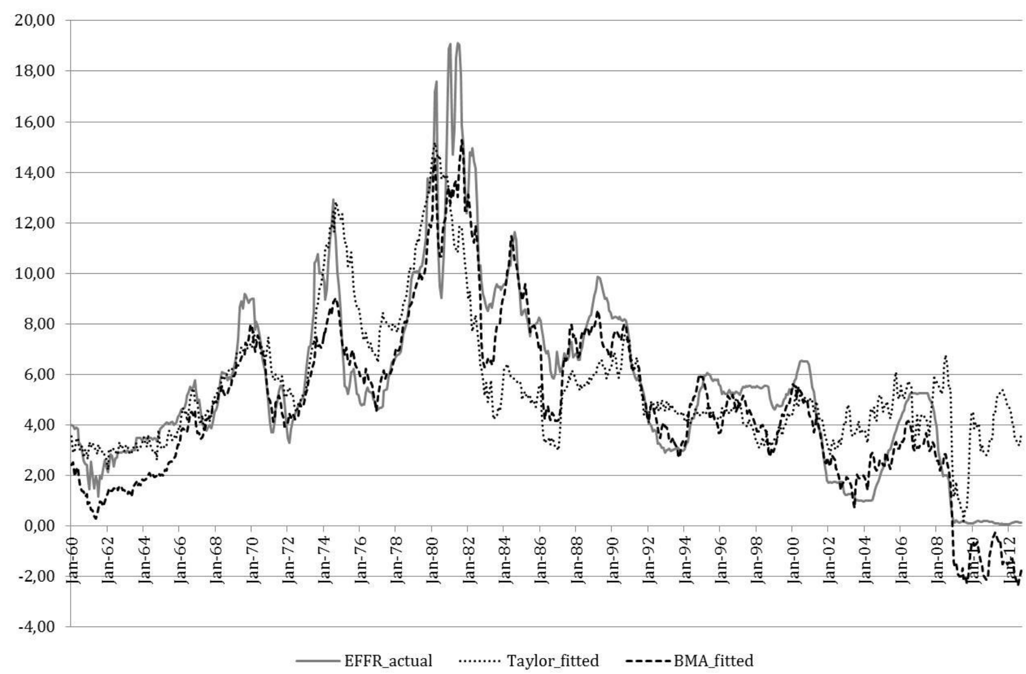

Figure 3: Actual vs. fitted values (sample 1960:01-2012:09)

At first glance, the BMA estimation performs very well. In most cases it can trace the general movement in the Federal Funds Rate. Some puzzles remain, however. Between 1960 and 1967 the estimated Federal Funds Rate is always one to two percentage points below the actual Funds Rate. The second oil price shock 1979/1980 made it much more difficult to predict the

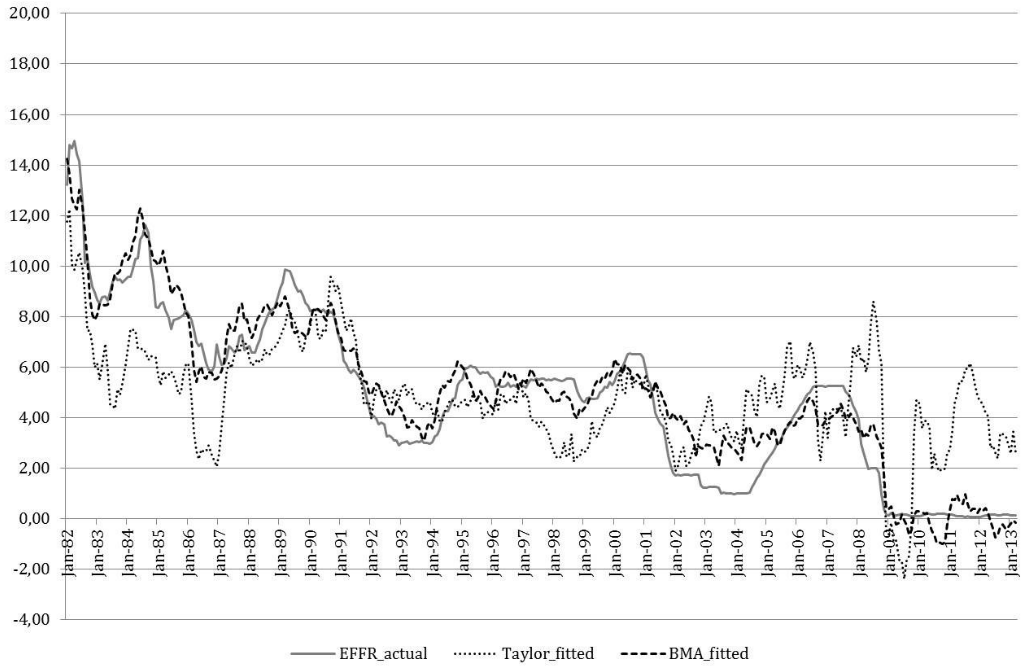

Figure 4: Actual vs. fitted values (sample 1982:01-2013:03)

FED's decisions. Moreover, Paul Volcker tried to squeeze out inflation conducting contractionary monetary policy. As the focus was more on monetary aggregates, interest rates and also the Federal Funds Rate were much more volatile than in other periods.[12] This is in line with the study of Boivin and Giannoni (2006) who find that the FED responded more strongly to increases in inflation during the eighties. After the oil price shock, there remain two further large discrepancies in the eighties: one in 1983[13] and the other one in 1986. In both cases, the EFFR was underestimated. After 1995 the Funds Rate was relatively stable, while the model average predicted more fluctu-

[12]This can be explained by the fact that the FED did not set explicit targets for the Federal Funds Rate after October 1979. This situation lasted until 1982 when Volcker declared that the FED does not rely on monetary aggregates any more. Cook (1989) finds evidence that the Federal Funds Rate during the Volcker era was driven to some extent by market forces and not by the FED's decisions.

[13]This could be explained to some extent by the implementation of the contemporaneous reserve accounting system (CRA) which leads to a larger volatility in the Federal Funds Rate (Lasser, 1992).

ations. The model average performs relatively well after the burst of the New Economy bubble in 2000 until 2006. Then the Federal Funds Rate was higher than predicted. After the financial crises the estimated values of the model average are below the zero-bound. While this is not possible, we did not use any different estimator in explaining the FED's decision to solve that problem. McGough et al. (2005) argue that the FED could use long-term interest rates as their policy instruments. Thus, ten-year government bond yields could be a proxy for the Federal Funds Rate with no zero-bound. However, this proposal is rejected by Woodford (2005) who criticises that this approach is impractical. We also believe that it is most appropriate to use short-term interest rates even though they have a zero lower bound. Furthermore, the figure shows the estimates of a simple Taylor rule. The model average outperforms the Taylor rule with some exceptions. The Taylor rule outperforms the model average at the very beginning of the time series. Between 1973 and 1975, the residuals of the model average are large while the Taylor rule traces the FED's decisions better. The overall fit of the model average is good. The R-squared of the model average from the first sample is 0.8454. Thus, 84.54% of the variation in the Federal Funds Rate can be explained by our model average. The Taylor rule, on the other hand, can explain only 55.30% of the variation in the EFFR. Accordingly, the model average outperforms the Taylor rule significantly. This is also evident from the Root Mean Square Errors (RMSE) of both estimations. The Taylor rule has a RMSE of 2.3557 while the RMSE of the model average is only 1.3852.

The fit of the estimates of the model average in the 1982-2013 sample is even better although there are some discrepancies, too. The fit of the Taylor rule is worse than in the previous estimation. The residuals of the Taylor rule are especially large in the years between 1983 and 1987. The difference between the estimates of the Taylor rule and the actual values is again large between 1997 and 2000. The performance of the Taylor rule is even worse in the years after 2002 in comparison to the previous estimation. Not only the residuals of the Taylor rule are large but it also does not predict changes in the FED's decisions correctly. The fit of the BMA estimates of the 1982-2013 sample is even better with an R-squared of 0.9025. The Taylor rule, on the other hand, reaches an R-squared of only 0.4139. The RMSE confirms the result that the model average outperforms the Taylor rule significantly. The RMSE of the model average is 1.0014 while it is 2.4562 for the Taylor rule.

Finally, it has to be emphasised that the estimated values do not reflect optimal decisions. They merely show the fit of the respective model. Over-or underestimations cannot be interpreted as periods in which the monetary policy was too contractionary or too expansionary. Moreover, the deviations of the estimates from the actual Federal Funds Rate may also be explained by changes in preferences of the FED. Ball (1995) and Tootell (1999) show that the preferences or goals followed by the FED changed over time. This explains why it is much more difficult to have a good fit over the long-run since there were regime changes. From 1960 to 2012, there were six different chairmen of the FED. The 1982 - 2013 sample refers to three different chairmanships. However, it is not only the chairman who decides on monetary policy. Thus, changes in the composition of the Board of Governors may be important as well. Furthermore, members of the Broad of Governors might change their attitudes over time.

6. Conclusion

The first aim of this study was to identify those variables which are of major importance for the FED's decisions. This study applied the approach of Bayesian Model Averaging to solve the problem of model uncertainty. Over the long-run, inflation, unemployment rates, and long-term interest rates are the crucial variables in explaining the Federal Funds Rate. This is in line with the goals defined in the Federal Reserve Act. In the estimation period from 1973 to 2012, federal deficits were also of relevance in addition to the previously mentioned variables. In the shortest sample, long-term interest rates, M2, unemployment rates, and consumer price inflation are the most relevant variables for the FED's decisions. Thus, the FED increases interest rates when inflation, long-term interest rates, and the volume of money go up. On the other hand, it lowers interest rates if unemployment rates and federal deficits increase.

We used the BMA framework to select the models with the best fit. The best model in the long sample consists of inflation, unemployment rates, and long-term interest rates. Those variables are part of each of the top 2000 models. In the sample from 1973 to 2012, also the federal deficit is included in the five best models. In the 1982-2013 sample, inflation, unemployment rates, long-term interest rates, and M2 are part of the best model. This demonstrates that the FED does not only rely on their three main targets but also on other variables.

Finally, a model average was constructed via BMA. The fit of the estimated values is very good. The model average substantially outperforms a simple Taylor rule. All in all, Bayesian Model Averaging proved to be a useful approach in such cases where there is at least some degree of model uncertainty. With a solid foundation in Bayesian econometrics it allows to draw inferences about the importance of potential explanatory variables and, in the end, leads to an average of a large number of models which includes all information with optimal weights.

The topic considered in this study offers the opportunity for further research, for example, on structural breaks or changes in the decision makers' preferences. A further approach would be to estimate a dynamic reaction function considering interest rate smoothing. It would also be interesting to have similar studies for other central banks in order to compare their behaviour with that of the FED.

AppendixA. Further Statistics

	Sample 1960:01-2012:09	Sample 1973:02-2012:09	Sample 1982:01-2013:03 rtd*
MC^3 draws	$1.0 \cdot 10^6$	$1.0 \cdot 10^6$	$1.0 \cdot 10^6$
MC^3 burn-ins	$1.0 \cdot 10^5$	$1.0 \cdot 10^5$	$1.0 \cdot 10^5$
Mean number of regressors	3.50	5.56	4.57 (4.47)
Number of models visited (number of times a model was accepted including burn-ins)	110701	281606	148162 (127745)
Number of possible regressors	10	12	9
Model space	1024	4096	512
Number of observations	633	476	375

* Corresponding values of the non rtd sample are given in brackets.

Table A.5: General statistics of the BMA estimation

Variable	**PIP**	**Post. Mean**	**Post. SD**	**Cond. Pos. Sign**
infcpi	1.0	0.3372	0.0279	1.0
un	1.0	−0.4488	0.04903	0
il	1.0	1.057	0.02759	1.0
def	0.9336	−0.4977	0.2026	0
*m*3	0.5569	0.02962	0.03061	1.0
y	0.4202	−0.08163	0.1098	0
nx	0.2893	0.0002756	0.0004965	1.0
stock	0.1025	0.001709	0.006507	1.0
ex	0.06797	0.002849	0.01577	1.0
prod	0.0675	−0.001865	0.01185	0.02461
infppi	0.06253	0.001012	0.006423	0.9996
oil	0.05994	0.0003068	0.001889	1.0

Table A.6: MC^3 results (sample 1973:02-2012:09)

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
infcpi	0.3494	0.3419	0.3281	0.3374	0.3261
un	−0.4385	−0.4578	−0.4493	−0.4294	−0.4442
il	1.056	1.05	1.061	1.067	1.064
def	−0.4904	−0.5056	−0.584	−0.5609	−0.5886
*m*3	0	0.05061	0.05456	0	0.05555
y	0	0	−0.1968	−0.1799	−0.2032
nx	0	0	0	0	0.0009817
stock	0	0	0	0	0
ex	0	0	0	0	0
prod	0	0	0	0	0
infppi	0	0	0	0	0
oil	0	0	0	0	0

Table A.7: Top-5 models - Posterior mean of the estimated coefficients (sample 1973:02-2012:09)

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