



Federal Reserve Bank of Chicago

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Abstract

Economic activity depends on agents' real-time beliefs regarding the persistence in the shocks they currently perceive to be hitting the economy. This paper uses an unobserved components model of forecast revisions to examine how the professional forecasters comprising the Blue Chip Economic Consensus have viewed such shocks to GDP over the past twenty years. The model estimates that these forecasters attribute more of the variance in the shock to GDP to permanent factors than to transitory developments. Both shocks are significantly correlated with incoming high-frequency indicators of economic activity; but for the permanent component, the correlation is driven by recessions or other periods when activity was weak. The forecasters' shocks also differ noticeably from those generated by some simple econometric models. Taken together, the results suggest that agents' expectations likely are based on broader information sets than those used to specify most empirical models and that the mechanisms generating expectations may differ with the perceived state of the business cycle.

1. Introduction

Economic activity depends crucially not just on the actual source of the shocks to the economy, but also on economic agents' real-time perceptions of the nature of these shocks. In particular, the behavior of households and businesses will depend on the degree to which they believe the economy is experiencing a permanent shift in its productive capacity as opposed to a transitory fluctuation about a trend path for output. For example, regardless of its ultimate persistence, a fluctuation in labor income that currently is perceived to be permanent will have a larger immediate impact on consumption and overall economic activity than one that is thought to be transitory. Accordingly, agents' perceptions of shocks and how well they compare with the eventual path for actual output are important for the historical interpretation of business cycles. Furthermore, learning about factors influencing economic agents' perceptions of shocks can help business cycle researchers specify theoretical and empirical models with expectational structures that are consistent with those observed in the economy.

There is a long history of empirical studies investigating the decomposition of actual GDP into permanent and transitory components; and today the economic and statistical identification of these shocks are standard features of most models used in business cycle analysis.¹ But there has been little work on identifying how economic agents have viewed fluctuations in GDP in real time.² This paper does so by examining how one group of well-informed agents--professional economic forecasters--have interpreted the shocks to the economy that they have experienced over the past twenty years. Specifically, I estimate the persistence and propagation patterns in the shocks to GDP perceived by the panel of forecasters comprising the Blue Chip Economic Indicators Consensus Outlook. I do so using a statistical model of the revisions to the short-, medium-, and long-horizon Blue Chip projections. I also consider how the

¹ Early statistical decompositions, such as those by Beveridge and Nelson (1981), Nelson and Plosser (1982), Watson (1986), Campbell and Mankiw (1987a, 1987b), Clark (1987), and Cochrane (1988), were based on univariate time series models for output. Later, Shapiro and Watson (1988), Blanchard and Quah (1989), Cochrane (1994) and others extended the analysis to multivariate frameworks. These studies produced a wide range of estimates of the relative importance of permanent and transitory shocks to GDP and in the patterns over which these impulses affect macroeconomic aggregates.

² One example is Edge, Laubach, and Williams (2004), who examine how forecasters revise their views of long-run productivity growth.

forecasters' views of shocks compare with the results from some simple econometric specifications that have been used in the academic literature to identify permanent and transitory shocks to GDP.

There are three broad statistical findings. First, the Blue Chip forecasters attribute more of the variance in the shock to the level of GDP to permanent factors than they do to transitory developments. Second, the shocks to the Blue Chip forecasts differ in a number of ways from those identified by the statistical GDP models. Third, both the permanent and transitory Blue Chip shocks are significantly correlated with incoming high-frequency indicators of economic activity; and for the permanent component, the relationship varies with the state of the business cycle.

Turning to the details of the results, on average, the forecasters comprising the Blue Chip Consensus perceive that about 30 percent of the current shock to real GDP reflects transitory factors while about 70 percent is due to a permanent change in the level of output. This estimate of the relative importance of permanent versus transitory shocks is in the upper half of the range found in the literature that estimates such decompositions in the published GDP data and is larger than the estimates generated by most of the GDP models that I consider.³ The transitory shocks are thought to have an economically and statistically significant impact on output for at least 1-1/2 years while the full effect of permanent shocks become incorporated into GDP in about one year. These impulse response patterns are similar to those from most of the GDP models that I estimate.

By construction, the revision to the forecast from an econometric model is a function of the model's most recent forecast errors. In contrast, both the permanent and transitory shocks to the Blue Chip forecasts are essentially uncorrelated with last-period's forecast error. Instead, the Blue Chip revisions are more heavily influenced by the incoming high-frequency data on economic activity. Such data are not included in the statistical GDP models I consider; nor are they generally included in larger forecasting models, which usually project GDP based solely on quarterly aggregates from the national accounts. Furthermore, there are some economically interesting relationships

³ As discussed below, the variance decomposition of the current-period forecast revision differs from the forecast-error-based variance decompositions of GDP itself made in the papers cited in footnote 1. Section 5 adjusts for the differences and compares the Blue Chip forecast revisions to comparable revisions from

between the high-frequency indicators and the shocks to the Blue Chip forecasts. The correlation between the indicators and the transitory shocks does not appear to vary cyclically, but the correlation with the permanent shock appears to be driven largely by behavior during recessions or periods of sluggish growth. There also are relatively large perceived permanent shocks following the 1987 stock market crash, the onsets of the 1990 and 2001 recessions, and following September 11, 2001--events that forecasters thought would be associated with weak economic activity. Though sample-size limitations mean these results are tentative, they do suggest that forecasters view recessions or shocks associated with unusual, but identifiable, events more as permanent reductions in output than transitory deviations in production from trend or a reallocation of production across time.

The results relating past forecast errors and high-frequency indicators to the Blue Chip shocks suggest that there is an important difference between the information sets used by professional forecasters and the national income accounts data generally used to estimate quarterly econometric models of aggregate economic activity. In addition, forecasters may process information differently if they see data or events suggesting the economy is threatened with a recession than if it is in the midst of an expansion. Such differences can not be captured by linear econometric models with identically distributed error terms. These results also are relevant for researchers seeking to construct expectationally consistent models of business cycle behavior.

My empirical findings are generated using a relatively flexible unobserved components model of the revisions to the Blue Chip forecasts. The model exploits the simple observation that only permanent shocks can affect output in the very long run. Thus the revision made today to the projection of GDP at a far-distant forecast horizon reflects only the shocks that forecasters think will be permanent. The difference between these permanent shocks and the revision to the projection for current GDP then identifies the transitory shock. Finally, the correlations between the revisions to projections at different forecast horizons reveal the impulse response patterns that describe how forecasters think the effects of the shocks on output will play out over time.

four time-series models that calculate permanent and transitory shocks to GDP. I find that the Blue Chip attributes a larger proportion of the forecast revision to permanent factors than do three of the four models.

Working with the observed forecast revisions eliminates the need for a detailed analysis of how the projections actually are constructed. This is useful because the Blue Chip forecast is not the simple unadulterated output of a single statistical model with a corresponding mechanical representation of shocks and impulse responses. Instead, many forecasters comprise the Blue Chip panel, and virtually all of them make judgmental adjustments to model projections or base their forecasts on a wide range of statistical and anecdotal sources. Nonetheless, regardless of how the forecasts are constructed, any time a forecaster revises a projection, he or she takes a stand on the new information they think will influence GDP and the degree to which the shocks will either dissipate over time or become permanently embedded into the economy. These judgments can be inferred from the observed forecast revisions. Throughout the paper I will refer to these judgments as forecasters' perceptions of the permanent and transitory shocks. This terminology highlights the fact that the shocks are not generated by any particular statistical model and that they are real-time evaluations that never undergo ex-post adjustments to calibrate them to the actual path for GDP that eventually transpired.

2. The Data

2.1 The Blue Chip panel and data availability

Many private- and public-sector economists regularly sell macroeconomic forecasts to clients or release them to the public. One of the most widely used summaries of such projections is the "Consensus Outlook" published by the Blue Chip Economic Indicators. The Blue Chip Consensus is the simple arithmetic average of the projections made by the Blue Chip panelists. There are 52 forecasters in the current panel.

The Blue Chip Consensus is interesting for a number of reasons. First, the forecasts are made by the economic staffs at major investment banks, financial services firms, large commercial banks, industrial companies, economic consulting firms, and university-affiliated forecasting projects. Accordingly, the projections encompass expectations for the macroeconomy held by organizations making large financial commitments or selling services to business clients. Second, the Blue Chip Consensus is

commonly used as a benchmark against which to compare other forecasts. For example, both the Administration and Congressional Budget Office compare their official forecasts with the Blue Chip Consensus in their annual analyses of the United States Budget.

Third, the average is likely the most important moment of the distribution of forecasts with regard to how expectations may feedback onto aggregate activity. One reason is that the Consensus averages out perennially optimistic or pessimistic forecasters. Indeed, Bauer, Eisenbeis, Waggoner, and Zha (2003) show that the Consensus does a better job in predicting calendar-year average growth rates than the projections of most of the individual forecasters.

On the 10th of each month, Blue Chip publishes a Consensus forecast for each quarter in the current and subsequent calendar years. This projection period is too short to separately identify transitory events expected to last a year or two from developments expected to have a permanent impact on the level of economic activity. However, twice a year the Blue Chip surveys its respondents for projections covering the next 12 years. In addition to the regular quarterly projections, each March and October the panel also is queried for calendar-year annual forecasts for each of the next 6 years and for the average pace of activity over the subsequent 5-year period (the 7 through 12-year-ahead forecast period).⁴ These forecasts thus provide semi-annual information on how forecasters interpret the effect of incoming shocks on the path of GDP *both* over the next several quarters and for many years to come.⁵ Since I need to observe near-, medium-, and long-horizon forecasts made at the same point in time, this paper uses only the forecasts made in March and October.

Let $gdp(t+k)$ be the value of the logarithm of real GDP k periods from now and $f_t gdp(t+k)$ be the forecast made in period t of $gdp(t+k)$; $k = 0, 1, 2, \dots, K$. As a practical matter, forecasters provide projections for GDP growth, $f_t \Delta gdp_t(t+k) = f_t gdp(t+k) - f_t gdp(t+k-1)$. Given that I observe forecasts two times a year, I work with semi-annual time series of projections for half-year periods. Specifically, when t is in March, the $k =$

⁴ The individual Blue Chip forecasts are not available at the quarterly or long-run forecast horizons—they are only published for the averages of the current and next calendar-year.

⁵ The Blue Chip is better suited for studying shocks and propagation than another popular forecast data set, the Survey of Professional Forecasters (SPF). The SPF publishes forecasts for average growth over a 10-year period. However, the SPF only began doing so in 1992; it only conducts the long-run survey once a year; and the SPF medium-term forecasts are limited to the current and subsequent four quarters.

0 forecast is of growth between the fourth quarter of the previous year and the second quarter of the current year; the $k=1$ forecast is of growth between the second and fourth quarters, and so on. If t is in October, the $k = 0$ forecast is for growth between the second and fourth quarters of the current year. In March, forecasts for $k = 0, 1, 2, 3$ can be constructed from the quarterly projections; in October, the quarterly numbers can generate forecasts for $k = 0, 1, 2$. For larger k , I interpolated the 2 through 6-year-ahead annual projections to the half-year frequency to generate semi-annual projections for up to $k = 9$. The long-run GDP forecast, $f_t \Delta gdp(lr)$, denotes the forecast of average growth made at time t for the 7 through 12-year-ahead period. The complete set of short-, medium- and long-term forecasts begins in March 1982; the sample I use runs through the first half of 2005. Appendix 1 provides further details regarding timing conventions and the methodology used to distribute the annual forecasts to a semi-annual basis.

2.2 The historical data

Figure 1 presents some of the data. The time axes in the graphs denote the period being forecast. The solid lines in each panel are forecasts for half-year growth rates: the top-left panel plots forecasts made for the current half-year period ($k = 0$); the top-right panel the projection of semi-annual growth made one-half year earlier ($k = 1$); and the bottom panels the forecasts made one-year earlier ($k = 2$). The dashed lines in the top and lower left panels are the actual values for GDP growth as estimated by the third or final NIPA estimates.⁶ The dashed line in the lower-right panel is what forecasters were assuming for long-run growth at the time the forecast was made. The shading marks recessions as designated by the NBER.

The figure highlights several characteristics of these forecasts (see Krane 2003 for further details). First, the short-term forecasts can move around substantially, particularly during periods of economic weakness. In contrast, the medium and longer-run forecasts are much smoother. Indeed, as seen in the lower-right panel, even the one-year-ahead forecast appears to be fairly well anchored by the assumptions for longer-run growth.

Second, the forecast errors can be large. As seen in table 1, the root-mean-squared error (RMSE) for growth in the current half-year period is about 1-1/2 percentage point; the RMSEs for the longer-horizon forecasts are between 1-3/4 and 2 percentage points. These RMSEs compared with a standard deviation in actual half-year growth of about 2 percentage points. As seen in the graphs, the increase in the RMSEs at longer horizons largely reflects the fact that these forecasts vary only modestly from the long-run growth projections and therefore miss recessions. Third, the assumptions concerning long-run growth exhibit low-frequency variation; notably, they drifted down during the late 1980s and then moved up rather rapidly around the turn of the millennium.

Although the forecast errors are large, they pass some simple tests for rationality. As seen on the first column of table 1, the mean errors are not statistically different from zero. More formally, in the regression:

$$\Delta gdp(t+k) = a + b f_t \Delta gdp(t+k) + e_t(k) \quad (1)$$

$f_t \Delta gdp(t+k)$ fails as a rational forecast of $\Delta gdp(t+k)$ if the joint null hypothesis that $a = 0$ and $b = 1$ is rejected. As seen in the last column of table 1, one cannot reject this hypothesis for any value of k in the Blue Chip data. That said, this is not a resounding victory: with the exception of the $k = 0$ forecast, a often is well above zero and b well below one, but the standard errors are large enough that one cannot reject the null.

Figure 2 looks at the relationship between the current state of the economy and the projected path for GDP growth. The solid lines plot the differences between the forecasts for semi-annual growth made k periods ahead and the assumption for long-run growth at that time, $f_t \Delta gdp(t+k) - f_t \Delta gdp(lr)$. The time axis refers to the dates the forecasts are made. The dashed line is the most recent value of the three-month moving average in the Chicago Fed National Activity Index, or CFNAI-MA3, that is known at time t . The CFNAI-MA3 is an index that captures the comovement in 85 monthly indicators of economic activity. Thus, it measures common information about economic

⁶ Note that I assume forecasters were not predicting the effects of comprehensive revisions of the NIPA; accordingly the actual data in 1999, 1995, 1991, and 1985 were adjusted by the average changes in long-run growth that occurred with the comprehensive revisions to the NIPA in those years.

activity contained in a wide range of high-frequency indicators available to the professional forecasters.⁷

In the near term ($k=0, 1$), we see a large positive correlation between $f_t \Delta gdp(t+k) - f_t \Delta gdp(lr)$ and the CFNAI-MA3. This indicates that forecasters are building in some persistence of the current observed strength or weakness in the economy into their projections for the next year. For longer-run forecasts ($k = 2, 4$), however, there is a negative correlation between $f_t \Delta gdp(t+k) - f_t \Delta gdp(lr)$ and the current state of the economy. This suggests that forecasters are looking for some future offset to current high or low rates of growth. However, it is not clear from the graphs to what degree medium-term forecast adjustments offset near-term movements. To the degree that they do, the forecasters think the shocks hitting the economy are transitory; to the degree that they do not, the forecasters perceive a permanent element in the shocks hitting the economy.

Of course, these characterizations are only suggestive. Importantly, we do not know how much of the swings in the CFNAI-MA3 reflect informational surprises. And, as just noted, the relative scale of the various adjustments is unclear. For these, I turn to a more formal statistical model.

3. A Statistical Model to Identify the Perceived Shocks to GDP

3.1 A model of forecast revisions

This section presents a model of forecasters' real time views regarding the size and persistence of the shocks to GDP that they observe. The model is based on some general assumptions about how forecasters view the time series properties for GDP.

Specifically, I assume that the forecast of the logarithm of GDP is the conditional expectation:

⁷ The CFNAI is the first principle component of 85 monthly time series measuring production, employment, sales, construction, orders, and inventories. The index is normalized to have a value of zero when all of the indicators are moving along their long run trends. Given publication lags, the monthly

$$f_t gdp(t+k) = E[gdp(t+k) | \Omega_t] \quad (2)$$

where Ω_t is the information set used to construct the forecasts. I make no assumptions on whether or not Ω_t encompasses a formal model of economic activity. I do, however, assume Ω_t reflects a view that $gdp(t)$ is the sum of a permanent or trend component, $gdp^p(t)$, and a transitory component, $gdp^{tr}(t)$. The change in the permanent component of GDP includes an expected average trend rate of growth, α_t . As in any business cycle model, the permanent component reflects the underlying production technology and wealth endowment of the economy, while the transitory component represents monetary policy shocks, temporary changes in production possibilities, or factors that shift the allocation of spending across time. Accordingly, as one looks ahead from time t to time $t+k$, the actual value of $gdp(t+k)$ will converge to $gdp^p(t+k)$ as the transitory factors run their course and $gdp^{tr}(t+k)$ approaches zero. These properties are summarized in the system of equations (3):

$$\begin{aligned} gdp(t) &= gdp^p(t) + gdp^{tr}(t) \\ f_t gdp(t+k) &= f_t gdp^p(t+k) + f_t gdp^{tr}(t+k) \\ \lim_{k \rightarrow \infty} f_t gdp^{tr}(t+k) &= 0 \\ \lim_{k \rightarrow \infty} [f_t gdp(t+k) - f_t gdp^p(t+k)] &= 0 \\ \lim_{k \rightarrow \infty} [f_t gdp^p(t+k) - f_t gdp^p(t+k-1)] &= \alpha_t. \end{aligned} \quad (3)$$

In order to isolate the perceived shocks to these components, I will work with the change made between period $t-1$ and period t in the forecast of period- $t+k$ GDP; this forecast revision is denoted $f_t^r gdp(t+k)$:

$$\begin{aligned} f_t^r gdp(t+k) &= f_t gdp(t+k) - f_{t-1} gdp(t+k) \\ &= [f_t gdp^p(t+k) - f_{t-1} gdp^p(t+k)] + [f_t gdp^{tr}(t+k) - f_{t-1} gdp^{tr}(t+k)] \\ &= f_t^r gdp^p(t+k) + f_t^r gdp^{tr}(t+k). \end{aligned} \quad (4)$$

indicators in the CFNAI-MA3 are generally between one or two months old. For more information on the CFNAI, see Evans, Chin, and Pham-Kanter (2002).

Because the revisions are changes in conditional expectations, they reflect the new information that forecasters choose to incorporate in their GDP projections. These shocks cause revisions to the forecasts of both the permanent and transitory components of GDP, $f_t^r gdp^p(t+k)$ and $f_t^r gdp^t(t+k)$, respectively.⁸ The variability in the $f_t^r gdp(t+k)$ and the correlations between the $f_t^r gdp(t+k)$ and $f_t^r gdp(t+j)$ (revisions made at the same point in time to projections of GDP at different forecast horizons) thus can be used to identify both the perceived permanent and transitory shocks to output and how the shocks are expected to propagate or dissipate over time. But to identify the shocks and response patterns, I need to specify a parametric time-series model for the forecast revisions.

I assume that two factors may cause forecasters to revise their projections for permanent GDP. The first is e_t , a shock that causes a permanent increase in the level of GDP. The shock is normalized to have a unit impact on the projection for output in the current period. Forecasters, however, may believe it takes a few periods before e_t completely work its way into output; its effect on $gdp^p(t+k)$ --the impulse response--is measured by the parameter, θ_k .⁹ The complete impact is assumed to take R periods, so that $\theta_k = \theta_R$ for all $k \geq R$. The second factor that can cause a revision to the outlook for permanent GDP is a change in forecasters' assumptions of the average long-run growth rate in GDP, which I denote w_t ; after k periods, this would cumulate into a revision in the outlook for $gdp^p(t+k)$ of $k w_t$. I assume that w_t is observable and equal to the change in the long-run forecasts made at time t and $t-1$, $f_t \Delta gdp(lr) - f_{t-1} \Delta gdp(lr)$. Because shocks to tastes and technology that could lead to changes in $gdp^p(t+k)$ may cause both a jump in the level and a permanent change in the growth rate of output, I allow for a covariance, θ_{lr} , between e_t and w_t . In sum, then, the revision in the level of permanent GDP is:

⁸ See Berger and Krane (1985) for a discussion of the use of forecast revisions to identify the information sets used by forecasters' and to test for broader concepts of forecast efficiency.

⁹ This differs from many univariate models decomposing permanent and transitory changes in GDP, which assume the full impact of e_t on permanent output is instantaneous.

$$\begin{aligned}
f_t^r \text{gdp}^p(t+k) &= (k+1)w_t + \theta_k e_t \\
w_t &= f_t \Delta \text{gdp}(lr) - f_{t-1} \Delta \text{gdp}(lr) \\
\theta_0 &= 1; \\
\theta_k &\text{ unrestricted for } 1 \leq k \leq R; \\
\theta_k &= \theta_R > 0 \text{ for } k \geq R \\
E[w_t e_t | \Omega_\tau] &= \theta_{lr}.
\end{aligned} \tag{5}$$

I also assume that transitory factors influence GDP; the perceived transitory shock in period t is denoted by u_t . The impact of u_t on the current level of GDP is normalized to unity. This shock may influence GDP for some time, and the impulse response on $\text{gdp}^r(t+k)$ is measured by the parameter, ρ_k . However, because it is transitory, the effect of this shock eventually dissipates to zero; the model incorporates this restriction by assuming there is some $J \geq 0$ such that $\rho_j = 0$ for $j > J$. This means that the revisions to the forecasts for transitory GDP may be written as:

$$\begin{aligned}
f_t^r \text{gdp}^r(t+k) &= \rho_k u_t \\
\rho_0 &= 1; \\
\rho_k &\text{ unrestricted for } 1 \leq k < J; \\
\rho_k &= 0 \text{ for } k \geq J.
\end{aligned} \tag{6}$$

I also assume that u_t is independent of e_t and any changes in assumptions about long-run growth at all leads and lags. All of the shocks are assumed to have conditional zero means and constant variances:

$$\begin{aligned}
E[e_t | \Omega_{t-1}] &= E[w_t | \Omega_{t-1}] = E[u_t | \Omega_{t-1}] = 0 \\
E[e_t u_{t+i} | \Omega_{t-1}] &= E[w_t u_{t+i} | \Omega_{t-1}] = 0 \\
E[e_t^2 | \Omega_{t-1}] &= \sigma_e^2; E[w_t^2 | \Omega_{t-1}] = \sigma_w^2; E[u_t^2 | \Omega_{t-1}] = \sigma_u^2.
\end{aligned} \tag{7}$$

Given equations (5), (6), and (7), the observed revisions made at time t to the forecasts for actual GDP in period $t+k$ can be written as:

$$\begin{aligned} k=0: f_t^r gdp(t) &= w_t + e_t + u_t \\ k < R: f_t^r gdp(t+k) &= (k+1)w_t + \theta_k e_t + \rho_k u_t \\ k \geq J: f_t^r gdp(t+k) &= (k+1)w_t + \theta_R e_t, \end{aligned} \tag{8}$$

where, for convenience, I set $R = J-1$.

Note that if the forecasts were being mechanically generated from a single semi-annual statistical model of the economy, then the forecast revisions--and hence w_t , e_t , and u_t --would be functions of only the model's last forecast error. But there is no such model underlying the Blue Chip Consensus. Instead, w_t , e_t , and u_t reflect any and all information that forecasters build into their projections at time t . Importantly, the forecast error learned in period t reflects only the news revealed in $gdp(t-1)$ (since GDP is published with a lag); but a host of additional factors influencing current and future GDP also are learned at that time, and these will be included in the shocks in my model.¹⁰ Note, though, that a transitory shock learned today that is thought to influence GDP *only* in period $t-1$ would not show through in u_t . This means that the variance decomposition of the $k = 0$ forecast revision could attribute more variation to the permanent shock than many of the forecast-error based decompositions of actual GDP estimated in the literature.

3.2 Identification

The system of equations (8) is my basis for estimation. In particular, the structural parameters can be recovered from the variance-covariance structure of the $f_t^r gdp(t+k)$. This structure is:

¹⁰ This is particularly important since I am working with semi-annual data, and a good deal of such information becomes available during a half-year period. Furthermore, as discussed in appendix 1, the forecast errors may contain certain measurement errors that are not in the $k = 0$ revisions.

$$k=0: \text{Var}[f_t^r \text{gdp}(t)] = \sigma_w^2 + \sigma_e^2 + \sigma_u^2$$

$$k \neq 0: \text{Var}[f_t^r \text{gdp}(t+k)] = (k+1)^2 \sigma_w^2 + \theta_k^2 \sigma_e^2 + (k+1)\theta_k \theta_{lr} + \rho_k^2 \sigma_u^2$$

$$\begin{aligned} \text{Cov}[f_t^r \text{gdp}(t), f_t^r \text{gdp}(t+k)] = \\ (k+1)\sigma_w^2 + \theta_k \sigma_e^2 + (k+1+\theta_k)\theta_{lr} + \rho_k \sigma_u^2 \end{aligned} \quad (9)$$

$$\begin{aligned} \text{Cov}[f_t^r \text{gdp}(t+j), f_t^r \text{gdp}(t+k)] = \\ (j+1)(k+1)\sigma_w^2 + \theta_j \theta_k \sigma_e^2 + [(j+1)\theta_k + (k+1)\theta_j]\theta_{lr} + \rho_j \rho_k \sigma_u^2 \end{aligned}$$

$$k \geq J: \text{Var}[f_t^r \text{gdp}(t+k)] = (k+1)^2 \sigma_w^2 + \theta_k^2 \sigma_e^2.$$

The system of equations (9) is useful for thinking about identification and estimation. A natural candidate for an estimator is a method-of-moments system constructed by substituting the sample analogs for the theoretical moments in (9). Because J is large, there are enough moment conditions to solve for all of the σ^2 's, θ_k 's, and ρ_k 's. Indeed, since there are more equations than unknowns, there exist more efficient estimators than simple method-of-moments. In particular, similar moment conditions are embedded in the likelihood function defined by the Kalman filter model described below, and parameter estimates can be obtained by maximum likelihood. The Kalman filter also produces estimates of e_t , and u_t .

As a practical matter, forecasters provide projections for GDP growth. The revisions to these forecasts, $f_t^r \Delta \text{gdp}(t+k)$, are:

$$\begin{aligned} k=0: \quad f_t^r \Delta \text{gdp}(t) &= w_t + e_t + u_t \\ k < J: \quad f_t^r \Delta \text{gdp}(t+k) &= w_t + (\theta_k - \theta_{k-1}) e_t + (\rho_k - \rho_{k-1}) u_t \\ k=J: \quad f_t^r \Delta \text{gdp}(t+j) &= w_t - \rho_{k-1} u_t \\ k \geq J: \quad f_t^r \Delta \text{gdp}(t+k) &= w_t. \end{aligned} \quad (10)$$

I estimate (10) using the Kalman filter and construct $f_t^r gdp(t+k)$ from $\sum_{i \leq k} f_t^r \Delta gdp(t+i)$.

3.3 Aggregation and measurement error

The Consensus forecast is the simple average of the projections of the individual members in the Blue Chip panel. As such, the model of forecast revisions is meant to capture the average perceptions of shocks and propagation patterns. For it to do so, I need to add measurement error to the model.

Let the subscript “ i ” denote the i^{th} forecaster’s forecast revisions ($f_{it}^r \Delta gdp(t+k)$), perceptions of permanent and transitory shocks (w_{it} , e_{it} , u_{it}), and coefficients on the dissemination processes (θ_{ik} , ρ_{ik}). The $f_{it}^r \Delta gdp(t+k)$ are specified as in (10) with “ i ” subscripts on the parameters and shocks. The Consensus values for each of these variables and parameters are then the simple averages of the N forecaster-specific values.

Consider first the $k = 0$ Consensus forecast revision:

$$\begin{aligned} f_t^r \Delta gdp(t) &= \frac{1}{N} \sum_{i=1}^N f_{it}^r \Delta gdp(t) = \frac{1}{N} \sum_{i=1}^N w_{it} + \frac{1}{N} \sum_{i=1}^N e_{it} + \frac{1}{N} \sum_{i=1}^N u_{it} \\ &= w_t + e_t + u_t. \end{aligned} \tag{11}$$

Because all the idiosyncratic factors average out, the $k = 0$ revision reflects the average of the individual forecasters’ views of the permanent and transitory shocks. Similarly, for $k > J$, the consensus revisions accurately reflect w_t .

However, for $0 < k \leq J$, the Consensus forecast revision contains forecaster-specific effects. In particular,

$$\begin{aligned}
f_t^r \Delta gdp(t+k) &= \frac{1}{N} \sum_{i=1}^N f_{it}^r \Delta gdp(t+k) \\
&= \frac{1}{N} \sum_{i=1}^N w_{it} + \frac{1}{N} \sum_{i=1}^N (\theta_{ik} - \theta_{ik-1}) e_{it} + \frac{1}{N} \sum_{i=1}^N (\rho_{ik} - \rho_{ik-1}) u_{it} \\
&= w_t + (\theta_k - \theta_{k-1}) e_t + \frac{1}{N} \sum_{i=1}^N [(\theta_{ik} - \theta_{ik-1}) - (\theta_k - \theta_{k-1})] e_{it} \\
&\quad + (\rho_k - \rho_{k-1}) u_t + \frac{1}{N} \sum_{i=1}^N [(\rho_{ik} - \rho_{ik-1}) - (\rho_k - \rho_{k-1})] u_{it}.
\end{aligned} \tag{12}$$

This revision differs from the average effects modeled in equation (10) by the terms in the summations over e_{it} and u_{it} . Without information on individual forecasts, we cannot estimate these extra terms. Instead, I model them as measurement errors, $v_t(k)$,

$$v_t(k) = \frac{1}{N} \sum_{i=1}^N [(\theta_{ik} - \theta_{ik-1}) - (\theta_k - \theta_{k-1})] e_{it} + \frac{1}{N} \sum_{i=1}^N [(\rho_{ik} - \rho_{ik-1}) - (\rho_k - \rho_{k-1})] u_{it}$$

to be added to equation (10) for $0 < k \leq J$. I assume $E[v_t(k)^2] = \sigma_{vk}^2$; $E[v_t(k) v_\tau(j)] = 0$ for all t and τ , and $j \neq k$, and $E[v_t(k) e_t] = E[v_t(k) u_t] = E[v_t(k) w_t] = 0$ for all k and t .¹¹

3.4 Making the model operational: the state space representation

Define the following matrices:

¹¹ As discussed in appendix 1, measurement error also is induced into the system due to the fact that for periods beyond which the quarterly forecasts are published, the semi-annual projections are constructed by distributing annual-average forecasts to the two halves of the year.

$$\begin{aligned}
F_t^r \Delta GDP &= \begin{bmatrix} f_t^r \Delta gdp(t) \\ f_t^r \Delta gdp(t+1) \\ \vdots \\ f_t^r \Delta gdp(t+J) \\ f_t^r \Delta gdp(lr) \end{bmatrix} \\
S_t &= \begin{bmatrix} u_t \\ e_t \\ w_t \end{bmatrix} \quad \Sigma_S = E[S_t S_t'] = \begin{bmatrix} \sigma_u^2 & 0 & 0 \\ 0 & \sigma_e^2 & \theta_{lr} \\ 0 & \theta_{lr} & \sigma_w^2 \end{bmatrix} \\
B &= \begin{bmatrix} 1 & 1 & 1 \\ \rho_1 - 1 & \theta_1 - 1 & 1 \\ \rho_2 - \rho_1 & \theta_2 - \theta_1 & 1 \\ \vdots & \vdots & \vdots \\ \rho_{J-1} - \rho_{J-2} & \theta_{J-1} - \theta_{J-2} & 1 \\ -\rho_{J-1} & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix} \\
v_t &= \begin{bmatrix} 0 \\ v_t(1) \\ \vdots \\ v_t(J) \\ 0 \end{bmatrix} \quad \Sigma_v = E[v_t v_t'] = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{v1}^2 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \sigma_{vJ}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}. \tag{13}
\end{aligned}$$

The vector S_t is an unobserved state variable. The observed forecast revision process, $F^r \Delta GDP_t$, is described by the state-space model:

$$F^r \Delta GDP_t = B S_t + v_t. \tag{14}$$

The log likelihood function for the revision process (excluding constants), L , and the Kalman filter updating equations for the state variables are:

$$L = -\frac{1}{2} \sum_{t=1}^T \log |B' \Sigma_s B + \Sigma_v| - \frac{1}{2} \sum_{t=1}^T F' \Delta GDP_t' (B' \Sigma_s B + \Sigma_v)^{-1} F' \Delta GDP_t$$

$$S_{t|t-1} = 0 \tag{15}$$

$$S_{t|t} = \Sigma_s B (B' \Sigma_s B + \Sigma_v)^{-1} F' \Delta GDP_t.$$

Estimates of the θ 's, ρ 's, σ^2 's can be obtained by maximizing the likelihood function and estimates of the fundamental shocks u_t , e_t , and w_t can then be found by applying the Kalman filter updating equations.

Note that because $k = 0, 1, \dots, 9$, I set $J = 9$. The full set of revision series run from the second half of 1982 the first half of 2005. This means I have 23 years of semi-annual data and 10 revisions with each observation, leaving 460 observations. Of course, given that the half-year forecasts are interpolated from annual data beyond $k = 3$, as a practical matter, I am effectively working with 322 independent observations. The model contains 29 parameters.

4. Estimation Results

4.1 The revision process

Table 2 shows the model estimates. The first and third columns show the parameters directly estimated by (15), the revisions to growth (in annual rates), $\rho_k - \rho_{k-1}$, and $\theta_k - \theta_{k-1}$, while the second and fourth columns give the implied revisions (in percentage points) to the level of GDP.¹² The bottom rows give estimates for σ_u^2 , σ_e^2 , σ_w^2 , and θ_{lr} . Bootstrapped standard errors are in parentheses.

Consider first the transitory shocks. After raising growth on impact, these shocks have little effect on projected growth for the next year. They then reduce growth over the following year and a half as GDP returns to its permanent level. In terms of the level of GDP, the ρ_k indicate the transitory shocks have an economically meaningful influence for

¹² Because the forecasts are recorded as semi-annual growth at an annual rate, I need to multiply the ρ_k and θ_k by 0.5 to calculate the effects on the level of GDP.

about 2 years but then dissipate quickly. The effect of the shock is statistically significant for 1-1/2 years. The sum of the coefficients is 1.15. This means that integrating over time, the transitory factors are perceived on average to produce a net positive or negative change in GDP from its permanent level as opposed to a zero-sum shift in the timing of output between today and tomorrow.

Turning to the permanent shock, one interesting result is that its projected effect does not occur entirely at the time of the shock: $\theta_1 - \theta_0 = 0.27$, indicating an additional 27 basis point (annual rate) increase in output in the half year following the shock. But with a t-ratio of 1.6, this extra growth effect has only marginal statistical significance. That said, the extra boost does not dissipate; this is seen in the coefficients for the effects on the level of output, which are above 0.6 for all $k > 0$. Accordingly, there is some suggestive evidence that forecasters believe e_t is not a simple random walk, though given the standard errors, one cannot reject the hypothesis that these gains are no greater than the impact effect at the usual levels of statistical significance.

As seen in the bottom row of the table, the variance of the permanent shock, σ_e^2 , is more than twice as large as the variance of the transitory shock, σ_u^2 . Accordingly, two-thirds of the changes that forecasters make to their projections of GDP in the current half-year reflect perceptions of permanent gains or losses in output. Finally, $\theta_{lr} = 0.04$; this correlation between e_t and w_t indicates that forecasters see a small positive relationship between a permanent shock to the level of output and a perceived change in the trend growth in GDP. This relationship, however, is not statistically significant.

4.2 The scaled responses and variance decomposition

Figure 3 combines the shock and response information by plotting the revisions to the k-period-ahead forecasts of the level of GDP scaled by the standard errors of the shocks. The upper panel plots the effect of the transitory shock, $\sigma_u \rho_k$; the middle panel the effect of the permanent shock, $\sigma_e \theta_k$; and the bottom panel the combined effects of the permanent shock and the shock to long-run growth, $k[\sigma_e^2 (\theta_k - \theta_{k-1}) + \sigma_w^2 + 2 \theta_{lr}]^{1/2}$. The horizontal axes plot the forecast horizon, k. The panels also plot two-standard error bounds for each set of responses; these are calculated from bootstrapping the $\sigma_u \rho_k$, $\sigma_e \theta_k$,

and $[\sigma_e^2(\theta_k - \theta_{k-1}) + \sigma_w^2 + 2\theta_{lr}]^{1/2}$. Table 3 gives the corresponding decomposition of the variance of the revision between transitory and permanent components and measurement error.

As seen in the upper panel of the figure, the scaled transitory effects are statistically significant for up to a year and a half. Furthermore, any noticeable future offsetting response in production is of marginal statistical significance. As seen in the middle panel, the upslope in the response to the permanent level shock, e_t , differs from the flat line one would see if $gdp^p(t)$ were a random walk; though given the standard errors, there is little statistical significance in this pattern. Finally, in the long-run, the e_t and w_t shocks together add to growth at a rate of one-tenth of a percentage point per year (lower panel).

With regard to the variance decomposition (table 3), the variance of the revision to the level of output in the current half year period is 0.33 percentage point (not at an annual rate).¹³ Of this, about one-quarter is assumed to reflect transitory factors, two-thirds the permanent e_t shocks, and the remaining 6 percent the shock to long-run growth, w_t , and its interaction with e_t . Only between 12 and 15 percent of the $k = 1$ and $k = 2$ revision variance reflects transitory factors, while e_t accounts for 58 to 66 percent. Naturally, over time, the revisions to the trend growth become increasingly important; w_t and $\text{cov}(e_t, w_t)$ account for nearly 30 percent of the level revision by 2-1/2 years. Measurement error accounts for about 15 percent of the variance in the $k \geq 2$ revisions. Recall the interpretation of measurement error as the variability in forecaster-specific views of shocks and impulse responses about the average view captured by the Consensus. The small amount of variability in the total revision that this error accounts for suggests a strong tendency for individual forecasters' perceptions of economic events to cluster around a viewpoint common to all of the Blue Chip panelists.

To sum, forecasters believe that transitory shocks influence the path of real GDP over the next 1-1/2 to 2 years. The transitory factors are perceived to largely reflect net positive or net negative influences on production for some limited period of time as opposed to a shift in a fixed level of output between today and tomorrow. Even in the

near-term, however, permanent shocks are believed to be a more important influence on output than transitory shocks. Finally, the forecasters may not believe that the permanent factors are best modeled as a simple random walk, but may instead take some time to become fully reflected in GDP.

4.3 The time series of the shocks

Figures 4a and 4b plot the perceived shocks to GDP. The solid lines in the top panel of each figure are the transitory shocks, u_t , the solid lines in the middle panels are the permanent shocks to the level, e_t , and the solid lines in the bottom panels are the changes in the long-run growth rate, w_t . The u_t and e_t plotted here are the values of the unobserved components generated by the Kalman smoother.¹⁴ The shaded periods mark NBER recessions. Figure 4a compares u_t , e_t , and w_t with the error learned in time t for the $k = 0$ forecast made in time $t-1$, $gdp(t) - f_{t-1} gdp(t-1)$ (shown by the dashed lines in each panel). The bottom panel of figure 4a also compares w_t with the average revisions to historical growth in the GDP that occurred with comprehensive revisions to the national income accounts in 1985, 1991, 1996, and 1999 (the bars; see appendix 1). Figure 4b compares the shocks to the incoming information on the current state of the economy as summarized by the CFNAI-M3 in the second month of semi-annual period t (the dashed lines).

First, comparison of the u_t and e_t in the top two panels of both figures highlights the greater variability in the permanent shock. For example, 17 values of e_t are greater than 3/4 percentage point in absolute value and 10 are greater than 1 percentage point; the corresponding counts for u_t are just 10 and 3. Second, there are some large negative permanent shocks at the times of discrete events that hit the economy; notable ones occur with the stock market crash in 1987, the onsets of the recessions in late 1990 and early

¹³ Recall that the revisions to the level are not at annual rates. The revision in the level is 0.5 times the revision to the semi-annual growth rate, so the 0.33 percentage point level revision variance equals 0.25 times the 1.31 percentage point variance in the $k=0$ growth rate revision cited earlier.

¹⁴ By construction, the forward filtered u_t and e_t are serially uncorrelated, but there is no reason for the smoothed estimates to be. Still, a regression of u_t on u_{t-1} finds a small and statistically insignificant coefficient. The e_t are also serially uncorrelated. That said, $f_t^r \Delta gdp(t)$ itself exhibits some serial correlation; a regression of it on $f_{t-1}^r \Delta gdp(t-1)$ yields a coefficient on the lag of 0.37 and an adjusted R^2 of 0.14. However, the $f_t^r \Delta gdp(t+k)$ for $k > 0$ are not correlated with any $f_{t-1}^r \Delta gdp(t+j)$, $j \geq 0$.

2001, and the forecast following September 11, 2001. Indeed, if these four observations are excluded, σ_u^2 changes little but σ_e^2 falls by about one-third. Apparently, forecasters saw these events as unusual but identifiable discrete shocks that had the potential to noticeably and permanently disrupt economic activity without any offsetting recovery in production once events had run their course.

Next, consider the relationships between the shocks and the forecast errors shown in figure 4a. There are not any obvious regular relationships between these errors and u_t , e_t , or w_t . There are, however, a few interesting case studies. One was in the mid 1980s, when there appears to be some negative correlation between the forecast errors and both shocks. Apparently forecasters were having trouble judging the timing of the strong recovery from the 1981-1982 recession. This episode seemed to influence forecasters later in the decade, when there were several negative valuations for both e_t and w_t . Another interesting period was during the boom of the late 1990s. Here, a string of positive forecast errors led to two years of small upward revisions to the permanent level of output and an upgrading of views regarding long-run growth. Finally, the comprehensive revisions to the national income accounts appear to have influenced forecasters to revise their perceptions of the long-run growth rate of output, particularly so with the 1999 revision.

Turning to figure 4b, the CFNAI-MA3 and u_t exhibit some positive comovement throughout the sample period, consistent with the evidence shown in figure 2. The CFNAI-MA3 and e_t move together during recessions, but no clear pattern emerges during other periods. And other than during the late 1990s, the changes in perceptions of long-run growth and the CFNAI-MA3 appear to be uncorrelated.

In order to provide some statistical description of these relationships, table 4 presents a regression of the $k = 0$ forecast revision on the forecast error in last period's $k = 0$ forecast and the last four months of CFNAI-MA3 data that became available between the times the $t-1$ and t forecasts were made. The first column considers the total revision while the second and third columns run separate regressions for the revisions due to the transitory and permanent shocks.

As seen by the p-values reported in the table, despite the examples in the 1980s and 1990s noted above, the previous half-year's GDP forecast error has virtually no

statistical explanatory power for the current-period revisions. In the eyes of the Blue Chip forecasters, their previous forecast error does not consistently reveal useful information about the course of activity going forward. In contrast, the CFNAI-MA3 data are highly statistically significant in all three regressions. The effect is strongest in the equation for the transitory shock; indeed a simple regression of u_t on the CFNAI-M3 terms has an R^2 of nearly 40 percent.

Furthermore, there is some statistical support for the pattern found in figure 4b of forecasters reacting more to incoming data during periods of economic weakness. The third and fifth columns in table 4 allow for a separate coefficient on the most recent CFNAI-MA3 value known at time t if it is less than -0.5 . This occurs in 7 of the 46 semi-annual observations.¹⁵ The coefficient is statistically significant in the regressions for the overall revision; indeed, it drives out the statistical significance of the other CFNAI-MA3 variables. In the regression for the transitory shock, the threshold CFNAI-MA3 variable has a coefficient of -0.22 , indicating that forecasters perceive some offset to recessionary declines in output from higher production in latter periods. However, the magnitude of this offset is small and the coefficient is not close to being statistically significant. In contrast, the threshold variable has a coefficient of 1.26 and a p -value of 0.02 in the regression of the permanent shock; its inclusion even drives out the statistical influence of the other CFMAI-MA3 variables in the regression.¹⁶

These regressions are consistent with forecasters believing that large permanent declines in output characterize recessions. This contrasts with say Friedman's (1964) "plucking" model in which recessions represent a drop in output and then a recovery to trend--and thus reflect a temporary loss in production--as well as alternative models in which the lost output is made up for by above trend production sometime during the subsequent expansion. It is, however, consistent, with the permanent losses in output found in Hamilton's (1989) Markov-switching model of recessions. Furthermore, the large negative values for e_t following the stock market crash in 1987 and September 11,

¹⁵ The specific dates are 1982:H2, 1990:H2, 1991:H1, 1992:H1, 2001:H1, 2001:H2, and 2003:H1. Accordingly, 5 fall during recessions and 2 during periods of sluggish recovery.

¹⁶ A univariate regression of e_t on the negative threshold CFNAI-MA3 variable has an R^2 of 0.23 , the same as the base regression. Note also that if I instead put a positive threshold CFNAI-MA3 variable (values greater than 0.5) in the regression, its coefficient is small and statistically insignificant (-0.32 with a p -value of 0.21).

2001 are consistent with the idea that forecasters think such special and readily identifiable adverse shocks will generate unusually large permanent reductions in economic activity. Of course, with only three recessions and a couple of such special events in the sample, one should not overemphasize the statistical substance of these results. Still, they suggest that forecasters think that the data generating process for GDP differs between recessions and expansions. Linear models with independent and identically distributed error processes cannot encompass such a view of the business cycle.¹⁷

In addition, the correlations between forecast revisions and incoming high-frequency measures of economic activity are instructive for empirical modeling. First, the correlations suggest that these indicators may be useful additions to the lagged endogenous variables typically employed to instrument expectational variables in Euler equations or current-period variables in structural vector autoregressions. Second, the linkage between expectations and the high-frequency indicators may help explain why such variables prove helpful in modeling the term structure of interest rates (see, for example, Ang and Piazzesi (2003) and Evans and Marshall (2002)). Namely, the term structure incorporates expectations for the path of economic activity from today through the long run; and according to my results, high frequency indicators appear to be important determinants of changes in agents' expectations of both transitory fluctuations in GDP and permanent shifts in economic activity.

5. Comparing the Results to Time Series Models for GDP

5.1 Some statistical models for permanent and transitory shocks to GDP

The specification above motivates the separation of forecast revisions into permanent and transitory components from a simple univariate time series model for GDP. So it is natural to ask how the Blue Chip revisions compare with the

¹⁷ This result also suggests that the state-space model (13) can be improved by incorporating some type of non-standard specification for σ_e^2 that recognizes the possibility of large negative realizations of e_t during recessions or periods following unusual economic events.

decompositions into permanent and transitory shocks generated from statistical specifications of the process for actual GDP. Are forecasters patterning their perceptions of shocks along the lines estimated by these models?

This section compares the Blue Chip forecast revisions with comparable forecast revisions from four time-series models for GDP. Because these models generally are estimated using quarterly data, one needs to aggregate their impulse responses to the semi-annual frequency. As described in appendix 2, if the Wold representation of a quarterly univariate statistical model for forecasting GDP growth

$$(1-L)gdp(t) = \omega^*(L)\varepsilon(t) \quad (16)$$

where $\omega^*(L)$ is a square sumable lag polynomial with $\omega^*_0 = 1$ and $\varepsilon(t)$ is the shock or vector of shocks to GDP, then there exists the following semi-annual correspondence between the Blue Chip revisions and those from the quarterly statistical model:

$$\begin{aligned} \text{Blue Chip : } f_t^r gdp(t+k) &= f_t gdp(t+k) - f_{t-1} gdp(t+k) \\ \text{Statistical Model : } f_\tau^r gdp(t+k) &= \sum_{i=1}^{2(k+1)+1} \omega_i \varepsilon(\tau-2) + \sum_{i=1}^{2(k+1)} \omega_i \varepsilon(\tau-1) \\ \omega_i &= \sum_{j=0}^i \omega_j^* \end{aligned} \quad (17)$$

$\tau-2 = \text{first quarter of half - year period } t-1$

$\tau-1 = \text{second quarter of half - year period } t-1.$

I consider four simple econometric models that are designed to identify both a permanent and a transitory shock to real GDP and how these shocks propagate over time: the Beveridge-Nelson (1981) decomposition; a univariate unobserved components (UC) model similar to Clark (1987) or Campbell and Mankiw (1987a, b); the Blanchard-Quah (1989) bi-variate structural VAR in GDP growth and the level of the unemployment rate; and the Campbell-Krane (2005) multivariate structural VAR. The Beveridge-Nelson decomposition assumes $gdp^p(t)$ follows a random walk and that $\Delta gdp(t)$ can be described by an ARMA model. The UC model assumes both $\Delta gdp^p(t)$ and $gdp^{tr}(t)$ follow ARMA

processes. The Blanchard-Quah model identifies the transitory shock to GDP through the assumption that it has no effect on the long-run level of GDP. The Campbell-Krane model is a 6-variable VAR in private GDP, nondurables and services consumption, durables consumption and residential investment, the federal funds rate, core PCE inflation, and food and energy inflation. In the spirit of Cochrane (1994), it identifies the permanent shock by restricting it to be the only shock in the VAR that has a long-run influence on the level of consumption. It is the only one of the models also explicitly designed for forecasting. Appendix 2 describes the models in more detail.

5.2 Estimation results

I use AIC and BIC information criteria to identify the models, picking an AR(2) model in the growth rate in GDP in the Beveridge-Nelson case; a simple random walk for $gdp^p(t)$ and an AR(2) for $gdp^{tr}(t)$ in the UC model, and a third-order VAR in the Blanchard-Quah case. Campbell-Krane used similar specification criteria to choose lag length and contemporaneous zero restrictions in their model.¹⁸

Figure 5a compares the Blue Chip forecast revisions to permanent and transitory shocks (scaled by the standard deviations of the shocks) with those implied by the two univariate models for GDP. The black and blue lines in each panel replot the scaled Blue Chip revisions shown in figure 3 and their two-standard error bounds. The green lines in the top two panels are the GDP model estimates of the impulse responses of a transitory shock on the level of GDP; the green lines in the bottom panels are the model responses to a permanent shock. Figure 5b shows plots for the multivariate models. As seen in the graphs, there are noticeable differences between the scaled impulse responses of the models and of the Blue Chip forecasts.

¹⁸ The first three models are estimated using currently published quarterly data for the period 1967-2005. I chose to start in 1967 because in 1982, the first year in my Blue Chip sample, forecasters undoubtedly would have been considering the history of the previous 15 years when making their assessments of the shocks hitting the economy. I also decided to give the model some “extra” information by estimating 3 different constant terms to allow for changes in long-term growth—one for the period 1967-1973; one for 1974-1995, and one for 1996 and on. This was done since α_t is observed to change over time. For reasons discussed in their paper, the Campbell-Krane model is estimated using data from 1984 onwards. Note that the Campbell-Krane model does not identify a single transitory shock; the transitory shock referred to in this paper is the covariance weighted average of the 5 transitory shocks found in the model.

Qualitatively, the pattern of the Blue Chip revisions to transitory shocks resembles those in the UC, Blanchard-Quah, and Campbell-Krane models: the entire initial shock remains in the level of GDP for about a year and then dissipates quickly towards zero. However, the magnitudes of the responses are much different. All three of these models see the transitory shock inducing forecast revisions of between 1 and 1-1/2 percentage points of GDP over the next year, while the Blue Chip innovation in response to a transitory shock is about 1/3 percentage point. The initial response of the Blue Chip forecasters to a transitory shock is of similar magnitude to that from a Beveridge-Nelson decomposition. However, the Beveridge-Nelson transitory shock only has a palpable effect on the $k = 0$ forecast, as compared with longer-lived effects in the Blue Chip.

With regard to the permanent shock, both univariate models assume e_t follows a random walk, while the multivariate models share the Blue Chip feature that the impulse from a permanent shock takes some time to feed into GDP. The Blue Chip and Blanchard-Quah impulses share a similar upward sloping pattern, while the Campbell-Krane impulses exhibit some hump shaped behavior. The variances of the permanent shock are of similar magnitude in all of the forecasts with the exception of the Beveridge-Nelson decomposition, where it is about three times the size of the Blue Chip.

5.3 The influence of high-frequency data on the differences between the revisions from the Blue Chip Consensus and the econometric models

One reason that the impulses and shocks differ across the Blue Chip and model forecasts is the difference in conditioning sets. The revisions to the statistical GDP models' projections are functions of lagged forecast errors. Accordingly, they are functions only of GDP in the Beveridge-Nelson and unobserved components models, of GDP and the unemployment rate in the Blanchard-Quah specification, and of private GDP, consumption, durables and residential investment, interest rates, and inflation in the Campbell-Krane model. In contrast, the revisions to the Blue Chip forecasts encompass any information forecasters care to incorporate.

As seen in section 4, the Blue Chip forecasters appear to discount the persistence of past forecast errors but revise their projections noticeably in response to the

information contained in high-frequency indicators of economic activity. By construction the econometric models do not ignore their past errors; but what would the responses of these models look like if they incorporated high-frequency data?

I reran all of the time series models using the value of the CFNAI-MA3 in the third month of quarter $t-1$ as an exogenous explanatory variable. Table 5 shows the standard deviations of the $k = 0$ forecast revisions--which are the sum of all the period- t shocks--for the Blue Chip forecasts, the base case statistical models, and the statistical models that include the CFNAI.

The base-case (left-hand columns) illustrate the results cited in the discussion of the impulse responses in section 5.2: with the exception of the transitory Beveridge-Nelson and permanent Blanchard-Quah shocks, both the permanent and transitory shocks to the Blue Chip are smaller than the corresponding shocks in the models'--and often substantially so. And the Beveridge-Nelson model is the only specification that attributes at least as high of a share of the revision variance to the permanent shock as the Blue Chip does.¹⁹

The standard deviations of the GDP models' $k = 0$ revisions are markedly smaller when the CFNAI is added to their specifications (right-hand columns). Furthermore, incorporation of the CFNAI eliminates all of the transitory shock estimated by the univariate Beveridge-Nelson and UC models. The standard deviations of both shocks in the Blanchard-Quah model are now nearly identical to those in the Blue Chip, and the variation in the transitory shock Campbell-Krane model is much closer to the Blue Chip. That said, the pattern of the impulse responses in the Blue Chip and adjusted Blanchard-Quah models (not shown) differ substantially: the adjusted Blanchard-Quah transitory response declines linearly to zero instead of having a hump shaped. Furthermore, the correlation between that model's $k = 0$ forecast revision and the Blue Chip's is small (10 percent). In contrast, the impulse response pattern in the Campbell-Krane model does not

¹⁹ Of course, part of the reason that the Blue Chip revision may be small is that the Consensus forecast is the simple arithmetic average of about 50 individual forecasts. To the extent that averaging smooths out idiosyncratic reactions, the variance in the Consensus' forecast revisions will be less the average variance of the revisions made by the individual forecasters. While individual quarterly forecasts are not available for the Blue Chip panel, some subgroup averages are. As described in appendix 3, these subgroups can be used to calculate a potential upper bound for the smoothing effect. The calculations suggest the standard deviation of the Consensus forecast revision understates the average standard deviation of the individual forecasters' revisions by only about 20 percent.

change much from the base case; it merely shifts down by the change in the standard deviation of shocks. Still, like the Blanchard-Quah model, the correlation between the adjusted model and Blue Chip revisions is small (12 percent).

In sum, the Blue Chip forecast revisions more resemble those of multivariate models of GDP than the univariate decompositions. Even with these models, however, there are important differences between the revision processes. Some of the differences in the variation in the shocks may reflect the use of the incoming high-frequency data by the Blue Chip forecasters. In particular, the differences in the standard deviations close a good deal when the CFNAI-MA3 is added to the statistical models; nonetheless, the models still produce a much different pattern of behavior than is implied by the Blue Chip forecast revisions.

Conclusions

This paper uses a statistical model of the forecast revisions to infer forecasters' implicit decomposition of news into permanent and transitory shocks to GDP. According to this model, on average, the forecasters comprising the Blue Chip Consensus perceive that about 30 percent of the shock to real GDP reflects transitory changes while about 70 percent is due to a permanent change in the level of output; expect transitory shocks to dissipate in about 1-1/2 to 2 years; and believe there may be a half-year delay before the entire permanent shock to GDP is in place in the data. These results differ a good deal from those of some small-scale models designed to identify permanent and transitory shocks to GDP: the total shocks to the Blue Chip forecast are smaller than the models', and their decompositions generally see a much larger role for transitory shocks.

One reason for the differences between the models' and the Blue Chip results likely revolves around the fact the Blue Chip forecasts are much more heavily influenced by the incoming high-frequency data on economic activity than by past forecast errors. This effect is particularly pronounced during recessions or periods of economic weakness. The results also suggest that forecasters see downturns or expected periods of sluggish activity associated with unusual, but identifiable, events as comprising more permanent than transitory reductions in output.

One lesson of this paper is that even for broad aggregates such as GDP, agents' expectations are likely based on a good deal more information than what is incorporated into quarterly econometric models using data from the national income accounts. In addition, the result that expectations are more sensitive to incoming data during economic downturns than during expansions suggests that it may be fruitful to consider models that allow for shock processes or propagation mechanisms to differ according to the state of the business cycle. These observations are relevant for researchers who are attempting to build internally consistent expectations into equilibrium models of the business cycle or are considering how to more efficiently capture expectations in econometric models.

Appendix 1. Data Issues

1. The timing relationships between the March and October Blue Chip surveys and the national income accounts.

I let the data for March represent the first semi-annual period of the year and the data for October the second semi-annual period. At the time the October Blue Chip is published, the most recent published National Income and Product Account (NIPA) data are the third, or “final,” estimates for the second quarter. This means the most recent history is a final estimate of growth for the previous semi-annual period--the fourth quarter of last year to the second quarter of the current year. In March, the most recent historical NIPA semi-annual data are the second estimates for growth between the second and fourth quarters of the previous year. The revisions between the second and third estimates of the NIPA usually are small. Accordingly, while the most recent history in March is not quite the final estimate for growth in the second half of the previous year, it is not too far from it (annual revisions aside--see below). Still, the October forecasts contain one more month of data for the $t = 0$ semi-annual period. I could have accounted for this difference by including additional measurement errors to the model, but chose not to do so for reasons of parsimony.

2. Modeling the $k = 0$ forecast revisions instead of the forecast errors.

As noted in section 3, w_t , e_t , and u_t reflect the shocks to the $k = 0$ forecast, not the shocks thought to have hit GDP in period $t-1$. An alternative structure would have been to start the model with the forecast error for last-period's GDP, which is also the $k = -1$ forecast revision,

$$f_t^r gdp(t-1) = gdp(t-1) - f_{t-1} gdp(t-1). \quad (18)$$

Note that this error is learned at time t .

As discussed in section 3.1, one reason to prefer the $k = 0$ over the forecast errors is that the latter exclude important information relevant to the GDP forecast. Others relate to well-known difficulties in defining forecast errors that mean they likely contain measurement error that is not be present in the $k = 0$ revisions. In order to isolate the true forecast error, one needs to know if forecasters are predicting the first-published GDP

estimate or a revised number (see McNees, 1973). If they are predicting revised data, then it is necessary to substitute a value for $gdp(t-1)$ learned after period t into equation (18). So one must decide on the appropriate revised value to use--the one associated with the final quarterly number, or perhaps one following an annual revision--and also separately identify the information learned with each revision to the estimate of GDP. Errors in specifying the data being forecast or differences between the vintages of GDP being projected by the panelists add measurement error to the model and thus complicate the identification of shocks. The issue is particularly problematic for this paper because at the semi-annual frequency, forecasters learn two quarters of data instead of one between each observation. The use of forecast revisions starting with period $k = 0$ avoids all such issues: Since no published values for GDP are needed to construct the revisions, there is no need make any judgment on the vintage of GDP that is being forecast.

Major revisions to the national accounts are another problem. Annual revisions are published each July, and four comprehensive revisions to the NIPA also occurred during the sample.²⁰ The annual and comprehensive revisions fold in a wide range of information from annual surveys, quinquennial economic censuses, and other data sources that do not strictly reflect new information learned between time $t-1$ and t . The revisions--particularly the comprehensive ones--can also include changes in statistical methodologies. Accordingly, the forecast errors made in periods spanning these revisions will reflect a variety of measurement issues in addition to the fundamental economic shocks affecting activity and thus their use would add measurement error to my model. In contrast, the $k = 0$ revisions that span such periods will reflect only the information forecasters think are of consequences for future growth.

3. Distribution of annual forecasts to semi-annual frequency.

I first construct the annual average levels implied by the $k = 0$ through $k = 3$ forecasts made in March or the $k = -1$ through $k = 2$ forecast made in October. I then

²⁰ This means that any forecast errors between the March and October projections reflect the effects of the annual revisions. The comprehensive NIPA revisions took place in December 1985, December 1991, January 1996, and October 1999, which influences forecast errors for the second halves of 1985, 1991, 1995, and 1999. In general, no annual revisions are made to the NIPA if a comprehensive benchmark is to come later in the year.

apply the published Consensus average annual growth rate forecasts for 2 through 5-year-ahead to these data to calculate annual levels for these years.

I then distribute the annual numbers to half-year levels according to an algorithm that minimizes the difference in the change in GDP between adjacent semi-annual periods subject to the constraint that the averages of half-year levels equal the annual level. That is, it chooses $f_i gdp^l(t+k)$ and $f_i gdp^l(t+k+1)$ to minimize $\sum \eta_{t+k}^2$ subject to the constraint $f_i gdp^l(t+k) + f_i gdp^l(t+k+1) = f_i gdp^l(t+k, t+k+1)$ where the “ l ” superscript refers to the level of GDP, k is the first half-year period, $k+1$ is the second half-year period, $f_i gdp^l(t+k, t+k+1)$ is the published annual forecast, and

$$\begin{aligned} f_i \Delta gdp^l(t+k) &= f_i \Delta gdp^l(t+k-1) + \eta_{t+k} \\ f_i \Delta gdp^l(t+k+1) &= f_i \Delta gdp^l(t+k) + \eta_{t+k+1} \end{aligned}$$

The resulting levels are used to construct half-year growth rates for $k \geq 4$ (for March) and $k \geq 3$ (for October).²¹ I generate forecast up through $k = 9$. Conceptually, the 6-year-ahead forecasts would allow me to interpolate values for $k = 10$ and $k = 11$ as well; I chose not to do so to avoid any end-point issues that may arise with the interpolation procedure.

This procedure produces the following forecasts:

$$\begin{aligned} f_i gdp^l(t+k+1) &= \lambda f_i gdp^l(t+k, t+k+1) + \beta_1(L) f_i gdp^l(t+k-1) + \beta_2(L^{-1}) f_i gdp^l(t+k+2) \\ f_i gdp^l(t+k) &= (1-\lambda) f_i gdp^l(t+k, t+k+1) + \beta_3(L) f_i gdp^l(t+k-1) + \beta_4(L^{-1}) f_i gdp^l(t+k+2) \end{aligned}$$

λ is a weight between 0 and 1, the $\beta_i(L)$ are second-order lag polynomials that capture the smoothing of changes, and $\beta_1(L) + \beta_3(L) = \beta_2(L) + \beta_4(L) = 0$. So while this smoothing adds some measurement error to the resulting forecasts, by construction, the errors

²¹ This means there is a slight difference between how the semi-annual growth rates are measured for small k —which are second-to-fourth and fourth-to-second quarter changes—and the larger k —which are first-half-to-second half and second half-to-first-half changes. Any measurement errors due to differences between two-quarter and half-year growth rates will be absorbed by the $v_i(k)$. (This difference could have been avoided by distributing the annual data to the quarterly frequency; the cost of doing so would have been additional measurement error induced by the distribution process.)

average out over the two halves of the year. Note, too, that any such measurement error will be absorbed in the $v_t(k)$.

As an alternative to this procedure, one could estimate the model using the published revisions to annual-average forecasts. The revision to the annual forecast for the log level of GDP is $\log[0.5 \cdot \{\exp((k+1)w_t + \theta_{k+1}e_t + \rho_{k+1}u_t) + \exp(kw_t + \theta_k e_t + \rho_k u_t)\}]$, which does not lend itself to the linear structure of the Kalman filter described in section 3. One could instead use the first-order Taylor expansion of the annual forecast revision about $w_t = e_t = u_t = 0$, which is $0.5 \cdot [(2k+1)w_t + (\theta_{k+1} + \theta_k)e_t + (\rho_{k+1} + \rho_k)u_t] + v_t'(k+1, k)$, where $v_t'(k+1, k)$ is measurement error. But by construction, $v_t'(k+1, k)$ will be correlated with w_t , e_t , and u_t ; accounting for these correlations requires a significant number of parameters and complicates the structure of the Kalman filter. In contrast, any measurement error added by the distribution algorithm described above averages out over the two halves of the year. This means while the individual θ_k and ρ_k may be biased for $k \geq 3$, the estimates of $\theta_{k+1} + \theta_k$ and $\rho_{k+1} + \rho_k$ will be unbiased.

Appendix 2: Econometric Models

1. The Beveridge-Nelson (1981) decomposition.

This decomposition notes that equation (16) can be written as

$$\begin{aligned} gdp(\tau) &= \omega^*(1)[\varepsilon(\tau) + \varepsilon(\tau-1) + \dots + \varepsilon(1)] + \phi(L)\varepsilon(\tau) \\ \phi_j &= -\sum_{i=1}^{\infty} \omega_{j+i}^* \end{aligned} \quad (19)$$

$\omega^*(1)[\varepsilon(\tau) + \varepsilon(\tau-1) + \dots + \varepsilon(1)]$ represents the permanent component of GDP and $\phi(L)\varepsilon(\tau)$ is the transitory component. The decomposition is calculated by first estimating an ARIMA model for the growth in GDP, finding the Wold representation, and then calculating (19).

2. Univariate unobserved components model.

$$\begin{aligned} \rho^{ar}(L)gdp^{tr}(t) &= \rho^{ma}(L)u_t \\ \theta^{ar}(L)(1-L)gdp^p(t) &= \alpha + \theta^{ma}(L)e_t \end{aligned} \quad (20)$$

u_t is the shock to transitory output and e_t is the shock to permanent output. This implies an observation equation for gdp growth:

$$\Delta gdp(t) = \alpha' + \frac{(1-L)\rho^{ma}(L)}{\rho^{ar}(L)}u_t + \frac{\theta^{ma}(L)}{\theta^{ar}(L)}e_t \quad (21)$$

where $\alpha' = \alpha/\theta(1)$. The $\rho^{ar}(L)$, $\rho^{ma}(L)$, $\theta^{ar}(L)$, $\theta^{ma}(L)$, α' , σ_e^2 and σ_u^2 can be estimated using the Kalman filter.

3. Blanchard-Quah bivariate VAR representation of GDP and the unemployment rate.

The Wold representation of this model is:

$$\begin{bmatrix} (1-L)gdp(\tau) \\ un(\tau) \end{bmatrix} = \sum_{j=0}^{\infty} C(j)v(\tau-j) \quad (22)$$

where $C(0)$ is a 2 by 2 identity matrix and $v(t)$ is a 2 by 1 vector of reduced form errors with covariance matrix Φ . This model can be used to separate permanent from transitory shocks to GDP by assuming that shocks to the unemployment rate can not have a permanent effect on the level of GDP. This is done by considering the Wold representation of the structural VAR:

$$\begin{bmatrix} (1-L)gdp(\tau) \\ un(\tau) \end{bmatrix} = \sum_{j=0}^{\infty} A(j)\varepsilon(\tau-j) \quad (23)$$

where the $\varepsilon(\tau)$ are a 2 by 1 vector of structural errors. The Blanchard-Quah assumption is equivalent to saying that the lower right-hand entry of $A(1)$ equals zero. This imposes the restriction that lower right hand entry of $C(1)A(0)$ is zero and that $A(0)A(0)' = \Phi$.

4. The Campbell-Krane model.

This model is a 6 variable VAR in: 1) the log difference in personal consumption expenditures for nondurables and services excluding housing (C); 2) the log ratio of private GDP (Y) to C; 3) the log ratio of expenditures for consumer durables and residential investment (D) to C; 4) the federal funds rate; 5) PCE inflation excluding food and energy; 6) inflation in PCE food and energy. The model is based on the ideas that: 1) the permanent income hypothesis implies that any permanent shock to the productive capabilities of the economy will alter C and; 2) balanced growth implies that Y/C and D/C will be stationary.²² This means the permanent shock to production can be identified by restricting it to be the only shock that has a long-run impact on C and by restricting

²² As a practical matter, the ratios Y/C and D/C and PCE inflation excluding food and energy exhibit some important low-frequency variation. Accordingly, as discussed in Campbell and Krane, the model is estimated in deviations of these variables from their 40-quarter lagged moving average.

any shock in the model from having a long-run impact on Y/C, D/C, or the other variables in the VAR.²³

A couple modifications are necessary to make the model compatible with the other data presented in the paper. First, the impulses to log Y are calculated by adding the impulses to log(Y/C) and log C. Second, the impulses to transitory shocks represent the weighted sum of the responses of Y to all other shocks in the system other than the permanent income shock. Finally, the impulse responses of Y are multiplied by the ratio of the standard deviation of total GDP to the standard deviation of private GDP to give appropriate scaling relative to the impulses presented in the paper.

5. Derivation of equation (17).

Consider the Wold representation of a quarterly univariate statistical model for forecasting GDP growth:

$$(1-L)gdp(t) = \omega^*(L)\varepsilon(t) \quad (24)$$

where $\omega^*(L)$ is a square sumable lag polynomial with $\omega^*_0 = 1$. It is convenient to work with the following representation for the level of GDP:

$$\begin{aligned} gdp(t) &= \omega(L)\varepsilon(t) \\ \omega_i &= \sum_{j=0}^i \omega_j^* \end{aligned} \quad (25)$$

so that the revision to the q-quarter-ahead forecast made at time t can be written as:

$$f^r gdp_\tau(t+q) = \omega_q \varepsilon(t) \quad (26)$$

The k = 0 Blue Chip projection is the outlook for real GDP in the second quarter of the current half-year period. Since data for the first quarter of the half year are not yet known (see appendix 1), this corresponds to a two-quarter-ahead (q = 2) forecast. In

²³ The relative importance of transitory shock to the one-step-ahead forecast error estimated by the Campbell-Krane model is similar to that found in Cochrane (1994), who used data for 1947-1989. Both of these models identify the permanent shock by allowing it to be the only one affecting consumption in the long run. These results thus indicate that the use of consumption to identify permanent shocks generalizes from Cochrane's simple bivariate system to a larger-scale restricted VAR and to the "post-great-moderation" sample period (see also, Campbell and Krane).

general, the k-period-ahead semi-annual forecast corresponds to a $2k+2$ -quarter-ahead forecast. In terms of forecast revisions, the $k = 0$ revision, for example, reflects the difference between the $q = 4$ forecast made in semi-annual period $t-1$ and the $q = 2$ forecast made in semi-annual period t . In terms of quarterly forecasts this is the sum of the revisions between consecutive $q = 4$ and $q = 3$ forecasts and $q = 3$ and $q = 2$ forecasts. Suppose period t is the first half of the year; then this revision is the sum of the influence of first $e(Q3)$ and then $e(Q4)$ onto the projection for GDP in the following second quarter. In terms of (1.11), the total revision is:

$$\omega_1 \varepsilon(Q3) + \omega_2 \varepsilon(Q3) + \omega_3 \varepsilon(Q3) + \omega_1 \varepsilon(Q4) + \omega_2 \varepsilon(Q4)$$

More generally, we have the following correspondence between the semi-annual Blue Chip revisions and those from the quarterly statistical model:

$$\begin{aligned}
 \text{Blue Chip : } f_t^r \text{ gdp}(t+k) &= f_t \text{ gdp}(t+k) - f_t \text{ gdp}(t+k) \\
 \text{Statistical Model : } f_\tau^r \text{ gdp}(t+k) &= \sum_{i=1}^{2(k+1)+1} \omega_i e(\tau-2) + \sum_{i=1}^{2(k+1)} \omega_i \varepsilon(\tau-1)
 \end{aligned}
 \tag{27}$$

$\tau - 2 = \text{first quarter of half - year period } t - 1$
 $\tau - 1 = \text{second quarter of half - year period } t - 1$

Appendix 3 The Influence of Averaging Forecasts

The Consensus forecast is the simple arithmetic average of about 50 individual forecasts. To the extent that averaging smooths out idiosyncratic reactions, the Consensus' forecast revisions will be less variable than the revisions that the individual forecasters make. How might this smoothing influence the empirical results?

The $k = 0$ period forecast revision of each individual forecaster i , $f_{it}^r gdp(t)$, may be written as the sum of the Consensus (average) forecast and an idiosyncratic component, z_{it} , which reflects the range of views on the permanent and transitory shocks to output. By construction $\sum_{i=1,50} z_{it} = 0$. As a statistical matter, I assume the z_{it} are mean zero and independently and identically distributed across forecasters and are independent from the consensus revision:

$$\begin{aligned}
 f_{it}^r gdp(t) &= f_t^r gdp(t) + z_{it} \\
 z_{it} &= (w_{it} - w_t) + (e_{it} - e_t) + (u_{it} - u_t) \\
 E[z_{it}] &= 0; \text{Var}[z_{it}] = \sigma_z^2 \text{ for all } i \\
 \text{Var}[f_i^r gdp_t(t)] &= \text{Var}[f_t^r gdp(t)] + \sigma_z^2
 \end{aligned} \tag{28}$$

Note that the set up in equation (28) allows for the possibility for forecaster fixed effects; that is, for some forecasters to always predict that growth will be higher or lower than average. These fixed effects, however, are differenced out in the forecast revisions.

Individual forecasters' quarterly projections are needed to calculate σ_z^2 directly, and the only individual forecasts published by the Blue Chip are for growth on a calendar-year average basis for the current and subsequent year.²⁴ However, since 1992

²⁴ For example, in terms of the semi-annual frequency I am working with, the forecast made in March for calendar-year average growth in the current year is $[fgdp_M^l(H1) + fgdp_M^l(H2)]/[gdp^l(H1_{t-1}) + gdp^l(H2_{t-1})]$, where $gdp^l(H1_i)$ is the level of gdp in half-year i of year t and the subscript M refers to the fact that the forecast is being made in March. In October, the forecast (the subscript O) for calendar-year average growth in the current year is $[gdp^l(H1_t) + fgdp_O^l(H2_t)]/[gdp^l(H1_{t-1}) + gdp^l(H2_{t-1})]$. Accordingly, the forecast revision between March and October reflects both the forecast error for growth in the first half of the year

Blue Chip has been publishing quarterly forecasts for the average of the highest 10 forecasts made by the panelists and for the average of the lowest 10 forecasts. If these forecasters were the same individuals each time period, then the assumptions behind equation (28) would mean that the differences between the revisions to the consensus forecasts and the revisions to the group made up by combining the top-10 and bottom-10 forecasters would be observations on $\sum_{i=1,20} z_{it}/20$ and the variances of the differences would be estimates of $\sigma_z^2/20$. The forecasters in the top and bottom 10 averages are not the same across periods. But the forecasters moving into and out of these groups are more likely to have done so because they made a larger revision than the average forecaster. This means that the variance of the differences between the consensus and subgroup revisions likely overestimate $\sigma_z^2/20$, and so can be used to bound σ_z^2 .²⁵

I constructed time series of $\sum z_{it}/20$ from the top 10 and bottom 10 averages and estimated σ_z^2 's from a 5000 replication bootstrap of this time series. This gave an estimate for σ_z^2 of 0.16. The bootstrap estimate of $\text{Var}[f_t^r \text{ gdp}_t(t)]$ of 0.28, so that under the assumptions in equation (28), the average standard deviation of the individual forecasters' $k = 0$ revisions is 0.66 percentage point. This compares with a 0.55 percentage point standard deviation for the Consensus revisions over the 1992-2005 period. So the Consensus forecast understates the average variability of the individual forecasters by only about 20 percent.²⁶

Furthermore, it is unlikely that smoothing out the idiosyncratic variation means that the relationships between individual forecaster's revisions and the incoming data differs substantially from what was estimated using the Consensus outlook. I regressed the time series for $\sum z_{it}/N$ from the top 10, bottom 10, and combined subgroups on the same CFNAI data and realized forecast error as shown in table 4. None of the variables were statistically significant in explaining the $\sum z_{it}/N$. This supports the view that the

and the revision to growth in the second half of the year, and so cannot be used to back out the appropriate semi-annual series.

²⁵ Intuition also says that $\sum \Delta z_{it}/10 > 0$ for the top ten average and $\sum \Delta z_{it}/10 < 0$ for the bottom ten.

However, $\sum \Delta z_{it}/10$ is -0.03 for both series.

²⁶ Of course, the bottom and top 10 averages likely are not random draws from the consensus pool. Indeed, one would not want to assume that the forecasts themselves are random distributed about the consensus outlook: some forecasters will always be optimistic and some will always be pessimistic. However, the assumption that the revisions are randomly distributed about the consensus revision is less stringent since the revisions difference out any forecaster fixed effects. Combining the top 10 and bottom 10 averages also should help produce more efficient estimates of σ_z^2 .

idiosyncratic components of individual forecasters' revisions are relatively random disturbances about the Consensus and not systematically related to the incoming data.

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Table 1: Summary Statistics for the Blue Chip Consensus Forecast Errors					
	Errors		$\Delta gdp(t+k) = a + b f_t \Delta gdp(t+k) + e_t(k)$		
Forecast Horizon, k	Mean	RMSE	<i>a</i>	<i>b</i>	p-value a=0, b=1
0	0.33 (0.23)	1.53	0.38 (0.49)	0.97 (0.17)	0.37
1	0.20 (0.28)	1.85	0.93 (1.18)	0.71 (0.43)	0.70
2	0.17 (0.29)	1.95	2.11 (1.64)	0.30 (0.57)	0.43
3	0.28 (0.28)	1.86	1.12 (1.28)	0.69 (0.42)	0.58
4	0.38 (0.26)	1.70	0.65 (1.61)	0.90 (0.52)	0.37

Standard errors in parentheses. p-values for a=0, b=1 test based on Newey-West corrections for autocorrelation in $e_t(k)$

Table 2: The Revision Process				
Forecast Horizon, k	Response to Transitory Shock		Response to Permanent Shock	
	Growth $\rho_k - \rho_{k-1}$	Level $0.5 \rho_k$	Growth $\theta_k - \theta_{k-1}$	Level $0.5 \theta_k$
0	1.00 NA	0.50 NA	1.00 NA	0.50 NA
1	-0.06 (0.27)	0.47 (0.13)	0.27 (0.17)	0.63 (0.08)
2	-0.06 (0.26)	0.44 (0.17)	-0.00 (0.15)	0.63 (0.11)
3	-0.33 (0.16)	0.28 (0.22)	0.04 (0.12)	0.65 (0.15)
4	-0.46 (0.21)	0.05 (0.27)	0.08 (0.15)	0.69 (0.20)
5	-0.41 (0.20)	-0.16 (0.30)	0.07 (0.15)	0.72 (0.26)
6	-0.11 (0.15)	-0.22 (0.26)	-0.02 (0.09)	0.71 (0.27)
7	0.13 (0.23)	-0.15 (0.16)	-0.09 (0.11)	0.67 (0.25)
8	0.18 (0.20)	-0.06 (0.07)	-0.06 (0.09)	0.63 (0.23)
9	0.13 NA	0.00 NA	0.00 NA	0.63 (0.23)
Shock Variances	σ_u^2 σ_w^2	0.36 0.01	σ_e^2 θ_{lr}	0.87 0.04 (0.03)

Forecast horizon k corresponds to semi-annual periods. Standard errors in parentheses. NA indicates a fixed parameter with no standard error.

Table 3: GDP Level Forecast Revision Variance Decomposition						
Forecast Horizon k	Revision Variance (percentage points)	Contribution to the Variance of the Forecast Revision (share of revision variance)				
		Transitory Shock, u_t	Permanent Shocks:			Measurement Errors, v_t
			e_t	w_t	$cov(e_t, w_t)$	
0	0.33	0.27	0.66	0.01	0.05	0.00
1	0.53	0.15	0.66	0.02	0.08	0.08
2	0.58	0.12	0.58	0.05	0.11	0.15
3	0.63	0.04	0.58	0.07	0.14	0.16
4	0.70	0.00	0.58	0.11	0.17	0.14
5	0.78	0.01	0.54	0.13	0.18	0.13
6	0.83	0.02	0.49	0.17	0.19	0.13
7	0.83	0.01	0.42	0.22	0.20	0.15
8	0.85	0.00	0.37	0.26	0.21	0.15
9	0.93	0.00	0.34	0.30	0.22	0.15

Table 4: The Influence of Forecast Errors and the Current State of the Economy on the $k = 0$ Blue Chip GDP Forecast Revisions						
	Revision					
	Total		Transitory Shock u_t		Permanent Shock e_t	
Lagged Error	-0.07 (0.48)	-0.03 (0.72)	-0.16 (0.19)	-0.17 (0.17)	-0.04 (0.84)	0.04 (0.84)
Σ CFNAI's	0.42 (0.00)	0.11 (0.42)	0.68 (0.00)	0.81 (0.01)	0.45 (0.03)	-0.29 (0.24)
CFNAI < -0.5		0.52 (0.03)		-0.22 (0.48)		1.26 (0.02)
R^2	0.37	0.43	0.41	0.43	0.23	0.33
p-values in parentheses						

Table 5: Effect of Including CFNAI in the GDP Models						
	Standard Deviations of $k = 0$ Forecast Revisions					
	Base Models			Models with CFNAI		
	Total	Transitory Shock	Permanent Shock	Total	Transitory Shock	Permanent Shock
Beveridge-Nelson	1.65	0.12	1.53	1.03	0.00	1.03
Unobserv. Comp.	1.41	0.91	0.65	0.99	0.00	0.99
Blanchard-Quah	1.71	1.19	0.29	0.64	0.42	0.46
Campbell-Krane	1.52	1.33	0.56	0.77	0.60	0.37
Memo: Blue Chip	0.57	0.31	0.46	0.57	0.31	0.46

Figure 1: GDP Forecasts

Half-Year Growth (annual rate)

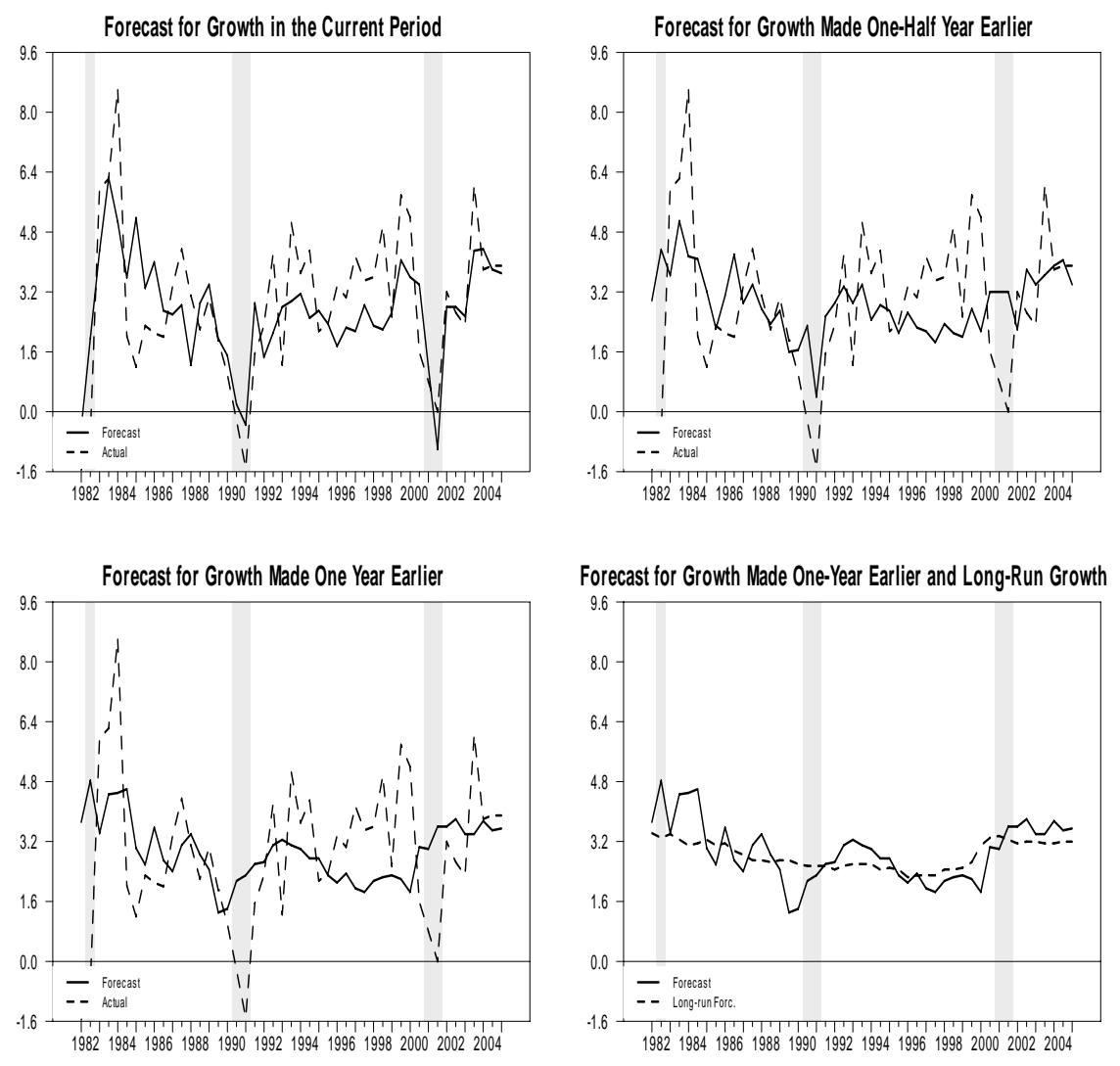


Figure 2: The Current State of the Economy and the GDP Forecasts

Deviations from Long-Run Growth Forecast

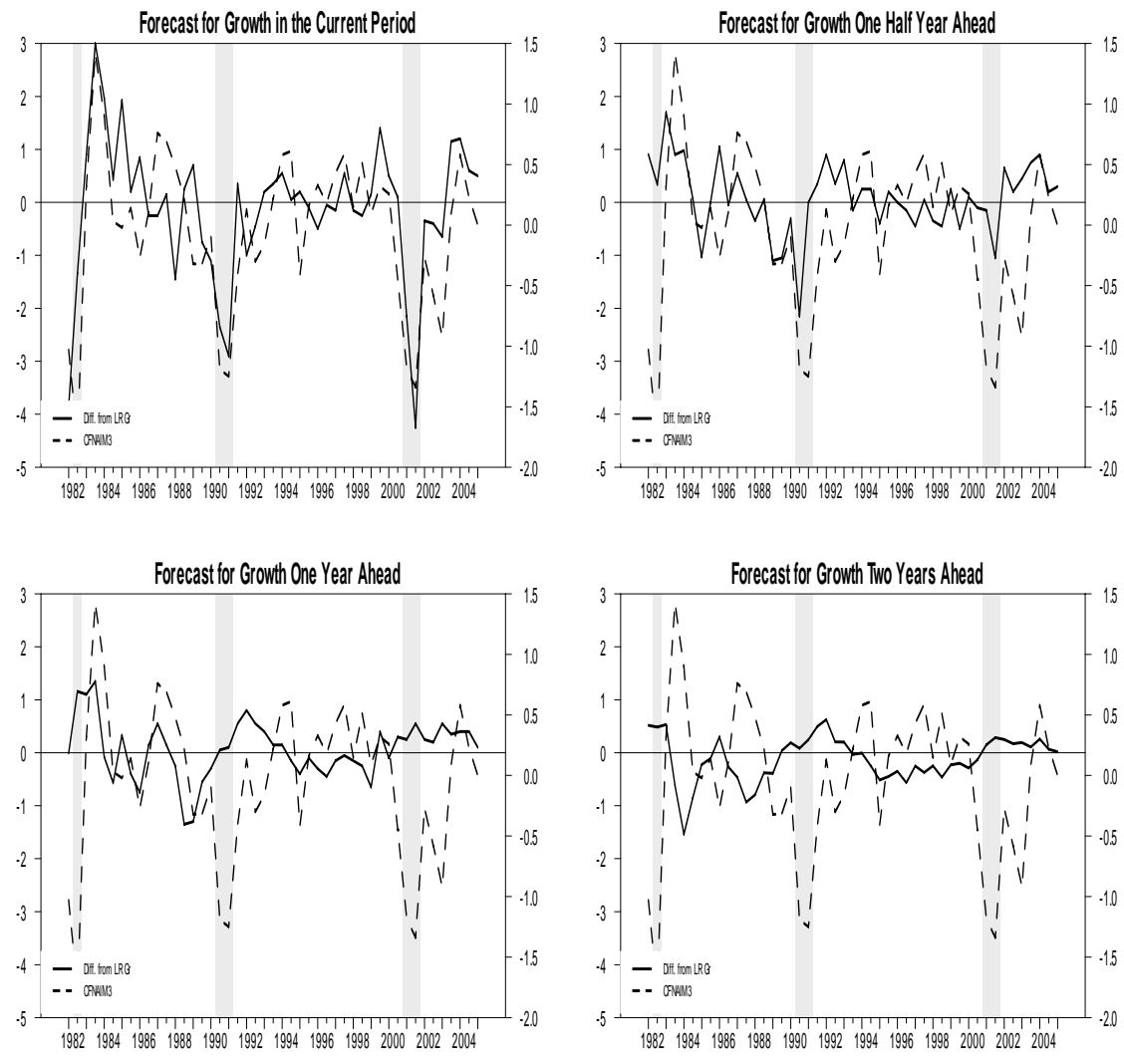


Figure 3: Responses to Shocks: Revisions to Forecasts for the Level of GDP

Scaled by Standard Deviation of Shocks; with Two Std-Error Bounds

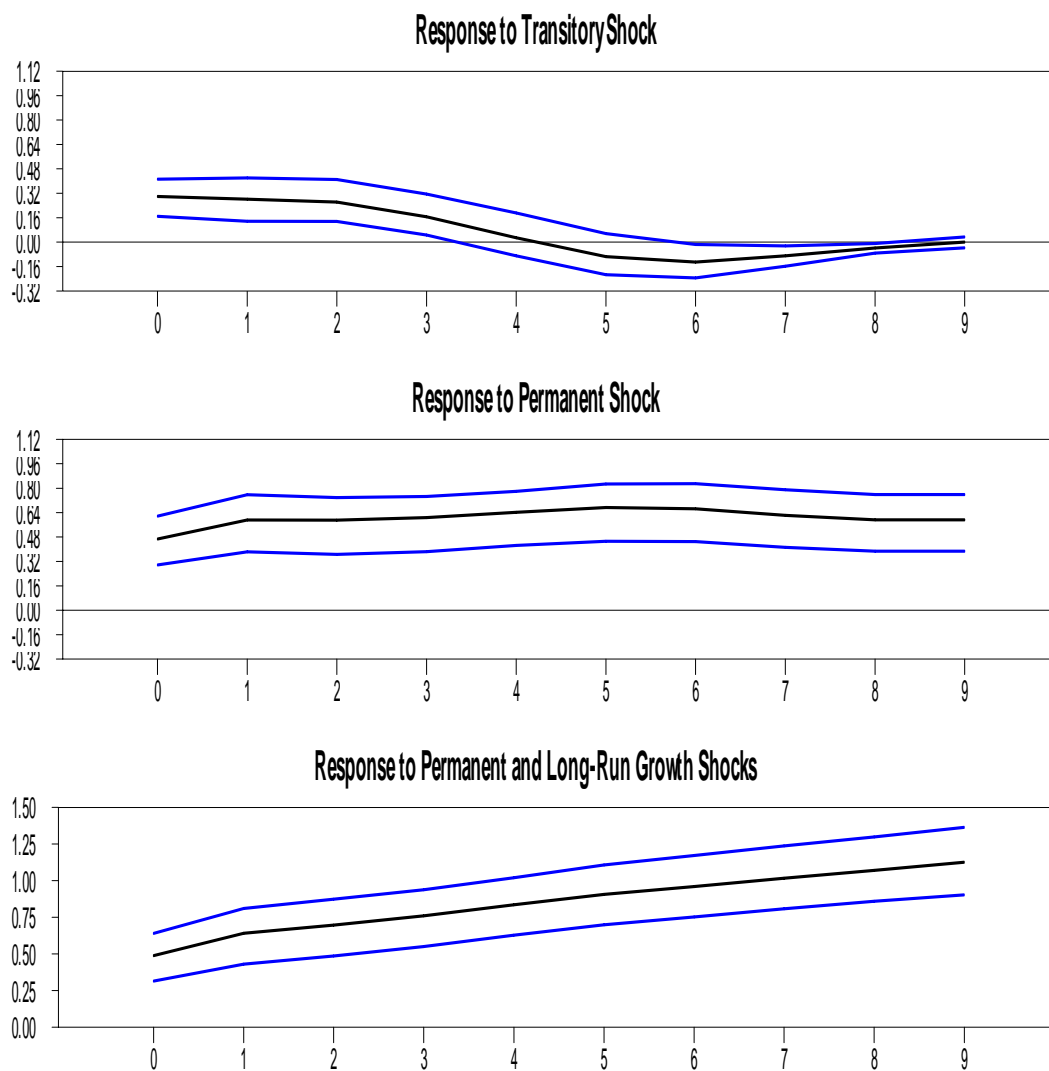


Figure 4a: Perceived Shocks to GDP and Forecast Errors

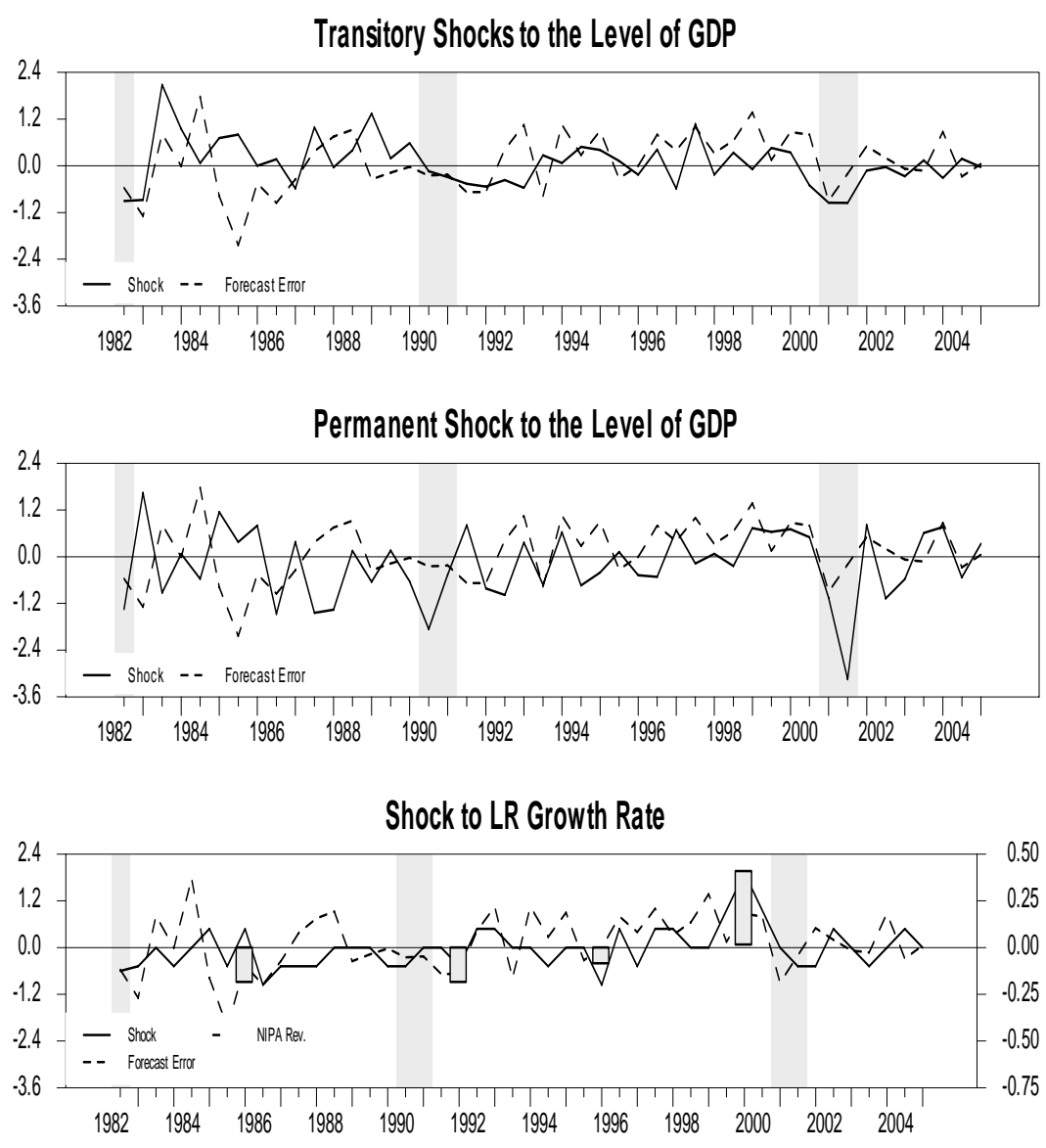


Figure 4b: Perceived Shocks to GDP and the Current State of the Economy

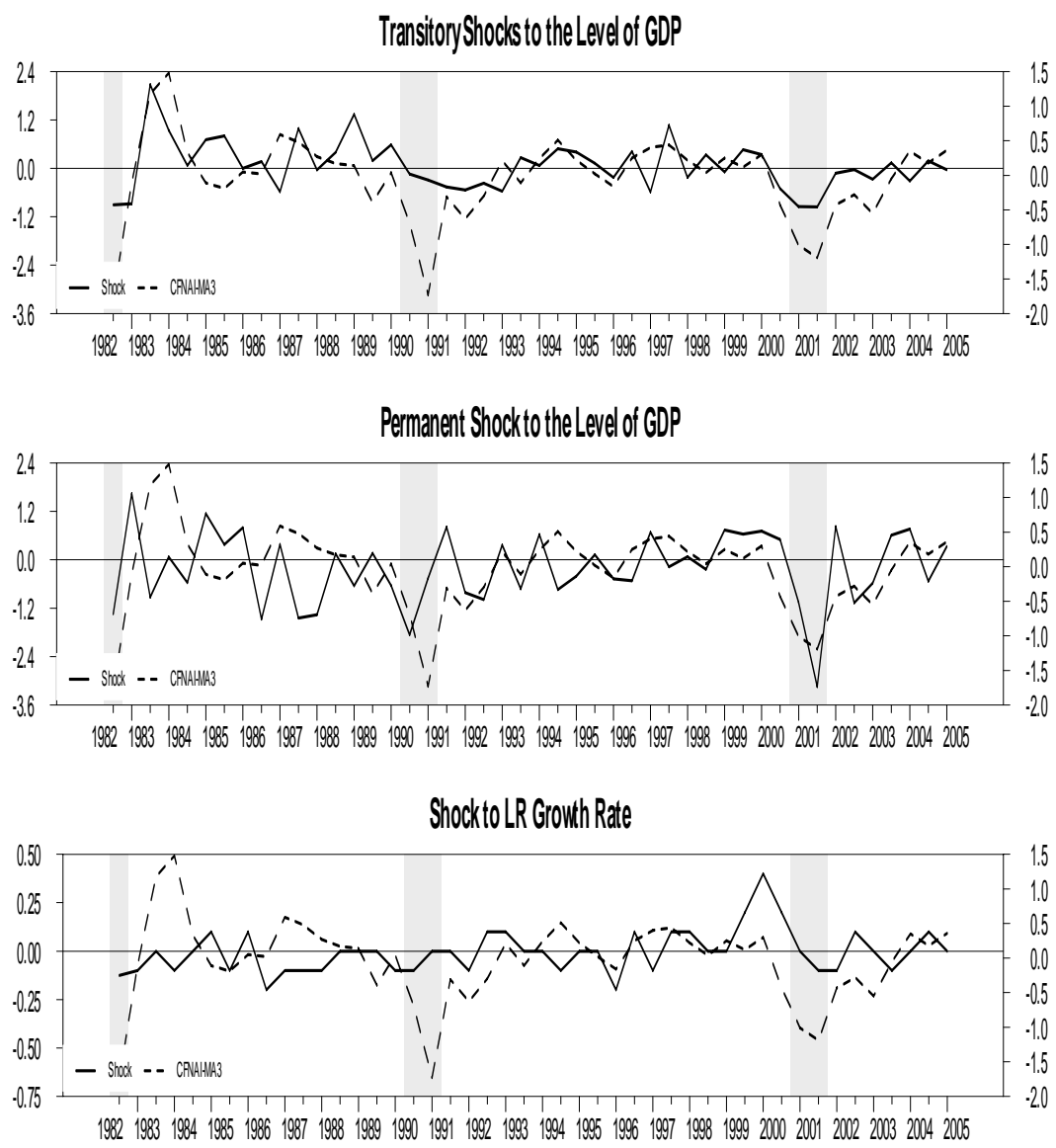


Figure 5a: Responses to Shocks: Blue Chip and Univariate Models

Responses Scaled by Standard Deviations of the Shocks

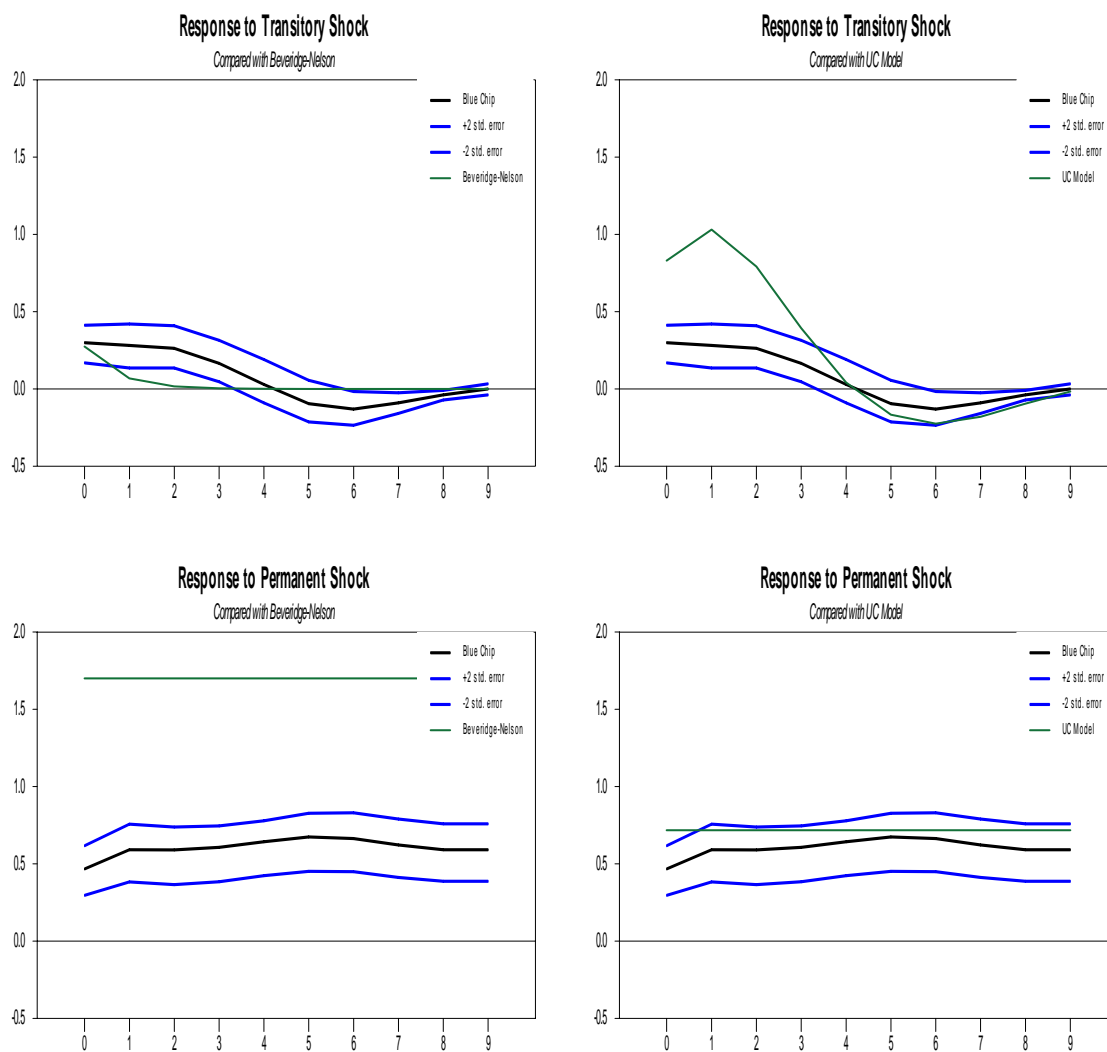
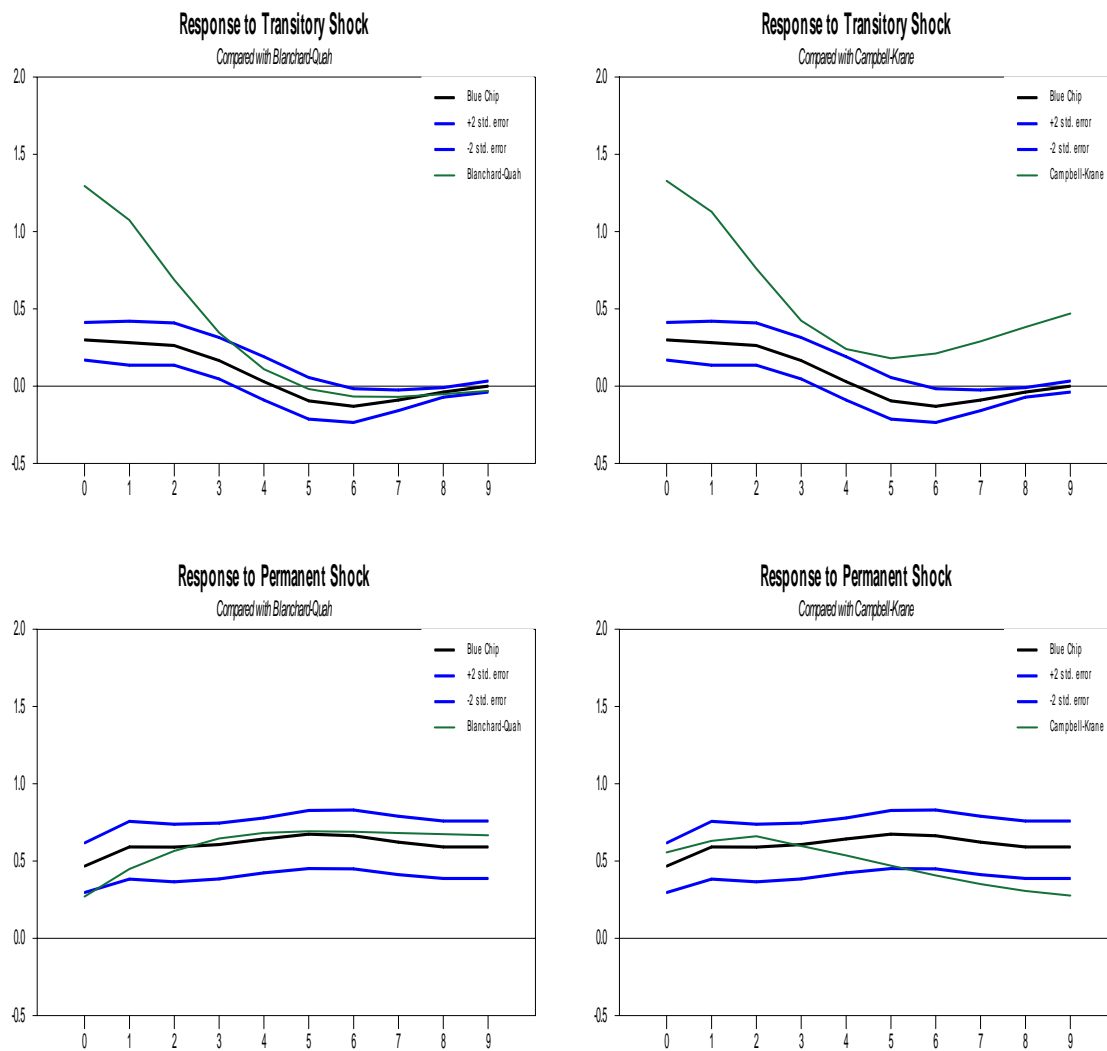


Figure 5b: Responses to Shocks: Blue Chip and Multivariate Models

Responses Scaled by Standard Deviations of the Shocks



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