Explaining the great moderation: it is not the shocks

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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 labelled 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 a change in the propagation mechanism of the shocks (change in the structure - "good policy" hypothesis).

On inflation, although there are some exceptions, studies have mostly concluded that the decline in volatility is due to credible monetary policy which, since the early eighties, has stabilized inflationary expectations via commitment to a nominal anchor (see, for example Stock and Watson, 2002, 2003; Ahmed, Levin, and Wilson, 2004; Cogley and Sargent, 2005). On 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 dynamics properties of these two variables differs. For inflation, the evidence points to an increase in persistence and therefore not only to a change in variance, but also in the autocorrelation structure (see, for example Stock and Watson, 2007). For 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 on 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. Since the mid-eighties, and in contrast with what happened in 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, diminished relative predictability can only be explained 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 on the good luck-good policy/change in structure hypothesis change when we use information sets of different size. In this paper we pursue this evaluation through Vector Auto Regressive (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 US

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 US, the standard deviation of yearly real GDP growth went from 2.7 in the first sample to 1.28 in the second, the standard deviation of yearly GDP deflator inflation from 2.7 to 0.75. The mean remained roughly unchanged for GDP growth while it basically halved for inflation[2]. Similar numbers are obtained for other OECD countries, but we will here focus on the US.

Is this fact to be attributed to exogenous causes (the shocks) or 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**
Kahn, McConnell, and Perez-Quiros (2002)	Propagation: Inventories
McConnell and Perez-Quiros (2000)	Propagation: Inventories
Stock and Watson (2002)	Shocks 90%
Stock and Watson (2003)	Shocks 80-120%
Boivin and Giannoni (2006)	Shocks 50-75%
Canova, Gambetti, and Pappa (2007)	Propagation and shocks
Dynan, Elmendorf, and Sichel (2006)	Propagation: Financial innovation
Justiniano and Primiceri (2006)	Shocks: Investment wedge∗
Primiceri (2005)	Shocks
Sims and Zha (2006)	Shocks
Arias, Hansen, and Ohanian (2007)	Shocks: TFP
Canova, Gambetti, and Pappa (2007)	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]Precisely, the average annual growth rates were 3.33 and 3.03 for GDP in the pre and Great Moderation 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 not exclude the possibility that this finding reflects changes in un-modelled 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 while the lower panel to GDP. Each of the two panels are divided in two sections: on the left we report pre-Great Moderation results while on the right those 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 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

Notes: 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, such picture dramatically changed in the post-1985 period, when the MSFE incurred by the Greenbooks and the Survey of Professional Forecasters is not statistically different than those based on 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 is 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 only driven by one shock, and provided that the forecast error is a good estimate of the structural shock u_t, declining predictability should indicate a decrease of 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, it must be the case that one or more of the following facts are also true: (i) the institutional forecasters provide a poor forecast; (ii) there is more than one shock driving GDP and their relative importance has changed with shocks implying less predictable dynamics becoming more sizeable; (iii) the models used in the literature omit relevant information for estimating the structural shocks.

Possibility (i) is unlikely since institutional forecasters are quite accurate (see, for example, Sims, 2002).

Possibility (ii) is also unlikely since, 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.

Let us 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:

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

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:

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

Clearly, if, as the evidence suggests, the spectral density has only changed by a proportional factor, 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.

[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 $\frac{\text{var(forecast error)}}{\sigma_y^2}$.

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:

$$\Delta y_t^{pre84} = (1 + 2L)u_t^{pre84}$$
$$\Delta y_t^{post84} = (1 + .5L)u_t^{post84}$$

with $\text{var}(u_t^{post84}) = \text{var}(u_t^{pre84})$.

Notice that in this example, 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 $u_t^{pre84} = \sum_{j=1}^{\infty}[(-1/2)^j \Delta y_{t+j}^{pre84}]$. If the econometrician wrongly assumes that the shock is an innovation with respect to GDP growth and estimates it through a simple univariate model, he will end up estimating:

$$\Delta y_t^{pre84} = (1 + .5L)e_t^{pre84}$$

where $e_t^{pre84} = \frac{1+2L}{1+.5L}u_t^{pre84}$. The estimated shock e_t^{pre84} has a larger variance than the structural shock u_t^{pre84} ($\text{var}(e_t^{pre84}) = 4\text{var}(u_t^{pre84})$) and this will lead him to overestimate 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. Since the shock u_t is non-fundamental with respect to Δy_t, it can only be recovered either using future observations on Δy_t or using other variables. As discussed by Forni, Giannone, Lippi, and Reichlin (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 is the case in which the monetary authorities shifted from implementing a passive interest rate policy (pre 1979 period) to implementing an active one (see, for example Clarida, Gali, and Gertler, 2000). In mainstream neo-Keynesian models a passive policy is shown to be de-stabilizing, implying an indeterminate equilibrium. In this case, as pointed out by Castelnuovo and Surico (2006) and Canova and Gambetti (2007), the standard log-linearized three-equations 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 have a larger variance than that of the structural shocks. Moreover, the model will not do well in predicting. The implication is that any counterfactual exercise based on a three variables VAR, trying to explain the Great Moderation would be misleading. Again, this is an example where the shocks are non-fundamental for a trivariate 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 they are therefore misspecified.

To evaluate the role of shocks in the Great Moderation, we should then study models of different size.

When do we know that 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 by increasing the number of variables included in the model we do not improve on 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 (see 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 including six and seven variables, respectively those used by Sims and Zha (2006) in their VAR specification and by Smets and Wouters (2007) for estimating a DSGE model of the US economy and, finally, a VAR with nineteen variables, including all the variables typically used in macro models. We don't 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 for capturing the structural shocks since, by adding extra variables, results do not change significantly.

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 OLS. For larger models 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 US short term interest rates are well described by linear functions of inflation and real activity (Taylor rules).

The VARs are estimated in the two sub-samples separately:

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

$$\Delta X_t = A_{post84}(L)\Delta X_{t-1} + e_{post84,t} \quad e_{pre84,t} \sim \text{WN}(0, \Sigma^{post84})$$

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:

$$\Delta X_t^* = \hat{A}_{post84}(L)\Delta X_{t-1}^* + e_{pre84,t}^*, \quad e_{pre84,t}^* \sim \text{WN}(0, \hat{\Sigma}_{pre84}).$$

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

$$\Delta X_t^{**} = \hat{A}_{pre84}(L)\Delta X_{t-1}^{**} + e_{post84,t}^{**}, \quad e_{post84,t}^{**} \sim \text{WN}(0, \hat{\Sigma}_{post84})$$

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

[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.

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 50% 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 20% of the decline for inflation (good luck for GDP and mostly good policy for inflation). For the large model, the decline in shocks volatility explains only about 50% of the decline in GDP standard deviation while 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 since, 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 to be attributed to a decline in the variance of the shocks and given that 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 the evidence based on the forecasts produced by the Fed and the professional forecasters indicates.

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

Our analysis suggests that what the literature on the Great Moderation attributes to “luck” might instead to 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 stand for 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, given our results, such model must be larger than the medium scale standard DSGE model with six or seven variables.

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