Volatility, Predictability and Uncertainty in the Great Moderation: Evidence From the Survey of Professional Forecasters

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Abstract: An emerging and influential literature finds a large and significant decline or "great moderation" in macroeconomic volatility since the middle of the 1980's. In this paper I estimate the extent to which the decline in annual and quarterly real GDP volatility can be attributed to changes in macroeconomic uncertainty and macroeconomic predictability. I use forecasts of future real GDP growth from the Survey of Professional Forecasts (SPF) as a proxy for the predictable component of real GDP growth. The results indicate that declining predictability has played a significant role in the great moderation. Prior to the great moderation, professional forecasters could explain roughly 30% of the variance of output growth. After the onset of the great moderation, the predictive ability of professional forecasts is essentially eliminated. This decline in predictability implies that interpreting the decline in raw output volatility or the decline in the volatility of output shocks identified from a fixed parameter autoregressive model overstates the decline in macroeconomic uncertainty by between 20-40%. The significance of the decline in real GDP predictability is assessed in two ways. First, I investigate the quantitative implications of the resulting overstatement of uncertainty on forecasts of the equity premium. Second, I employ the decline in the volatility of the predictable component of real GDP growth to identify whether or not "good policy" has played a role in the great moderation. I find evidence that good policy has played a significant role in moderating real GDP volatility since the middle of the 1980's.

Key Words: Volatility, Predictability, Uncertainty, Forecasting, Equity Premium.

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1. Introduction

In the last five years, an emerging body of macroeconomic research has documented a considerable decline in U.S. macroeconomic volatility beginning in the mid-1980's. A descriptive literature, beginning with Kim and Nelson (1999), McConnell and Perez-Quiros (2000) and Blanchard and Simon (2001), estimates that since 1984 macroeconomic volatility, broadly defined, has declined by roughly 40%. A recent contribution by Stock and Watson (2003), suggests that this "great moderation" is a robust feature of the macroeconomic landscape shared across a range of different sectors within the U.S. economy as well as across international borders.[1]

While these studies clearly document a sharp decline in total macroeconomic volatility, the provenance of this decline is less well-documented. One potential source of the decline could be a reduction in the volatility of unanticipated macroeconomic shocks. Alternatively, however, the decline could stem from a decline in the volatility of the predictable component of macroeconomic activity. A decline in the volatility of either the unpredictable or predictable component of real activity would result in a decline in total macroeconomic volatility. Understanding how these two sources contribute to the great moderation in macroeconomic volatility is important for evaluating the welfare implications of the decline as well as its potential effects on other aspects of the macroeconomy. Asset pricing models, for example, predict that the long-run return on the stock market is determined in part by the amount of macroeconomic uncertainty faced by investors but is insensitive to the extent of macroeconomic predictability. Accordingly, the likely effects of the great moderation on the stock market hinge on whether the great moderation is primarily a consequence of a decline in the volatility of the predictable or unpredictable component of macroeconomic activity.

In this paper, I decompose the volatility of U.S. real GDP growth into a component that is related to the volatility of the predictable component of real GDP growth and a component that is due to the

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[1]Stock and Watson (2003) document a significant decline in the volatility of annual real GDP per capita growth in Canada, France, Germany, Italy, Japan and the United Kingdom as well as in the United States.

volatility of unanticipated macroeconomic shocks. Specifically, I identify the predictable component of real GDP growth from the survey responses of professional forecasters contained in the Survey of Professional Forecasters (SPF) between 1969 and 2003. Using these data, I am able to trace the source of the decline in macroeconomic volatility. Previous work documenting the decline in macroeconomic volatility has typically relied on autoregressive, time-series models to distinguish the predictable from the unpredictable component of real GDP growth. The SPF forecast data are better suited to distinguishing the predictable from the unpredictable component of real GDP growth for two reasons. First, the SPF forecast data represent the real-time, actual expectations of economic participants who are actively engaged in tracking the future path of the macroeconomy. Secondly, I show that over the sample period, the SPF forecasts are of either similar or superior quality relative to those generated from an autoregressive model. Consequently, the SPF forecast data provide a more realistic estimate of actual expected future growth and are more informative about the roles of changing uncertainty and predictability in the great moderation.

The SPF forecast data indicate that both macroeconomic uncertainty and predictability have exhibited a substantial decline since 1984. In the case of predictability, the information content of growth forecasts has deteriorated sharply relative to a benchmark autoregressive model. Before 1984 forecasts constructed from an autoregressive model for real output growth were considerably less accurate than those elicited from professional forecasters. After 1984, the accuracy of the autoregressive and SPF forecasts are very similar. Consequently, attributing the entire decline in real GDP volatility to a reduction in uncertainty tends to overstate the size of the reduction in macroeconomic uncertainty. A portion of the decline in real GDP volatility is accounted for by the decline in real GDP predictability and not real GDP uncertainty. When uncertainty is measured using a root mean squared error (RMSE) criteria, I find that failing to account for the decline in predictability overstates the decline in quarterly real GDP growth uncertainty by 20%. Examining annual real GDP growth forecasts suggests an even larger overstatement ranging from between 25% to 62%.

A key question surrounding the facts of the great moderation is whether the decline in macroeconomic volatility since the mid-1980's is the result of “good policy”, “good luck” or both. Stock and Watson (2003), for example, examine the evidence in favor of a monetary policy explanation for the great moderation and come to mixed conclusions. I employ the significant decline in macroeconomic predictability to identify whether “good policy”, broadly construed, has played a role in the great moderation. Specifically, I find that after 1984, SPF forecasts of future growth are considerably less sensitive to shocks to current economic fundamentals such as oil prices and other broad measures of macroeconomic activity. This indicates a recognition by economic forecasters of a change within the structure of the macroeconomy that makes future economic growth less dependent on current economic shocks. This kind of change in the mechanism for transmitting shocks through the economy over time is directly in line with what would be considered the benefits of “good policy”.

The remainder of this paper is organized as follows. Section 2 discusses the SPF forecasts as well as the autoregressive model typically employed for forecasting real GDP growth. The information content of the SPF forecasts relative to autoregressive forecasts over the 1969-2003 period is documented and the implications for volatility measurement are discussed. Section 3 documents the role that declining predictability has played in contributing to the decline in real GDP volatility. In particular, I examine the extent to which ignoring the role of declining predictability overstates the decline in real GDP uncertainty. The size of the overstatement is then interpreted in terms of measuring the effects of the change in real GDP uncertainty on the long-run equity premium of the U.S. stock market. Section 4 examines the factors that have contributed to the decline in the volatility of the predictable component of real GDP growth. The findings are interpreted in terms of the role “good policy” has played in the great moderation. Section 5 concludes and discusses directions for future research.

2. Identifying the Predictable and Unpredictable Components of Real GDP Growth: Autoregressive Forecasts vs. SPF Forecasts

Identifying the extent to which macroeconomic uncertainty, in general, and real GDP growth uncertainty, in particular, has declined since the mid-1980's requires an estimate of the unpredictable component of real GDP growth. Consider the following fundamental decomposition of output growth an its variance,

$$\begin{aligned} y_{t,t+h} &= E(y_{t,t+h}|\Omega_t) + e^u_{t,t+h} \\ Var(y_{t,t+h}) &= Var(E(y_{t,t+h}|\Omega_t)) + E(Var(e^u_{t,t+h})) \end{aligned}, \qquad (1)$$

where $y_{t,t+h}$ represents h-period output growth, $E(y_{t,t+h}|\Omega_t)$ represents the conditional expectation of output growth based on the full time t information set, Ω_t, and e^u_t is the unpredictable component of real GDP growth.[2] In this way, the variance of real GDP growth can be decomposed into the variance of its predictable and unpredictable components. A reduction in the variance of output growth that arises from a change in $E(Var(e^u_{t,t+h}))$ is considered a reduction in uncertainty. A reduction in the variance of output growth that arises from a reduction in $Var(E(y_{t,t+h}|\Omega_t)$ is considered a reduction in predictability.[3] As discussed in the introduction, reductions in macroeconomic volatility that arise from a reduction in uncertainty could have vastly different implications than those that arise from a reduction in predictability.

[2] Real output growth is approximated using the log-difference in the level of real GDP.

[3] The term predictability here is synonymous with the phrase, “variance of the predictable component”. Later, the term predictability will be used in the context of R^2. The context will make clear which sense of predictability is being referred to.

2.1 Autoregressive Models for the Predictable Component of Real GDP Growth

In econometric studies of the decline in macroeconomic volatility, the predictable component of output growth is often estimated using a time-series or other econometric forecasting model to construct estimates of the conditional mean. These estimates are then used, along with the data, to identify the unpredictable component of output growth. In the context of the recent great moderation literature, the vast majority of researchers have focused on autoregressive specifications in modeling the conditional mean of output growth.[4] In the case of a first-order autoregressive specification (henceforth, AR(1)) the econometric model takes the form,

$$y_{t,t+h} = \alpha + \rho y_{t-h,t} + \sigma \varepsilon_{t,t+h}, \tag{2}$$

where ρ is the parameter that governs the persistence of real GDP growth, α determines the mean of real GDP growth and σ represents the volatility of real GDP growth shocks. Much of the evidence in favor of the great moderation comes from examining the estimated residuals,

$$e_{t,t+h} = y_{t,t+h} - \hat{\alpha} - \hat{\rho} y_{t-h,t}, \tag{3}$$

where $\hat{\alpha}$ and $\hat{\rho}$ are estimated parameters. McConnell and Perez-Quiros (2000), for example find a large and significant decline after 1984 in the volatility of residuals from an AR(1) model in the case of quarterly real GDP growth between 1953:2 and 1999:2. Stock and Watson (2002) find a similar decline in the volatility of residuals from an AR(4) model in the case of annual real GDP growth. Moreover, both sets of authors also find that the only compelling source of structural change within these autoregressive models is in the volatility of growth shocks, σ. Both McConnell and Perez-Quiros (2000) as well as Stock and Watson (2002) test for structural change in both the mean and persistence parameters of their autoregressive specifications and find no evidence in favor of structural change in either of these parameters.

[4] Kim, Nelson and Piger (2001), McConnell and Perez-Quiros (2000), Stock and Watson (2002,2003) and Stock and Watson (2003) use autoregressive specifications in modeling real GDP growth. ...

These findings clearly document, in a rigorous fashion, that the volatility of real GDP growth has declined precipitously since 1984. These studies, however, are less informative as to whether the volatility decline is due to changes in macroeconomic uncertainty or predictability. If the residuals from the AR(1) specification are identified with unanticipated real GDP growth shocks, then all of the decline in macroeconomic volatility is due to a decline in the volatility of the unpredictable component of real GDP growth. Identifying, however, the residuals from the AR(1) model with the unpredictable component of real GDP growth requires an assumption that no other variables available to economic participants besides lagged growth rates are useful for forecasting future growth. Specifically, this assumption equates $e_{t,t+h}$ with $e^{u}_{t,t+h}$.

There are reasons to suspect that this identifying assumption may not be satisfied. Autoregressive models describe $E(y_{t,t+h}|Y_{t-h,t})$ which may be highly informative for understanding how well past output growth forecasts future output growth, but may be a very noisy proxy for $E(y_{t,t+h}|\Omega_t)$ for at least two reasons. First, the information set consisting of lagged growth rates is clearly much smaller than the information set available to investors, firms and other economic agents attempting to forecast future real activity. The considerable amount of time and energy spent on forecasting future growth by government agencies, investors and firms would itself suggest that future growth is affected by more than just its own past. Second, the dependence of future growth on its own past may well exhibit important non-linearities. Regime-switching models of the type considered by Hamilton (1989) and others indicate that non-linearities are an important feature of the U.S. business cycle suggesting that concerns about the restrictive nature of linear models, autoregressive or otherwise, may not be completely unwarranted.

2.2 Nonparametric Measures of the Predictable Component of Real GDP Forecasts: The Survey of Professional Forecasters

In this paper, I use an estimate of the conditional expectation of real GDP growth, $E(y_{t,t+h}|\Omega_t)$, which is not derived from an econometric model. I make use of real-time forecasts elicited from professional forecasters in the Survey of Professional Forecasts (SPF). The forecasts are for both quarterly ($h=1$) and annual ($h=4$) real GDP growth. The forecasts are observed over the period between 1969:1 and 2003:2 in the case of the quarterly forecast horizon and between 1971:2 and 2002:4 in the case of the annual forecast horizon.[5] The Survey of Professional Forecasters is the oldest quarterly survey of macroeconomic forecasters in the United States. The survey was originally conducted by the American Statistical Association and the National Bureau of Economic Research. Since 1990, the survey has been administered by the Federal Reserve Bank of Philadelphia. Each quarter, the survey asks professional forecasters from the academic, government and private sectors to forecast a variety of macroeconomic aggregates ranging from consumer prices and corporate profits to aggregate investment and real GDP.[6]

The use of the SPF in measuring the expectations of economic agents is not novel. The forecasts contained in the SPF have been used repeatedly as measures of conditional expectations and many authors find that these forecasts dominate those from econometric, time-series models. In particular, Hafer and Hein (1985), find that SPF forecasts for inflation outperform predictions from interest-rate based models or other econometric time-series models. Su and Su (1975), also find that the SPF forecasts are more accurate than those generated from econometric time-series models. Apart from the previous evidence suggesting the superiority of the SPF forecasts, using these forecasts to identify the unpredictable component of real GDP growth, $e^u_{t,t+h}$, has several additional advantages over the method that employs an autoregressive model. First, these forecasts are conditioned on the full information set of

[5]Throughout the paper the notation yyyy:q is used to denote the qth quarter of year yyyy.

[6]Croushore (1993), provides a detailed description of the SPF and surveys the academic literature as well as the practical uses the survey has served since its inception in 1968.

professionals who allocate a considerable amount of time and other resources to forecasting future real activity. As such, these forecasts are constructed form a rich and evolving information set which likely incorporates any changes in the predictive power of different leading macroeconomic indicators over time. Secondly, these forecasts are not constrained to adhere to any pre-specified rule about how changes in the information set influence the forecast. Accordingly, these forecasts are flexible enough to incorporate the effects of any non-linearities or changes in the importance of different leading indicators that are relevant for future growth expectations.

2.3 The Information Content of SPF and Autoregressive Forecasts: 1969-2003

In order to gauge how informative the SPF forecasts are relative to autoregressive forecasts, I compare the predictive accuracy and relative information content of these two forecasts over the 1969-2003 period. Both quarterly ($h=1$) and annual ($h=4$) growth forecasts are examined. I focus on the case of the AR(1) model because of its prevalence in the literature and because the difference between the predictions of an AR(1) model and a more general AR(p) model are minor in both quarterly and annual real GDP growth data. Specifically, I estimate the parameters of the model,

$$y_{t,t+h} = \alpha + \rho y_{t-h,t} + \varepsilon_{t,t+h}, \tag{4}$$

using the full sample of data. As discussed previously, I do not allow for any time variation in either α or ρ due to the substantial research that fails to find any significant evidence of time variation in these parameters using both similar data and a similar sample. Furthermore, the AR(1) model is a simple and parsimonious model that is widely used among macroeconomists for forecasting purposes. Once the model is augmented to allow for breaks in the mean and the persistence parameter the relevance of the model as a benchmark forecasting model comes into question. In particular, the effects of "look-ahead bias" that arise from conditioning the model on the observed data may make such a model more of a descriptive device rather than a putative forecasting model.

Measures of predictability and forecast accuracy are constructed using the full sample estimates in the case of the AR(1) and in the case of the SPF forecast I treat the median of all recorded forecasts within a period as that period's representative forecast. Use of the median forecast follows a long line of research using survey data on expectations. While other methods of aggregating forecasts such as the mean or a trimmed mean could also be employed, I focus on the use of the median because of its robustness properties and because of its prevalence in the previous literature.

Predictability and forecast accuracy measures are computed over the entire sample, 1969-2003 as well as two subsamples. The sub-samples are chosen to coincide with the dating of the great moderation. While different authors disagree on the exact dating of the great moderation, most authors agree that the large decline in volatility began during 1984. McConnell and Perez-Quiros (2000) estimate a break date of 1984:1 using quarterly real GDP growth data between 1953:2 through 1999:2. Using the same methods as these authors but a slightly different sample, 1969:1 through 2003:2, I estimate a break date of 1984:3. Since the SPF forecast data are only available over this latter sample, I use a break date of 1984:3 in dating the great moderation.

First consider the R^2 measure of predictability. Specifically, consider the R^2 of h-step ahead forecasts from both the AR(1) and the SPF. While other measures of predictability such as the R^2 of multi-step ahead forecasts may also be relevant for gauging the relative accuracy of the AR(1) versus SPF forecasts, the h-step ahead R^2 is an important and widely reported metric of predictability. Recall that the h-step ahead R^2 is defined as,

$$R_h^2 = 1 - \frac{\sum_{t=1}^{T} e_{t,t+h}^2}{\sum_{t=1}^{T} (y_{t,t+h} - \bar{y})^2}, \tag{5}$$

where $e_{t,t+h}$ is the forecast residual from either the AR(1) or the SPF forecast. Over the period 1969-

2003, the R^2 of the quarterly SPF forecasts is 22.3% as compared to only 6.5% for the AR(1) forecast.[7] While these estimates suggest that the SPF forecasts are considerably more accurate than those generated from the AR(1), examining the one-step ahead R^2 pre and post great moderation points to a large decline in the predictive content of the SPF forecasts. Prior to 1984:3, SPF forecast exhibited an R^2 of 29.95% with observed real GDP growth as compared to only 7.4% for the AR(1) model. After the great moderation, the R^2 of the AR(1) model falls slightly to 4.7% but the predictive accuracy of the SPF is completely eliminated. The sample estimate of the R^2 between observed and forecasted growth is -4.26%, indicating that professional forecasters' ability to predict future growth is dominated by the (ex post) mean growth rate.[8]

The results are similar when comparing the R^2 of annual real GDP forecasts. The sample R^2 of SPF annual real GDP forecasts is 21.7% as compared to 0.7% for the AR(1) model over the entire sample period. Before the large decline in macroeconomic volatility SPF forecasts were considerably more accurate than the AR(1) model. The R^2 between the actual and forecasted growth rates is 28.28% in the case of the SPF forecasts as compared with a point estimate of -4.1% in the case of the AR(1). After 1984:3, the roles of the SPF and AR(1) forecasts are reversed with the SPF forecasts exhibiting a negative point estimate of -16.53% and the predictive accuracy of the AR(1) rising to 6.4%.

While the R^2 estimates provides a useful measure of the accuracy of the SPF and AR(1) forecasts, a more complete analysis of these forecasts requires an analysis of their relative merits in forecasting output. In particular, it is important to know whether the AR(1) forecasts are extraneous when compared

[7] At this point it is worth noting that use of the full-sample estimates in constructing the AR(1) forecast residuals maximizes the in-sample R^2. Hence, the population R^2 of the AR(1) model is certainly lower than 6.5%.

[8] Recall that the point estimate of R^2 is not constrained to lie in the unit interval since the forecast errors are not constrained to have a sample mean of zero over either subsample, or even over the entire sample in the case of the SPF forecasts.

with the SPF forecasts. A finding that the AR(1) forecasts are completely irrelevant when compared with the SPF forecasts would indicate that measuring the predictable and unpredictable components of output growth with the AR(1) model is problematic. Alternatively, a finding that the SPF forecasts are redundant in the presence of the AR(1) forecasts would cast serious doubt on the interpretation of the SPF forecasts as "optimal expectations" of future growth. In order to examine the relative predictive power of the two forecasts, I estimate a forecast encompassing regression of the form,

$$y_{t,t+h} = \beta_0 + \beta_{AR} f^{AR}_{t,t+h|t} + \beta_{SPF} f^{SPF}_{t,t+h|t} + \beta_1 D_{1984:3} + \beta_{AR,1} D_{1984:3} * f^{AR}_{t,t+h|t} + \beta_{SPF,1} D_{1984:3} * f^{SPF}_{t,t+h|t} + \eta_{t,t+h}\,, \quad (6)$$

where $f^{AR}_{t,t+h|t} = \hat{\alpha} + \hat{\rho} y_{t-h,t}$ and $f^{SPF}_{t,t+h|t}$ are forecasts for either quarterly or annual real GDP growth. I also allow for the possibility that the relative information content of the two forecasts may differ before and after the great moderation. Accordingly, the specification includes a full set of interactions with $D_{1984:3}$ which is a dummy variable taking the value one after 1984:3 and zero otherwise. Under the null hypothesis that the SPF forecasts are both rational, in the sense that they provide unbiased forecasts, and optimal, in the sense that no other information is relevant for forecasting future growth, we would expect the following parameter values in the encompassing regression, $(\beta_0, \beta_{AR}, \beta_{SPF}, \beta_1, \beta_{AR,1}, \beta_{SPF,1}) = (0,0,1,0,0,0)$.

I present estimates of the encompassing regression along with three Wald tests for both quarterly and annual forecasts in Table I. The first Wald statistic tests the joint hypothesis that the SPF forecasts completely encompass the autoregressive forecasts $(\beta_0, \beta_{AR}, \beta_{SPF}, \beta_1, \beta_{AR,1}, \beta_{SPF,1}) = (0,0,1,0,0,0)$. The second statistic tests the hypothesis that the SPF forecasts encompass the AR(1) forecasts prior to the great moderation, $(\beta_0, \beta_{AR}, \beta_{SPF}) = (0,0,1)$. The third Wald statistic examines the hypothesis that there is no difference in the parameters pre and post great moderation, $\beta_1 = \beta_{AR,1} = \beta_{SPF,1} = 0$.

The first column of Table 1 presents the results for the quarterly growth forecasts. Over the entire sample there is some evidence that the SPF forecasts encompass the full sample AR(1) forecasts. The

Wald test of this hypothesis rejects at the 10% level but not at the 5% level. The results do indicate, however, that the SPF forecasts encompass the AR(1) forecasts before the onset of the great moderation. Over this period, the sample estimate of the coefficient on the SPF forecasts is nearly one (0.99) and the coefficients on the constant and AR(1) forecast are both small and insignificant. The Wald test fails to reject the hypothesis that the SPF forecasts dominate the AR(1) forecasts over the first half of the sample at any conventional significance level. Mirroring the results from the previous analysis of R^2, the superiority of the SPF forecasts relative to the AR(1) alternative deteriorates in the second half of the sample. While a Wald test of the restriction of no difference in parameters pre and post great moderation fails to find any evidence in favor of a change in the parameters, the point estimates indicate that during the period of the great moderation, the SPF forecasts and AR(1) both contribute equally to forecasting future growth.[9]

The pattern in the results for annual forecasts are similar to those from the quarterly forecasts. The hypothesis that the SPF forecasts dominate the AR(1) forecasts over the entire sample is less credible for these annual forecasts. The Wald test rejects this hypothesis at the 5% level but not the 1% level. Examining the full set of results makes it clear that this rejection stems from the erosion of the information content of the SPF forecasts relative to the AR(1) after the onset of the great moderation. Before 1984:3, there is considerable evidence that annual SPF forecasts dominate the AR(1) forecasts. The associated Wald test is unable to reject this hypothesis at any conventional significance level. Also, the point estimates are similar to those from the quarterly forecast data. The coefficient on the SPF forecasts is very close to unity (1.08) and precisely measured. The coefficients on the constant and the AR(1) forecasts are larger than in the case of the quarterly forecasts but are indistinguishable from zero. Furthermore, the loading on the AR(1) forecast is estimated to be negative, suggesting a serious

[9]The point estimate of the loading on the SPF and AR(1) forecasts are 0.50 and 0.64, respectively, and the constant term is very small,-0.1, after 1984:3.

deficiency in the AR(1) forecasts prior to the great moderation. The estimates from the encompassing model in the second half of the sample indicate that the quality of the annual SPF forecasts eroded even more precipitously than the quarterly forecasts. The point estimates show that the SPF forecasts contain little information for forecasting future growth, $\hat{\beta}_{SPF} = 0.17$. This conclusion, however, should be tempered by the fact that the encompassing results also indicate that the AR(1) forecast is far from an optimal forecast. The estimated loading on the AR(1) forecast is well in excess of unity (2.60) and the forecast is badly biased in the sense that the estimated constant term is very large (-5.0%). Viewed in this light, the annual forecast encompassing results suggest that neither the SPF or the AR(1) model provides a particularly informative forecast for future growth during the great moderation.

Taken as a whole, the forecast encompassing results provide convincing evidence that SPF forecasts provide a more accurate representation of expected future growth than do forecasts from the AR(1) model. Prior to the great moderation the encompassing tests for both quarterly and annual forecasts indicate that SPF forecasts dominate those from the AR(1). As a result, using the AR(1) model to identify the predictable and unpredictable component of real GDP growth attributes some portion of the predictable component of output growth to the unpredictable component. After the onset of the great moderation, the informational advantage of professional forecasters over the AR(1) model declines sharply. In the case of quarterly forecasts, the encompassing tests suggest that the SPF forecasts are comparable with those from the AR(1). In the case of the annual forecasts, the empirical properties of both sets of forecasts are at odds with the notion of being measures of conditional expectations. In any event, there is reason to prefer the SPF forecasts to the AR(1) forecasts when measuring the predictable component of real GDP growth both before and after the great moderation. Unlike the AR(1) forecasts, the SPF forecasts are real-time expectations elicited before the realization of real GDP. As such, the SPF forecasts are not subject to any model selection or estimation biases that arise in the context of estimated models. More importantly, these forecasts provide the best available estimate of what can be reasonably considered to be known about the future path of the macroeconomy at the time the surveys were conducted.

3. The Decline in Real GDP Forecastability and Uncertainty

The coincidence of the great moderation in real GDP volatility and in the predictive ability of professional forecasters implies that at least part of the decline in real GDP volatility is due to declining predictability rather than declining uncertainty. The previous section documents that SPF forecasts of real GDP growth at both the annual and quarterly frequency have experienced a large decline in predictability since the beginning of the great moderation. Recall, that the R^2 of the SPF quarterly real GDP growth forecasts declined from 29.9% between 1969:1 and 1984:3 to a negative point estimate -4% between 1984:4 and 2003:2. Compare this decline in the R^2 of the SPF forecasts to the change in R^2 that would occur if real GDP growth were adequately modeled as an AR(1) with only a one-time change in the variance of output shocks as assumed, for example, in the work of McConnell and Perez-Quiros (2000). Recall that in the case of an AR(1), the population R^2 is simply ρ^2 so that a one-time change in the variance of real GDP growth shocks would imply no loss in predictability, as measured by R^2, whatsoever.[10] This feature of the AR(1) model further implies that all of the decline in the volatility of real GDP growth would be attributed to a reduction in uncertainty leaving no scope for a reduction in predictability.

Accounting for the effects of declining real GDP growth predictability can have important consequences for measuring the change in real GDP uncertainty. In order to make this point concrete, assume that the relevant measure of uncertainty is the forecast's mean squared error (MSE). One

[10] One might contend that structural changes in ρ coinciding with the change in the volatility of real GDP growth shocks could have occurred which would result in a change in predictability. While true, the evidence presented by McConnell and Perez-Quiros (2000) as well as Stock and Watson (2002) provide evidence against this hypothesis. Tests of structural change in the mean and persistence of real GDP growth fail to find any evidence in favor of a structural break.

convenient way of expressing forecast MSE is,

$$MSE = E[(y_{t,t+h} - f_{t,t+h|t})^2] = var(y_{t,t+h}) * (1 - R^2)\ , \tag{7}$$

where $f_{t+h,t|t}$ is the real GDP forecast with corresponding R^2. Accordingly, the ratio of forecast MSE across two subperiods is simply, $\frac{MSE_1}{MSE_0} = \frac{var_1(y_{t,t+h})}{var_0(y_{t,t+h})}\frac{(1-R_1^2)}{(1-R_0^2)}$. In the context of an autoregressive model

for real output growth with fixed mean and persistence parameters, the ratio of the forecast MSE is simply, $\frac{MSE_1}{MSE_0} = \frac{var^1(y_{t,t+h})}{var^0(y_{t,t+h})}$. In the case of the SPF quarterly growth forecasts, the substantial decline in

R^2 indicates that measuring the decline in macroeconomic uncertainty from a pure autoregressive model for output growth overstates the decline by, $\frac{(1-R_1^2)}{(1-R_0^2)} = 1.485$, 48.5% in the case of MSE and by 21.9% in

the case of RMSE (root mean squared error).

I report the RMSE from the AR(1) forecast and the SPF forecasts across the two subperiods, 1969:1 - 1984:3 and 1984:4 - 2003:2 in Table II. In all calculations, RMSE is defined as,

$$RMSE = \sqrt{\frac{1}{T}\Sigma_{t=1}^{T} e_{t,t+h}^2}\ , \tag{8}$$

where $e_{t,t+h}$ is the forecast error from either the AR(1) model, $e_{t,t+h} = y_{t+h,t} - \hat{\alpha} - \hat{\rho} y_{t-h,t}$, or the SPF forecasts, $e_t = y_{t+h,t} - f_{t,t+h|t}$. The annual RMSE calculations are shown for each quarter separately and averaged across all quarters. Annual forecasts made in different quarters are analyzed separately because there is reason to expect that annual forecasts made in different quarters behave differently. Fourth quarter forecasts, for example, coming at the end of the calendar year when many firms, investors and government agencies make plans for the coming year may be made using more time and effort, and may therefore be expected to be more accurate, than forecasts made during other quarters.

The results for forecasts of quarterly real GDP growth confirm the R^2 calculations above. As noted previously, during the 1969:1 - 1984:3 subperiod, the SPF forecasts were more accurate than those from the AR(1). In particular, the RMSE of the SPF forecasts was 13% smaller than that of the AR(1). After 1984, the forecastability of real GDP growth eroded relatively quickly. Over the entire 1984:4 - 2003:2 subperiod, the RMSE of the SPF forecasts was 4% worse than that of the AR(1) model. This implies that using the AR(1) to measure the change in real GDP uncertainty, as measured by RMSE, overstates the decline by 20% relative to the SPF forecasts. Analyzing annual growth forecasts suggest that using the AR(1) model to identify the unpredictable component of real GDP growth results in an even larger overstatement of the change in macroeconomic uncertainty. The pooled sample of annual growth forecasts indicates that the SPF forecasts were 28% more accurate, in the RMSE sense, before 1984 and 20% less accurate thereafter. This implies a 36% overstatement in the reduction of annual real GDP RMSE. The estimates of the overstatement using annual forecast data range from between 25% in the case of third quarter annual forecasts to 62% in the case of fourth quarter annual forecasts.

While the point estimates contained in Table II suggest that the decline in forecastability that has accompanied the reduction in real GDP volatility has led to an overstatement in the size of the decline in real GDP uncertainty, I now move to a more formal test of this hypothesis. In particular, I specify and estimate a model for the AR(1) and the SPF forecasts that restricts the MSE of both forecasts to be proportional to each other. In particular, the SPF forecasts may have a lower MSE than the AR(1) forecasts but the percentage change in the MSE from both sets of forecasts is restricted to be identical across both sets of forecasts. The model is specified as,

$$\begin{aligned}
y_{t,t+h} &= \alpha + \rho y_{t-h,t} + \varepsilon_{t,t+h} \\
e_{t,t+h} &= y_{t,t+h} - f_{t,t+h|t} \\
E[(\varepsilon_{t,t+h})^2|\Omega_t] &= \sigma^2_{0,\varepsilon}(1+\kappa D_{1,t}) \\
E[(e_{t,t+h})^2|\Omega_t] &= \sigma^2_{0,e}(1+\kappa D_{1,t}) \\
D_{1,t} &= 1(t \geq T^*) \\
T^* &= 1984{:}3
\end{aligned}, \tag{9}$$

where $y_{t,t+h}$ is the growth in real GDP and $f_{t,t+h|t}$ is the associated forecast from the SPF. The model is estimated by GMM using both the quarterly and annual forecast data. The model contains five parameters, $(\alpha,\ \rho,\ \kappa,\ \sigma^2_{0,AR}, \sigma^2_{0,SPF})$, and was estimated using six moments leaving one degree of overidentification for Hansen's J-statistic.

The model estimates and specification test are contained in Table III. The estimation results clearly indicate that forecast uncertainty did decline significantly after 1984. Across both quarterly and annual forecast horizons, the estimated decline in RMSE is remarkably consistent, ranging between 46%-49%. The J-statistic, however, indicates that the assumption of an identical proportional decline in forecast uncertainty across the AR(1) and SPF forecasts is at odds with the data. The specification test is rejected at the 3% level in the case of the quarterly forecasts and at the 6% level in the case of the (pooled) annual forecasts. These results confirm the interpretation given to the point estimates contained in Table II. Inferences drawn from the AR(1) model may lead to an overstatement in the reduction of macroeconomic uncertainty since 1984. The source of the overstatement is the attendant decline in predictability. At precisely the time that real GDP shocks became less volatile, the economy became less predictable. The decrease in predictability has resulted in a smaller decline in uncertainty than would have resulted if there had been no decline in predictability after 1984.

3.2 Evaluating the Size of the Overstatement in Macroeconomic Uncertainty on Estimates of the Equity Premium

The preceding analysis provides evidence that the actual decline in real GDP uncertainty has been smaller than that suggested by the AR(1) model for output growth. The importance of the magnitude of the overstatement, however, has not been addressed. Determining its economic relevance demands a precise framework for evaluating the consequences of decreased economic uncertainty. In this section, I briefly examine a simple economic model of asset prices and show how its quantitative predictions would change once the overstatement in macroeconomic volatility is taken into account. I focus on the case of asset prices for two reasons. First, asset markets play a central role in the macroeconomy and the link between macroeconomic fundamentals and asset prices represents one of the key questions addressed by modern macroeconomic research. Secondly, some recent research has attempted to link the decline in macroeconomic volatility since the mid-1980's to the behavior of asset prices since the 1990's. In particular, Lettau, Ludvigson and Wachter (2003) have argued that the great moderation explains a significant portion of the increase in U.S. asset values since the 1990's.

Their reasoning follows from the predictions of the classic consumption capital asset pricing model (CCAPM). Consider a standard, complete markets economy with a single source of non-diversifiable consumption risk that grows at a stochastic rate, $\Delta\tilde{c}_t$, per period. Further, consider a representative agent endowed with iso-elastic utility and coefficient of relative risk aversion, γ. Finally, consider a stock with a risky investment return, $\tilde{R}_t$, and a risk-free bond with certain return R^f. Within this framework, it is well known (Cochrane, 2001), that the expected equity premium on the stock may be approximated as,

$$E(\tilde{R}_{t+1} - R^f|\Omega_t) \approx \gamma\sigma_t(\Delta\tilde{c}_{t+1})\sigma_t(\Delta\tilde{R}_{t+1})\rho_t\,, \tag{10}$$

where $\sigma_t^2(x_{t+1})$ represents the conditional variance of x_{t+1}, $\sigma_t(x_{t+1}) = E[(x_{t+1} - E(x_{t+1}|\Omega_t))^2|\Omega_t]$, and likewise ρ_t represents the conditional correlation between stock returns and undiversifiable consumption growth.

The expression for the equity premium in (10) makes clear the dependence of the equity premium on investors' uncertainty about future consumption and asset returns. Changes in the volatility of the predictable component of either future consumption or asset returns that are unaccompanied by changes in the volatility of their unpredictable components has no effect on the equity premium. Now, consider the effect of a one time "great moderation" in the volatility of the uncertain component of consumption growth from $\sigma_0(\Delta\tilde{c}_t)$ to $\sigma_1(\Delta\tilde{c}_t)$ on the equity premium holding the volatility of asset returns, the correlation between consumption and asset returns as well as preferences fixed. Simple calculation yields that this kind of change in macroeconomic uncertainty yields a proportional change in the equity premium of,

$$E^1(\tilde{R}_t - R^f) = \kappa E^0(\tilde{R}_t - R^f)\,, \tag{11}$$

where the constant of proportionality is simply the ratio of the RMSE of consumption growth,

$$\kappa = \frac{\sigma_1(\Delta\tilde{c}_t)}{\sigma_0(\Delta\tilde{c}_t)}\,.$$

Now consider evaluating the likely effects of the great moderation on the equity premium.

Before doing so, however, note that the equity premium depends on consumption growth uncertainty and that this paper focuses on output growth. While permanent income hypothesis considerations suggest that the two should not coincide empirical evidence suggests that they have. Stock and Watson (2003), for example, document a similar decline in the volatility of consumption growth and real GDP growth before and after 1984.[11] In what follows, I simply assume that the trend in consumption growth volatility and that the breakdown between the predictable and unpredictable components of consumption mirror those of GDP.[12]

If the entire decline in macroeconomic volatility since 1984 is assumed to be the result of declining uncertainty, i.e. a decline in $\sigma_t(\Delta\tilde{c}_{t+1})$, then estimates of the decline in RMSE identified from the quarterly AR(1) model contained in Table II would suggest that the post 1984 equity premium would decline by 55% ((1-0.45)*100%). The previous results reported in this paper suggest, however, that this results in an overstatement of the likely decline. A portion of the decline in macroeconomic volatility since 1984 is due to declining predictability which is unrelated to declining uncertainty. The results from the SPF forecast data suggest that uncertainty has only declined by 46% ((1-0.54)*100%). Accordingly, making inferences from relying on the drop in total volatility results in a 20% overstatement ((1-0.54/0.45)*100%) of the probable decline in the equity premium.

While a 20% overstatement may not seem very large, investment return calculations can be extremely sensitive to assumed rates of return. Consider, the problem of estimating the solvency position of the Social Security system in thirty years time. Whether the assumed equity premium is 5% or 6% can have large consequences for the future viability of Social Security. To take a more pragmatic example,

[11] Stock and Watson (2003) report that the ratio of the standard deviation of consumption growth between 1960-1983 to the standard deviation of consumption growth between 1984-2002 to be 0.6. The ratio of non-consumption components of GDP growth over the same period is roughly 0.74 and the ratio of the volatility of goods production is 0.72.

[12] The SPF in principle, could be used to examine the properties of real consumption growth. Survey participants, however, were only asked about real consumption expenditures after the third quarter of 1981, making an analysis pre and post great moderation infeasible.

imagine estimating the amount of time it will take an initial investment to double in size. The Rule of 70 indicates that a 20% overstatement of the decline in the rate of return implies a 20% overstatement in the amount of time needed to double one's initial investment.[13] For example, an investor who uses a 5% rate of return estimate instead of an estimate of 6% will overestimate the amount of time needed to double her initial investment by over two years. These considerations suggest that a 20% overstatement in the decline of the equity premium may be important. At least, they suggest that the effect of declining predictability on the decline in total macroeconomic volatility should be accounted for when measuring the decline in macroeconomic uncertainty that has occurred since 1984.

Using annual GDP growth rates to estimate the decline in macroeconomic volatility leads to an even larger overstatement. Again, Table II shows that the ratio of the standard deviation of annual output growth shocks as measured by the AR(1) has declined by 56% ((1-0.44)*100%) which would result in an estimate of a 56% decline in the equity premium. The annual SPF forecast data contained in Table II, however, suggest that the volatility of the uncertain component of GDP has only declined by 40% ((1-0.60)*100%) since the beginning of the great moderation, implying that the earlier estimate results in a 36% ((1-0.60/0.44)*100%) overstatement in the decline of the equity premium. Estimates of the overstatement using different annual forecasts from different quarters range between 25% to 62%. These estimates from annual forecast data suggest even more strongly that the decline in predictability since the great moderation may be important for interpreting the likely effects of the great moderation on the equity premium.

4 The Role of "Good Luck" and "Good Policy" in the Great Moderation: Evidence From the Decline in the Predictable Component of Real GDP Growth

In light of the sheer size of the decline in macroeconomic volatility documented by Kim and

[13] The Rule of 70 states that the amount of time needed to double an initial investment that grows at r% per year is approximately 70/r.

Nelson (1999), McConnell and Perez-Quiros (2000) and Stock and Watson (2002,2003) among others, a key question surrounding the decline has been to what extent the decline is related to either good luck or good policy. One potential explanation for the drop in volatility is simply that the U.S economy has not been hit by any of the large shocks that were considerably more frequent during the 1970's and 1980's. From an historical perspective, the decades since the mid-1980's have not seen a major OPEC oil crisis, a major military conflict with the scope of the Vietnam war or a major political crisis on the scale of the Watergate scandal. This has led some to argue that the decline in volatility since 1984 is simply a matter of "good luck". Another interpretation of the decline in volatility is that improved economic conditions have led to a more stable, less volatile economy. Improved monetary policy, reductions in barriers to trade and more sectoral diversification across the U.S. economy have all been considered as potential examples of "good policy" which may have led to the decline in macroeconomic volatility. Exactly what is meant by the phrase "good policy" is itself still an open question. In general, I interpret the phrase "good policy" to mean any structural change in the macroeconomy, whether as a result of some specific policy or simply through technological progress or some other maturation of the economic environment that leads to a more stable economy.

Understanding the role that structural changes in the U.S. economy (i.e., good policy) have played in contributing to the decline in macroeconomic volatility is both important and difficult. Consider the fundamental decomposition of the variance of real GDP growth,

$$Var(y_{t,t+h}) = Var(E(y_{t,t+h}|\Omega_t)) + E(Var(e^u_{t,t+h})) ,$$

which decomposes the variance of output growth into the variance of its observable and unobservable components. Suppose that these components could be perfectly observed both before and after the great moderation so that there is no measurement error in either $\Delta Var(E(y_{t,t+h}|\Omega_t))$ or $\Delta E(Var(e^u_t))$.

Consider using the change in the variance of the unpredictable component to identify whether good policy has played a role in the great moderation. The identification problem here seems insurmountable. Arguably, either good luck, in the way of fewer large shocks, or unexpected good policy that reduced the size of these shocks could explain a decline in $\Delta E(Var(e_t^u))$. The only way to plausibly identify whether good policy played a role in reducing the variance of the unpredictable component of output would be by observing the unexpected shocks to policy that were unobserved by investors, firms and other agents engaged in forecasting the economy's movements. Given the considerable information advantage these agents have over econometricians, even with the benefit of hindsight, this informational requirement appears extremely difficult to satisfy.

Examining the causes for the decline in the variability of the predictable component of output growth, however, may be more promising. Economic forecasts for future growth are conditioned on information available to forecasters. Typically, this information takes the form of information about the current state of the macroeconomy. Formally, imagine that forecasts of future growth are generated from the simple model,

$$E(y_{t,t+h}|\Omega_t) \equiv f_{t,t+h|t} = x_t'\beta , \tag{12}$$

where x_t represents those current indicators which forecasters deem useful for forecasting future output growth and β represents the sensitivity of future growth forecasts to current conditions. Implicitly, β represents forecasters' understanding of how current shocks or conditions of the macroeconomy are related to the future of the macroeconomy. In this way, β summarizes the forecasters' understanding of the mechanism through which current shocks to the economy feed forward to future output growth. Unlike, the unpredictable component of output growth, economists have an understanding of at least some of the variables, x_t, that influence future expected growth. As a result, it may be possible to investigate how changes in shocks to the forecasts' driving variables, x_t, and changes in the sensitivity of forecasts to these shocks, β, have contributed to the decline in predictability since 1984.

Consider decomposing the variance of the predictable component of output growth as follows,

$$Var(E(y_{t,t+h}|\Omega_t)) = Var(f_{t,t+h|t}) = \beta' E((x_t - \mu_x)(x_t - \mu_x)')\beta\ , \tag{13}$$

a change in the variability of the predictable component of output that stems from a decline in the variance of the forecasts's driving shocks, x_t, is difficult to interpret. Plausibly, either good luck in the way of fewer large driving shocks or some unobserved good policy which reduces the size or frequency of these shocks could explain such a decline. A decline that results, however, from a reduction in the forecast's sensitivity to current shocks, β, represents a systematic change in the way that economic forecasts respond to current economic conditions. In this way, changes in β, represent a systematic change in the manner that economic shocks are propagated through the economy over time. This kind of structural change within the macrocoenomy is squarely in line with what is referred to as the benefits of "good policy". Whether such a change is the result of some improved monetary or other governmental policy or the result of some reduction in market frictions or improvements in technology is impossible to identify with these data. Ultimately, a complete analysis of this question would require the identification of specific policies and changes in the macroeconomy which could have contributed to the decline in the forecast's sensitivity to current macroeconomic conditions.

I examine the sensitivity of the SPF's quarterly and anuual growth forecasts to two broad measures of macroeconomic conditions. The first indicator I employ in this anlaysis is an index of fuel prices obtained from the CPI. I examine the effect of fuel price shocks to forecasts of future growth because of the prominent role that energy prices play in determining future production. It is hard to think of any industry that is unaffected by the price of fuel and energy. Moreover, given the historical link between fuel prices and the business cycle it would seem inappropriate not to examine how fuel prices affect forecasts of future growth. The second indicator is Stock and Watson's (1989) experimental coincident indicator (XCI). The XCI is a weighted average of four broad aggregate measures of macroeconomic activity: industrial production, real personal income, real manufacturing and trade sales and employee hours in non-agricultural establishments. The weights evolve over time and are estimated using a dynamic factor model. The exact details of the index's construction can be found by consulting Stock and Watson (1989). I focus on the XCI because it represents a very broad summary measure of the current state of the macroeconomy.

In order to assess how the roles of these macroeconomic indicators have changed before and after the great moderation, I estimate the following model,

$$f_{t,t+h|t} = (\alpha + \alpha_1 D_{1984:3}) + (\beta_{FUEL} + D_{1984:3}\beta_{FUEL,1})\%\Delta FUEL + (\beta_{XCI} + \beta_{XCI,1}D_{1984:3})\%\Delta XCI + \eta_t \,, \quad (14)$$

where, as before, $D_{1984:3}$ is a dummy variable that takes on the value one after 1984:3. I transform both the XCI and the fuel price series to growth rates to account for the fact that forecasts are for future growth and not future levels. The final model is estimated by OLS and the results are contained in Table IV.

The estimates contained in Table IV suggest that the influence of both shocks to fuel prices and the coincident indicators have been reduced since the onset of the great moderation. The signs of all interaction terms for both the quarterly and annual forecasts are as expected and the Wald test of the null hypothesis that all interaction terms are zero is rejected at any reasonable significance level. After 1984, both fuel price changes and changes in the XCI become considerably less important for future growth forecasts. The estimated size of the reduction in sensitivity is large. In the case of fuel prices the effect of the fuel price shock to expected future growth is nearly eliminated after 1984 in the case of both quarterly and annual forecasts. The effect of shocks to the coincident indicators on future growth forecasts is also significantly reduced. In the case of quarterly forecasts, the point estimates suggest a 60% reduction in the sensitivity of real GDP forecasts to a current shock to the XCI. In the case of the annual forecasts the sensitivity is reduced by 80% after 1984. These results indicate a recognition among professional forecasters of a significant change in the mechanism that transmits shocks through the economy. After

1984, the future expected path of the macroeconomy is less sensitive to its current position. This reduction in sensitivity suggests that good policy, of some form, has played a role in reducing macroeconomic volatility since 1984.

This conclusion, however, requires qualification. First, an underlying assumption used in this analysis is that forecasts are linearly related to the observed current state of the economy. This assumption is not uncontroversial. One of the reasons motivating the use of the SPF forecasts as measures of expected growth is that they may account for important nonlinear relationships between current and future macroeconomic conditions. The results in the case of the oil price shocks are particularly subject to this criticism. The declining sensitivity of macroeconomic conditions to fuel price fluctuations has previously been documented by Hooker (1996) and Hamilton (1996, 2003). It is worth noting, however, that the results contained in Table IV are slightly more nuanced than those reported by Hooker (1996) and Hamilton (1996,2003). These results document that ex-ante expectations about future macroeconomic conditions, rather than the macroeconomic conditions themselves, have become less sensitive to fuel price shocks since 1984. Hamilton (2003) argues that the reduced sensitivity of the U.S. economy results from a complex nonlinear relation between oil price shocks and output. In particular, Hamilton argues that oil price increases that follow previous decreases do not constrain output. Furthermore, Hamilton argues that only oil price shocks that result in severe disruptions in supply are important for determining future output. According to Hamilton (2003), none of the oil price shocks observed since the 1980's meet this standard. While there may well be a subtle nonlinear relationship between oil prices and future output these considerations do not explain the results for the XCI. It is unclear that the same considerations which imply a nonlinear relation between oil prices and future growth also holds for the relation between current employment, industrial production, sales, personal income and future output. In this sense, the preponderance of the evidence presented in Table IV points to a general decline in the sensitivity of future output to current overall macroeconomic conditions.

Another cause for concern with these results is that the explanatory value of both fuel prices and the XCI for growth forecasts has declined considerably since 1984. Before 1984, these two variables explained over one-half of the variation in growth forecasts. After 1984, these indicators explain between 3-10% of the variance of SPF forecasts. Accordingly, unmeasured factors which affect future growth forecasts have become considerably more important since 1984. Consider decomposing growth forecasts into its observable and unpredictable component,

$$\begin{aligned} f_{t,t+h|t} &= x_t^{\prime}\beta + \eta_t \\ \eta_t &= z_t^{\prime}\gamma \end{aligned}, \tag{15}$$

where z_t represents factors, unobserved to the econometrician, which influence growth forecasts and γ measures the forecast's sensitivity to these unobserved factors. Examples of these factors include investor sentimment or consumer confidence but could also include real measures of economic activity that are not well correlated with either fuel prices or the XCI such as the productivity of service related industries. Interpreting the decline in β since 1984 as a sign that the economy is more resilient and less sensitive to current shocks could be inappropriate if the variance of $z_t^{\prime}\gamma$ itself increased after 1984. This would naturally arise, for example, if the economy was progressing towards a service based economy and as a result the economy's future path was becoming more tightly linked to the productivity of service related industries and less related to fuel prices and industrial production which are comparatively more informative about the state of the "bricks and mortar" component of the economy. While this possibility is certainly an issue, it is worth noting that the volatility of the unmeasured factors that affect output have also declined considerably since 1984. In the case of both quarterly and annual forecasts, the standard deviation of the unmeasured factors has dropped by roughly 50% since 1984. In the case of quarterly forecasts, for example, the standard error of the regression reported in Table IV when estimated using data between 1969:1 and 1984:3 was 1.93% per quarter. After 1984, the standard error of the regression drops to 0.92%. This drop in the variance of the unmeasured factors suggests that shocks to both the measured and unmeasured factors that influence future forecasts have become less important since the beginning of the great moderation.[14]

Forecasts of future growth have become significantly less sensitive to a broad set of current macroeconomic indicators since the beginning of the great moderation. This reduction in forecast sensitivity represents a structural change in the dynamics of how shocks are transmitted through the macroeconomy over time. This change in the shock transmission mechanism is squarely in line with what is considered to be the benefits of "good policy". The source of this decline in forecast sensitivity is not identifiable with these data. Whether the decline in the dependence of the macroeconomy's future on its own past is the result of more sectoral diversification, benefits in technological progress or from reductions in other market frictions is an interesting and challenging question for future research.

5. Conclusion

A wide body of research convincingly shows that macroeconomic volatility has declined substantially since 1984. This great moderation represents one of the most prominent features of the modern macroeconomic landscape. This paper uses forecast's of annual and quarterly real GDP growth to isolate the predictable and unpredictable component of real GDP growth between 1969-2003. The SPF forecasts reveal that the period of the great moderation represents a moderation in volatility, uncertainty and, importantly, predictability. Before 1984, professional forecasters were considerably more adept than a simple autoregressive model at forecasting future growth. After 1984, the tow sets of forecasts are comparable. This decline in the predictability of future real GDP growth implies that only a portion of

[14]Of course, one could argue that the variance of the unmeasured factors, z_t, dropped while the sensitivity to these factors, γ, rose, resulting in a net decrease in the total variance. While this would be problematic for the interpretation provided here, it seems both unlikely and is impossible to explore without a better understanding of the precise composition of those unmeasured factors.

the decline in real GDP volatility is due to a decline in macroeconomic uncertainty. Using either the decline in raw volatility or the decline in the volatility of growth shocks identified from a fixed parameter AR(1) model overstates the decline in macroeconomic uncertainty by between 20%-40%. This overstatement has important consequences on evaluating the economic implications of the great moderation. In the case of the equity premium, it was shown that overstating the decline in macroeconomic uncertainty leads to a similar overstatement in the expected decline in the equity premium. Finally, I argue that the decline in the variation of the predictable component of ral GDP growth is informative about the role that good policy has played in moderating macroeconomic volatility. I find that since 1984, forecasts of future growth have become significantly less sensitive to a broad set of current macroeconomic indicators. Theis decline in sensitivity suggest a systematic change within the macroeconomy which has made the future less sensitive to the past. This systematic reduction in the dependence of the future on the past is arguably a benefit of a systematic change in the structure of the macroeconomy which is directly in line with the interpretation of what is commonly meant by the phrase "good policy".

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Table 1
Encompassing Tests
SPF vs. AR(1)

	Quarterly 1969:2 - 2002:4	Annual 1971:4 - 2002:2
Parameter Estimates		
β_0	0.49	5.00
	(1.22)	(4.0)
β_{AR}	-0.07	-1.72
	(0.41)	(1.30)
β_{SPF}	0.99	1.08
	(0.22)	(0.18)
β_1	-0.59	-10.00
	(2.13)	(0.05)
$\beta_{AR,1}$	0.71	4.32
	(0.69)	(1.70)
$\beta_{SPF,1}$	-0.49	-0.91
	(0.37)	(0.46)
Wald Statistics		
$(\beta_0,\beta_{AR},\beta_{SPF},\beta_1,\beta_{AR,1},\beta_{SPF,1}) = (0,0,1,0,0,0)$	11.67	14.23
	(0.07)	(0.03)
$(\beta_0,\beta_{AR},\beta_{SPF}) = (0,1,0)$	0.30	0.79
	(0.96)	(0.50)
$(\beta_1,\beta_{AR,1},\beta_{SPF,1}) = (0,0,0)$	0.72	9.79
	(0.54)	(0.02)

This table reports OLS estimates from the encompassing model,
$y_{t,t+h} = \beta_0 + \beta_{AR} f^{AR}_{t,t+h|t} + \beta_{SPF} f^{SPF}_{t,t+h|t} + \beta_1 D_{1984:3} + \beta_{AR,1} D_{1984:3} * f^{AR}_{t,t+h|t} + \beta_{SPF,1} D_{1984:3} * f^{SPF}_{t,t+h|t} + \eta_{t,t+h}$. Newey-West (1987) standard errors are reported in parentheses under the parameter estimates. The left column reports results using quarterly real GDP forecasts and the right column presents estimates using annual forecasts. The last three rows present a set of Wald statistics. The first statistic tests the hypothesis that the SPF forecasts encompass the AR(1) forecasts over the entire sample period. The second statistic tests whether the SPF forecasts encompass the AR(1) forecasts prior to the great moderation. The last statistic tests wheter there is any difference between the encompassing parameters before and after the great moderation. The asymptotic p-value of each test is reported in parentheses under the value of the statistic.

Table II
RMSE of Quarterly and Annual Real GDP Forecasts
1969-2002

	Pre-Moderation	Post-Moderation	$\frac{RMSE_{post}}{RMSE_{pre}}$
Quarterly Forecasts			
SPF	3.98	2.13	0.54
AR(1)	4.58	2.04	0.45
Annual Forecasts			
Pooled Sample			
SPF	2.53	1.51	0.60
AR(1)	3.07	1.36	0.44
First Quarter			
SPF	2.91	1.51	0.52
AR(1)	3.26	1.33	0.41
Second Quarter			
SPF	2.50	1.58	0.63
AR(1)	3.04	1.39	0.46
Third Quarter			
SPF	2.52	1.39	0.55
AR(1)	3.00	1.33	0.44
Fourth Quarter			
SPF	2.13	1.56	0.73
AR(1)	2.96	1.33	0.45

This table reports the RMSE of the median SPF annual real GDP forecast and the AR(1)annual real GDP forecast between 1972 and 2002. The table displays RMSE for annual quarter to quarter forecasts for each of the four quarters during the year. All numbers are reported in annual percentage terms.

Table III
GMM Estimates of A Restricted Variance Model of Real GDP Forecasts and Residuals
1969:1 - 2003:2

	α	ρ	$\sigma^2_{0,AR}$	$\sigma^2_{0,SPF}$	κ	J-Statistic
Quarterly Forecasts						
	2.08 (0.69)	0.29 (0.10)	4.45^2 (1.94)	4.12^2 (1.04)	-0.76 (0.05)	4.54 (0.03)
Annual Forecasts						
Pooled Sample	2.50 (0.49)	0.05 (0.09)	3.20^2 (0.68)	2.87^2 (0.74)	-0.76 (0.07)	3.47 (0.06)
First Quarter	2.77 (0.55)	0.03 (0.09)	3.17^2 (1.05)	2.91^2 (0.81)	-0.78 (0.09)	1.90 (0.17)
Second Quarter	2.52 (0.42)	0.09 (0.08)	3.14^2 (0.65)	2.78^2 (0.84)	-0.77 (0.08)	2.97 (0.08)
Third Quarter	2.99 (0.45)	-0.02 (0.12)	3.11^2 (0.84)	2.78^2 (1.18)	-0.79 (0.07)	0.66 (0.42)
Fourth Quarter	2.80 (0.48)	0.11 (0.11)	2.89^2 (0.75)	2.39^2 (1.09)	-0.78 (0.08)	2.57 (0.11)

This table reports GMM estimates from the model, $y_t = \alpha + \rho y_{t-1} + \varepsilon_t$, $E(\varepsilon_t^2|\Omega_{t-1}) = \sigma^2_{0,AR}(1 + \kappa D_t)$, $E(e_t^2|\Omega_{t-1}) = \sigma^2_{0,SPF}(1 + \kappa D_t)$. Asymptotic standard errors are reported in parentheses under the parameter estimates. In the case of the variance parameters, the Delta method has been used in reporting the asymptotic standard error of the volatility rather than the variance. The model is estimated separately for the annual forecasts of each quarter within the year as well as a pooled sample which imposes parameter constancy across forecasts generated in different quarters. The last column of the table reports the test of the model's overidentifying restrictions and has an asymptotic $\chi^2(1)$ distribution. The asymptotic p-value of this test is reported in parentheses under the value of the J-statistic. A Newey-West, HAC weighting matrix was used in model estimation.

Table IV
Current Macroeconomic Conditions and
SPF Real GDP Forecasts

	Quarterly	**Annual**
$\%\Delta FUEL$	-20.31	-5.13
	(4.66)	(1.45)
$\%\Delta XCI$	96.53	20.19
	(12.65)	(5.33)
$D_{1984:3}$	-0.58	-1.16
	(0.48)	(0.36)
$\%\Delta FUEL * D_{1984:3}$	20.87	4.72
	(5.22)	(1.55)
$\%\Delta XCI * D_{1984:3}$	-58.32	-16.02
	(30.74)	(8.50)
Wald Statistic	17.31	11.36
	(0.00)	(0.00)
R^2_{69-84}	51.00%	61.33%
σ_{69-84}	1.93%	1.10%
R^2_{84-03}	9.50%	3.10%
σ_{84-03}	0.92%	0.58%

This table presents OLS estimates of the regression, $f_{t,t+h} = x_t'\beta + \eta_t$, where $f_{t,t+h}$ is either the quarterly or annual SPF forecast. Newey-West (1987) standard errors are reported in parentheses. The Wald Statistic reports the test and asymptotic p-value, in parentheses, associated with the null hypothesis that all interaction terms are zero. The R^2 that results from computing the regression between 1969-1984 and 1984-2003 along with the standard error of the regression over these periods is also reported.