Explaining the Great Moderation: It is not the shocks

Domenico Giannone, European Central Bank and CEPR,
Michele Lenza, European Central Bank,
Lucrezia Reichlin, European Central Bank and CEPR

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Abstract

This paper shows that the explanation of the decline in the volatility of GDP growth since the mid-eighties is not the decline in the volatility of exogenous shocks but rather a change in their propagation mechanism.

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1 Introduction

One of the most interesting facts of the last twenty years is that the volatility of output growth and inflation in all OECD economies has declined, a phenomenon that has been labeled as the Great Moderation. The literature has tried to establish whether the volatility decline should be attributed to exogenous causes that is, the decline in the volatility of shocks (the "good luck" hypothesis), or to a change in the propagation mechanism of the shocks (change in the structure – "good policy" hypothesis).

Regarding inflation, studies with few exceptions have concluded that the decline in volatility is due to credible monetary policy which has since the early eighties stabilized inflationary expectations via commitment to a nominal anchor (see e.g. Stock and Watson 2002, 2003; Ahmed, Levin and Wilson 2004; Cogley and Sargent 2005). Regarding output, on the other hand, the consensus supports the "good luck" hypothesis (a summary review of the empirical findings is provided in Section 2).

One explanation of why different conclusions have been reached for output and inflation is that the evolution of the dynamic properties of these two variables differs. For inflation, the evidence points to an increase in persistence and therefore to a change not only in variance but also in the autocorrelation structure (see e.g. Stock and Watson 2007). For gross domestic product (GDP), it has been shown that the the spectral density of output growth before and during the Great Moderation period differs only by a proportional factor (Ahmed, Levin and Wilson 2004) and that the coefficient of the univariate autoregressive model for GDP growth is time invariant (Stock and Watson 2002). Both pieces of evidence suggest no change in the autocorrelation function of the process. However, there is another stylized fact concerning output and inflation that suggests that the "good luck" explanation for GDP might not be the right one. In the Great Moderation sample, the ability to predict output and inflation beyond what can be predicted on the basis of a simple random walk model (relative predictability) has decreased. The evidence on inflation is well known: Atkenson and Ohanian (2001) and, more recently, Stock and Watson (2007) have shown that the ratio between the mean squared error of any (simple or complex) forecast and the variance of the process has increased in the last twenty years. Recent evidence (D'Agostino, Giannone and Surico 2006; De Mol, Giannone and Reichlin 2006) points to the same phenomenon for GDP. Ever since the mid-eighties and in contrast with the seventies both the professional forecasters and the Federal Reserve Board (Greenbook forecasts) have been unable to outperform the forecast obtained by a naive model in which tomorrow is predicted to be the same as today.

How can we reconcile the good luck view with the evidence of invariant dynamic properties of GDP and diminished relative predictability? This paper makes the point that, if the autocorrelation function of the univariate process has not changed, then diminished relative predictability can be explained only by the cross-covariances between GDP and other variables used by the Greenbooks and the professional forecasters in computing their forecast. Relative predictability depends on the model and, therefore, on the information we condition our forecast on. But if multivariate information matters, then any estimate of the role of the shocks for explaining the Great Moderation must take it into account. If not, we incur an omitted variable problem with the consequence of not obtaining a consistent estimate of the structural shocks. It is therefore important to evaluate whether conclusions about good luck versus good policy – change in structure are altered when we use information sets of different size. In this paper we pursue this evaluation through vector autoregressive (VAR) analysis. We consider VARs of different size from a minimum of four to a maximum of nineteen variables, both nominal and real. To overcome problems of overfitting in the larger models, we will use Bayesian shrinkage as suggested in Banbura, Giannone and Reichlin (2007).

2 Some facts for the United States

Let us consider quarterly data for GDP and GDP deflator in the samples 1959–1983 (pre–Great Moderation) and 1984–2007 (Great Moderation).[1] In the United States, the standard deviation of yearly real GDP growth declined from 2.7 in the first sample to 1.28 in the second, the standard deviation of yearly GDP deflator inflation declined from 2.7 to 0.75. The mean remained roughly unchanged for GDP growth while nearly halving for inflation.[2] Similar numbers are obtained for other OECD countries, but here we focus on the United States.

Can these facts be attributed to exogenous causes (the shocks) or rather to changes in the propagation mechanism? Table 1 summarizes results obtained by the empirical literature using a variety of statistical techniques.

Table 1 Shocks or propagation? Summary of the findings on GDP

Authors	Results
McConnell and Perez-Quiros (2000)	Propagation: Inventories
Kahn, McConnel and Perez-Quiros(2002)	Propagation: Inventories
Stock and Watson (2002)	Shocks 90%
Stock and Watson (2003)	Shocks 80-120%
Primiceri (2005)	Shocks
Boivin and Giannoni (2006)	Shocks 50-75%
Dynan, Elmedorf and Sichel (2006)	Propagation: Financial innovation
Justiniano and Primiceri (2006)	Shocks: Investment wedge
Sims and Zha (2006)	Shocks
Arias, Hansen, and Ohanian (2007)	Shocks: Total Factor Productivity
Canova, Gambetti and Pappa (2006)	Propagation and shocks
Castelnuovo (2007)	Shocks
Gali and Gambetti (2007)	Propagation and shocks
Mojon (2007)	Shocks: Monetary policy shocks
Smets and Wouters (2007)	Shocks

Clearly, the majority view is that the explanation on the decline in GDP growth volatility is in the decline in shock volatility.[3]

[1] More precisely, our pre–Great Moderation sample ranges from the first quarter of 1959 to the fourth quarter of 1983 and the Great Moderation sample from the first quarter of 1984 to the first quarter of 2007.

[2] The average annual growth rates were 3.33 and 3.03 for GDP in the two periods while GDP deflator inflation declined from 4.77 to 2.48.

[3] In presence of model miss-specification, changes in structure might show up as changes in the size of exogenous shocks. Structural explanations for the Great Moderation, however, might still be uncovered by looking at the nature of the shocks in the spirit of Chari, Kehoe and McGrattan (2007). For example, Justiniano and Primiceri (2006) find that the Great Moderation is entirely explained by investment-specific shocks, but they can not exclude the possibility that this finding reflects changes in unmodeled financial frictions.

Let us now turn to predictability. In Table 2 we report findings in D'Agostino, Giannone and Surico (2006) on the relative performance of institutional forecasters: the Federal Reserve (Greenbooks) and the Survey of Professional Forecasters (SPF). The upper panel in Table 2 refers to inflation and the lower panel to GDP. Each of the two panels are divided in two sections: on the left we report pre–Great Moderation results and on the right we report results of the Great Moderation.[4] In each section, we report statistics on the forecast based on the random walk model[5] (Naive), Greenbook forecasts (GB), and the Survey of Professional Forecasters (SPF) for the four forecasting horizons (h) from one to four quarters ahead. In particular, the "Naive" column reports the mean squared forecast error (MSFE) of the random walk forecasts, while the GB and SPF columns report, respectively, the *ratio* of the MSFE of the Greenbook and Survey of Professional Forecasters to the corresponding MSFE of the random walk.

Table 2 Greenbook (GB) and Survey of Professional Forecasters (SPF): Relative Mean Squared Forecast Errors

Inflation

Pre-85 h	Naive	GB	SPF	*Post-85* h	Naive	GB	SPF
1	0.54	0.30***	0.27***	1	0.08	0.58**	0.82
2	1.72	0.21**	0.24**	2	0.17	0.93	1.15
3	3.51	0.21**	0.25*	3	0.28	0.97	1.39
4	5.69	0.23*	0.32*	4	0.39	1.18	1.82

GDP

Pre-85 h	Naive	GB	SPF	*Post-85* h	Naive	GB	SPF
1	25.82	0.37**	0.45**	1	3.77	0.73	0.77
2	19.01	0.44**	0.41**	2	2.51	0.77	0.70
3	15.39	0.40***	0.45***	3	2.15	0.85	0.73
4	13.18	0.42***	0.46***	4	2.03	0.89	0.74

Note: Asterisks denote rejection of the null hypothesis of equal predictive accuracy between each model and the random walk at 1% (***), 5% (**), and 10% (*) significance levels.

Table 2 shows that inflation and GDP forecasts achieved MSFEs significantly lower than the naive forecasts in the pre-1985 period. However, this picture changed dramatically after 1985, when the MSFE of the Greenbooks and the Survey of Professional Forecasters no longer differ statistically from those of a naive forecast. From these results, one can conclude that relative predictability has strongly declined in the Great Moderation sample.

3 Shocks or Propagation? The role of information

Let us denote real GDP growth as Δy_t and assume that it can be represented by

$$\Delta y_t = \mu + \Psi(L) u_t,$$

where μ is the unconditional mean and u_t an i.i.d. scalar shock with variance σ_u^2. Denote the variance of Δy_t by σ_y^2.

[4]Notice that D'Agostino, Giannone and Surico (2006) splits the sample in 1985.

[5]In each period the random walk for the price variable predicts that the annual growth rate of inflation h periods ahead is the same as the last observed in sample, while the random walk for GDP predicts that the annual GDP growth rate h periods ahead will be equal to the average GDP growth observed up to the period in which the forecast is made.

We are interested in understanding changes in the ratio σ_u^2/σ_y^2. The variance of the structural shock u_t is estimated as the forecast error of an econometric model; therefore, the empirical ratio is related to the measure of relative predictability defined as[6]

$$P = 1 - \frac{\text{Var(forecast error)}}{\sigma_y^2}.$$

If GDP is driven by one shock only and if the forecast error is a good estimate of the structural shock u_t, then declining predictability should indicate a decrease in the ratio between the variance of shocks and the variance of the process. This decline would contradict most of the empirical evidence supporting the good luck hypothesis.

Therefore, if that evidence is accurate, then one or more of the following facts are also true: (i) the institutional forecasters provide a poor forecast; (ii) there are two or more shocks driving GDP and their relative importance has changed, with shocks that entail less predictable dynamics becoming more sizable; (iii) the models used in the literature omit relevant information for estimating the structural shocks.

Possibility (i) is unlikely because institutional forecasters are quite accurate (see e.g. Sims 2002). Possibility (ii) is also unlikely because, if the relative importance of the shocks had changed, we would have observed a significant change in the shape of the spectral density. The evidence does not support such change (on this point see Ahmed, Levin and Wilson 2004).

Possibility (iii) requires some discussion. We first denote the spectral density of Δy_t as $S_y(\theta)$ with $\theta \in (-\pi,\ \pi)$. Let us now see what this implies for predictability on the basis of a univariate model.

The variance of the forecast error associated with a univariate model can be derived from the spectral density as

$$\sigma_e^2 = \exp\left(\frac{1}{2\pi}\int_{-\pi}^{+\pi} \ln(S_y(\theta))d\theta\right),$$

and a measure of relative predictability associated to that model can be obtained by dividing σ_e^2 by the variance of Δy_t, which is the integral of the spectral density:

$$\tilde{P} = 1 - \frac{\exp\left(\frac{1}{2\pi}\int_{-\pi}^{+\pi} \ln(S_y(\theta))d\theta\right)}{\frac{1}{2\pi}\int_{-\pi}^{+\pi} S_y(\theta)d\theta}.$$

If, as the evidence suggests, the spectral density has changed by only a proportional factor, then clearly relative predictability based on the univariate model cannot have changed. Since predictability by institutional forecasters has declined, this suggests that the univariate model is misspecified.

Let us now consider the following example, which mimics the evidence on diminished volatility of the series, diminished predictability, and no change in the autocorrelation function:

[6] In Table 2 we reported, among other things, the ratios between the MSFE of the Greenbook and Survey of Professional Forecasters GDP forecasts with respect to the MSFE of the random walk. Such ratios can be considered as measures of Var(forecast error)/σ_y^2.

$$\Delta y_t^{pre84} = (1+2L)u_t^{pre84},$$
$$\Delta y_t^{post84} = (1+0.5L)u_t^{post84},$$

with $\mathrm{Var}(u_t^{post84}) = \mathrm{Var}(u_t^{pre84})$.

Observe in this example that although the autocorrelation function has not changed, the change in volatility in the second period is explained by a change in propagation while the variance of the shocks has remained the same. Predictability defined in terms of the structural shock declines in the post-1984 sample.

Key here is that the process in the pre-1984 sample is not invertible and that $u_t^{pre84} = \sum_{j=1}^{\infty}[(-1/2)^j \Delta y_{t+j}^{pre84}]$. If the econometrician wrongly assumes that the shock is an innovation with respect to GDP growth and estimates it through a simple univariate model, then he will end up estimating:

$$\Delta y_t^{pre84} = (1+0.5L)e_t^{pre84},$$

where $e_t^{pre84} = \frac{1+2L}{1+0.5L}u_t^{pre84}$. The estimated shock e_t^{pre84} has a larger variance than the structural shock u_t^{pre84} ($\mathrm{Var}(e_t^{pre84}) = 4\mathrm{Var}(u_t^{pre84})$), and this will lead the econometrician to over-estimate the importance of the shocks relative to the propagation in the pre-1984 sample and to conclude that predictability has not changed.

The important point here is that a regression of GDP on its past leads to an omitted variables problem. Because the shock u_t is non-fundamental with respect to Δy_t, it can be recovered only by using either future observations on Δy_t or other variables. As discussed by Forni et al. (2007), the shock can be recovered as the forecast error of a larger model, including those variables that may help forecasting GDP growth.

This point remains true for more general cases of models with more than one shock. An interesting illustration was when the monetary authorities shifted from a passive interest rate policy (pre-1979 period) to implementing an active one (see, e.g. Clarida, Gali and Gertler 2000). In mainstream neo-Keynesian models, a passive policy is shown to be destabilizing, which implies an indeterminate equilibrium. In this case, as pointed out by Castelnuovo and Surico (2006) and Canova and Gambetti (2007), the standard log-linearized three-variables neo-Keynesian model for the output gap, inflation, and the nominal rate cannot be approximated by a VAR on those three variables. In the indeterminate regime, expectations variables must be included in order to estimate the shocks consistently. This is another example of an omitted variables problem. In this case, the estimated shocks are a mix of structural shocks, forecast errors, and their lags and this mix has a larger variance than that of the structural shocks. Moreover, the model will not perform well in predicting. The implication is that it would be misleading to explain the Great Moderation via any counterfactual exercise based on a three-variables VAR. Again, this is an example where the shocks are non fundamental for a three-variables system.

The lesson of this discussion is very simple. In a time-series model, the split between shocks and propagation depends on the conditioning information set. Shocks estimated on the basis of small models may not be good estimates of structural shocks. This suggests that the explanation of results that attribute the Great Moderation to the good luck hypothesis is that the models used to estimate the shocks did not include enough information and were therefore misspecified. Therefore, when evaluating the role of shocks in the Great Moderation, we should study models of different size.

How do we know whether the size of the forecasting model is appropriate? Loosely speaking, we should consider the model size appropriate when it is sufficient to make forecasts that is, increasing the number of variables included in the model no longer improves the forecasting performance. Having established the size, we can then identify structural shocks as linear combinations of the innovations obtained from the estimated VAR. On this point, see Giannone and Reichlin (2006).

4 Large models: The great moderation revisited

In this section we perform counterfactual exercises to assess the role of shocks versus propagation in explaining the declined volatility. This approach has been extensively used in the literature (Stock and Watson 2002, 2003; Ahmed, Levin and Wilson 2004; Primiceri 2005; Justiniano and Primiceri 2006; Smets and Wouters 2007). Our exercise is based on four model specifications: a small VAR with GDP, GDP deflator, federal funds rate, and commodity prices (as in Stock and Watson 2003); two larger systems of six and seven variables, used, respectively, by Sims and Zha (2006) in their VAR specification and by Smets and Wouters (2007) for estimating a dynamic stochastic general equilibrium (DSGE) model of the U.S. economy; and, finally, a VAR with nineteen variables, including all the variables typically used in macro models. We do not consider larger VARs as done in Banbura, Giannone and Reichlin (2007), since the empirical results of that paper suggest that a VAR with about twenty macroeconomic variables, which closely correspond to those used in this paper, is enough to capture the structural shocks since adding extra variables does not significantly change the results.

Table 3 lists the variables considered in the four models.

Table 3. VAR specifications

Large VAR	Small VAR	Sims - Zha	Smets - Wouters
GDP	x	x	x
GDP deflator	x	x	x
Federal Funds rate	x	x	x
Commodity prices	x		
Consumer prices			
Consumption			x
Investment		x	x
Change in inventories			
Producer price index			
Interest rate 1 year			
Interest rate 5 years			
Interest rate 10 years			
Hours worked			x
Hourly compensation			x
Capacity utilization			
Stock Prices			
M2		x	
Total Reserves			
Unemployment rate		x	

Data are quarterly, ranging from the first quarter of 1959 to the first quarter of 2007.[7] The small model is estimated by ordinary least squares (OLS). For larger models

[7]The models are estimated with data in log-levels except for interest rates, capacity utilization, unemployment rates, and changes in inventories, for which we do not take logarithms.

we face an issue of overfitting, which we address by using Bayesian shrinkage (see Banbura, Giannone and Reichlin 2007; De Mol, Giannone and Reichlin 2006). In practice we use a Litterman (random walk) prior whose tightness is set so that the in-sample fit of the interest rate equation in the large VAR models is fixed at the level achieved by the simple four-variables monetary VAR. This choice is grounded on the evidence that U.S. short-term interest rates are well described by linear functions of inflation and real activity (Taylor rules).

The VARs are estimated separately in the two subsamples:

$$\Delta X_t = A_{pre84}(L)\Delta X_{t-1} + e_{pre84,t} \quad e_{pre84,t} \sim \mathrm{WN}(0, \Sigma^{pre84}),$$

$$\Delta X_t = A_{post84}(L)\Delta X_{t-1} + e_{post84,t} \quad e_{post84,t} \sim \mathrm{WN}(0, \Sigma^{post84}).$$

First counterfactual exercise: How much of the Great Moderation can be explained by a change in the propagation?

In this exercise we simulate shocks assuming that their covariance matrix has remained unchanged at the level of the pre-84 sample estimates ($\hat{\Sigma}_{pre84}$) and feed them through the propagation mechanism estimated for the post-1984 sample ($\hat{A}_{post84}(L)$). Precisely, we consider the following counterfactual processes:

$$\Delta X^*_t = \hat{A}_{post84}(L)\Delta X^*_{t-1} + e^*_{pre84,t}, \quad e^*_{pre84,t} \sim \mathrm{WN}(0, \hat{\Sigma}_{pre84}).$$

If the counterfactual GDP standard deviation is the same as the actual standard deviation observed in the post-1984 sample, then this should indicate that the change of propagation mechanisms fully explains the Great Moderation. The change in shocks plays a role if, instead, the counterfactual decline in volatility is smaller than observed.

Second counterfactual exercise: How much of the Great Moderation can be explained by a change in the shocks?

In this exercise we assume that the propagation mechanisms has remained unchanged at the level of the pre-1984 estimates ($\hat{A}_{pre84}(L)$) and feed them with shocks simulated using the covariance matrix estimated in the post-1984 sample ($\hat{\Sigma}_{post84}$). That is:

$$\Delta X^{**}_t = \hat{A}_{pre84}(L)\Delta X^{**}_{t-1} + e^{**}_{post84,t}, \quad e^{**}_{post84,t} \sim \mathrm{WN}(0, \hat{\Sigma}_{post84}).$$

If the counterfactual GDP standard deviation is the same as the actual standard deviation observed in the post-1984 sample, then this should indicate that a change in shocks fully explains the Great Moderation. The change in propagation mechanisms plays a role if, instead, the counterfactual decline in volatility is smaller than observed.

Since the two exercises might not provide symmetric answers to the question of what caused the Great Moderation, we report results in separate tables. Table 4a refers to the first and Table 4b to the second counterfactual exercise.

Table 4a First counterfactual exercise: Changes in propagation only

Coefficients	Shocks	Std. Deviation GDP growth	Inflation
		Observed	
Pre 84	Pre 84	2.68	2.66
Post 84	Post 84	1.28	0.75
		Small	
Post 84	Pre 84	2.33	1.34
		Sims and Zha	
Post 84	Pre 84	1.75	0.92
		Smets and Wouters	
Post 84	Pre 84	1.90	0.93
		Large	
Post 84	Pre 84	1.30	0.69

Table 4a shows that, in the small model, the change in propagation explains none of the decline in the standard deviation of GDP and half of the decline in the standard deviation of inflation (good luck for GDP and both good luck and good policy for inflation), while in the large model the change in propagation explains all the decline in standard deviation both for GDP and inflation (good policy in both cases).

Table 4b Second counterfactual exercise: Changes in shock only

Coefficients	Shocks	Std. Deviation GDP growth	Inflation
		Observed	
Pre 84	Pre 84	2.68	2.66
Post 84	Post 84	1.28	0.75
		Small	
Pre 84	Post 84	1.21	2.23
		Sims and Zha	
Pre 84	Post 84	1.42	2.28
		Smets and Wouters	
Pre 84	Post 84	1.54	2.41
		Large	
Pre 84	Post 84	1.90	2.42

As for the second counterfactual exercise, in the small model the change in shocks volatility explains all the decline in GDP standard deviation and a fifth of the decline in inflation (good luck for GDP and mostly good policy for inflation). In the large model, the decline in shocks volatility explains about a half of the decline in GDP standard deviation but almost none of the decline in inflation volatility (good policy for inflation and both good luck and good policy for GDP).

Summing up, both exercises give qualitatively similar results. The degree to which shocks or propagation explain the Great Moderation depends on the size of the model. Smaller models tend to favor changes in exogenous shocks as an explanation for the great moderation, understating the role of changes in the structure of the economy.

5 Summary, conclusions, and implications of the results

The paper has considered VAR models of different size and estimated them over the pre-Great Moderation and the Great Moderation samples to evaluate the role of shocks in explaining the observed decline in output volatility. We have found that results based on counterfactual exercises change with the dimension of the model. The large model attributes the Great Moderation to a change in propagation rather than a change in shocks volatility.

We make the point that the larger model is the one to be trusted bacause, when variables that Granger-cause GDP are not included in the estimated model, the shock we estimate does not correspond to the structural shock. In general, if the decline in output growth volatility is attributed to a decline in the variance of the shocks then, since the dynamic properties of output growth do not show any significant change, this should imply that predictability remained the same since the eighties. This implication is counterfactual, as indicated by the evidence based on forecasts produced by the Fed and professional forecasters.

We conclude that the finding that "good luck" explains the Great Moderation is based on models that are excessively naive either univariate or small dimensional and that do not accurately reflect the information processed both by markets and central banks when producing their forecasts. Because such analysis is contaminated by omitted variables problems, the estimation of the shocks is not consistent and this leads to over-estimating their variance in the first period.

Our analysis suggests that what the literature on the Great Moderation attributes to "luck" might better be attributed to "ignorance". We focus on the omitted variables problem, but the point is more general. Models are generally miss-specified. In structural models, shocks represent features that either are exogenous to the model or that we don't understand. The more detailed is the model, the smaller are the shocks and the more limited is their role relative to the internal propagation mechanism. Our results suggest that it might be possible to construct a structural model in which the Great Moderation is explained by a change in the structure and not by a change in the residuals. However, our results indicate that such a model would have to be larger than the medium-scale standard DSGE model with six or seven variables.

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