Judging the DSGE Model by Its Forecast

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Abstract

We study the forecasting ability of the standard estimated medium scale dynamic stochastic general equilibrium model. We show that although the model forecasts have lower root mean squared error compared to judgmental and statistical forecasts, the absolute forecasting ability is very poor. We argue that average forecasting ability during the Great Moderation is not a good metric to judge a model's validity. We then offer alternative ways of using forecasts to judge the model. Importantly, we also highlight the importance of data and sample choices in the model's forecasting ability. With the proper data treatment and choice of sample period when macroeconomic aggregates were indeed forecastable (pre-Great Moderation) the model provides a good forecasting performance.

---PRELIMINARY AND INCOMPLETE, DO NOT CITE---

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1. Introduction

The forecasting performance of the DSGE models has been an issue of considerable interest to policymakers and researchers alike. This interest has two facets: An interest in the forecasting ability of DSGE models *per se* given the possibility of using such models for forecasting at policy institutions and an interest in the forecasting ability of DSGE models as a way to validate (or invalidate) the model itself. In this paper we argue that these two questions are fundamentally different and in particular on the second issue that the model's forecasting ability – particularly, over some sample periods – need not necessarily tell us anything about the empirical validity of the model. We then offer different ways of addressing this issue.

The use of a model's forecasting performance to make inferences about its empirical relevance dates back at least to the influential paper of Atkeson and Ohanian (2001) who documented the inability of Phillips curve models to outperform simple random walk forecasts and thus called into question the ability of New Keynesian models to explain inflation data well. The analysis of forecast performance has also been used extensively in the DSGE modeling literature. Smets and Wouters (2007), most notably, documented the competitive forecasting performance of their richly-specified DSGE model relative to respective alternative models (specifically, Bayesian VAR models) and dramatically altered consensus opinion about the empirical relevance of DSGE models. Subsequently, for central bank modeling teams evaluating the DSGE models that they have developed for practical use, establishing the competitive forecast performance of these models has become standard practice. Associated with this, the benchmark against which DSGE model forecasts are evaluated has also broadened so as to include also official staff or committee macroeconomic forecasts. In addition, the use of real-time data in this literature has become quite common. Overwhelmingly, this literature has found favorable results for DSGE model, in that in all cases DSGE models have been found to be competitive with alternative models, including official forecasts.

While previous research documented the competitive *relative* forecast performance of DSGE models, Edge and Gürkaynak (2010) also examined *absolute* forecast performance – in this case using the Smets and Wouters (2007) model – and here found more discouraging results. In particular, whereas relative forecasting performance of the DSGE model was found to be competitive, the absolute forecasting performance was found to be very poor. Ultimately, however, this should not have been surprising given the sample period for evaluating forecast performance. In particular – like all DSGE-model research on forecast performance – Edge and Gürkaynak's analysis was undertaken over the Great Moderation period, which is a period that (following Stock and Watson, 2007) is now well-known to be characterized by a lack of persistent fluctuations in the data generating process. Given this feature of the data and the fact there is very little to be forecasted in this period, making inferences about the empirical validity of a model based on its forecasting performance is not a well-grounded exercise. This point is especially valid for inflation, usually one of the key variables of interest in forecasting exercises.

The fact that DSGE-model forecast performance analysis on Great Moderation data is not amenable to any interpretation regarding the validity of the underlying model was pointed out by Edge and Gürkaynak (2010). However, Edge and Gürkaynak did not pursue the question that immediately follows this observation – and that we pick-up in this paper – which is the question of whether there are way of using the forecasting ability of the model to assess the model itself. An obvious exercise in this vein is to study the DSGE-model forecast performance prior to the Great Moderation, when macroeconomic aggregates were known to be persistently varying and to at least have the potential to be forecast by a model. We do that and more in this paper.

Extending our sample period back to before the Great Moderation – in particular, the early 1970s – presents one significant constraint on our analysis, which is the absence of real-time data. Thus, for our forecast-performance analysis in the period prior to the Great Moderation we have no choice but to conduct our analysis using current vintage data. This switch to current vintage data means that the forecast-performance results from Edge and Gürkaynak, which were undertaken entirely on real-time data, will not be directly comparable with those that we will generate on earlier periods of data. Thus, to ensure the comparability of our results in the Great Moderation and pre-Great

Moderation forecast evaluation periods we first revisit the results of Edge and Gürkaynak and compare the out of sample forecasting performance of the model using real time and current vintage data for the period both are available. We find the difference to be very minor, a contribution that will help future researchers who da not have easy access to real time data.

Revisiting the results of Edge and Gürkaynak so as to use current vintage rather than real-time data is not a wholly straightforward exercise, in as much as more than just the data upon which the model is estimated ends up changing. For example, in Edge and Gürkaynak forecasts generated by the DSGE model (estimated in real-time) were compared with the first-final release of the data series in question. Clearly, this is no longer possible, or sensible, when the model is estimated on current vintage data; indeed in this case it is realizations of the current vintage of data that are the appropriate point of comparison. Since the model's forecast performance over the Great Moderation sample used in Edge and Gürkaynak forms the basis of our subsequent comparisons (with pre-Great Moderation forecast results), understanding how and why these results differ from those in Edge and Gürkaynak on real-time data is important. Consequently, Appendix A (to be included) shows how the forecast performance of the DSGE model changes when the analysis moves to use current vintage data and, in particular, documents each necessary increment of this change. Section two of the paper reports only the highlights of these results.

There is, however, one notable and deliberate change that we make from Edge and Gürkaynak that is not the result of our move to work with current vintage. Rather, this change is motivated by a data issue with Edge and Gürkaynak (2010) that came to light only quite late in the course of writing that paper and thus could not be changed in time for that paper's publication. In particular, as noted previously, Edge and Gurkaynak undertake all of their DSGE model forecast analysis using the Smets and Wouters (2007) model and following as closely possible all of the assumptions and the data definitions used by these authors.[1] This includes using the population series used by Smets and Wouters, that Edge and Gürkaynak subsequently found to be problematic. As explained in section two, the series is calculated on a "best levels" basis, which results in some very large jumps and drops in the series that we know is not a true feature of the data. In this paper we use a smoothed population series, which is much closer to the true population series. Interestingly – and as we discuss in section two – we find that using a more appropriate population series does improve the model's forecasting performance of real GDP growth.

The main part of our analysis begins in section three. In particular, after establishing that Edge and Gürkaynak's main result of poor absolute forecasting performance of our

[1] The Smets and Wouters model is used in Edge and Gürkaynak – as well as in our analysis – in preference to the other variants of Bayesian estimated DSGE models in existence, such as Edge et al (2010) and Gali et al(200x), which are extensions on the canonical Smets and Wouters model. These latter models add more features to the Smets and Wouters model but do not qualitatively change the model's forecasting performance. Consequently, we focus on the benchmark Smets and Wouters model, which is well known and well understood and abstract from the more recent variants of the model, which do not have a material effect on our broad conclusions.

DSGE model holds true also in current-vintage data, we turn to consider the model's forecasting performance prior to the Great Moderation. The results for this exercise are given in section 3. In particular, we document better absolute forecasting performance of our DSGE model in the pre-Great Moderation period.

Having documented better absolute forecasting performance in the pre-Great Moderation period – in contrast to the poor absolute performance in the Great Moderation – we then turn in section four [to be added] to consider whether reduced forecast performance with the Great Moderation is an outcome that the DSGE model would predict given the data upon which it is estimated. In particular, for each estimated version of the model (of which, given 37 years of data, there are about 150), we simulate multiple realizations of data from the model as well as a forecast and evaluate forecast performance. Effectively, this lets us test whether the model's forecasting performance of true data in different subsamples is in line with the model implication of what its forecasting ability should be.

2. Data and sample periods

As noted above, Edge and Gürkaynak use real-time data for all of their analysis, where as in this paper we use current vintage data. As a result, a requisite step in our analysis is to verify that the results obtained by Edge and Gürkaynak using real-time data hold true when current vintage data (over the same sample period) are instead used. Another important initial step in our analysis is to correct for the population series that is used in the estimation of the model. Indeed, we make this change to the data and analysis first.

Many of the observable variables that are used to estimate the Smets and Wouters model enter the model in normalized per capita value form, which means that the level of population shows up in many parts of the model. The published US population series, shown in Figure 1, is calculated on a "best levels" basis. That is, when new information about population becomes available – such as with decennial censuses – the population in the census year (and thereafter) is adjusted in line with the new data but population in preceding years is not. This leads to very sharp – and implausible – jumps in the population series, which in – reality is quite smooth. Figure 1 shows a large number of such jumps, while a smoothed series – which is taken from the Federal Reserve Board's US (FRB/US) model – displays the expected gentle low frequency movements in population growth.

Population in the model is important in two aspects, first because the variables entering estimation are normalized by the series, second because the resulting per capita GDP growth forecast of the model is then multiplied with the population growth number to make it compatible with the released aggregate GDP growth number and with other forecasts. The erratic population growth series damages the model in both dimensions.

A natural first instinct is to use the smooth the population series for all purposes in estimation of the model and generation of the forecasts. This, however, does not wholly solve the problem. Another key ingredient of the model, the employment series, shown in Figure 2, has similar methodology issues to the population series and thus also exhibits similarly erratic behavior.[2] While population growth can safely be thought of as a very smooth series and can therefore be smoothed as shown in Figure 1, a similar smoothing procedure would change the cyclical properties of the employment series. Importantly, employment never appears alone in the model; what matters is the employment rate, that is employment divided by population. Having one of the series smoothed and the other one unsmoothed leads to a very erratic employment rate which significantly hurts the model fit and forecast performance.

We therefore choose to use the un-smoothed population series when normalizing employment, leading to a smoothed employment rate, and using smoothed population when normalizing other variables such as consumption, investment, and GDP, leading to conceptually appropriate data series used in estimation. Importantly we also use the smoothed population series when we convert the per capita GDP growth forecasts into aggregate GDP growth forecasts.

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[2] Note that this erratic behavior is a feature of the employment series reported in the Employment Report's household survey. The employment series taken from the Employment Report's establishment survey does not exhibit these jumps and neither does the employment series reported in the Labor Productivity and Costs release. However, it is the household survey employment series that Smets and Wouters used in their paper and , so as to follow their methodology as close as possible, we continue to use this employment series.

While we are able to use real-time data for forecasts in the Great Moderation period, the compensation series is not available as real-time data going further back. We therefore use final vintage data in all data series when we look at the forecasting performance of the model over the longer sample. This means we can no longer use the Fed's Green Book forecast as a competitor to the model as the Green Book forecasts are done in real time and hence should be compared to real-time model forecasts and to real-time realizations (first final releases of data). We therefore use the random walk forecast, as in Atkeson and Ohanian (2001), as the benchmark against which we judge the model's forecasting performance. To see what effect the change from real-time data to final vintage data has, we do the same forecasting exercise for the Great Moderation period using both real-time and final vintage data sets. It turns out the nature of the autocorrelation properties of macroeconomic aggregates change when one uses final vintage as opposed to real-time data and therefore the model forecast performance also changes.

The rest of the data choices are standard and are not material for the paper's results. We therefore relegate this discussion to the data appendix (to be included), which describes all of the data used in the paper in detail.

There are two sample periods that we use. The Great Moderation sample, where forecasts are generated over the 1992-2006 sample, which overlaps with Edge and Gürkaynak, and a second sample period, one starting from 1970, which includes a substantial number of forecast episodes before the Great Moderation, and importantly includes the period that Romer and Romer (2000) has shown inflation to be forecastable.

To have enough observations to estimate the model parameters before forecasting begins, we extended the data sets back to 1950 (as opposed to 1965 in Edge and Gürkaynak). In a sign that the model parameters, in particular the policy rule estimates, were not stable over this period, the model forecast performance was badly affected by the inclusion of more data at the beginning of the sample. We therefore chose to use 20 years of data to estimate parameters before forecasting at each forecast date, that is, we used a 20 year rolling window in parameter estimation, when doing estimation over the long sample, consistently for both the pre-Great Moderation and the Great Moderation samples.

3. Results of the forecasting exercise

We begin with showing the forecasting power performance of the DSGE model, Bayesian VAR forecast, and a random walk forecast in the Great Moderation sample, using real-time data, and with priors that are identical to those of Smets and Wouters. This is effectively the same forecasting exercise carried out by Edge and Gürkaynak but with the random walk forecast replacing the green book forecasts as a competitor. In this paper we do not employ the green book or blue-chip forecasts for comparison purposes as we often use final vintage data for forecasting and these judgmental forecasts are only available as real-time forecasts.

Figure 3 shows the relative root mean square error of the DSGE model on the left panels with respect to random walk forecasts, on the right panels with respect to Bayesian VAR forecasts, and on the top panels for inflation, the bottom panels for GDP growth. The model either matches or outperforms both random walk and Bayesian VAR forecasts for both inflation and GDP growth.

Table 1, on the other hand, shows the absolute forecasting performance of these tree forecasting methods. It turns out all three are extremely poor forecasters with essentially no forecasting power, as measured by the R^2, in capturing changes in inflation or GDP growth.

This is not an entirely negative result as along the optimal policy path policy may well be moving against any forecastable changes in the objective variables and hence all fluctuations in these variables may be due to unforecastable shocks. The problem is, inflation and GDP growth should not both be unforecastable according to the model. In particular a class of models do imply that optimal policy can (in fact, must) simultaneously close the output gap and set inflation equal to target. This property—known as the “divine coincidence”—is a feature of new Keynesian models with only one nominal rigidity. The current canonical model, the model we are working with, differs from this in two aspects. First the forecasting exercise is carried out for GDP growth, not output gap and closing the output gap may still leave the GDP growth forecastable and more importantly the model has real rigidities and therefore is not subject to divine coincidence. That is, if policy chooses to close all forecastable inflation gaps then there should be some forecastability in output growth.

But note from the discussion about data above that the models GDP growth forecasts are particularly hurt by the bizarre population series used as the series multiply the per capita GDP growth forecasts of the model the form the aggregate forecast and therefore introduce a lot of noise into the model forecast. This would clearly lead to an attenuation bias in the GDP growth regressions presented above.

We therefore next turn to the data sets that uses a smoothed population growth series for all purposes except for calculating the employment rates (to make sure that the employment rate itself is a smoothed series) as discussed above. Figure 4 and Table 2 shows the relative and absolute forecasting performance of the forecasting methods of interest. As the actual series to be forecasted have not changed, the change in the population series has no implications for the random walk forecast. But this change does help the model forecast as expected.

The change in the performance of the inflation forecast is minor but the improvement in the GDP growth forecast is remarkable. This is to be expected of the population series affect the GDP growth forecast both through the estimation of the parameters and directly as a multiplicative factor in the forecast generation, while inflation is only affected at the estimation stage. It turns out, the Kalman filter in the model correctly attributes most of the spikes in the GDP per capita in the raw data to error processes, rather than to fitted GDP per capita (Figure 5). Hence, the model fit is not overly affected by the spikes in the population series. This makes the inflation and per capita GDP growth forecasts be less affected by the erratic behavior of these series as well. However when the resulting per capita values are multiplied by population growth to attain the aggregate GDP growth forecast, all of the noise is reintroduced. This is why the population growth series affect the GDP growth forecast so much and the inflation forecast so little.

We use this combination of nonsmooth population for employment rate and smooth population for all other purposes in the balance of the paper. We hope this will become standard practice in the literature as well.

At this stage we note that the mild forecastability of GDP growth and the continued on forecastability of inflation are more supportive of the validity of the model as the model itself implies there should be some forecastability of at least one of these variables. On the other hand the test clearly is not a conclusive one without first knowing what the model implies about forecastability itself. This is a topic we return to below [to be added].

The next step is to look at the impact of using final vintage data on the forecasting performance. We do this for the Great Moderation period where we know the real-time forecasting performance as well so that we can isolate the effect of using the final vintage data. This will be useful when we look at the forecastability in 1970s, a period when we only have access to final vintage data.

Figure 6 and Table 3 show the relative and absolute forecasting abilities of the forecast models we are considering. It is interesting to note that with final vintage data the random walk forecast's performance improve somewhat. This reflects the fact that the data is smoother and has more persistent changes, relative to when the same period is studied using the real-time data.

Figure 7 and Table 4, show they forecasting ability of the model and its competitors before the Great Moderation. The model has a much higher absolute ability to forecast in the pre-Great Moderation period. This is obviously because there is more to be forecasted, changes in macroeconomic aggregates are more persistent before the Great Moderation and the model captures much of this persistence.

This is an important finding, and the main finding of this paper. The DSGE models' failure to forecast changes in inflation (zero R^2 in forecasting regressions) in the usual Great Moderation sample turns out not to carry over to the pre-Great Moderation period. A model that is fundamentally "wrong" and is therefore unable to forecast would be unable to forecast in any sample. Here, we show that the model does forecast inflation when is forecastable by other methods (in particular by a random walk) and indeed has a higher R^2 in short horizons.

In terms of relative RMSE, random walk and the DSGE model have about the same average forecast error in one quarter ahead forecasts, with the random walk outperforming as horizon increases. Unlike the Great Moderation samples, whoever, this time the comparison is between two good forecasts—both methods have substantial forecasting ability for inflation in the pre-Great Moderation period.

Figure 8 shows the rolling relative forecast ability of the model and Figure 9 shows the corresponding rolling R^2 values of forecasting regressions for the model, random walk and Bayesian VAR forecasts. These show that the forecastability results presented above are not due to temporary spikes in the series in the two subsamples, and there are secular differences between the pre-Great Moderation and Great Moderation samples in terms of forecastability.

Lastly, we look at the rolling estimates of the Taylor rule in Figure 10, which is a candidate in explaining why the forecastability changed over time. While taking a position on the good luck versus good policy explanation of Great Moderation is beyond the scope of this paper, we note that the policy rule becomes much more aggressive during the Great Moderation, which would imply lower forecastability.

4. Conclusions

In this paper we undertook a careful study of the forecasting performance of the canonical estimated DSGE model. Our work contributes in three ways to the literature. First, we show that moving from real time to final vintage data series does not make a noticeable change in terms of the relative or absolute forecasting ability of the model. Second, more importantly, we discuss fit and forecasting implications of the population series used in the literature, showing that this significantly hurts the mode, especially in forecasting GDP growth, and offering a way of correctly smoothing the population series. We show that this makes a noticeable change to the GDP growth forecasting ability of the model.

The main contribution of the model uses the final vintage and correctly smoothed population data to assess the forecasting ability of the DSGE model in the pre-Great Moderation sample for the first time. We find that the model does an admirable job of forecasting inflation in this period especially in short horizons. This is important as, unlike in the Great Moderation sample, we know that inflation was forecastable in this period. Hence, forecasting ability is a valid test of the relevance of the model itself and the model passes this test.

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DSGE

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.372**	0.444*	0.442	0.455	0.470	0.612**
	(0.172)	(0.250)	(0.306)	(0.278)	(0.291)	(0.262)
Constant	0.419**	0.366	0.376	0.355	0.340	0.205
	(0.202)	(0.290)	(0.341)	(0.313)	(0.314)	(0.283)
R-squared	0.080	0.073	0.057	0.062	0.065	0.074
Observations	112	112	112	112	112	112

BVAR

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.0279	-0.0521	0.0919	0.0708	0.0995	0.0323
	(0.119)	(0.126)	(0.139)	(0.130)	(0.141)	(0.206)
Constant	0.796***	0.893***	0.741***	0.759***	0.721***	0.793***
	(0.142)	(0.176)	(0.186)	(0.177)	(0.193)	(0.257)
R-squared	0.001	0.003	0.010	0.006	0.010	0.001
Observations	112	112	112	112	112	112

Random Walk

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.245**	0.0323	0.0578	0.0133	-0.171	-0.0532
	(0.115)	(0.125)	(0.114)	(0.130)	(0.144)	(0.181)
Constant	0.624***	0.811***	0.794***	0.824***	0.966***	0.869***
	(0.116)	(0.147)	(0.124)	(0.0838)	(0.120)	(0.128)
R-square	0.062	0.001	0.003	0.000	0.030	0.003
Observations	112	112	112	112	112	112

Table1a : Absolute Forecasting Performance of Competing Models for Aggregate GDP Growth using Unsmoothed Population Growth

DSGE

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.558***	0.312	0.301	0.377	0.235	0.209
	(0.113)	(0.196)	(0.291)	(0.255)	(0.201)	(0.170)
Constant	0.226***	0.336***	0.337**	0.292**	0.358***	0.370***
	(0.0530)	(0.0932)	(0.134)	(0.123)	(0.106)	(0.112)
R-squared	0.198	0.050	0.037	0.052	0.018	0.012
Observations	112	112	112	112	112	112

BVAR

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.456***	0.211	0.214*	0.209*	0.0880	-0.0818
	(0.0986)	(0.141)	(0.116)	(0.108)	(0.0919)	(0.126)
Constant	0.245***	0.363***	0.353***	0.348***	0.421***	0.548***
	(0.0571)	(0.0951)	(0.0771)	(0.0783)	(0.0636)	(0.105)
R-squared	0.136	0.030	0.032	0.033	0.006	0.005
Observations	112	112	112	112	112	112

Random Walk

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.456***	0.211	0.214*	0.209*	0.0880	-0.0818
	(0.0986)	(0.141)	(0.116)	(0.108)	(0.0919)	(0.126)
Constant	0.245***	0.363***	0.353***	0.348***	0.421***	0.548***
	(0.0571)	(0.0951)	(0.0771)	(0.0783)	(0.0636)	(0.105)
R-squared	0.174	0.024	0.046	0.099	0.042	0.012
Observations	112	112	112	112	112	112

Table1b: Absolute Forecasting Performance of Competing Models for Inflation using Unsmoothed Population Growth

DSGE

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.511***	0.666***	0.656*	0.777***	0.981***	1.082***
	(0.187)	(0.249)	(0.334)	(0.293)	(0.297)	(0.277)
Constant	0.245	0.110	0.146	0.0320	-0.161	-0.227
	(0.227)	(0.294)	(0.368)	(0.324)	(0.306)	(0.280)
R-squared	0.116	0.123	0.094	0.113	0.154	0.148
Observations	112	112	112	112	112	112

BVAR

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.0343	0.0858	0.179	0.264	0.212	0.348*
	(0.0858)	(0.125)	(0.140)	(0.164)	(0.198)	(0.194)
Constant	0.793***	0.751***	0.652***	0.546**	0.589**	0.434
	(0.103)	(0.152)	(0.191)	(0.233)	(0.273)	(0.267)
R-squared	0.002	0.008	0.034	0.063	0.034	0.073
Observations	112	112	112	112	112	112

Random Walk

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.245**	0.0323	0.0578	0.0133	-0.171	-0.0532
	(0.115)	(0.125)	(0.114)	(0.130)	(0.144)	(0.181)
Constant	0.624***	0.811***	0.794***	0.824***	0.966***	0.869***
	(0.116)	(0.147)	(0.124)	(0.0838)	(0.120)	(0.128)
R-squared	0.062	0.001	0.003	0.000	0.030	0.003
Observations	112	112	112	112	112	112

Table2a: Absolute Forecasting Performance of Competing Models for Aggregate GDP Growth using Smoothed Population Growth

DSGE

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.539***	0.258	0.204	0.184	-0.0398	0.0252
	(0.114)	(0.206)	(0.303)	(0.273)	(0.218)	(0.181)
Constant	0.235***	0.361***	0.385***	0.390***	0.506***	0.472***
	(0.0546)	(0.0992)	(0.141)	(0.135)	(0.121)	(0.120)
R-squared	0.182	0.034	0.017	0.012	0.000	0.000
Observations	112	112	112	112	112	112

BVAR

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.0349	-0.00312	-0.0136	0.0463	-0.00378	-0.126
	(0.0860)	(0.0844)	(0.100)	(0.120)	(0.130)	(0.118)
Constant	0.453***	0.487***	0.498***	0.445***	0.487***	0.605***
	(0.0823)	(0.0885)	(0.108)	(0.131)	(0.140)	(0.138)
R-squared	0.003	0.000	0.000	0.005	0.000	0.028
Observations	112	112	112	112	112	112

Random Walk

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.432***	0.162	0.228	0.334***	0.219*	0.121
	(0.0963)	(0.148)	(0.186)	(0.120)	(0.119)	(0.160)
Constant	0.278***	0.407***	0.378***	0.328***	0.380***	0.429***
	(0.0455)	(0.0774)	(0.0829)	(0.0554)	(0.0585)	(0.0744)
R-squared	0.174	0.024	0.046	0.099	0.042	0.012
Observations	112	112	112	112	112	112

Table 2b: Absolute Forecasting Performance of Competing Models for Inflation using Smoothed Population Growth

DSGE

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.665**	0.716*	0.426	0.777*	0.226	0.258
	(0.267)	(0.402)	(0.395)	(0.422)	(0.287)	(0.570)
Constant	0.235	0.228	0.534	0.184	0.719**	0.697
	(0.330)	(0.464)	(0.439)	(0.432)	(0.272)	(0.530)
R-squared	0.124	0.096	0.027	0.085	0.006	0.007
Observations	56	56	56	56	56	56

BVAR

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.0790	0.0302	0.361**	0.293**	0.330***	0.312***
	(0.144)	(0.176)	(0.146)	(0.117)	(0.0973)	(0.0917)
Constant	0.904***	0.950***	0.703***	0.743***	0.724***	0.745***
	(0.171)	(0.205)	(0.166)	(0.124)	(0.140)	(0.126)
R-squared	0.008	0.001	0.103	0.062	0.076	0.068
Observations	56	56	56	56	56	56

Random Walk

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.0965	0.306**	-0.0793	0.165	-0.0141	0.162**
	(0.154)	(0.119)	(0.129)	(0.122)	(0.164)	(0.0706)
Constant	0.876***	0.678***	1.035***	0.775***	0.942***	0.772***
	(0.185)	(0.174)	(0.163)	(0.163)	(0.157)	(0.108)
R-squared	0.009	0.093	0.006	0.026	0.000	0.025
Observations	56	56	56	56	56	56

Table 3a : Absolute Forecasting Performance of Competing Models for Aggregate GDP Growth for Final Vintage Great Moderation Sample using Smoothed Population Growth

DSGE

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.384**	0.164*	0.0653	0.0569	-0.0961	-0.362
	(0.148)	(0.0826)	(0.0983)	(0.141)	(0.179)	(0.252)
Constant	0.339***	0.449***	0.501***	0.509***	0.591***	0.761***
	(0.0701)	(0.0546)	(0.0836)	(0.122)	(0.153)	(0.204)
R-squared	0.112	0.025	0.004	0.003	0.007	0.071
Observations	56	56	56	56	56	56

BVAR

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	-0.173	-0.203	-0.230*	-0.153	-0.257*	-0.294**
	(0.113)	(0.127)	(0.137)	(0.160)	(0.148)	(0.127)
Constant	0.662***	0.693***	0.723***	0.666***	0.755***	0.798***
	(0.105)	(0.119)	(0.139)	(0.168)	(0.153)	(0.142)
R-squared	0.067	0.087	0.105	0.046	0.139	0.174
Observations	56	56	56	56	56	56

Random Walk

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.555***	0.512***	0.529***	0.522***	0.358**	0.496**
	(0.118)	(0.149)	(0.180)	(0.141)	(0.152)	(0.228)
Constant	0.236***	0.263***	0.259***	0.267***	0.351***	0.288**
	(0.0604)	(0.0705)	(0.0932)	(0.0721)	(0.0668)	(0.111)
R-squared	0.291	0.241	0.243	0.232	0.108	0.183
Observations	56	56	56	56	56	56

Table 3b : Absolute Forecasting Performance of Competing Models for Inflation for Final Vintage Great Moderation Sample using Smoothed Population Growth

DSGE

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.888***	0.945***	0.905***	1.019***	1.136***	0.975***
	(0.153)	(0.194)	(0.205)	(0.225)	(0.241)	(0.246)
Constant	0.0835	0.102	0.148	0.0170	-0.0637	0.0300
	(0.223)	(0.264)	(0.281)	(0.293)	(0.310)	(0.334)
R-squared	0.310	0.257	0.175	0.165	0.156	0.092
Observations	61	61	61	61	61	61

BVAR

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	-0.0367	0.315	-0.186	-0.190	-0.0400	-0.0796
	(0.192)	(0.216)	(0.221)	(0.263)	(0.121)	(0.136)
Constant	0.920**	0.593*	1.115***	1.115***	1.020***	1.004***
	(0.346)	(0.354)	(0.263)	(0.268)	(0.228)	(0.224)
R-squared	0.001	0.042	0.014	0.014	0.001	0.003
Observations	61	61	61	61	61	61

Random Walk

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.255**	0.162	0.0825	0.0473	-0.0909	-0.0961
	(0.116)	(0.113)	(0.0745)	(0.0948)	(0.0974)	(0.0998)
Constant	0.665***	0.767**	0.866***	0.893***	1.059***	1.008***
	(0.239)	(0.292)	(0.269)	(0.261)	(0.274)	(0.273)
R-squared	0.066	0.027	0.007	0.002	0.009	0.010
Observations	61	61	61	61	61	61

Table 4a : Absolute Forecasting Performance of Competing Models for Aggregate GDP Growth for Pre Great Moderation Sample using Smoothed Population Growth.

DSGE

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.859***	0.807***	0.717***	0.575*	0.339	0.163
	(0.0893)	(0.107)	(0.182)	(0.316)	(0.444)	(0.476)
Constant	0.355***	0.491***	0.645**	0.853*	1.134*	1.323**
	(0.117)	(0.158)	(0.280)	(0.444)	(0.576)	(0.609)
R-squared	0.584	0.414	0.255	0.139	0.040	0.008
Observations	61	61	61	61	61	61

BVAR

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	-0.189	-0.202	-0.240	-0.292	-0.301*	-0.297*
	(0.150)	(0.172)	(0.199)	(0.189)	(0.173)	(0.155)
Constant	1.734***	1.731***	1.748***	1.792***	1.786***	1.765***
	(0.186)	(0.210)	(0.230)	(0.220)	(0.200)	(0.188)
R-squared	0.044	0.049	0.068	0.104	0.112	0.111
Observations	61	61	61	61	61	61

Random Walk

	1Q	2Q	3Q	4Q	5Q	6Q
Slope	0.755***	0.665***	0.615***	0.573***	0.403**	0.311
	(0.0844)	(0.116)	(0.131)	(0.162)	(0.197)	(0.263)
Constant	0.380***	0.508***	0.570**	0.633**	0.887**	1.015*
	(0.124)	(0.176)	(0.225)	(0.292)	(0.387)	(0.509)
R-squared	0.567	0.419	0.338	0.291	0.138	0.079
Observations	61	61	61	61	61	61

Table 4b : Absolute Forecasting Performance of Competing Models for Inflation for Pre Great Moderation Sample using Smoothed Population Growth.

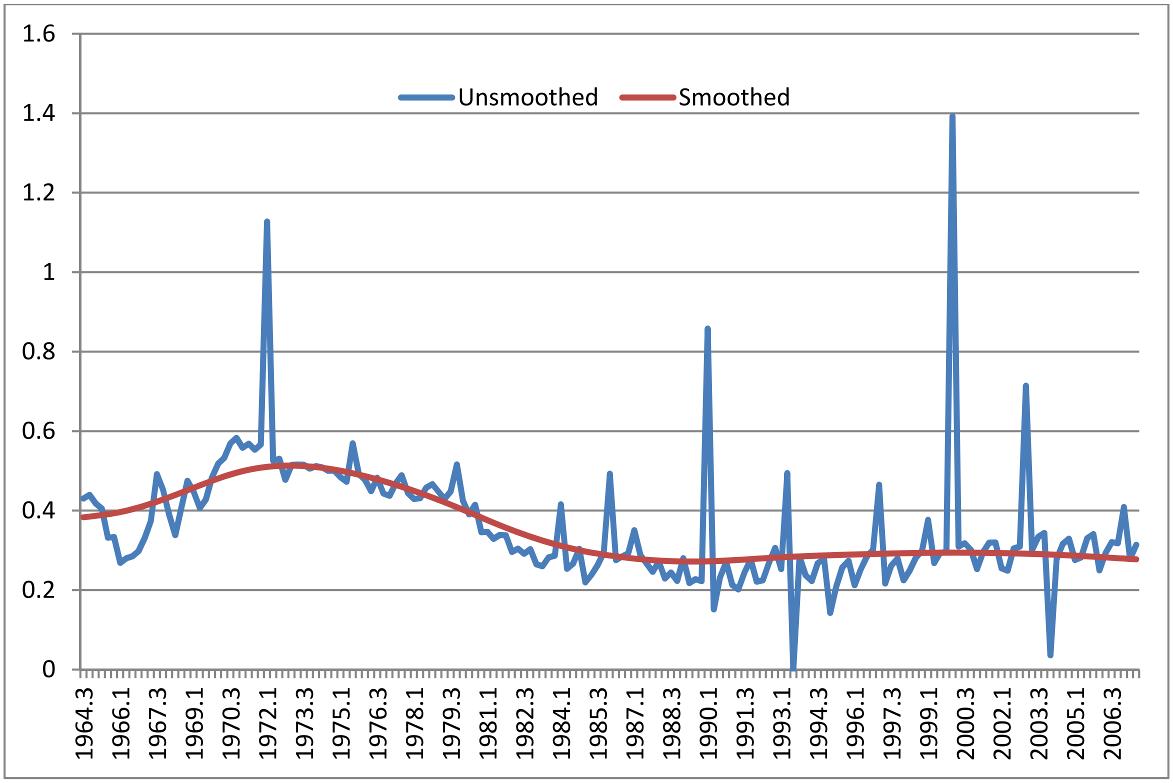


Figure 1: Unsmoothed (Smets-Wouters) and Smoothed (FRB/US) Population Growth

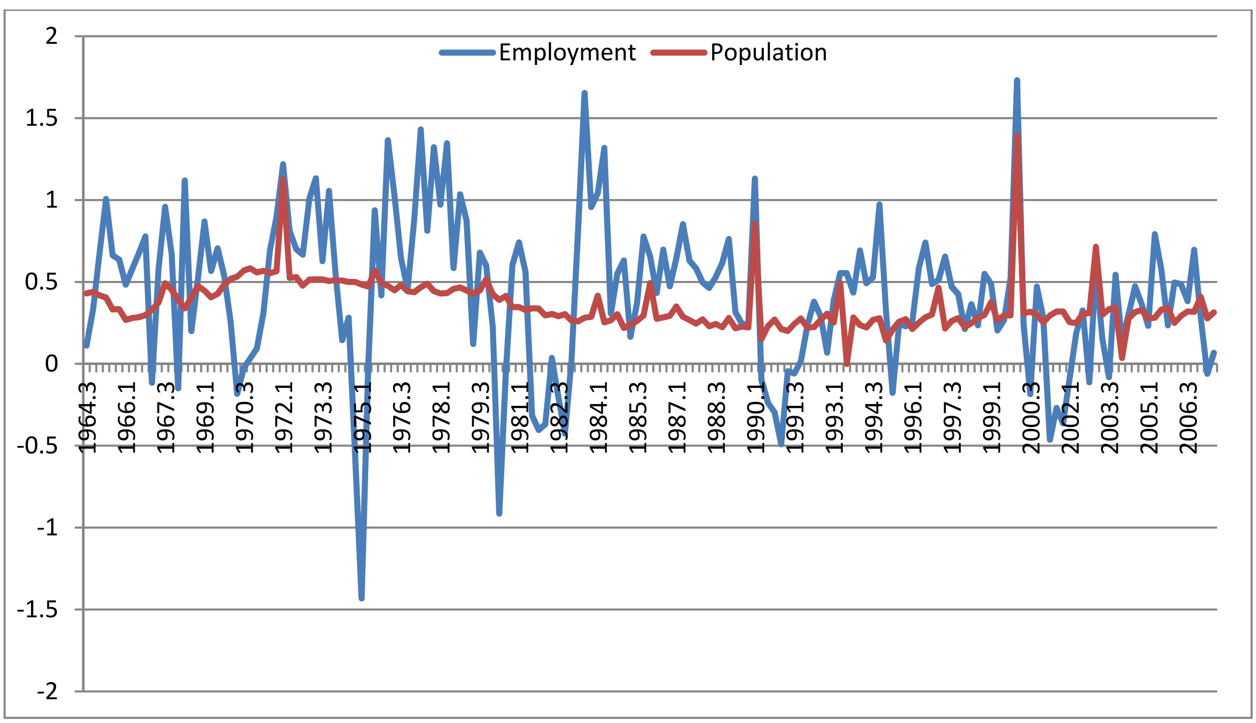


Figure 2: Employment and Population Growth

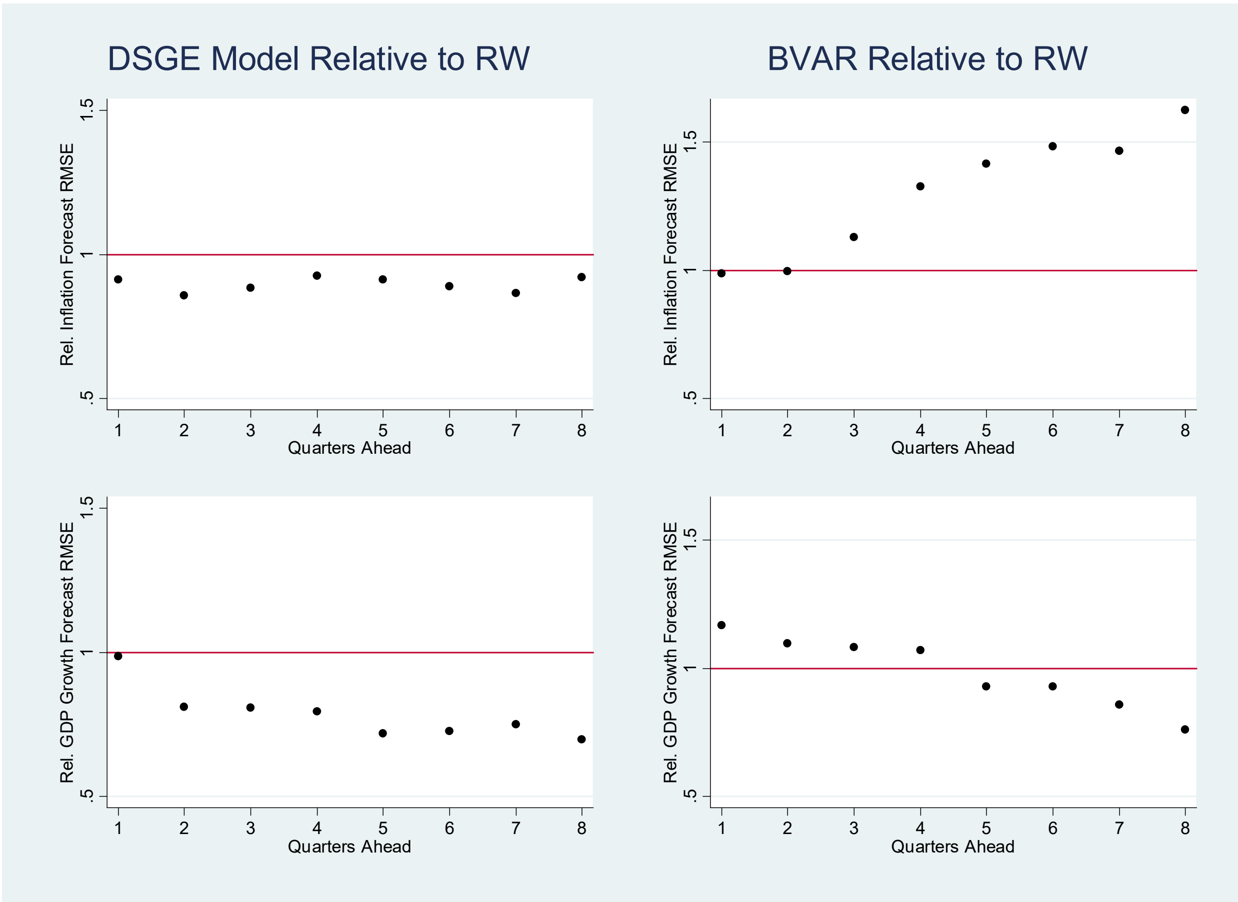


Figure 3: Relative RMSEs for Aggregate GDP Growth and Inflation using Unsmoothed Population Growth

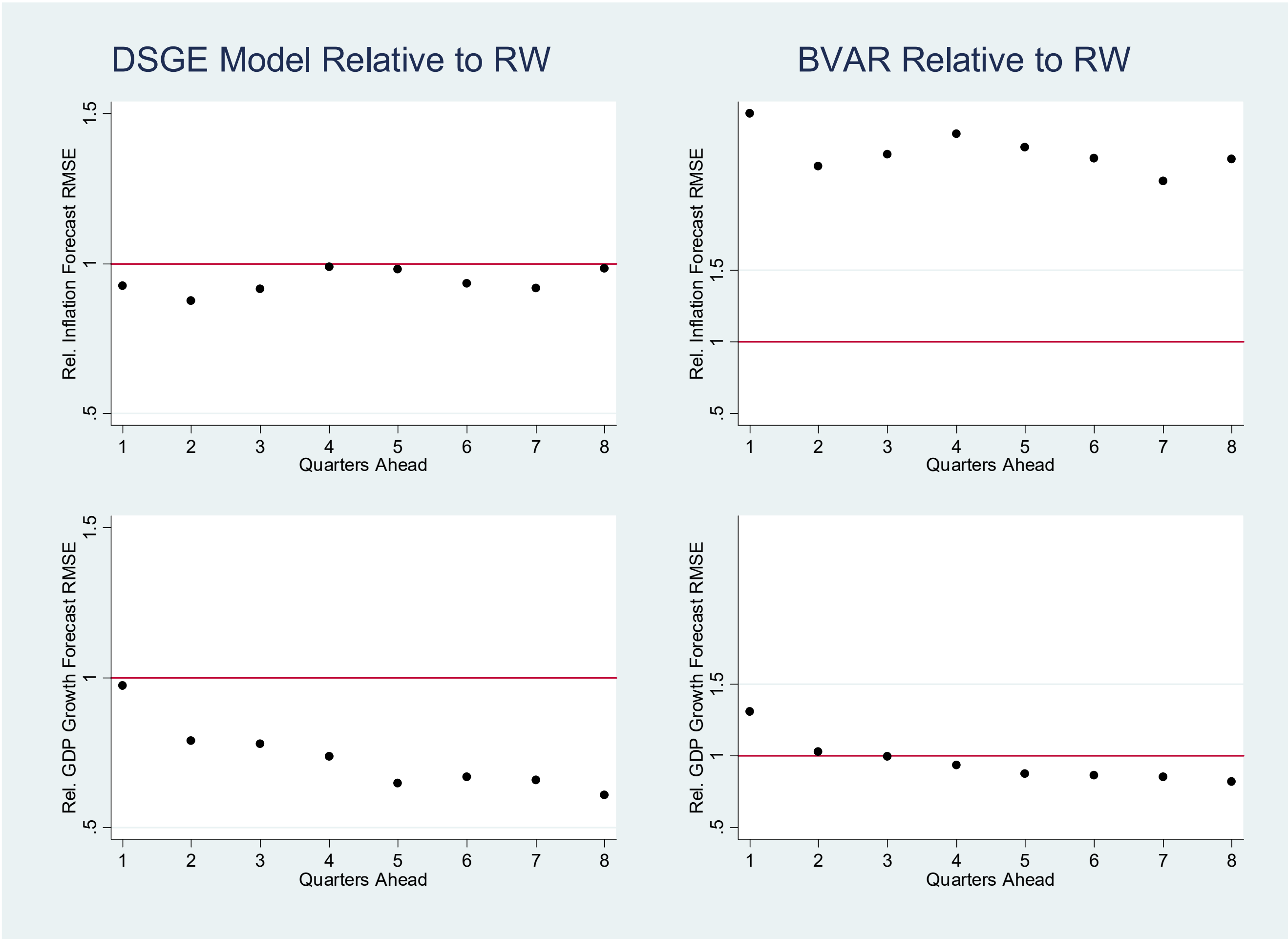


Figure 4: Relative RMSEs for Aggregate GDP Growth and Inflation using Smoothed Population Growth

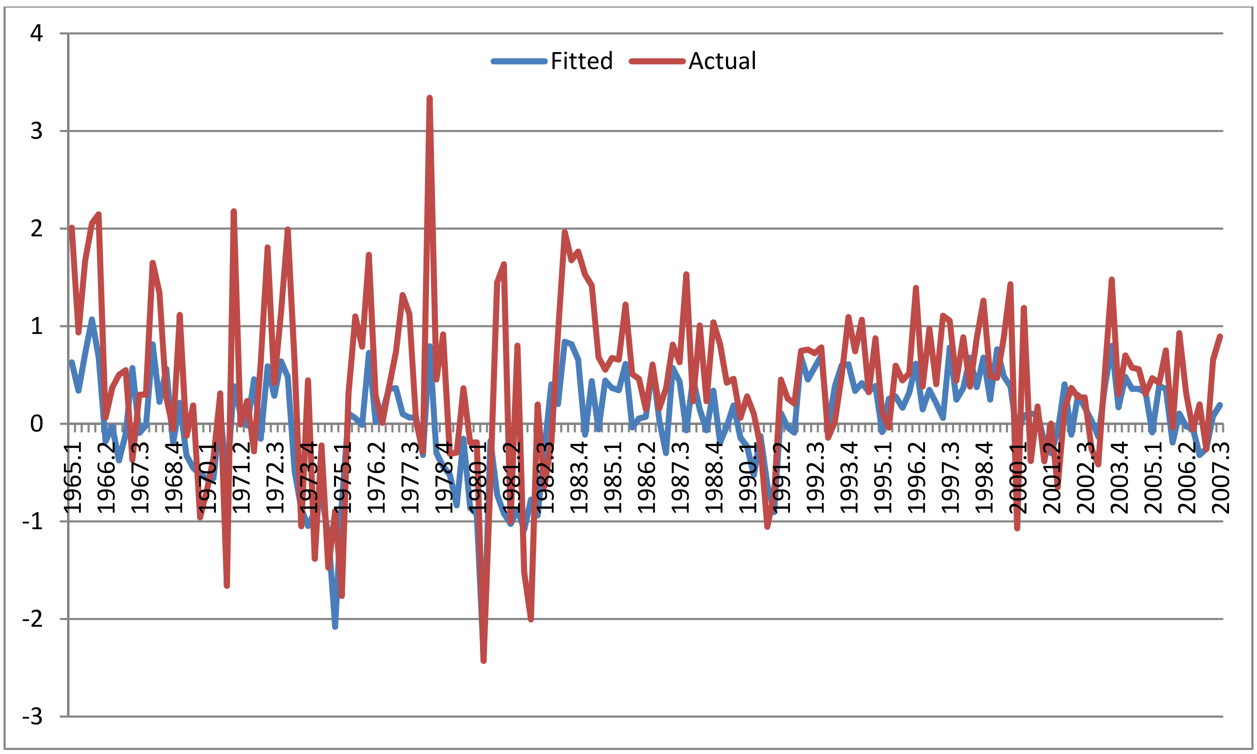


Figure 5: Fitted vs. Raw GDP per capita

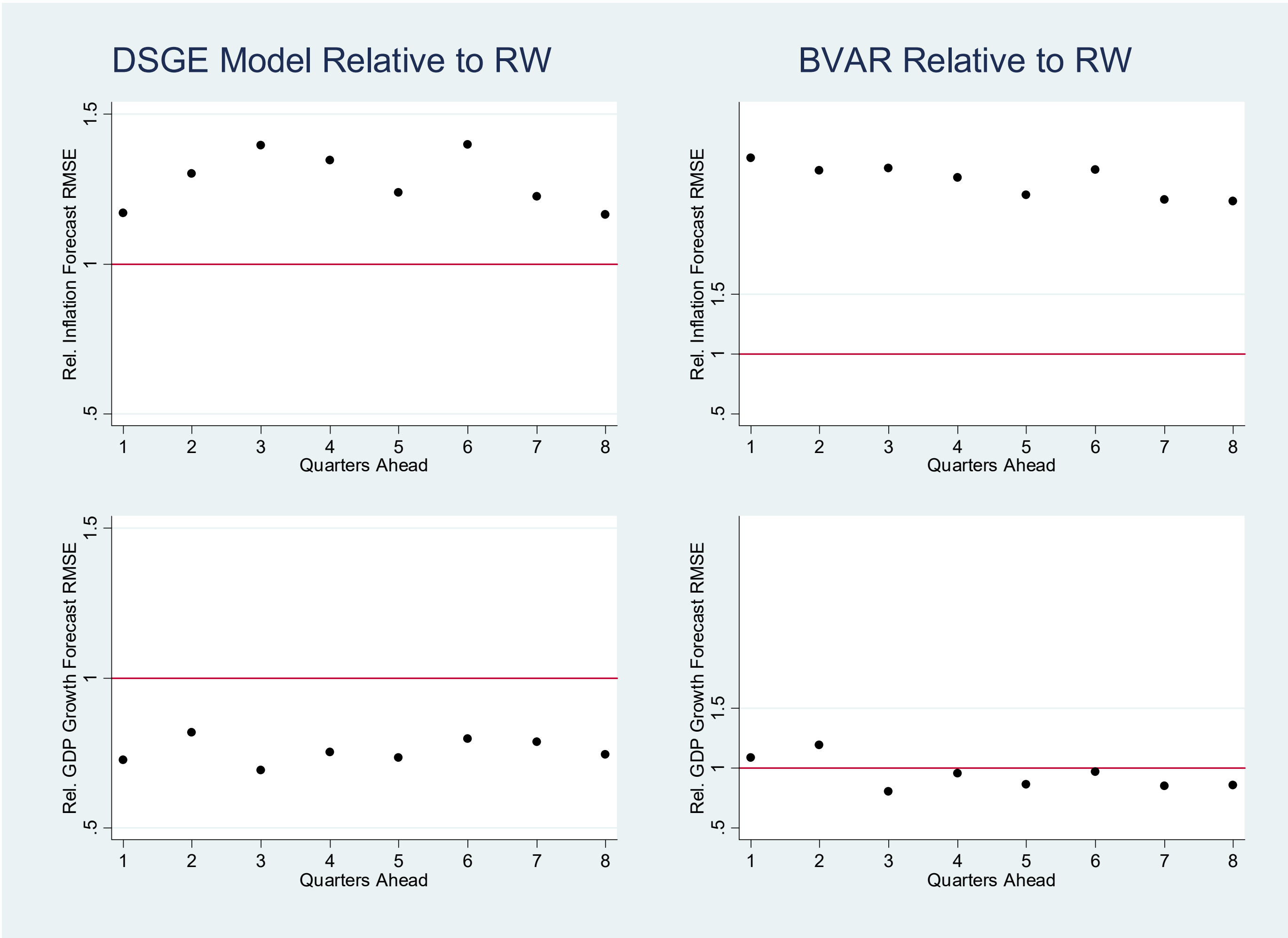


Figure 6: Relative RMSEs for Aggregate GDP Growth and Inflation with Final Vintage Great Moderation Sample using Smoothed Population Growth

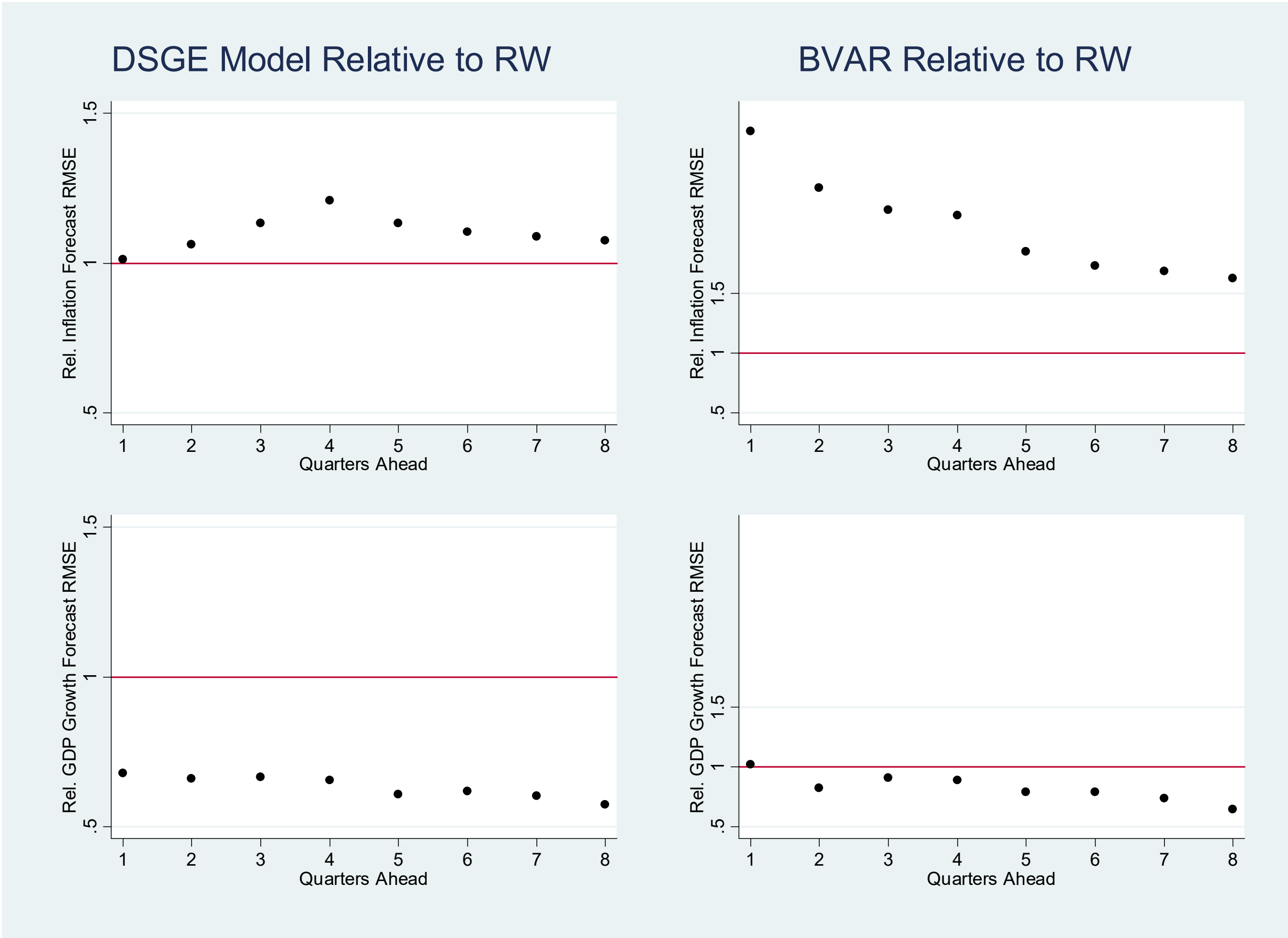
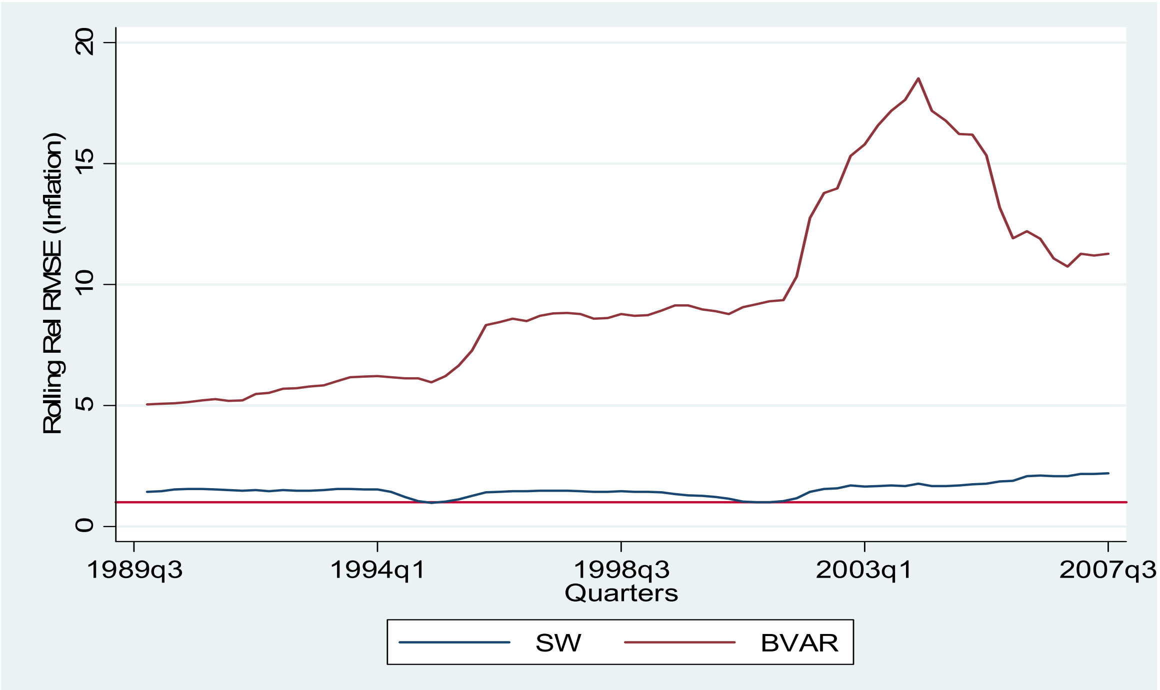


Figure 7: Relative RMSEs for Aggregate GDP Growth and Inflation with Final Vintage Pre Great Moderation Sample using Smoothed Population Growth


Rolling Rel RMSE (Inflation)
20
15
10
5
0
1989q3
1994q1
1998q3
2003q1
2007q3
Quarters
SW
BVAR

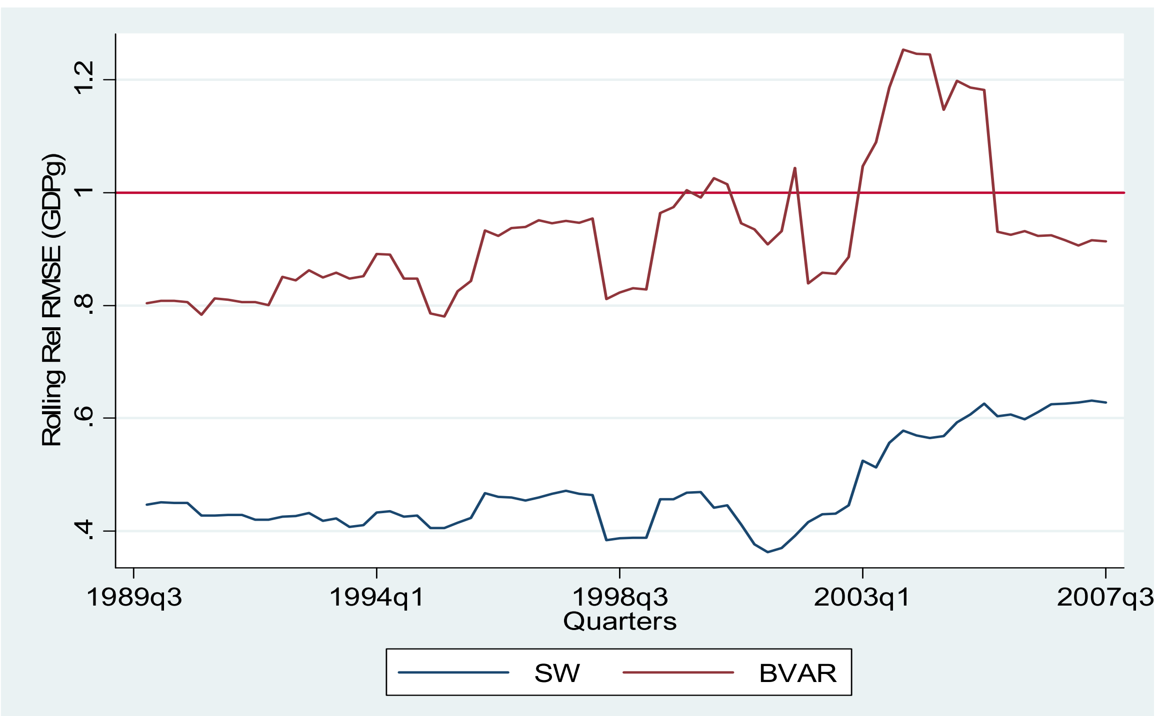
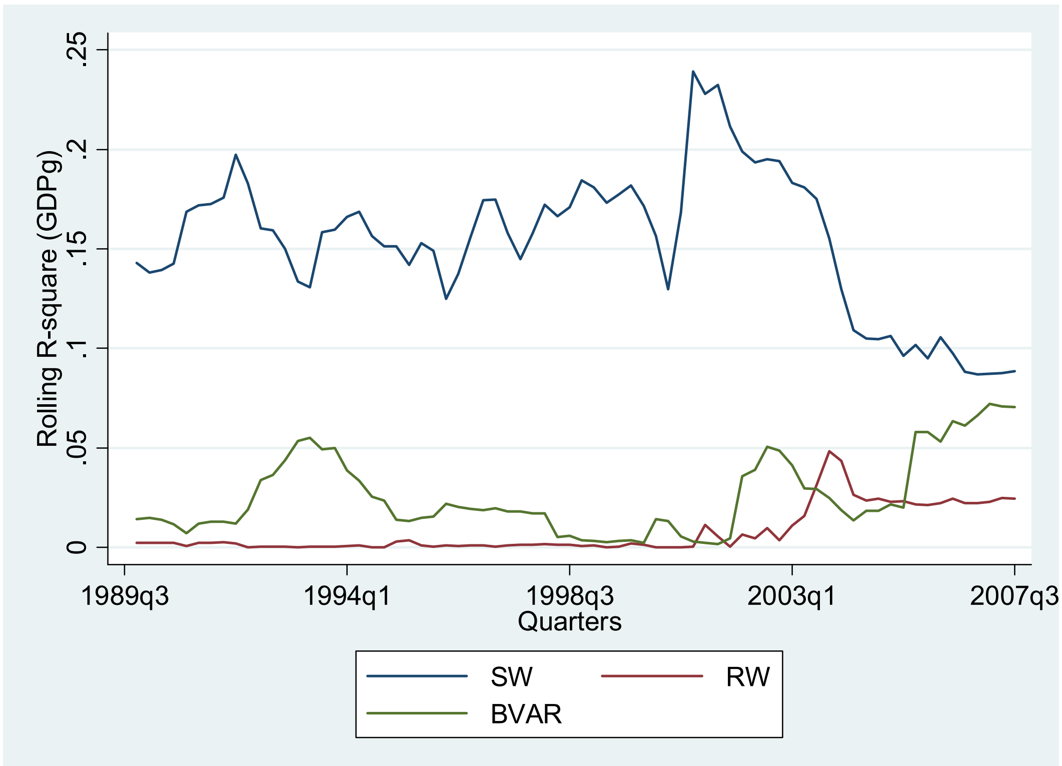

Rolling Rel RMSE (GDPg)
1.2
1
.8
.6
.4
1989q3
1994q1
1998q3
2003q1
2007q3
Quarters
SW
BVAR

Figure 8: 20-year Rolling 4-quarter Ahead RMSEs for Aggregate GDP Growth and Inflation using Final Vintage and Smoothed Population Growth



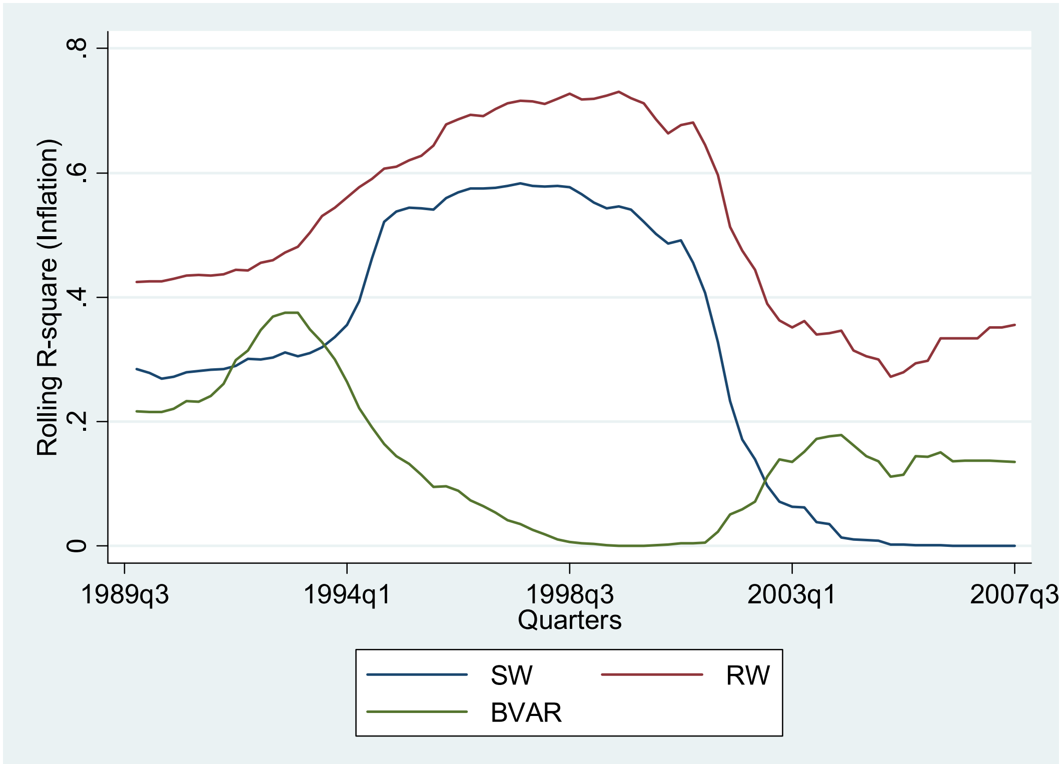
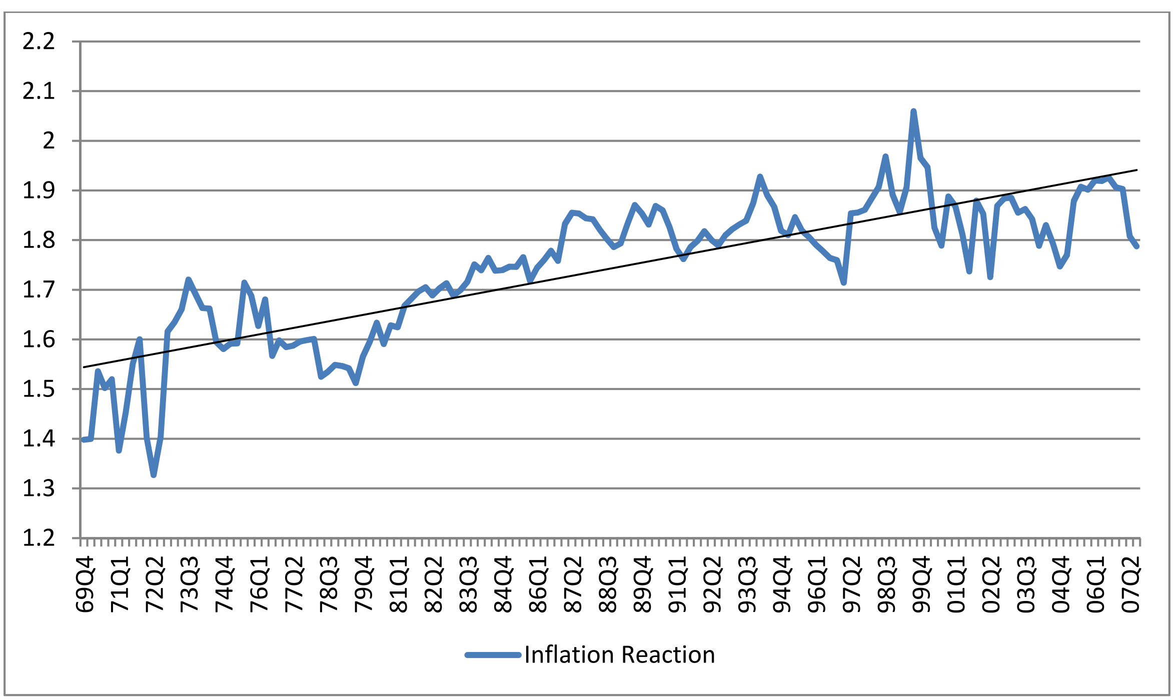


Figure 9: 20-year Rolling 4-quarter Ahead R-square for Aggregate GDP Growth and Inflation using Final Vintage and Smoothed Population Growth



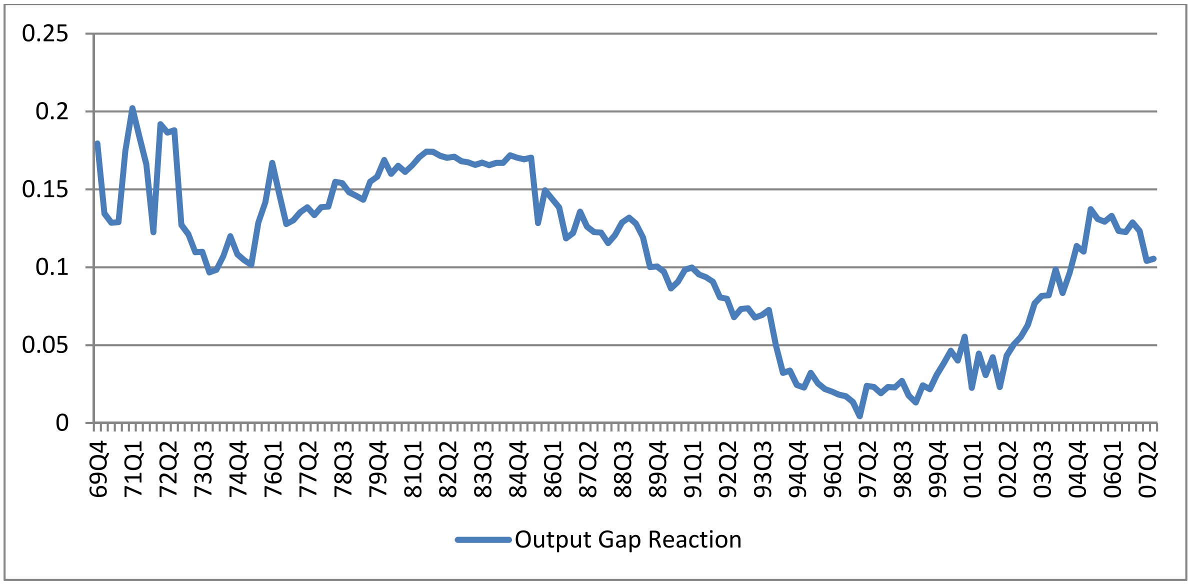


Figure 10: Estimated 20-year Rolling Taylor Rule Parameters.