Forecasting growth and levels in loglinear unit root models

van Garderen, K.J.

Publication date
2005

Document Version
Submitted manuscript

Citation for published version (APA):

General rights
It is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), other than for strictly personal, individual use, unless the work is under an open content license (like Creative Commons).

Disclaimer/Complaints regulations
If you believe that digital publication of certain material infringes any of your rights or (privacy) interests, please let the Library know, stating your reasons. In case of a legitimate complaint, the Library will make the material inaccessible and/or remove it from the website. Please Ask the Library: https://uba.uva.nl/en/contact, or a letter to: Library of the University of Amsterdam, Secretariat, Singel 425, 1012 WP Amsterdam, The Netherlands. You will be contacted as soon as possible.
Discussion Paper: 2005/04

Forecasting Growth and Levels in Loglinear Unit Root Models

Kees Jan van Garderen

(this replaces the earlier Discussion Paper: 2004/04)

www.fee.uva.nl/ke/UvA-Econometrics

Amsterdam School of Economics
Department of Quantitative Economics
Roetersstraat 11
1018 WB AMSTERDAM
The Netherlands
Forecasting Growth and Levels in Loglinear Unit Root Models

Kees Jan van Garderen*

University of Amsterdam

30 September 2005

Abstract

This paper considers unbiased prediction of growth and levels when data series are modelled as a random walk with drift and other exogenous factors after taking logs. We derive the unique unbiased predictors for growth and its variance. Derivation of level forecasts is more involved because the last observation enters the conditional expectation and is highly correlated with the parameter estimates, even asymptotically. This leads to conceptual questions regarding conditioning on endogenous variables and we prove that no conditionally unbiased forecast exists. We derive forecasts that are unconditionally unbiased and take into account estimation uncertainty, non-linearity of the transformations, and the correlation between the last observation and estimate which is quantitatively more important than estimation uncertainty and future disturbances together. The exact unbiased forecasts are shown to have lower MSFE than usual forecasts. We derive exact unbiased estimators of the MSFE and show that they can successfully be used in the construction of forecast intervals. The results are applied to a disaggregated eight sector model of UK industrial production.

JEL classification: C20; C22; C53.

Keywords: loglinear unit root models, stochastic growth, unbiasedness, parameter uncertainty.

* Faculty of Economics and Econometrics, University of Amsterdam, Roetersstraat 11, 1018WB Amsterdam, The Netherlands. tel:+31-20-5254220, fax:+31-205254349; K.J.vanGarderen@uva.nl
1 Introduction

Many macro- and other economic series appear to be stationary after applying a log-transformation and taking first differences. In the seminal paper of Nelson and Plosser (1982), for instance, the natural logs of all the data are taken, except for the bond yield, and they argue that with the exception of unemployment all the series could well belong to the difference stationary class. A common modelling strategy found in many empirical studies in economics is therefore to model the variables in log-differences if the hypothesis of a unit root in the log of the variables cannot be rejected. In this paper we will assume that taking log-differences is indeed correct and renders the series stationary, but that interest is in predicting the growth and level of the original, untransformed variables. This leads to a number of interesting issues not encountered in linear stationary settings, even when abstracting from the complication of testing for a unit root. We allow for exogenous regressors and the aim of the paper is to highlight these issues, to provide solutions for the problems encountered, and to investigate the quantitative importance of the results.

In order to set out the principal issues involved, we consider the following specific example of the model we have in mind, which is the Cobb-Douglas production function with time varying technology as employed by Rosanna (1995) in the context of optimizing firms and Binder and Pesaran (1999) in the growth literature:

\[ Y_t = Z_t \lambda \lambda_t^\beta L_t^{\beta L} K_t^{\beta K}, \]

\[ \ln(Z_t) \equiv z_t = \beta_0 + \delta t + u_t, \]

\[ u_t = u_{t-1} + \epsilon_t, \]

with \( \epsilon_t \) i.i.N. The term \( z_t \) represents technological progress which is assumed to grow deterministically over time, and further has a stochastic trend. The normality assumption allows explicit solutions in the problems we want to analyze. The model was also used in Garderen, Lee, and Pesaran (2000) in comparing various nonlinear aggregate and disaggregate models based on predictions of the output level \( Y \).

The central issue is forecasting one or more step ahead output level \( Y_{T+h} \), and predicting growth \( G_{h,T} = 100(Y_{T+h} - Y_T)/Y_T \) based on observations up to and including time \( T \). We focus on unbiased
forecasts since, in the absence of knowledge of the real cost of forecast errors, one often starts out with a square loss function and use the Mean Squared Forecasting Error (MSFE) criterion for assessing the quality of predictors. It is easily shown that the conditional mean given the available information at time $T$ minimizes the MSFE. This theoretical result assumes the parameters are known, but if the parameters in this conditional mean function are estimated, the predictions are no longer unbiased, as was pointed out by Goldberger (1968) in the context of Cobb-Douglas production functions with i.i.d. data.

After taking log-differences the model becomes:

$$\Delta y_t = \delta + \Delta l_t \beta_L + \Delta k_t \beta_K + \varepsilon_t,$$

where small letters indicate that logs have been taken. The transformed model is easily estimated, forecasting is standard, and inference is straightforward. The inverse transformation (exponentiation) is nonlinear and the nonstationary nature of the log variable gives rise to further complications, mainly in forecasting the level $Y$. We want to highlight the following issues.

First, the current level $y_T$ is highly informative about future levels, but it is also very informative about the unknown parameter values. The nonstationarity causes the estimators associated with any variable trending in the levels to be highly correlated with the current level of the dependent variable. In a weakly dependent situation the influence of $y_T$ on the estimator would be of order $1/T$ and dropping the last observation in a strict i.i.d. setting would actually make estimator independent of $y_T$. In the presence of a unit root this is no longer the case. Current $y_T$ is correlated with all $y_t$’s in the past and the covariance does not go to zero due to the stochastic trend. The covariance between $y_T$ and the estimator is of order 1 and the correlation does not disappear asymptotically. Hence forecasts like $\hat{Y}_{T+1} = Y_T \exp\{\hat{\delta} + \Delta l_{T+1} \hat{\beta}_L + \Delta k_{T+1} \hat{\beta}_K + \frac{1}{2} \hat{\sigma}^2\}$, which seem reasonable and are in common use (either with or without the last term $\frac{1}{2} \hat{\sigma}^2$), are significantly biased and not even consistent predictors of the conditional expectation.

Second, the nonlinearity of the inverse transformation (taking exponentials) causes the expectation to differ from the exponential of the mean. In linear settings unbiasedness of predictors can be proved by symmetry arguments in certain cases, but these arguments do not apply in the presence...
of nonlinear transformations. Furthermore, the variance of the random walk component of the log-
series is increasing linearly over time and increasingly affects the expected value of the levels of the
original series. See also Granger and Newbold (1976) who consider forecasting series that are non-
linearly transformed, including exponential transformations and consider quadratic transformations
for non-stationary variables. They also compare different predictors and the loss involved, but do
not consider estimation uncertainty (the optimal forecast is the theoretical conditional mean) and
no explanatory variables. Ariño and Franses (2000) consider forecasting levels from a VAR in log-
transformed time series. They find that the VAR analogue of $\hat{Y}_{T+1}$ with the equivalent term $\frac{1}{2} \hat{\sigma}^2$
to correct for the nonlinear transformation of the white noise performs better than without it, but
abstract from estimation uncertainty and correlation with conditioning variables $Y_T$.

The third issue is that of parameter uncertainty and the relation between the forecast horizon, $h$,
and the number of observations $T$. Sampson (1991) analyses, in a standard linear setting, the way
in which parameter uncertainty affects the way conditional forecast variances grow as the forecast
horizon increases. He shows that parameter uncertainty causes the conditional forecast variance to
increase with the square of the forecast horizon (when $T$ increases as a multiple of $h$) in the unit
root setting instead of rate $h$. He actually shows that the same holds in a trend stationary setting,
where the forecast variance is bounded in the absence of parameter uncertainty. Clements and Hendry
(1999, p111 ff.) also stress the importance of estimation uncertainty, but show that when $T$ and
$h$ are both allowed to increase proportionally, as in Sampson (1991), that the forecast variance of the
difference stationary model outgrows that of the trend stationary model, the ratio of the two going
to infinity. The exponential transformation only exacerbates the situation and the variance increases
even faster. Phillips (1979) also analyzes the role of parameter estimation in forecasting from stable
AR(1) models and discusses conditioning on the last observation explicitly.

One fundamental issue in this paper concerns conditioning and unbiasedness and in particular how
to define unbiasedness when conditioning on past observations when there is high correlation between
parameter estimates and conditioning variables. For prediction purposes we would like to condition on
all information available at time $T$. Conditioning on past observations, however, means that estimators
are fixed since they are deterministic functions of the conditioning variables. Probability statements
such as median- or mean unbiasedness are therefore vacuous since the distribution is degenerate: \( \hat{\delta} \) is fixed and never equal to \( \delta \) in the example above, irrespective of the estimator (function of the data) being used. This causes the predicament that expressions are either conditional on past observations and no statement about unbiasedness can be made, or we make unconditional predictions and average over all possible sample paths. Unconditional statements are undesirable because, for example, in a basic random walk model with zero initial value, the next observation will almost by definition be close to the last observation, whereas the unconditional prediction is always zero regardless of how far the process at time \( T \) has deviated from zero. Secondly, the unconditional variance of the process is increasing linearly with \( T \), whereas the conditional variance does not depend on \( T \) (only on \( h \)).

The issue becomes more subtle in the case of a unit root model with drift (and other exogenous variables) because of the correlation between the last observation and the estimator. If \( y_T \) is larger than the unconditional expectation, then the drift parameter will be overestimated. Using this overestimate leads to an over-prediction of future \( y_{T+h} \) and under-prediction when \( y_T \) is small. With the exponential transformation these effects do not average out, since over-prediction of the log variables will lead to a larger contribution to the MSFE than under-estimation.

One possible solution is to condition only on those variables that enter the conditional mean. In the leading example those are the exogenous variables and the endogenous variable \( Y_T \). This was also discussed and analyzed by Phillips (1979) for the AR(1) case with stable parameter values, but he notes that the Edgeworth expansions are not accurate for large autoregressive parameters. Appendix A.2 gives the relevant conditional distributions for the present case with a unit root and exogenous variables. The problem remains, however, that when a deterministic linear trend is included, the conditional distribution of the parameter estimates is still degenerate. E.g. if only a trend is included then \( \hat{\delta} = y_T / T \) and the difficulty is the same as when conditioning on the whole past, namely that \( \hat{\delta} \) is fixed. We show theoretically that when a linear trend is included no conditionally unbiased estimator exists at all. This important result holds obviously when conditioning on the whole past but more interestingly, also when conditioning only on the last observation.

We derive two exact unbiased estimators, one unconditionally unbiased estimator i.e. by directly solving the unconditional unbiasedness condition, and the second based on a conditional expression
using the last observation $Y_T$, but taking into account the correlation between the estimator and the last observation and requiring unbiasedness unconditionally. It is interesting that, although both predictors are derived from very different perspectives, they are actually identical.

We also derive an unbiased estimator of the MSFE. Given the skewness in the distributions of future levels of the series $Y_{T+h}$ and its unbiased forecasts, it is not obvious that this is a useful measure of uncertainty. We show however, that it can successfully be used in the construction of forecast intervals. These forecast intervals are constructed in a standard fashion, using basic normal quantiles, yet have coverage probabilities close to their nominal values, and this seems an interesting and practical contribution.

Finally, a minor comment about assuming it is known that the model is a unit root with drift. This means that there is no (pre-) testing for unit roots which proper inference procedures should take into account, but it would obscure the issues we wish to highlight here, but see for instance Ng and Vogelsang (2002). Secondly, the drift parameter is more accurately estimated in the first (log)-difference model where the Cramer-Rao lowerbound is attained, than the trend coefficient in (log-)levels. Parameter uncertainty is an important factor in adjusting the predictions and using a less accurate estimator would lead to larger effects.

The remainder of the paper is organized as follows. The next section discusses the basic model. Section 3 deals with predicting growth in this model and Section 4 deals with forecasting future levels, its MSFE, and constructing forecast intervals. Section 5 applies these results to eight sectors in the UK economy and compares our suggestions with common solutions. Section 6 concludes. Proofs are relegated to the appendix.

2 The Model

Consider the following loglinear unit root model, which includes the Cobb-Douglas production function with stochastic technology in the introduction as a special case:

\[
\ln Y_t = x_t' \beta + u_t, \quad t = 1, 2, ..., \tag{2}
\]

\[
u_t = u_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim I.I.N(0, \sigma^2), \tag{3}
\]
where \( x_t \) is a \((k \times 1)\) vector of regressors including a linear trend, \( \beta \) is a \((k \times 1)\) vector of unknown parameters, and \( \varepsilon_t \) are i.i.d. normal with mean zero and variance \( \sigma^2 \). The model implies that for the log-differences

\[
\Delta y_t = \Delta x_t' \beta + \varepsilon_t, \tag{4}
\]

where \( y_t = \ln Y_t \), and we assume that the following conditions hold throughout:

**Assumption 1.** \( y_t = \sum_{i=1}^{t} \Delta y_i \) and \( x_t = \sum_{i=1}^{t} \Delta x_i \). ■

**Assumption 2.** The matrix \( \Delta X = (\Delta x_1, \Delta x_2, \ldots, \Delta x_T)' \) has full column rank. ■

Assumption 1 is West’s (1988) condition (2.1) and avoids having to track the effects of the initial values on the mean, for instance. One could think of this as having subtracted the initial values from every observation, or simply as the initial values being zero in which case it is just an identity. Implicit in any case is that we condition on the initial value.

Assumption 2 ensures that the OLS estimator in (4) is uniquely defined. The assumption does imply that no constant term is included in \( x_t \), but that is related to the fact that the constant cannot be identified from the equation in first differences.

With these assumptions the parameters \( \beta \) and \( \sigma^2 \) are simply estimated using OLS in (4). Forecasting \( \Delta y_T \) is straightforward, as is forecasting the log-variable \( y_t \). Using Goldberger (1962) it is easily shown, see Lemma 6 in the appendix, that the optimal (minimum variance linear unbiased) predictor is given by:

\[
\hat{y}_{T+1} = y_T + \Delta x_{T+1}' \hat{\beta}. \tag{5}
\]

Exponentiation of \( \hat{y}_t \), however, does not lead to optimal forecasts for levels and growth of \( Y_t \). The first reason is that the transformation is non-linear and results in a well known bias. Second, and often ignored, \( y_T \) and \( \hat{\beta} \) are highly correlated, as stated in the following lemma and corollary, and this gives rise to an additional bias term.

**Lemma 1** If \( \hat{\beta} \) is the OLS estimator of the model in log-differences, then:

\[
\text{Cov} \left( y_T, \hat{\beta} \right) = \sigma^2 x_T' \left( \Delta X' \Delta X \right)^{-1}. \tag{6}
\]
Corollary 1 If $x_t$ includes a linear trend or is $I(1)$, such that $(\Delta X'\Delta X) = O_p(T)$ and $x_T = O_p(T)$, then
\[ Cov \left( y_T, \beta \right) = O(1), \] (7)
If $x_t$ consists of a linear trend only then for all $T$:
\[ Corr \left( y_T, \delta \right) = 1. \] (8)

The problem is that $y_T$ is very informative about the future levels $y_{T+h}$, while at the same time also contains much information about the parameter that needs to be estimated. If $y_T$ is high, then the estimate is also high, and if $y_T$ is low than the estimate is low. In a linear setting these effects may cancel out but exponentiation destroys the possible symmetry and bias results.

3 Predicting Growth

Growth in the model does not depend on the level $Y$. It is a function only of the disturbance term, parameters, and exogenous variables. At time $T$, growth over the next $h$ periods equals:
\[ G_{h,T} = 100(\exp \left\{ \Delta_h x'_{T+h} \beta + \sum_{i=1}^{h} \varepsilon_{T+i} \right\} - 1), \]
where $\Delta_h x_t = x_{T+h} - x_t$, and has expectation:
\[ E[G_{h,T}] = 100(\exp \left\{ \Delta_h x'_{T+h} \beta + \frac{h}{2} \sigma^2 \right\} - 1), \] (9)
which is easily shown using the Moment Generating Function (MGF) of a normal distribution.$^1$ The term $\frac{h}{2} \sigma^2$ is therefore due to the expectation of a nonlinear function of $\sum_{i=1}^{h} \varepsilon_{T+i}$. The expected growth can be estimated unbiasedly using a result in Van Garderen (2001) who also provides a method for deriving an unbiased estimate of the variance. This leads to:

Theorem 1 The Exact Minimum Variance Unbiased Growth Predictor is given by:
\[ \hat{G}_{h,T} = 100(\exp \left\{ \Delta_h x'_{T+h} \beta \right\} _0 F_1(m, m\beta \left( h - a_{T+h} \right) \sigma^2) - 1), \] (10)
where $\hat{\beta}$ and $\hat{\sigma}^2$ are the OLS estimators of the model in first differences, $m = (T - k)/2$ and $a_{T+h} = \Delta_h x'_{T+h} (\Delta X' \Delta X)^{-1} \Delta_h x_{T+h}.

$^1$If $z \sim N(\mu, \Sigma)$, then $MGF_z(r) = E \left[ e^{r'z} \right] = e^{r' \mu' + r' \Sigma}$. 

8
The Exact Minimum Variance Unbiased Estimator of the Variance is given by

\[ \overline{\text{var}}(\hat{G}_{h,T}) = 100^2 \exp\{2\Delta_h x_{T+h}^{T+h}\hat{\beta}\} \]
\[ \times \left[ _0F1(m; m \frac{1}{2}(h - aT+h)\hat{\sigma}^2)^2 - _0F1(m; m(h - 2aT+h)\hat{\sigma}^2) \right]. \] (11)

The \(_0F1\)-confluent hypergeometric function is defined in the Appendix as an infinite sum and can be thought of as a generalization of the exponential function. See also Abadir (2001) who reviews the use of hypergeometric functions in economics. The proof in Appendix A essentially uses the result that \(E[_0F1(m, m\hat{\sigma}^2z)] = \exp\{\hat{\sigma}^2z\}\), see Van Garderen (2001). The fact that the density is complete in a statistical sense (e.g. Lehmann and Cassella, 1998) leads to uniqueness.

Using these results we can attribute the term \(\frac{1}{2}\hat{\sigma}^2(h - aT+h)\) in \(\hat{G}_{h,T}\) to: (a) the uncertainty in the disturbances \(\varepsilon_{T+i}, i = 1, \ldots, h\), which leads to the term \(\frac{1}{2}\hat{\sigma}^2\) in the expected growth equation (9), and (b) the uncertainty in the estimate \(\Delta_h x_{T+h}^{T+h}\hat{\beta}\), since \(E[\exp\{\Delta_h x_{T+h}^{T+h}\hat{\beta}\}] = \exp\{\Delta_h x_{T+h}^{T+h}\hat{\beta} + \frac{1}{2}\hat{\sigma}^2aT+h\}\).

**Definition 1 Alternative Growth Predictors**

(A) **Approximate Unbiased Predictor** of Growth and its Variance:

\[ \hat{G}^{\text{app}}_{h,T} = 100 (\exp\{\Delta_h x_{T+h}^{T+h}\hat{\beta}\} - 1), \] (12)
\[ \overline{\text{var}}(\hat{G}_{h,T}) = 100^2 \exp\{2\Delta_h x_{T+h}^{T+h}\hat{\beta}\} \]
\[ \times \left[ \exp\{\hat{\sigma}^2(h - aT+h)\} - \exp\{\hat{\sigma}^2(h - 2aT+h)\} \right]. \] (13)

(B) **Naive Predictor**

\[ \hat{G}^{\text{naiv}}_{h,T} = 100 (\exp\{\Delta_h x_{T+h}^{T+h}\hat{\beta}\} - 1). \] (14)

(C) **Consistent Predictor**:

\[ \hat{G}^{\text{cons}}_{h,T} = 100 (\exp\{\Delta_h x_{T+h}^{T+h}\hat{\beta}\} + \frac{1}{2}\hat{\sigma}^2 - 1). \] (15)

The approximate unbiased predictor is based on an approximation of the hypergeometric function by an exponential function. It therefore only involves exponential functions and appears much easier to calculate than the exact one, but it should be noted that many packages, such as Mathematica, include the hypergeometric function as standard, and a Gauss version is available from the author.
A second alternative, referred to as the naive predictor, ignores the uncertainty in both future $\varepsilon_{T+i}$s and the estimation of $\beta$, and as a result is a biased and inconsistent estimator of expected growth. The bias effects work in opposite directions, however: ignoring the uncertainty in $\varepsilon$ leads to under-estimation and ignoring uncertainty in $\hat{\beta}$ leads to over-estimation. The naive predictor can in certain circumstances be better in terms of MSE than the other predictors.

The consistent predictor takes into account the uncertainty in future $\varepsilon_{T+i}$s, but ignores the uncertainty in the estimation of $\beta$ and $\sigma^2$. This parameter uncertainty goes to zero as the sample size increases, and the predictor is a consistent estimator of expected growth.

Exact expressions and estimators are available for the variance of the consistent and naive predictors, but when growth itself is not estimated unbiasedly, then there is little reason for using an unbiased estimator of the variance or MSFE.

### 4 Forecasting Levels

Predicting growth is essentially straightforward, and is only complicated by the nonlinear function involved as we have just seen. Forecasting future levels is more involved because future levels are not simply a function of parameters but also depend on the current level of the series. This current level is highly correlated with the parameter estimates, and ignoring this dependence leads to significant bias. For this reason the obvious estimator based on the unbiased growth predictor:

$$\hat{Y}_{T+h} = Y_T(1 + \hat{G}_{h,T}/100), \quad (16)$$

is not an unbiased forecast of the level. When the consistent growth estimator is used this would lead to:

$$\hat{Y}_{T+h} = Y_T \exp\{\Delta_{h}x'_{T+h}\hat{\beta} + \frac{b}{2}\hat{\sigma}^2\}, \quad (17)$$

which makes it clear that the correlation between current level $Y_T$ and $\hat{\beta}$ will cause problems for inference in general, and for unbiasedness in particular. Level forecasts based on growth estimates are generally not unbiased for three reasons: (a) the nonlinear exponential transformation, (b) the parameter uncertainty, (c) the fact that $Y_T$ and the estimator $\hat{\beta}$ are highly correlated. We will
therefore have to bias-correct predictors for these factors, or consider estimators based directly on the expectation of $Y_{T+h}$.

The unconditional expectation of period $(T+h)$’s level $Y_{T+h}$ and the conditional expectation $Y_{T+h}$ given the current level $Y_T$ are:

$$E[Y_{T+h}] = \exp\{x_{T+h}^\prime \hat{\beta} + \frac{T+h}{2} \sigma^2\}, \quad (18)$$

$$E[Y_{T+h}|Y_T] = Y_T \exp\{\Delta_h x_{T+h}^\prime \beta + \frac{h}{2} \sigma^2\}. \quad (19)$$

It seems therefore that there are two different ways of constructing an unbiased predictor for the level $Y_T$. The first is to note that the unconditional expectation of $Y_{T+h}$ depends only on parameters and to estimate this unbiasedly using Van Garderen (2001).

The second is to estimate the conditional expectation of $Y_{T+h}$ given $Y_T$ and adjust for the bias caused by the fact that $\hat{\beta}$ and $Y_T$ are correlated, to obtain a predictor that is unbiased. This leads to two forecasts that are both unbiased:

**Proposition 1** The Unconditional Level Forecast

$$F_{T+h} = \exp\{x_{T+h}^\prime \hat{\beta}\} \, _0F_1(m; m\hat{\sigma}^2 \, z_{T+h}), \quad \text{with},$$

$$z_{T+h} = \frac{1}{2}(T + h - x_{T+h}^\prime (\Delta X^\prime \Delta X)^{-1} x_{T+h}), \quad (20)$$

is unbiased.

**Proposition 2** The Conditional Level Forecast

$$F_{T+h|T} = Y_T \exp\{\Delta_h x_{T+h}^\prime \hat{\beta}\} \, _0F_1(m; m\hat{\sigma}^2 \, z_{T+h|T}), \quad \text{with},$$

$$z_{T+h|T} = \frac{1}{2}(h - 2x_{T+h}^\prime (\Delta X^\prime \Delta X)^{-1} \Delta_h x_{T+h}^\prime - \Delta_h x_{T+h}^\prime (\Delta X^\prime \Delta X)^{-1} \Delta_h x_{T+h}), \quad (21)$$

is unbiased.

The terms in $z_{T+h}$ and $z_{T+h|T}$ are easily attributed to sources of uncertainty. In $z_{T+h}$, the term $(T + h)$ originates from the total number of disturbances up to and including period $T + h$, and the second term is correcting for the parameter uncertainty when estimating $x_{T+h}^\prime \hat{\beta}$. In $z_{T+h|T}$: the term $h$ originates from the $h$ disturbance terms $\varepsilon_t$ in the future between time $T$ and $T + h$, the second term...
\[-2x_T' (\Delta X' \Delta X)^{-1} \Delta_h x'_{T+h} \] derives from the covariance between \(y_T\) and \(\Delta_h x'_{T+h} \hat{\beta}\), and the third term 
\[x'_{T+h} (\Delta X' \Delta X)^{-1} x_{T+h}\] is correcting for parameter uncertainty in the estimate \(\Delta_h x'_{T+h} \hat{\beta}\).

Although the predictors can be very different in practice and are derived from very different perspectives, they are in fact identical if a drift term is included as proved in Appendix A:

**Theorem 2** If the model includes a deterministic trend, such that \(\Delta X\) includes a constant term, then:

\[F_{T+h} = F_{T+h | T}.\]

This remarkable equality between the conditional and unconditional predictors can be explained by noting that the unconditional predictor \(F_{T+h}\) equals \(Y_T\) for the limiting case \(h = 0\) (but only if a constant is included).\(^2\) So, although we are averaging over all possible sample paths for \(\{Y_t\}\), each prediction based on any realized sample path still goes through (when varying \(h\)) the last observation \(Y_T\). The difference is that the conditional predictor \(F_{T+h | T}\) is an explicit function of \(Y_T\), whereas the unconditional predictor only depends implicitly on \(Y_T\), but behaves exactly the same.

It seems undesirable to average over all possible sample paths that \(Y\) can take. Given that the process goes through \(Y_T\) we should want to condition on the fact that, at time \(T\), the process goes through \(Y_T\). An alternative approach is to condition only on the terms that enter the conditional expectation, in this case \(Y_T\). In this approach we consider the conditional distribution given only \(Y_T\) and do not condition on previous values \(\{Y_1, \ldots, Y_{T-1}\}\). The problem is, however, that the conditional distribution of \(\hat{\beta}\) is still degenerate given \(Y_T\) only. For example, in the log-difference model with only a constant term, the estimated drift parameter is simply \(Y_T / T\) and hence a deterministic function of \(Y_T\) and it is impossible to find a predictor that is conditionally unbiased given \(Y_T\). This holds generally as stated in the following theorem.

**Theorem 3** If the model includes a deterministic trend, such that \(\Delta X\) includes a constant term, then no conditionally unbiased predictor of \(Y_{T+h}\) exists given either (a) \(\{Y_1, \ldots, Y_T\}\) or (b) only \(\{Y_T\}\).

\(^2\)With \(h = 0\) we have \(x'_{T+0} \hat{\beta} = x' \Delta X (\Delta X' \Delta X)^{-1} \Delta X' \Delta y = x' \Delta y = y_T\) and hence \(\exp(x' \hat{\beta}) = y_T\). \(z_T = 1/2(T - x' \Delta X (\Delta X' \Delta X)^{-1} \Delta X' \hat{\beta}) = 0\), and \(\alpha F_1(m, 0) = 1\) and hence \(F_{T+0} = Y_T\). For the conditional expressions note that by definition \(\Delta_0 x_t = x_{t+0} - x_t = 0\).
The proof is given in Appendix A, but (a) is obvious since any forecast is constant given \( \{Y_1, ..., Y_T\} \) and with probability 1 does not equal the conditional expectation of \( Y_{T+h} \). The more interesting part (b) is less obvious, but also follows from a degeneracy in the conditional distribution of \( \hat{\beta} \). The proof determines a condition that can only be satisfied when \( h = 0 \).

**Theorem 4** If the model includes a deterministic trend, such that \( \Delta X \) includes a constant term, then the unbiased level forecast has mean squared forecasting error, \( E[(F_{T+h} - Y_{T+h})^2] \):

\[
MSFE(F_{T+h}) = \exp\{2x_{T+h}'\beta + 2(T + h)\sigma^2\} \\
\quad \times \left[ \exp\{\sigma^2(h + a_{T+h})\}F_1(m; \sigma^4 z^2_{T+h}) - 1 \right],
\]

with \( a_{T+h} = \Delta_h x_{T+h}'(\Delta X' \Delta X)^{-1} \Delta_h x_{T+h} \). It can be estimated unbiasedly as:

\[
\overline{MSFE}(F_{T+h}) = \overline{F}_{T+h}^2 - \exp\{2x_{T+h}'\hat{\beta}\}F_1(m; -2m\sigma^2(h + a_{T+h})).
\]

The MSFE here is unconditional. In principal one would like a conditional expression given \( \{Y_1, ..., Y_T\} \) or \( \{Y_T\} \), and we did derive such a theoretical expression, but it is not useful in practice since it cannot be used to indicate the accuracy of the forecast. The reason is that no conditionally unbiased estimates for the terms \( F_{T+h}^2 \) and \( -2F_{T+h}Y_{T+h} \) exist. This can be proved in the same fashion as Theorem 3.

Generally a constant would be included in the log linear regression. If no constant is included then \( F_{T+h} \) and \( F_{T+h|T} \) are different and so are their MSFE’s (and estimators thereof) which are not equal to Theorem 4. The proof in Appendix A.2 is readily adapted, however, but the results would include three terms for MSFE and its estimate in both cases. If no constant is included, the conditional \( F_{T+h|T} \) should be used. It naturally satisfies \( F_{T|T} = Y_T \) always, whereas \( F_T \neq Y_T \) if no constant is included. The MSFE of unconditional \( F_{T+h} \) is much larger than that of the conditional predictor \( F_{T+h|T} \) (comparable to the second consistent estimator discussed below). The situation can be compared to the simple random walk model \( y_t = y_{t-1} + \varepsilon_t \) where the forecasts \( \hat{f}_{T+1} = 0 \) and \( \hat{f}_{T+1} = a_T(y_T/T) \), with \( a_T = T \) for conditional expression or \( T + 1 \) for forecasting from a model with a constant, are both unconditionally unbiased but \( \hat{f}_{T+1} \) has a much lower MSFE.
4.1 Alternative Level Forecasts

Other forecasts for $Y_{T+h}$ are available and, although they will be biased, need not necessarily be worse in terms of MSFE.

**Definition 2** Alternative forecasts:

(A) **Approximate unbiased forecast**:

$$F_{T+h}^{apu} = Y_T \exp\{\Delta_h x_{T+h}^\beta + \hat{\sigma}^2 z_{T+h|T}\}, \quad \text{with,}$$

$$z_{T+h|T} = \frac{1}{2}(h - 2x_T^\beta (\Delta X'\Delta X)^{-1} \Delta_h x_{T+h}^\beta - \Delta_h x_{T+h|^T} (\Delta X'\Delta X)^{-1} \Delta_h x_{T+h}),$$

and approximate unbiased estimator of the mean squared forecasting error:

$$\hat{\text{MSFE}}(F_{T+h}^{apu}) = (F_{T+h}^{apu})^2 - \exp\{2x_T^\beta - 2\hat{\sigma}^2(h + a_{T+h})\}. \quad (26)$$

(B) **Growth based forecast**:

$$F_{T+h}^{grow} = Y_T (1 + \hat{G}_{h,T} \frac{100}{100}). \quad (27)$$

(C) **Naive forecast**:

$$F_{T+h}^{naiv} = \exp\{x_T^\beta\}. \quad (28)$$

(D) **Consistent forecasts**:

$$F_{T+h}^{cons1} = Y_T \exp\{\Delta_h x_{T+h}^\beta + \frac{h}{2} \hat{\sigma}^2\}, \quad (29)$$

$$F_{T+h}^{cons2} = \exp\{x_T^\beta + \frac{T + h}{2} \hat{\sigma}^2\}. \quad (30)$$

The approximate unbiased forecast $F_{T+h}^{apu}$ is constructed by approximating the hypergeometric functions in the exact unbiased forecast and its MSFE, by using the exponentiated $\hat{\sigma}^2 z_{T+h|T}$, which corrects for uncertainty in $Y_{T+h}$ caused by disturbances $\varepsilon_t$, $\hat{\beta}$ and the correlation between $Y_T$ and $\hat{\beta}$, and by using $(h + a_{T+h})$ from Theorem 4 for the MSFE estimator. We will show below that in practice these are very close to the exact level and MSFE estimators.

The growth based forecast multiplies the current level with predicted growth, ignoring the correlation between $Y_T$ and $\hat{G}$. Any of the growth predictors could be used, but in the applications below
we have used the exact unbiased growth predictor to isolate the correlation effect between $Y_T$ and $\hat{G}$.
The naive growth predictor can also be used, especially since it can have the lowest MSFE as will be shown in Section 5, but is identical to the naive forecast.

The naive forecast simply substitutes the estimated parameters in the model function for $Y_{T+h}$. It ignores the uncertainty in future $\varepsilon_{T+i}$'s, $\hat{\beta}$, and the correlation between $Y_T$ and $\hat{\beta}$. We could also think of a conditional version $Y_T \exp\{\Delta_h x_{T+h}^T \hat{\beta}\}$, but this equals $F_{T+h}^{\text{naive}}$ identically if a time trend is included in $x_t$, similar to Theorem 2.

The consistent forecasts are based on the idea of substituting consistent estimators in the expressions for the conditional and unconditional mean of $Y_{T+h}$ respectively. They are not actually consistent since not even the bias goes to zero. They take into account the increased expectation due to the disturbances, but ignore the increased bias due to estimation uncertainty. Moreover, $F_{T+h}^{\text{cons}1}$ ignores the correlation between $\hat{\beta}$ and $Y_T$ and $F_{T+h}^{\text{cons}2}$ does not equal $Y_T$ for $h = 0$. The conditional and unconditional versions are very different here, even if a constant is included in the regression. The forecast $F_{T+h}^{\text{cons}2}$ was used in Garderen, Lee, and Pesaran (2000) in their prediction based criterion for deciding between aggregate and disaggregate nonlinear models. This choice turns out not to be optimal for forecasting as we will see below. Another alternative would be $\exp\{x_{T+h}^T \hat{\beta} + \frac{h}{2} \hat{\sigma}^2\}$, but, similar again to Theorem 2, equals $F_{T+h}^{\text{cons}1}$ identically if a time trend is included in $x_t$.

4.2 MSFE Estimation

Theorem 4 gives an unbiased estimate of the MSFE, but does not provide standard errors or an indication how useful the estimates are in constructing forecast intervals. We simulated a log-linear unit root model which includes a trend, a random walk with drift, and a stationary variable as explanatory variables with parameter values similar to estimates based on the data in Nelson and Plosser (1982) or Sampson (1991) to investigate the MSFE estimator. Table 6 in Appendix B illustrates the unbiasedness of the exact unbiased estimator and its purpose is to show that the approximate unbiased MSFE estimator of Definition 2(A) is very close to the exact unbiased MSFE estimator. There are cases where the difference between exact and unbiased are larger, but the results are typical for a range of parameter values and data generating mechanisms for $X$, including the sectoral
application in Section 5.

Table 6 only reports the first moment of these estimates and the standard deviations on these estimates are in fact very large. They are of a similar order of magnitude as the estimates themselves. There is, however, a large correlation between the MSFE estimate and the squared deviation $(F_{T+h} - Y_{T+h})^2$, ranging in the present model with $T = 50$ from 0.4 for $h = 5$ to 0.6 for $h = 20$. It may therefore still be possible to use the estimated MSFE to studentize the forecast for use in inference. This studentization results in a distribution that, apart from some skewness to the left, is not far from a standard normal distribution. Figure 1 shows the density of this studentized forecast estimated nonparametrically based on 100,000 replications and for three different sample sizes. The densities for the three different cases are remarkably close, and close to the standard normal distribution.

![Figure 1: Density of Studentized Forecast. $\sigma = 0.05267$, $\beta' = (0.05, 0.2, 0.4, 0.5)$. Based on 100,000 replications.](image-url)
4.3 Forecast Intervals

Given the closeness to the normal distribution of the standardized statistic, it is natural to check if confidence intervals based on the studentized statistic and the normal approximation provide a simple way of constructing confidence intervals with a reasonable coverage probability. Table 1 shows the percentage of $Y_{T+h}$’s that are included in the forecast intervals constructed in the standard fashion using the estimated MSFE and the $(1 - \alpha/2)$-quantile of the standard normal distribution $z_{1-\alpha/2} = \Phi(1 - \alpha/2)$, with confidence limits:

$$F_{T+h} \pm z_{1-\alpha/2} \frac{\text{MSFE}^{1/2}}{1}.$$

(31)

Table 1: Coverage Probabilities of Forecast Interval in %

<table>
<thead>
<tr>
<th>Nominal</th>
<th>$T = 25$</th>
<th>$T = 50$</th>
<th>$T = 100$</th>
<th>$T = 500$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h = 1$</td>
<td>$h = 5$</td>
<td>$h = 1$</td>
<td>$h = 5$</td>
<td>$h = 1$</td>
</tr>
<tr>
<td>90%</td>
<td>88</td>
<td>89</td>
<td>90</td>
<td>90</td>
</tr>
<tr>
<td>95%</td>
<td>94</td>
<td>93</td>
<td>94</td>
<td>95</td>
</tr>
<tr>
<td>99%</td>
<td>98</td>
<td>98</td>
<td>99</td>
<td>99</td>
</tr>
</tbody>
</table>

$\sigma = 0.05267, \beta^T = (0.05, 0.2, 0.4, 0.5)$. Based on 100,000 replications.

These coverage probabilities are surprisingly good, given the skewness of the distribution of $Y_{T+h}$. It was not obvious a priori that the MSFE is a good measure for use in inference. These results suggest, however, that in the context of this model it is reasonable to report the estimated MSFE as a measure of forecasting uncertainty for $F_{T+h}$ since standard confidence intervals constructed with the estimated MSFE have coverage probabilities that are close to their nominal values. It should be noted though, that the rejection probability for larger $h$ is predominantly due to rejection on the right hand side, i.e. the actual $Y_{T+h}$ being larger than the upper bound. One might therefore be able to shorten, and hence improve the confidence intervals, by increasing both the upper and lower limits, but this is not pursued here.
4.4 Forecast Horizon and Sample Size

We can use Theorem 4 to show the effects of increasing forecasting horizon $h$ in relation to the available number of observations $T$ on the forecasting accuracy. First note that in general the level of the series $Y_{T+h}$ tends to increase over time. So the first effect of increasing $T$ or $h$ is an increase in the squared expected level for both $Y$ and $F$ in period $T+h$: $E[Y_{T+h}]^2 = E[F_{T+h}]^2 = \exp\{2x_T \beta + (T+h)\sigma^2\}$.

We would like to distinguish this level effect from the second effect which relates to the squared difference in $Y$ and $F$ when divided by the expected level: $\text{MSFE}(F_{T+h})/E[Y_{T+h}]^2$

In order to illustrate this we can use the basic loglinear unit root model with drift to obtain:

$$\frac{\text{MSFE}(F_{T+h})}{E[Y_{T+h}]^2} = \exp\{(T+h)\sigma^2\} \left[ \exp\{\sigma^2 h (1 + h/T)\} \frac{1}{\alpha^4} \left( h(1 + h/T) \right)^2 \right] - 1.$$  \hspace{1cm} (32)

The term in square brackets is governed by the forecasting horizon $h$ when $T$ is large, but $T$ still plays an important role in the first term. Both $h$ and $T$ will increase the MSFE, even if divided by the expected level squared. This is shown in Figure 2.

Figure 2: MSFE/E[Y_{T+h}]^2 in loglinear unit root model with drift, $T : 25-500$, $h : 1-20$

---

3Unless $x_t \beta < -\frac{1}{2m} \sigma^2$, which can happen with e.g. a negative drift term, and does happen for the mining sector in the application below.
When $T$ is increasing, the ratio $\frac{\text{MSFE}(F_{T+h})}{E[Y_{T+h}]^2}$ is initially decreasing, but subsequently increases quickly when $h$ is larger.\(^4\) In order to explain the approximate linearity in $h$ that can be seen in the graph, note that for small $\sigma^2$ and $T$ fixed, the ratio in this loglinear unit root with drift model is approximately:

$$\frac{\text{MSFE}(F_{T+h}) \approx}{E[Y_{T+h}]^2} \sigma^2 \left( \frac{h^2}{T} \right) + \sigma^4 (hT + \frac{2}{5}h^2 + \frac{h^2}{2(T-1)}). \tag{33}$$

The figure further shows that, by letting $h$ and $T$ grow proportionally, as in Sampson (1991) or Clements and Hendry (1999), the increased uncertainty about the future dominates the increased accuracy in the estimation of unknown parameters, even when correcting for the fact that the level is exponentially increasing by dividing by $E[Y_{T+h}]^2$. Related is also West (1996), whose Assumption 4 allows $\lim_{T+h \to \infty} h/T = 0$, and parameters are estimated by regression functions, but interestingly, his Theorem 4.1 does not hold.\(^5\)

The MSFE tends to infinity as $T$ and/or $h$ go to infinity (unless growth is sufficiently negative). In order to investigate the effects of the forecast horizon, we can compare the unbiased forecast to the alternative forecasting methods. We simulated a variety of slightly more involved log-linear unit root models and we report here the results for the model used in Section 4.2, which included a trend, a random walk with drift, and a stationary variable as explanatory variables with parameter values similar to estimates based on the data in Nelson and Plosser (1982) or Sampson (1991). Changing the way in which the $X$ matrix is generated had some effect but did not qualitatively change the results, as long as a constant was included. We have calculated the MSFE for the alternative forecasts as a

\(^4\)Not for $h = 0$, since $F_T = Y_T$ and the measure is identically 0.

\(^5\)Taking as moment functional $f(.)$ the one step ahead MSFE, which in our notation is (West 1996 uses $R$ for $T$ and his $\pi$ becomes $\lim_{T+h \to \infty} h/T = 0$) we have for the theoretical expectation

$$E[f_{T+1}] = E(Y_{T+1} - E[Y_{T+1}])^2 = E(Y_{T+1} - E[F_{T+1}])^2 = \exp(2x_{T+1}^\prime \beta + \sigma^2(T + 1)) \{\exp(\sigma^2(T + 1)) - 1\}.$$  

The sample MSFE $f = \frac{1}{T} \sum_{t=T+1}^{T+1} (Y_t - F_t)^2 = (Y_{T+1} - F_{T+1})^2$ has expectation

$$E[f] = \exp(2x_{T+1}^\prime \beta + 2(T + 1)\sigma^2) \{\exp(\sigma^2(1 + \alpha_{T+1}))F_1(m; \sigma^4 z_{T+1}^2) - 1\}. \tag{33}$$

Hence the expectation of the difference equals:

$$E[f - E[F_{T+1}]] = \exp(2x_{T+1}^\prime \beta + 2\sigma^2(T + 1)) \left[1 - \exp(-\sigma^2(T + 1)) - \exp(\sigma^2(1 + \alpha_{T+1}))F_1(m; \sigma^4 z_{T+1}^2) + 1\right].$$

The second term in square brackets goes to 0 and the third goes to 1 and the third term does not tend to 2. So unless $(\alpha_{T+1} + \sigma^2(T + 1))$ goes to $-\infty$, $f - E[F_{T+1}]$ cannot be centered around 0. When the number of terms $P$ is increasing, as in West’s Assumption 4, this problem becomes worse as we increase $h$ and set $P = h$.\(^5\)
function of the forecasting horizon and for different sample sizes.

The exact unbiased forecast was uniformly best over all the experiments and all forecast horizons. It should be stressed that this general superiority should not have been anticipated in view of, for instance the superiority of the naive growth predictor.

Figure 3 graphs how much worse the alternative growth based, naive, and consistent estimators are relative to the exact unbiased forecast.

![Figure 3: MSFE deficiency.](image_url)

Figure 3: MSFE deficiency. $T = 25, \sigma = 0.05267, \beta^j = (0.05, 0.2, 0.4, 0.5)$. Based on 100,000 replications.

The figure shows that as we forecast further into the future the alternative forecasts become progressively worse. The extremely poor performance of the second consistent forecast is due to the fact that for the limiting case with $h = 0$, the predictor does not equal $Y_T$, whereas the other forecasts do, but instead is multiplied by the factor $e^{\beta^j T/2}$. The problem therefore becomes worse as $T$ increases. For example, in the same model with $T = 100$ and $h = 2$, it is 462% worse.

In Appendix C, we report the corresponding figure with $T = 50$ and 100, and a similar picture emerges. The relative MSFE deficiency for the growth based, naive, and first consistent forecasts
appears nearly linear as $h$ varies from 1 to 20, and ranges from less than 1% for $h = 1$ to over 16.2%, 8.4%, and 18.5% for $h = 20$.

5 Sectoral Production

In this section we make a comparison of the various predictors of growth and levels for eight industrial sectors. This serves two purposes. First, unbiasedness was motivated by the choice of MSFE as optimality criterion. Although the conditional mean minimizes the MSFE when the parameters are known, this is not necessarily true if the conditional mean is estimated, either unbiasedly or by substituting estimated parameters. Second, although there might be important theoretical differences between the various predictors, it could be that the differences in practice are not important. This seems to be the case for growth prediction, but for level forecasts we do find relevant practical differences.

We have applied the different forecasts using the same model and set of data as Garderen, Lee, and Pesaran (2000). The sectoral models are Cobb-Douglas production functions with stochastic technology of the type given in Equation (1), but moreover, include general- and sector specific productivity dummies for oil price shocks, major strikes, etc. For a full explanation see the original article where also various specification tests are reported. Tests for normality and functional form do not reject the model. The only difference with the original application is that we report estimates of the model without imposing constant returns to scale restrictions. We simulated the model using the estimated parameters and keeping the exogenous regressors fixed. For observations after 1995 the regressors where dynamically generated using a VAR(1) estimated with data from 1955-1995. The dependent variables $Y$ were then simulated according to the model. Tables 1 and 2 report the unweighted average over all sectors to indicate the general tendencies. The full results for all sectors and two sample periods are given in Appendix B. The unweighted parameter estimates average over the eight sectors are for the period : 1956-1980: $\bar{\delta}=0.014, \bar{\beta}_{\ln L}=0.241, \bar{\beta}_{\ln K}=0.430, \bar{\sigma}=0.027$, and for the period :1956-2005: $\bar{\delta}=0.024, \bar{\beta}_{\ln L}=0.373, \bar{\beta}_{\ln K}=0.258, \bar{\sigma}=0.036$.

Results on Growth.
Table 2 reports the average of the actual values in the simulations and for the various forecasts the average of the predicted values, their bias (including the exact unbiased where we know the bias is 0 from theory), and their MSE deficiency, defined as the percentage worse their MSE is relative to the best. The individual sectoral results are reported in the appendix.

There is very little to choose between the predictors in terms of bias or in terms of MSE. The naive predictor has a slight bias but is marginally better in terms of MSE. These results are not unexpected because the approximate relation between growth and logs. It can be seen that the average value of the drift term, and the average value of the standard deviation over the eight sectors are both very small. This means that the effect of the non-linear transformation on the expectation is also small.

Table 2: Sectoral Growth Predictions

<table>
<thead>
<tr>
<th>Growth</th>
<th>Actual</th>
<th>Exact</th>
<th>Approx.</th>
<th>Naive</th>
<th>Consistent</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Unbiased</td>
<td>Unbiased</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1956-1980</td>
<td>h = 5</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>11.38</td>
<td>11.38</td>
<td>11.38</td>
<td>11.38</td>
<td>11.61</td>
</tr>
<tr>
<td>Bias</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.22</td>
</tr>
<tr>
<td>MSFE deficiency</td>
<td>0.1%</td>
<td>0.1%</td>
<td>0.2%</td>
<td>0.6%</td>
<td></td>
</tr>
<tr>
<td>1956-2005</td>
<td>h = 10</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>31.86</td>
<td>31.89</td>
<td>31.89</td>
<td>31.22</td>
<td>32.13</td>
</tr>
<tr>
<td>Bias</td>
<td>0.02</td>
<td>0.03</td>
<td>-0.64</td>
<td>0.27</td>
<td></td>
</tr>
<tr>
<td>MSFE deficiency</td>
<td>0.3%</td>
<td>0.3%</td>
<td>*</td>
<td>0.8%</td>
<td></td>
</tr>
</tbody>
</table>

* indicates best in all sectors. Based on 100,000 replications.

Results on Levels

Table 3 gives the results for the level forecasts of sectoral production based on the same model.
The conditional unbiased forecast and unconditional unbiased forecast are identical because a time trend is included in the model, and results are given in column 3. For the growth based estimator $Y_T \hat{G}_{unb}$ the exact unbiased growth predictor is used. This estimator ignores the correlation between $Y_T$ and the estimator. The last row gives the percentage difference in MSFE from the minimum MSFE.

Table 3: Sectoral Level Forecasts

<table>
<thead>
<tr>
<th>Levels</th>
<th>Actual Level</th>
<th>Exact Unbiased</th>
<th>Approx. Unbiased</th>
<th>$Y_T \hat{G}$</th>
<th>Naive</th>
<th>Cons$_1$</th>
<th>Cons$_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1956-1980</td>
<td>$h = 5$</td>
<td>2.629</td>
<td>2.628</td>
<td>2.640</td>
<td>2.640</td>
<td>2.646</td>
<td>2.676</td>
</tr>
<tr>
<td>Mean</td>
<td>2.629</td>
<td>2.628</td>
<td>2.628</td>
<td>2.640</td>
<td>2.640</td>
<td>2.646</td>
<td>2.676</td>
</tr>
<tr>
<td>Bias</td>
<td>0.000</td>
<td>0.000</td>
<td>0.011</td>
<td>0.012</td>
<td>0.017</td>
<td>0.048</td>
<td></td>
</tr>
<tr>
<td>MSFE deficiency</td>
<td>*</td>
<td>0.0%</td>
<td>1.0%</td>
<td>1.0%</td>
<td>1.6%</td>
<td>6.9%</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>7.583</td>
<td>7.585</td>
<td>7.585</td>
<td>7.649</td>
<td>7.688</td>
<td>7.701</td>
<td>7.968</td>
</tr>
<tr>
<td>Bias</td>
<td>0.002</td>
<td>0.002</td>
<td>0.067</td>
<td>0.105</td>
<td>0.119</td>
<td>0.385</td>
<td></td>
</tr>
<tr>
<td>MSFE deficiency</td>
<td>*</td>
<td>0.0%</td>
<td>2.3%</td>
<td>4.2%</td>
<td>4.9%</td>
<td>28.8%</td>
<td></td>
</tr>
</tbody>
</table>

* indicates best in all sectors. Based on 100,000 replications

Table 4 shows the relative deficiencies in growth predictors and level forecasts for the period 1956-2005 for each sector. The naive growth predictor is best in every sector, but the differences with the other predictors are small and less than 0.7% for the exact unbiased predictor. When forecasting levels the naive estimator is no longer best and appreciably worse than the exact unbiased forecast and even worse than the growth based predictor. The exact unbiased forecast is best in all sectors. The worst performance for the alternative forecasts is in the mining sector where the growth based
forecast is 6.4% worse, the naive 12%, the first consistent 14%, and the second consistent 86% worse than the exact unbiased forecast.

The reason that the naive growth predictor performs well is that the nonlinear effects of future $\varepsilon$’s and estimation uncertainty in $\Delta_h x_{T+h} \beta$ partly cancel each other out. Following the comments below Theorem 1, we have $\sigma^2$ times $\frac{1}{2} h = 5$ related to future $\varepsilon$’s, and for parameter uncertainty $\sigma^2$ times $\frac{1}{2} a_{T+h}$, which on average over the eight sectors is about $-1.5$. The naive estimator, does not use $\hat{\sigma}^2$ and its variance does therefore not contribute to the MSE.

When forecasting the level, we can use the three terms in $z_{T+h/h}$ associated with future $\varepsilon$’s ($\frac{1}{2} h = 5$ here), estimation uncertainty in $\Delta_h x'_{T+h} \beta$, (here $-\Delta_h x'_{T+h}(\Delta X' \Delta X)^{-1} \Delta_h x_{T+h}/2$ : about $-1.5$ on average over the sectors, and the correction for the correlation between $Y_T$ and $\Delta_h x'_{T+h} \beta$ which is

The table below shows the relative deficiency versus best (*) in %:

<table>
<thead>
<tr>
<th>Growth (MSE)</th>
<th>Level (MSFE)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Exact Unb.</td>
</tr>
<tr>
<td>1956-2005</td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td>0.2</td>
</tr>
<tr>
<td>Mining</td>
<td>0.7</td>
</tr>
<tr>
<td>Manufact</td>
<td>0.0</td>
</tr>
<tr>
<td>Energy</td>
<td>0.6</td>
</tr>
<tr>
<td>Construc</td>
<td>0.4</td>
</tr>
<tr>
<td>Transprt</td>
<td>0.4</td>
</tr>
<tr>
<td>Communique</td>
<td>0.1</td>
</tr>
<tr>
<td>Oth Serv</td>
<td>0.1</td>
</tr>
<tr>
<td>Average</td>
<td>0.3</td>
</tr>
</tbody>
</table>

* indicates best. $h = 10$. Approximate unbiased growth predictor and level forecast not reported since practically indistinguishable from exact unbiased.
\[-x_T' (\Delta X' \Delta X)^{-1} \Delta_h x_{T+h} = -h = -10.6\] This correlation term is therefore twice as large as the correction for future \(\varepsilon\)'s and much larger than the estimation uncertainty term. The correlation between the level and the estimator is therefore quantitatively the most important factor.

The correlation term is \(-h\) for all \(T\) and remains important even asymptotically. Only the estimation uncertainty term goes to zero as \(T\) increases.

**Results on Forecast Intervals**

Table 5 reports the coverage probabilities of the forecast intervals for the eight industrial sectors using two time periods with 25 and 50 observations. We see that the coverage probabilities are again very close to their nominal values.

<table>
<thead>
<tr>
<th></th>
<th>1956-1980</th>
<th>1956-2005</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>90%  95%  99%</td>
<td>90%  95%  99%</td>
</tr>
<tr>
<td>Agriculture</td>
<td>88   93   98</td>
<td>89   94   98</td>
</tr>
<tr>
<td>Mining</td>
<td>88   93   98</td>
<td>88   93   97</td>
</tr>
<tr>
<td>Manufact</td>
<td>89   94   98</td>
<td>89   94   99</td>
</tr>
<tr>
<td>Energy</td>
<td>88   93   98</td>
<td>89   94   98</td>
</tr>
<tr>
<td>Construc</td>
<td>88   93   98</td>
<td>89   94   98</td>
</tr>
<tr>
<td>Transprt</td>
<td>88   93   98</td>
<td>89   94   99</td>
</tr>
<tr>
<td>Communuc</td>
<td>89   94   98</td>
<td>89   94   99</td>
</tr>
<tr>
<td>Oth Serv</td>
<td>88   94   98</td>
<td>89   94   98</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>88   93   98</td>
<td>89   94   98</td>
</tr>
</tbody>
</table>

6 The first column in \(\Delta X\) is \(x\) since \(x\) includes a deterministic trend. \(\Delta X' \Delta X = (\Delta X' \Delta X)^{-1} = (1, 0, ...\) and the first element of \(\Delta_h x_{T+h}\) is \(h\). Hence, \(-x_T' (\Delta X' \Delta X)^{-1} \Delta_h x_{T+h} = -x_T' (\Delta X' \Delta X)^{-1} \Delta_h x_{T+h} = -h\)
6 Conclusion

This paper has highlighted some of the issues involved when forecasting from log-linear unit root models with exogenous variables. Nonlinearity of the transformations of disturbances and estimators cause bias, which is well known. More important, however, is the high correlation between the last observation and parameter estimates. This correlation is often ignored but is in fact larger than the effects of future disturbances and parameter uncertainty together. This was shown using the expression for $z_{T+h|T}$. The effect of parameter uncertainty disappears with increasing sample size, but the correlation effect persists even asymptotically. This is a feature that is not limited to the stylized model employed in this paper but holds more generally. It also leads to deeper questions concerning conditioning on past information. We have shown that no conditionally unbiased estimator exists based on the regression estimates, which are statistically complete in this model, even when conditioning on only those terms that enter the conditional mean.

There are of course a various issues the paper has not dealt with, including structural breaks, serial correlation and heteroskedasticity in the transformed model, which is either trivial to deal with if the exact form is known, or analytically very complicated when it involves unknown parameters, or impossible to deal with exactly if its form is unspecified. Nor dynamic forecasts of exogenous variables, as e.g. Schmidt (1974), where the additional uncertainty would increase the bias correction term and would require the exact distribution of the vector autoregressive moving average estimators. We have concentrated on specific models that were helpful in highlighting the issues raised and allowed explicit finite sample solutions.

The paper is constructive in deriving the exact minimum variance unbiased growth predictor. More importantly, we derived two exact unbiased level forecasts. One is based on the unconditional expectation of the process at time $T+h$, and the other derived from the conditional expectation and is much better if no constant is included in the log-linear regression. A constant should be included in the regression however, in which case they are equal. We showed that the unbiased level forecast was better than five alternative forecasts and provided a very accurate and convenient approximate unbiased forecast that only involved exponential functions. We derived its MSFE and an estimator.
thereof. The MSFE estimator proved useful in standardizing the estimates and for constructing reliable confidence intervals.

We investigated the effects of increasing sample size and forecast horizon and showed that the MSFE increases with the number of observations even if the forecast horizon is fixed. For increasing forecast horizon, the exact unbiased forecast gets better relative to the alternative forecasts.
A Appendix: Theory

The following notation will be used. Given initial values \( y_0 = 0 \) and \( x_0 = 0 \), the model can be written as:

\[
y_t = x_t' \beta + u_t, \quad t = 1, 2, ..., T
\]

\[
u_t = u_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma^2)
\]

(34)

\( \mathbf{i}^T(T) = (1, ..., 1) \) is a \( T \times 1 \) vector of ones, \( L \) is the first differencing matrix,

\[
L = \begin{pmatrix} 1 & 0 \\ -1 & \ddots \\ \vdots & \ddots & \ddots \\ 0 & -1 & 1 \end{pmatrix}, \quad \text{with} \quad (L' L)^{-1} = \begin{pmatrix} 1 & 1 & \cdots & 1 \\ 1 & 2 & \cdots & 2 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 2 & \cdots & T \end{pmatrix}.
\]

\( y(t) = (y_1, y_2, ..., y_t)' \) is the \( t \times 1 \) column vector of observations from 1 up to \( t \), and \( X_{(t)} \) the associated \( t \times k \) matrix of regressors. The full sample quantities are written as \( y \) and \( X \). We have \( L y = L X \beta + Lu \), and hence:

\[
y \sim \mathcal{N}(X \beta, \sigma^2 (L' L)^{-1}).
\]

Because of assumptions 1 and 2 we may write:

\[
y_t = \sum_{s=1}^{t} \Delta x_s' \beta + \sum_{s=1}^{t} \varepsilon_s = x_t' \beta + S_t, \quad \text{with} \quad (35)
\]

\[
S_t = \sum_{s=1}^{t} \varepsilon_s = i_t(t) \varepsilon(t).
\]

A.1 Proofs

Proof of Lemma 1.

\[
\hat{\beta} = (\Delta X' \Delta X)^{-1} \Delta X' \Delta y,
\]

\[
= \beta + (\Delta X' \Delta X)^{-1} \Delta X' \varepsilon \sim N \left( \beta, \sigma^2 (\Delta X' \Delta X)^{-1} \right),
\]

\[
y_T = \sum_{s=1}^{T} \Delta x_s' \beta + \sum_{s=1}^{T} \varepsilon_s = x_T' \beta + S_T + \varepsilon_T. \quad \text{with} \quad E[y_T] = x_T' \beta.
\]
Hence:

\[
\text{Cov} (y_T, \beta) = E \left[ S_T \left( (\Delta X' \Delta X)^{-1} \Delta X' \epsilon \right) \right] = E \left[ \epsilon_T \epsilon_T' \Delta X' (\Delta X' \Delta X)^{-1} \right],
\]

\[
= \sigma^2 \epsilon_T \epsilon_T' \Delta X' (\Delta X' \Delta X)^{-1} = \sigma^2 x_T' (\Delta X' \Delta X)^{-1}.
\]

\[\Box\]

**Proof of Propositions 1.** Using Lemma 7 below, we have:

\[
E[F_{T+h}] = E_{\sigma^2 \beta | \sigma^2} \left[ \exp \{ x_{T+h} \beta \} \right] F_1 (m; z_{T+h}, z_{T+h}) | \sigma^2 | Y_T, \]

\[
= E_{\sigma^2 \beta | \sigma^2} \left[ \exp \{ x_{T+h} \beta + \frac{\sigma^2}{2} x_{T+h} (\Delta X' \Delta X)^{-1} x_{T+h} \} \right] F_1 (m; z_{T+h}, z_{T+h}) | \sigma^2 | Y_T, \]

\[
= \exp \{ x_{T+h} \beta + \frac{\sigma^2}{2} x_{T+h} (\Delta X' \Delta X)^{-1} x_{T+h} \} \exp \left\{ \frac{\sigma^2}{2} (T + h - x_{T+h} (\Delta X' \Delta X)^{-1} x_{T+h}) \right\}, \]

\[
= \exp \left\{ x_{T+h} \beta + \frac{T + h}{2} \sigma^2 \right\}, \]

\[
E[F_{T+h}],
\]

Hence \(F_{T+h}\) is unconditionally unbiased. \[\Box\]

**Proof of Propositions 2.** The conditional expectation, given \(Y_T\), of the conditional forecast can be derived using the results on conditional distributions given in the next subsection of this appendix, which gives:

\[
E[F_{T+h} \mid Y_T] = E_{\sigma^2 \beta \mid \sigma^2, Y_T} \left[ \exp \{ \Delta_h \epsilon_T' x_{T+h} \} \exp \left\{ \frac{\sigma^2}{2} (y_T - x_T') \right\} \right] F_1 (m; z_{T+h}, z_{T+h}) \mid \sigma^2 \mid Y_T, \]

\[
= Y_T \exp \{ \Delta_h \epsilon_T' x_{T+h} \} \exp \left\{ \frac{\sigma^2}{2} (y_T - x_T') \right\} \exp \left\{ \frac{\sigma^2}{2} (\Delta X' \Delta X)^{-1} \Delta_h \epsilon_T' x_{T+h} \right\} F_1 (m; z_{T+h}, z_{T+h}) \mid \sigma^2 \mid Y_T, \]

\[
= Y_T \exp \{ \Delta_h \epsilon_T' x_{T+h} \} \exp \left\{ \frac{\sigma^2}{2} (y_T - x_T') \right\} \exp \left\{ \frac{\sigma^2}{2} (\Delta X' \Delta X)^{-1} \Delta_h \epsilon_T' x_{T+h} \right\} \exp \left\{ \frac{\sigma^2}{2} (h - 2x_T' (\Delta X' \Delta X)^{-1} \Delta_h \epsilon_T' x_{T+h} - \Delta_h \epsilon_T' x_{T+h} (\Delta X' \Delta X)^{-1} \Delta_h \epsilon_T' x_{T+h}) \right\}, \]

\[
= Y_T \exp \{ \Delta_h \epsilon_T' x_{T+h} \} \exp \left\{ \frac{\sigma^2}{2} (h - 2x_T' (\Delta X' \Delta X)^{-1} \Delta_h \epsilon_T' x_{T+h} - \Delta_h \epsilon_T' x_{T+h} (\Delta X' \Delta X)^{-1} \Delta_h \epsilon_T' x_{T+h}) \right\}.
\]
Note that this expectation is not equal \((a.s.)\) to the conditional expectation \(E[Y_{T+h}|Y_T]\).

Now, using the fact that \((y_T - x_T' \beta) \sim N(0, T \sigma^2)\), it follows that:

\[
E[\exp\{\Delta_h x'_{T+h} (\Delta X' \Delta X)^{-1} x_T (y_T - x_T' \beta)\}] = \\
= \exp\left(\frac{1}{2} T \sigma^2 \Delta_h x'_{T+h} (\Delta X' \Delta X)^{-1} x_T x_T' (\Delta X' \Delta X)^{-1} \Delta_h x_{T+h}\right),
\]

and \(E[Y_T] = E[\exp(y_T)] = \exp(x_T' \beta + \frac{T}{2} \sigma^2)\). Hence:

\[
E[\exp(y_T + \Delta_h x'_{T+h} \beta + \sigma^2 \frac{h}{2} + \Delta_h x'_{T+h} (\Delta X' \Delta X)^{-1} x_T (y_T - x_T' \beta))] = \\
= E[\exp\left\{\left(y_T - x_T' \beta\right) \left(1 + \Delta_h x'_{T+h} (\Delta X' \Delta X)^{-1} \frac{x_T}{T}\right) + x_T' \beta + \Delta_h x'_{T+h} \beta + \sigma^2 \frac{h}{2}\right\}],
\]

\[
= \exp\left\{\frac{T \sigma^2}{2} \left(1 + \Delta_h x'_{T+h} (\Delta X' \Delta X)^{-1} \frac{x_T}{T}\right) \left(1 + \Delta_h x'_{T+h} (\Delta X' \Delta X)^{-1} \frac{x_T}{T}\right) + x_T' \beta + \sigma^2 \frac{h}{2}\right\},
\]

\[
= \exp\left\{\frac{T \sigma^2}{2} \left(1 + 2 \Delta_h x'_{T+h} (\Delta X' \Delta X)^{-1} \frac{x_T}{T}\right) + \Delta_h x'_{T+h} (\Delta X' \Delta X)^{-1} \frac{x_T x_T'}{T} (\Delta X' \Delta X)^{-1} \Delta_h x_{T+h}\right\}
\]
\[
+ x_T' \beta + \sigma^2 \frac{h}{2}\right\},
\]

\[
= \exp\left\{x_T' \beta + \sigma^2 \frac{T+h}{2} + \frac{1}{T} \Delta_h x'_{T+h} (\Delta X' \Delta X)^{-1} x_T x_T' (\Delta X' \Delta X)^{-1} \Delta_h x_{T+h}\right\}
\]
\[
+ \frac{\sigma^2}{2} \left(2 \Delta_h x'_{T+h} (\Delta X' \Delta X)^{-1} x_T\right),
\]

and as a consequence:

\[
E[F_{T+h}|T] = E[ Y_T \exp\{ \Delta_h x'_{T+h} \beta + \sigma^2 \frac{h}{2} + \Delta_h x'_{T+h} (\Delta X' \Delta X)^{-1} x_T \frac{(y_T - x_T' \beta)}{T}\}]
\]
\[
= \exp\{x_T' \beta + \frac{T+h}{2} \sigma^2\},
\]

showing that \(F_{T+h|T}\) is unconditionally unbiased.

**Proof of Theorem 2.** Using Assumption 1 we have \(x_T = \iota'_T \Delta X\). Now let \(P_{\Delta X} = \Delta X (\Delta X' \Delta X)^{-1} \Delta X'\) be the projection matrix onto the column space of \(\Delta X\), then \(\iota'_T \Delta X (\Delta X' \Delta X)^{-1} \Delta X' \iota'_T = \iota'_T P_{\Delta X} \iota'_T = \iota'_T \iota'_T = T\), since \(\Delta X\) includes a column of ones (i.e. \(\iota\)) associated with the constant (the drift
\[ z_{T+h} = \frac{1}{2} \left( T + h - (x_{T+h} - x_T + \dot{\beta}_T) \Delta X \right) \left( \Delta X' \Delta X \right)^{-1} \left( x_{T+h} - x_T + \dot{\beta}_T \right) \]

\[ = \frac{1}{2} \left( T + h - (x_{T+h} - x_T) \Delta X' \Delta X^{-1} (x_{T+h} - x_T) - \dot{\beta}_T \Delta X' \Delta X^{-1} \Delta X \dot{\beta}_T \right) \]

\[ = z_{T+h|T}. \]

Remains to be shown that \( x'_{T+h} \dot{\beta} = \ln Y_T + \Delta h x'_{T+h} \dot{\beta}. \) By Assumption 1 \( x'_T = \dot{\beta}_T \Delta X \) and by definition of \( \Delta h \) we have \( x'_{T+h} = x'_T + \Delta h x'_{T+h} \) and hence:

\[ x'_{T+h} \dot{\beta} = x'_T \dot{\beta} + \Delta h x'_{T+h} \dot{\beta}, \]

\[ = \dot{\beta}_T \Delta X \left( \Delta X' \Delta X \right)^{-1} \Delta X' \Delta y + \Delta h x'_{T+h} \dot{\beta}, \]

\[ = y_T + \Delta h x'_{T+h} \dot{\beta}, \]

since \( \dot{\beta}_T \Delta X \left( \Delta X' \Delta X \right)^{-1} \Delta X' = \dot{\beta}_T. \) Hence \( F_{T+h} = F_{T+h|h}. \]

**Proof of Theorem 3.** The conditional expectation \( E[Y_{T+h}|Y_T] = Y_T \exp\{ \Delta h x'_{T+h} \dot{\beta} + \frac{h}{T} \sigma^2 \}. \)

The statistic \( \left( \dot{\beta}, \sigma^2 \right) \) given \( Y_T \) is a complete sufficient statistic for the distribution of the distribution of \( Y_{(T-1)}|Y_T, X, \) which implies that any function \( f \left( \dot{\beta}, \sigma^2 \right) \) with expectation \( g \left( \beta, \sigma^2 \right) \) is essentially unique: if \( \tilde{f} \left( \dot{\beta}, \sigma^2 \right) \) is a function with the same expectation function \( g \left( \beta, \sigma^2 \right) \), then \( E_{\beta, \sigma^2} \left[ f \left( \dot{\beta}, \sigma^2 \right) - \tilde{f} \left( \dot{\beta}, \sigma^2 \right) \right] = 0 \) for all \( \beta, \sigma \in \Re^k \times \Re^+, \) but the completeness of \( \left( \dot{\beta}, \sigma^2 \right) \) means by definition that \( E_{\beta, \sigma^2} \left[ h \left( \dot{\beta}, \sigma^2 \right) \right] = 0 \) for all parameter values, implies that \( h \left( \dot{\beta}, \sigma^2 \right) = 0 \) a.e. and hence \( f = \tilde{f} \) a.e.. Since \( \dot{\beta} | Y_T \sim N(\mu, \Sigma) \) and for a fixed vector \( a \) we have \( E[\exp\{a' \dot{\beta}\}|Y_T] = \exp\{a' \beta + \frac{1}{2} a' \Sigma a\}, \) we know that the function must be proportional to \( \exp\{a' \dot{\beta}\} \) since the expectation function would otherwise not be log-linear in \( \beta. \) Hence, to find a conditional unbiased estimator we first need to solve:

\[ E_{\dot{\beta}|Y_T} \left[ \exp\{a' \dot{\beta}\} | Y_T \right] \propto \exp \left\{ \Delta h x'_{T+h} \dot{\beta} \right\}. \]

Terms involving \( Y_T \) and \( \sigma^2 \) are immaterial at this stage, since they, by the independence of \( \sigma^2 \) and \( \dot{\beta}, \) can be taken account of via the \( aF_1 \)-function. Using the conditional distribution of \( \dot{\beta} \) we have:

\[ E_{\dot{\beta}|Y_T} \left[ \exp\{a' \dot{\beta}\} | Y_T \right] = \exp \left\{ a' \beta + a' \left( \Delta X' \Delta X \right)^{-1} x_T \frac{-x'_T}{T} \beta \right\} \times \text{terms not involving } \beta. \]
Hence, we need to solve:

\[ a'(I_k - (\Delta X' \Delta X)^{-1} x_T x_T' \frac{1}{T})\beta = \Delta_h x'_{T+h}, \text{ for all } \beta \in \mathbb{R}^k. \]

Let \( B = (I_k - (\Delta X' \Delta X)^{-1} x_T x_T' \frac{1}{T}) \) and let \( B^+ \) denote its Moore-Penrose generalized inverse (explicit expressions for \( B \) and \( B^+ \) are given in Lemma 2 below), then:

\[ a'(I_k - (\Delta X' \Delta X)^{-1} x_T x_T' \frac{1}{T}) = \Delta_h x'_{T+h}, \]

has general solution (as derived by Penrose, see e.g. Magnus and Neudecker 1988, p37)

\[ a = B^+ \Delta_h x_{T+h} + (I_k - B^+ B')q, \]

with \( q \) an arbitrary \((k \times 1)\) vector, if and only if:

\[ B'B^+ \Delta_h x_{T+h} = \Delta_h x_{T+h}. \]  \( (36) \)

Lemma 2 below shows that \( B'B^+ = \begin{pmatrix} 0 & 0 \\ 0 & I_{k-1} \end{pmatrix} \). The first element of \( \Delta_h x_{T+h} \) equals \( h \), and not 0, and the consistency condition \( (36) \) cannot be satisfied. No \( a \) exists such that \( a'B = \Delta_h x'_{T+h} \). This implies that no conditional unbiased forecast based on the complete sufficient statistics exists. ■

Comment. Increasing \( a \) increases \( a' \beta \) but the expectation associated with the drift term is reduced by an equal amount from the conditional expectation. This is most clearly seen when \( x_t = t \), i.e. only a drift term is included in the regression. We then have \( a' \beta + a' (\Delta X' \Delta X)^{-1} x_T (-x_T')/T \beta = a\beta - a\beta = 0 \) for any \( a \).

**Lemma 2** The matrix \( B \) equals:

\[ B = \begin{pmatrix} 0 & b' \\ 0 & I_{k-1} \end{pmatrix}, \]

with \( b = -\frac{1}{T} x_{T:2:k} \) where \( x_T = (T, x'_{T:2:k})' \) and has Moore-Penrose inverse:

\[ B^+ = \frac{1}{1 + bb'} \begin{pmatrix} 0 & 0 \\ b & (1 + b'b)I_{k-1} - bb' \end{pmatrix}. \]

**Proof.** Since \( (\Delta X' \Delta X)^{-1} \Delta X' \Delta X = I_k \) and \( \iota \) is the first column of \( \Delta X \) we have \( (\Delta X' \Delta X)^{-1} \Delta X' = (1, 0, ..., 0)' \). Hence \( B = I_k - (1, 0, ..., 0)' x_T' \frac{1}{T} = I_k - (1, 0, ..., 0)' (1, \frac{1}{T} x'_{T:2:k}). \)
The second part of the Lemma is easily proved by verifying the four conditions of the Moore-Penrose inverse: (a) \( B^+B = \begin{pmatrix} 0 & 0 \\ 0 & I_{k-1} \end{pmatrix} \) and hence symmetric, (b) \( BB^+ \) is symmetric, (c) \( BB^+B = B \), and (d) \( B^+BB^+ = B^+ \). ■

**Proof of Theorem 4.** First write:

\[
E[(Y_{T+h} - F_{T+h})^2] = E(Y_{T+h}^2 - 2Y_{T+h}F_{T+h} + F_{T+h}^2).
\]

The first term (1) in Equation 37 equals:

\[
E[Y_{T+h}^2] = E[\exp\{2x_{T+h}^T\hat{\beta} + 2 \sum_{t=1}^{T+h} \varepsilon_t \}] = \exp\{2x_{T+h}^T\hat{\beta} + \frac{4}{2}(T+h)\sigma^2\},
\]

\[
= \exp\{2x_{T+h}^T\hat{\beta} + 2(T+h)\sigma^2\}.
\]

The second term (2): Since \( \sigma^2 \) independent of the other terms present which involve \( \varepsilon_t \) and \( \hat{\beta} \), we have with the unconditional predictor \( F_{T+h} = \exp\{x_{T+h}^T\hat{\beta}\} \alpha F_1(m; m\delta^2 z_{T+h}) \) with \( z_{T+h} = \frac{1}{2}(T + h - x_{T+h}^T(\Delta X'\Delta X)^{-1} x_{T+h}) \):

\[
E[Y_{T+h}F_{T+h}] = E[\exp\{2x_{T+h}^T\hat{\beta} + \sum_{t=1}^{T} \varepsilon_t + \sum_{i=1}^{h} \varepsilon_{T+i} + x_{T+h}^T\hat{\beta}\} \alpha F_1(m; m\delta^2 z_{T+h})],
\]

\[
= E[\exp\{2x_{T+h}^T\hat{\beta} + \frac{h}{2}\sigma^2 + (i' \varepsilon(T) + x_{T+h}^T(\Delta X'\Delta X)^{-1} \Delta X' \varepsilon(T)) + \sigma^2 z_{T+h}\}],
\]

\[
= \exp\{2x_{T+h}^T\hat{\beta} + \frac{h}{2}\sigma^2 +
\]

\[
+ \frac{1}{2}(i' + x_{T+h}^T(\Delta X'\Delta X)^{-1} \Delta X') \sigma^2 I_T(i + \Delta X(\Delta X'\Delta X)^{-1} x_{T+h}) + \sigma^2 z_{T+h}\}
\]

\[
= \exp\{2x_{T+h}^T\hat{\beta} + \frac{h}{2}\sigma^2 + \frac{1}{2}\sigma^2(T + x_{T+h}^T(\Delta X'\Delta X)^{-1} x_{T+h}) + \sigma^2 z_{T+h}\}; \text{ since } \Delta X' \varepsilon_T \text{ equals } x_T,
\]

\[
= \exp\{2x_{T+h}^T\hat{\beta} + \frac{1}{2}\sigma^2(T + h + 2x_{T+h}^T(\Delta X'\Delta X)^{-1} x_{T+h}) + \sigma^2 z_{T+h}\}
\]

\[
+ x_{T+h}^T(\Delta X'\Delta X)^{-1} x_{T+h} + T + h - x_{T+h}^T(\Delta X'\Delta X)^{-1} x_{T+h}),
\]

\[
= \exp\{2x_{T+h}^T\hat{\beta} + \frac{1}{2}\sigma^2(2T + 2h + 2x_{T+h}^T(\Delta X'\Delta X)^{-1} x_{T})\}.
\]

So,

\[-2E[Y_{T+h}F_{T+h}] = -2\exp\{2x_{T+h}^T\hat{\beta} + 2(T+h)\sigma^2\} * \exp\{-\sigma^2(T + h - x_{T+h}^T(\Delta X'\Delta X)^{-1} x_{T})\}.
\]

Now if a constant is included in the regression so that \( t \) is the first column of \( \Delta X \) then we have \( (\Delta X'\Delta X)^{-1} \Delta X' \Delta X_i = e_i \) and \( x_{T+h}^T(\Delta X'\Delta X)^{-1} x_{T} = x_{T+h}^T(\Delta X'\Delta X)^{-1} \Delta X' \epsilon = (T + \)
\[ h, ... (1, 0, ..., 0)' = T + h. \] Hence:
\[
-2E[Y_{T+h}F_{T+h}] = -2 \exp\{2x'_{T+h}\beta + 2\sigma^2(T + h)\}.
\]

The third term (3) in Equation 37 equals:
\[
E[F^2_{T+h}] = E[\exp\{2x'_{T+h}\beta\} F_1(m; m\tilde{\sigma}^2 z_{T+h})^2],
\]
\[
= \exp\{2x'_{T+h}\beta + \frac{4}{2}\sigma^2 x'_{T+h} (\Delta X'\Delta X)^{-1} x_{T+h} + 2z_{T+h}\sigma^2\} F_1(m; \sigma^4 z^2_{T+h}),
\]
\[
= \exp\{2x'_{T+h}\beta + 2\sigma^2(x'_{T+h} (\Delta X'\Delta X)^{-1} x_{T+h} + \frac{1}{2}(T + h - x'_{T+h} (\Delta X'\Delta X)^{-1} x_{T+h})) \} 
\times F_1(m; \sigma^4 z^2_{T+h}),
\]
\[
= \exp\{2x'_{T+h}\beta + \sigma^2(T + h + x'_{T+h} (\Delta X'\Delta X)^{-1} x_{T+h})\} F_1(m; \sigma^4 z^2_{T+h}),
\]
\[
= \exp\{2x'_{T+h}\beta + 2(T + h)\sigma^2\} \exp\{-\sigma^2(T + h - x'_{T+h} (\Delta X'\Delta X)^{-1} x_{T+h})\} F_1(m; \sigma^4 z^2_{T+h}).
\]

Combining the three terms gives
\[
E[(Y_{T+h} - F_{T+h})^2] = \exp\{2x'_{T+h}\beta + 2(T + h)\sigma^2\} \ast 
\left(1 - 2\exp\{-\sigma^2(T + h - x'_{T+h} (\Delta X'\Delta X)^{-1} x_{T+h})\} + 
\exp\{-\sigma^2(T + h - x'_{T+h} (\Delta X'\Delta X)^{-1} x_{T+h})\} F_1(m; \sigma^4 z^2_{T+h}) \right)
\]

Using \(x'_{T+h} (\Delta X'\Delta X)^{-1} x = T + h\) and \(x'_{T+h} (\Delta X'\Delta X)^{-1} x_{T+h} = T + 2h + \Delta_h x'_{T+h} (\Delta X'\Delta X)^{-1} \Delta_h x_{T+h}\),

when a constant is included, we obtain:
\[
E[(Y_{T+h} - F_{T+h})^2] = \exp\{2x'_{T+h}\beta + 2(T + h)\sigma^2\} \ast 
\left\{\exp\{\sigma^2(h + \Delta_h x'_{T+h} (\Delta X'\Delta X)^{-1} \Delta_h x_{T+h})\} F_1(m; \sigma^4 z^2_{T+h}) - 1 \right\}.
\]

The unbiased estimator of MSFE. First note that using the above we can write:
\[
E[(Y_{T+h} - F_{T+h})^2] = E[F^2_{T+h}] - \exp\{2x'_{T+h}\beta + 2(T + h)\sigma^2\}.
\]

The first term can be estimated unbiasedly by \(F^2_{T+h}\), and the second term using Van Garderen (2001)
in the familiar form \(\exp\{2x'_{T+h}\beta\} F_1(m; m\tilde{\sigma}^2 \tilde{z})\) with \(\tilde{z} = -2(h + \Delta_h x'_{T+h} (\Delta X'\Delta X)^{-1} \Delta_h x_{T+h})\) since:

34
\[
E\exp\{2x'_{T+h}\beta\}0F_1(m; -2m\sigma^2(h + a_{T+h})) = \\
= \exp\{2x'_{T+h}\beta + \sigma^2 \frac{4}{2} x'_{T+h} (\Delta' \Delta)^{-1} x_{T+h} - \sigma^2 2 \left( h + \Delta_h x'_{T+h} (\Delta' \Delta)^{-1} \Delta_h x_{T+h} \right) \} \\
= \exp\{2x'_{T+h}\beta + \sigma^2 2(T + 2h + \Delta_h x'_{T+h} (\Delta' \Delta)^{-1} \Delta_h x_{T+h} - \left( h + \Delta_h x'_{T+h} (\Delta' \Delta)^{-1} \Delta_h x_{T+h} \right) \} \\
= \exp\{2x'_{T+h}\beta + 2(T + h)\sigma^2 \}
\]

which is equal to the second term in the expression for the MSFE. ■

A.2 Conditional Distributions given \( Y_T \)

**Lemma 3** (a) Conditional distribution of \( y_{T+h} \) given \( y_T \):

\[
y_{T+h}|y_T \sim N \left( y_T + \Delta_h x'_{T+h}\beta; h\sigma^2 \right),
\]

(b) Conditional expectation of \( Y_{T+h} \) given \( Y_T \):

\[
E[Y_{T+h}|Y_T] = Y_T \exp \{ \Delta_h x'_{T+h}\beta + \frac{h}{2} \sigma^2 \},
\]

c) Unconditional expectation of \( Y_{T+h} \):

\[
E[Y_{T+h}] = \exp \{ x'_{T+h}\beta + \frac{T + h}{2} \sigma^2 \}.
\]

**Proof.** Using Equation (35) part (a) follows from:

\[
y_{T+h} = \sum_{s=1}^{T+h} \Delta s\beta + \sum_{s=1}^{T+h} \varepsilon_s \\
= y_T + \sum_{s=1}^{h} \Delta s x'_{T+s}\beta + \sum_{s=1}^{h} \varepsilon_{T+s}, \\
= y_T + \Delta_h x'_{T+h}\beta + \sum_{s=1}^{h} \varepsilon_{T+s},
\]

and calculating the mean and variance. Parts (b) and (c) follow from the moment generating function of a normal distribution: \( E[e^{r'z}] = \exp \{ r'\mu + \frac{1}{2} r'\Sigma r \} \) if \( z \sim N(\mu, \Sigma) \). ■

**Lemma 4** Conditional distribution of \( y_{(T-1)} \) given \( y_T \):

\[
y_{(T-1)} | y_T \sim N \left( X_{(T-1)}\beta + \begin{pmatrix} 1 \\ \vdots \\ \frac{1}{T} (y_T - x'_T\beta) \\ T - 1 \end{pmatrix}; \sigma^2 \Sigma \right),
\]

with
\[
\Sigma = \sigma^2 \begin{pmatrix} 1 & 1 & \cdots & 1 \\ 1 & 2 & \cdots & 2 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 2 & \cdots & T-1 \end{pmatrix} - \sigma^2 \frac{1}{T} \begin{pmatrix} 1 \\ 2 \\ \vdots \\ T-1 \end{pmatrix} \begin{pmatrix} 1 \end{pmatrix},
\]

**Proof.** The proof uses the following standard result on conditional multivariate normal distributions (e.g. Muirhead (1982) Theorem 1.2.11): If:

\[
\begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} \sim N \left( \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \right),
\]

where \(Y_1\) is \((n_1 \times 1)\), \(Y_2\) is \((n_2 \times 1)\), \(\mu\) and \(\Sigma\) partitioned accordingly, then:

\[
Y_1 | Y_2 \sim N \left( \mu_1 + \Sigma_{12} \Sigma_{22}^{-1} (Y_2 - \mu_2), \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} \right).
\]

Since \(y_{(T)} \sim N(X'_{(T)} \beta; \sigma^2 \Omega_{(T)})\) with:

\[
\Omega_{(T)} = \begin{pmatrix} 1 & 1 & \cdots & 1 \\ 1 & 2 & \cdots & 2 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 2 & \cdots & T-1 \end{pmatrix},
\]

we have \(\Sigma_{21} = \Sigma_{12} = \sigma^2 (1, 2, \cdots, T-1), \Sigma_{22} = \sigma^2 T\), and hence:

\[
\Sigma_{12} \Sigma_{22}^{-1} (Y_2 - \mu_2) = \begin{pmatrix} 1 \\ \vdots \\ T-1 \end{pmatrix} \frac{y_T - x_T' \beta}{T},
\]

\[
\Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21} = \frac{1}{T} \sigma^2 \begin{pmatrix} 1 \\ \vdots \\ T-1 \end{pmatrix}.
\]

Finally, since \(\Sigma_{11} = \sigma^2 \Omega_{(T-1)}\), the result follows. \(\blacksquare\)

**Lemma 5** The conditional distribution of \(\Delta y\) given \(y_T\) is a degenerate normal distribution:

\[
\Delta y | y_T \sim N_{\text{deg}} \left( \Delta X' \beta + v_{(T)} \frac{1}{T} (y_T - x_T' \beta), \sigma^2 M_{(T)} \right),
\]

36
with \( M_{i(T)} = (I_T - \frac{1}{T} t(T) i'(T) ) \)

**Proof** Using Lemma 4 the conditional distribution of \( y_{(T)} \) given \( y_T \) is a degenerate normal distribution

\[
y_{(T)} \mid y_T \sim N_{\text{deg}} \left( \begin{pmatrix} X_{(T-1)} \beta + \begin{pmatrix} 1 \\ \vdots \\ T-1 \end{pmatrix} (y_T - x_T' \beta) \\ y_T \end{pmatrix}, \begin{pmatrix} \Sigma_{(T-1)} & 0 \\ 0 & 0 \end{pmatrix} \right) .
\]

Since \( \Delta y_{(T)} = L(T) y_{(T)} \), we have that \( \Delta y_{(T)} \) is normally distributed with mean

\[
L(T) E[y \mid y_T] = \Delta X \beta + t(T) \frac{1}{T} (y_T - x_T' \beta),
\]

\[
L(T) \begin{pmatrix} \Sigma_{(T-1)} & 0 \\ 0 & 0 \end{pmatrix} L'(T) = (I_T - \frac{1}{T} t(T) i'(T)) = M_{i(T)}.
\]

Note that the distribution of \( \Delta y_{(T)} \mid y_T \) is degenerate since by assumption \( i'(T) \Delta y_{(T)} = y_T \).

**Theorem 5** Let \( \hat{\beta} = (\Delta X' \Delta X)^{-1} \Delta X' \Delta y \) and \( \hat{\sigma}^2 = \frac{\Delta y' M_{\Delta X} \Delta y}{n-k} \) then:

(A) \( \hat{\beta} \mid Y_T \sim N(\mu, \Sigma) \) with:

\[
\mu = E[\hat{\beta} \mid Y_T] = \beta + \frac{y_T - x_T' \beta}{T} (\Delta X' \Delta X)^{-1} x_T,
\]

\[
\Sigma = \text{Var}(\hat{\beta} \mid Y_T) = \sigma^2 \left( (\Delta X' \Delta X)^{-1} - \frac{1}{T} (\Delta X' \Delta X)^{-1} x_T x_T' (\Delta X' \Delta X)^{-1} \right),
\]

(B) \( (T-k) \frac{\hat{\sigma}^2}{\sigma^2} \mid Y_T \sim \chi^2_{T-k} \),

(C) \( \hat{\sigma}^2 \) and \( \hat{\beta} \) are conditionally and unconditionally independent.

**Proof**. (A) \( \hat{\beta} = (\Delta X' \Delta X)^{-1} \Delta X' \Delta y \). The distribution of \( \Delta y \) given \( y_T \) (or \( Y_T \)) is given in the previous lemma. The result follows by noting that \( \Delta X' i(T) = x_T \) and the mean and variance follow by basic matrix multiplication as follows:

\[
E[\hat{\beta} \mid Y_T] = (\Delta X' \Delta X)^{-1} \Delta X' E[\Delta y \mid Y_T],
\]

\[
= \beta + (\Delta X' \Delta X)^{-1} \Delta X' t(T) \frac{(y_T - x_T' \beta)}{T},
\]

\[
= \beta + (\Delta X' \Delta X)^{-1} x_T \frac{(y_T - x_T' \beta)}{T}.
\]
The expectation of a function of \( z(B) \) and \( z(C) \). We will use a conditional version of a theorem by Ogasawara and Takahashi (1951), and unconditionally normally distributed \( x \) since \( x = T \chi \). It follows since \( y = T \chi \), and hence with \( \chi \) fixed for given \( Y \).

Theorem: \( \beta \) is also independent of \( \Delta y/M \Delta x \Delta y/(T - k) \), conditionally and unconditionally. \( \blacksquare \)

Comment: \( M_{(T)} = (I_T - \frac{1}{T}T(T)'T) = (I_T - \bar{T}(T)'T)'^{-1}T'(T) \), is a projection matrix with \( T = 0 \). This implies that if the model only includes a time trend, and therefore \( \Delta x = T \), that the conditional variance of \( \beta | Y_T \) is 0, which is as it should be since in that case \( \beta = \frac{T}{T}y_T \), and fixed for given \( Y_T \).

Corollary 2 \( Y_T \exp \{ C \beta \} \) is conditionally independent of \( \hat{\sigma}^2 \), given \( Y_T \), for arbitrary, fixed matrix \( C \).

This is useful because it allows us to take expectations with respect to \( \beta \) first, before evaluating the expectation of a function of \( \hat{\sigma}^2 \).

Lemma 6 Goldberger (1962). Let:

\[
\begin{pmatrix}
  y_T \\
  y_{T+1}
\end{pmatrix} = \begin{pmatrix}
  X(T) \\
  x'_T
\end{pmatrix} \beta + \begin{pmatrix}
  \varepsilon(T) \\
  \varepsilon_{T+1}
\end{pmatrix}, \quad \begin{pmatrix}
  \varepsilon(T) \\
  \varepsilon_{T+1}
\end{pmatrix} \sim N \left( 0; \begin{pmatrix}
  \Omega_{11} & \omega_{12} \\
  \omega_{21} & \omega_{22}
\end{pmatrix} \right)
\]

38
then the Best Linear Unbiased Predictor of \( y_{T+1} \) is given by:

\[
\hat{y}_{T+1}^* = x'_{T+1} \hat{\beta}_{GLS} + \omega_2 \Omega^{-1} \Omega_1 1 e_{GLS,T}.
\]

Best in Goldberger (1962) means that the forecast minimizes \( E \left[ (\hat{y}_{T+1}^* - y_{T+1}) (\hat{y}_{T+1}^* - y_{T+1})' \right] \), subject to (i) linearity \( \hat{y}_{T+1}^* = C^* y_T \) and (ii) unbiasedness \( E[\hat{y}_{T+1}^* - y_{T+1}] = 0 \). Since in the unit root case \( \omega_2 \Omega^{-1} \Omega_1 = 1 \) we have for Model (1): \( \hat{y}_{T+1}^* = x'_{T+1} \hat{\beta} + 1.\hat{\sigma} + (y_T - x'_{T+1} \hat{\beta}) \) and hence we have the following:

**Corollary 3** In Model (1), the Best Linear Unbiased Predictor of \( y_{T+1} \) is given by:

\[
\hat{y}_{T+1}^* = y_T + \Delta x'_{T+1} \hat{\beta}.
\]

### A.3 Expectations involving exponentials and hypergeometric functions

**Definition 3** The hypergeometric function can be defined as the infinite sum:

\[
{\,}_0 F_1 (m, x) = \sum_{i=0}^{\infty} \frac{x^i}{i!(m)_i},
\]

where \( (m)_0 = 1 \) and \( (m)_i = m(m+1)...(m+i-1) \).

See e.g. Abadir (2001) who reviews the use of hypergeometric functions in economics or Van Garderen (2001) who further proves:

**Lemma 7** Let \( m \frac{\hat{\sigma}^2}{\sigma^2} \sim \chi^2_m \), then for any real constant \( z \) we have,

\[
E \left[ {\,}_0 F_1 \left( \frac{m}{2}; z \frac{m}{2} \hat{\sigma}^2 \right) \right] = \exp \{ z \sigma^2 \},
\]

\[
E \left[ \left\{ {\,}_0 F_1 \left( \frac{m}{2}; z \frac{m}{2} \hat{\sigma}^2 \right) \right\}^2 \right] = \exp \{ 2 z \sigma^2 \} \left\{ {\,}_0 F_1 \left( \frac{m}{2}; z^2 \sigma^4 \right) \right\}.
\]

**Proof** See Van Garderen (2001). ■
References


B Additional Graphs and Tables

Table 6: MSFE and Estimates

<table>
<thead>
<tr>
<th>$h$</th>
<th>$\text{Exact}$</th>
<th>$\text{Appr.}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\text{Theory}$</td>
<td>$\text{Simulation}$</td>
</tr>
<tr>
<td>1</td>
<td>5.5</td>
<td>5.5</td>
</tr>
<tr>
<td>2</td>
<td>11.2</td>
<td>11.2</td>
</tr>
<tr>
<td>3</td>
<td>12.1</td>
<td>12.2</td>
</tr>
<tr>
<td>4</td>
<td>11.9</td>
<td>12.0</td>
</tr>
<tr>
<td>5</td>
<td>49.3</td>
<td>49.9</td>
</tr>
<tr>
<td>6</td>
<td>45.2</td>
<td>45.8</td>
</tr>
<tr>
<td>7</td>
<td>72.5</td>
<td>73.6</td>
</tr>
<tr>
<td>8</td>
<td>69.4</td>
<td>70.2</td>
</tr>
<tr>
<td>9</td>
<td>97.9</td>
<td>99.5</td>
</tr>
<tr>
<td>10</td>
<td>555.7</td>
<td>563.6</td>
</tr>
</tbody>
</table>

$T = 25, \sigma = 0.05267, \beta = (0.05, 0.2, 0.4, 0.5). 100,000 \text{ replications}$
Figure 4: MSFE deficiency. $T = 25, \sigma = 0.05267, \beta' = (0.05, 0.2, 0.4, 0.5)$. 100,000 replications.

C Sectoral Results

1956-1980: $T = 25$, Forecasting horizon $h = 5$ nr simulations = 100,000.

<table>
<thead>
<tr>
<th>1956-1980</th>
<th>incept</th>
<th>dd72</th>
<th>d74</th>
<th>dd74</th>
<th>dd75</th>
<th>dd76</th>
<th>d80</th>
<th>dlli</th>
<th>dlki</th>
<th>$\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricult</td>
<td>0.029</td>
<td>-0.063</td>
<td>-0.135</td>
<td>-0.025</td>
<td>-0.147</td>
<td>0.035</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mining</td>
<td>0.002</td>
<td>-0.127</td>
<td>-0.116</td>
<td></td>
<td></td>
<td>0.329</td>
<td>0.262</td>
<td>0.030</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manufact</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.100</td>
<td>1.157</td>
<td>0.019</td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>0.036</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.319</td>
<td>0.715</td>
<td>0.040</td>
<td></td>
</tr>
<tr>
<td>Construc</td>
<td>0.006</td>
<td>-0.132</td>
<td></td>
<td>-0.061</td>
<td>0.518</td>
<td>0.387</td>
<td>0.027</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transprt</td>
<td>0.020</td>
<td></td>
<td></td>
<td>-0.066</td>
<td>0.009</td>
<td>0.429</td>
<td>0.028</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Communic</td>
<td>0.039</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.707</td>
<td>0.055</td>
<td>0.021</td>
<td></td>
</tr>
<tr>
<td>Oth Serv</td>
<td>-0.004</td>
<td></td>
<td></td>
<td>-0.053</td>
<td>0.610</td>
<td>0.582</td>
<td>0.017</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>0.014</td>
<td>-0.016</td>
<td>-0.016</td>
<td>-0.014</td>
<td>-0.008</td>
<td>-0.017</td>
<td>-0.023</td>
<td>0.241</td>
<td>0.430</td>
<td>0.027</td>
</tr>
</tbody>
</table>
### Growth: Average Actual and predicted

<table>
<thead>
<tr>
<th></th>
<th>1956-1980</th>
<th>Actual</th>
<th>Unb</th>
<th>ApprUnb</th>
<th>Naive</th>
<th>Consist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricult</td>
<td></td>
<td>15.949</td>
<td>16.000</td>
<td>16.000</td>
<td>15.835</td>
<td>16.188</td>
</tr>
<tr>
<td>Mining</td>
<td></td>
<td>-5.413</td>
<td>-5.397</td>
<td>-5.397</td>
<td>-5.533</td>
<td>-5.323</td>
</tr>
<tr>
<td>Manufact</td>
<td></td>
<td>2.550</td>
<td>2.539</td>
<td>2.539</td>
<td>2.472</td>
<td>2.567</td>
</tr>
<tr>
<td>Energy</td>
<td></td>
<td>30.448</td>
<td>30.403</td>
<td>30.403</td>
<td>30.255</td>
<td>30.775</td>
</tr>
<tr>
<td>Construc</td>
<td></td>
<td>-0.276</td>
<td>-0.299</td>
<td>-0.299</td>
<td>-0.174</td>
<td>0.013</td>
</tr>
<tr>
<td>Transprt</td>
<td></td>
<td>5.031</td>
<td>5.038</td>
<td>5.038</td>
<td>5.530</td>
<td>5.734</td>
</tr>
<tr>
<td>Communic</td>
<td></td>
<td>22.033</td>
<td>22.051</td>
<td>22.051</td>
<td>21.989</td>
<td>22.127</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td></td>
<td>11.380</td>
<td>11.383</td>
<td>11.383</td>
<td>11.380</td>
<td>11.605</td>
</tr>
</tbody>
</table>

### Growth : Bias

<table>
<thead>
<tr>
<th></th>
<th>1956-1980</th>
<th>Unb</th>
<th>ApprUnb</th>
<th>Naive</th>
<th>Consist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricult</td>
<td></td>
<td>0.050</td>
<td>0.050</td>
<td>-0.114</td>
<td>0.238</td>
</tr>
<tr>
<td>Mining</td>
<td></td>
<td>0.016</td>
<td>0.016</td>
<td>-0.120</td>
<td>0.090</td>
</tr>
<tr>
<td>Manufact</td>
<td></td>
<td>-0.011</td>
<td>-0.011</td>
<td>-0.078</td>
<td>0.018</td>
</tr>
<tr>
<td>Energy</td>
<td></td>
<td>-0.045</td>
<td>-0.045</td>
<td>-0.194</td>
<td>0.327</td>
</tr>
<tr>
<td>Construc</td>
<td></td>
<td>-0.024</td>
<td>-0.024</td>
<td>0.102</td>
<td>0.288</td>
</tr>
<tr>
<td>Transprt</td>
<td></td>
<td>0.007</td>
<td>0.007</td>
<td>0.499</td>
<td>0.703</td>
</tr>
<tr>
<td>Communic</td>
<td></td>
<td>0.018</td>
<td>0.018</td>
<td>-0.044</td>
<td>0.094</td>
</tr>
<tr>
<td>Oth Serv</td>
<td></td>
<td>0.010</td>
<td>0.010</td>
<td>-0.055</td>
<td>0.036</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td></td>
<td>0.003</td>
<td>0.003</td>
<td>0.000</td>
<td>0.224</td>
</tr>
<tr>
<td>Industry</td>
<td>Unb</td>
<td>ApprUnb</td>
<td>Naive</td>
<td>Consist</td>
<td></td>
</tr>
<tr>
<td>--------------</td>
<td>-----</td>
<td>---------</td>
<td>-------</td>
<td>---------</td>
<td></td>
</tr>
<tr>
<td><strong>1956-1980</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td>43.739</td>
<td>43.739</td>
<td>43.633</td>
<td>43.935</td>
<td></td>
</tr>
<tr>
<td>Manufact</td>
<td>5.835</td>
<td>5.835</td>
<td>5.832</td>
<td>5.840</td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>97.865</td>
<td>97.865</td>
<td>97.674</td>
<td>98.559</td>
<td></td>
</tr>
<tr>
<td>Construc</td>
<td>61.938</td>
<td>61.938</td>
<td>62.102</td>
<td>62.409</td>
<td></td>
</tr>
<tr>
<td>Transprt</td>
<td>145.387</td>
<td>145.387</td>
<td>146.964</td>
<td>147.774</td>
<td></td>
</tr>
<tr>
<td>Communic</td>
<td>18.551</td>
<td>18.551</td>
<td>18.533</td>
<td>18.586</td>
<td></td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>49.167</td>
<td>49.167</td>
<td>49.341</td>
<td>49.644</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Industry</th>
<th>Unb</th>
<th>ApprUnb</th>
<th>Naive</th>
<th>Consist</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1956-1980</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td>0.245</td>
<td>0.245</td>
<td>*</td>
<td>0.692</td>
</tr>
<tr>
<td>Mining</td>
<td>0.172</td>
<td>0.172</td>
<td>*</td>
<td>0.388</td>
</tr>
<tr>
<td>Manufact</td>
<td>0.049</td>
<td>0.049</td>
<td>*</td>
<td>0.121</td>
</tr>
<tr>
<td>Energy</td>
<td>0.196</td>
<td>0.196</td>
<td>*</td>
<td>0.906</td>
</tr>
<tr>
<td>Construc</td>
<td>*</td>
<td>0.000</td>
<td>0.265</td>
<td>0.760</td>
</tr>
<tr>
<td>Transprt</td>
<td>*</td>
<td>0.000</td>
<td>1.085</td>
<td>1.642</td>
</tr>
<tr>
<td>Communic</td>
<td>0.102</td>
<td>0.102</td>
<td>*</td>
<td>0.288</td>
</tr>
<tr>
<td>Oth Serv</td>
<td>0.046</td>
<td>0.046</td>
<td>*</td>
<td>0.105</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>0.101</td>
<td>0.101</td>
<td>0.169</td>
<td>0.613</td>
</tr>
</tbody>
</table>
### Levels: Average Actual and predicted

<table>
<thead>
<tr>
<th></th>
<th>1956-1980</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual</td>
<td>Unb</td>
<td>ApprUnb</td>
<td>(Y_T \hat{G}_{h,T})</td>
<td>Naive</td>
<td>Consist1</td>
<td>Consist2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agricult</td>
<td>2.284</td>
<td>2.285</td>
<td>2.285</td>
<td>2.295</td>
<td>2.299</td>
<td>2.302</td>
<td>2.338</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mining</td>
<td>0.821</td>
<td>0.821</td>
<td>0.821</td>
<td>0.824</td>
<td>0.825</td>
<td>0.826</td>
<td>0.835</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manufact</td>
<td>1.876</td>
<td>1.876</td>
<td>1.876</td>
<td>1.878</td>
<td>1.880</td>
<td>1.880</td>
<td>1.889</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construc</td>
<td>1.672</td>
<td>1.672</td>
<td>1.672</td>
<td>1.680</td>
<td>1.678</td>
<td>1.683</td>
<td>1.699</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transprt</td>
<td>1.719</td>
<td>1.719</td>
<td>1.719</td>
<td>1.734</td>
<td>1.726</td>
<td>1.737</td>
<td>1.754</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oth Serv</td>
<td>2.512</td>
<td>2.512</td>
<td>2.512</td>
<td>2.515</td>
<td>2.516</td>
<td>2.517</td>
<td>2.526</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>2.629</td>
<td>2.628</td>
<td>2.628</td>
<td>2.640</td>
<td>2.640</td>
<td>2.646</td>
<td>2.676</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Level : Bias

<table>
<thead>
<tr>
<th></th>
<th>1956-1980</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Unb</td>
<td>ApprUnb</td>
<td>(Y_T \hat{G}_{h,T})</td>
<td>Naive</td>
<td>Consist1</td>
<td>Consist2</td>
<td></td>
</tr>
<tr>
<td>Agricult</td>
<td>0.001</td>
<td>0.011</td>
<td>0.015</td>
<td>0.018</td>
<td>0.054</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mining</td>
<td>0.000</td>
<td>0.003</td>
<td>0.004</td>
<td>0.004</td>
<td>0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manufact</td>
<td>0.000</td>
<td>0.002</td>
<td>0.003</td>
<td>0.004</td>
<td>0.013</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>-0.003</td>
<td>-0.003</td>
<td>0.039</td>
<td>0.046</td>
<td>0.189</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construc</td>
<td>0.000</td>
<td>0.008</td>
<td>0.006</td>
<td>0.011</td>
<td>0.027</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transprt</td>
<td>0.000</td>
<td>0.015</td>
<td>0.007</td>
<td>0.018</td>
<td>0.035</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Communic</td>
<td>0.001</td>
<td>0.008</td>
<td>0.010</td>
<td>0.012</td>
<td>0.035</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oth Serv</td>
<td>0.000</td>
<td>0.003</td>
<td>0.004</td>
<td>0.005</td>
<td>0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>0.000</td>
<td>0.011</td>
<td>0.012</td>
<td>0.017</td>
<td>0.048</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1956-1980</td>
<td>Unb</td>
<td>ApprUnb</td>
<td>$Y_{T} \hat{G}_{h,T}$</td>
<td>Naive</td>
<td>Consist1</td>
<td>Consist2</td>
</tr>
<tr>
<td>----------------</td>
<td>-----------</td>
<td>-----</td>
<td>---------</td>
<td>------------------------</td>
<td>-------</td>
<td>----------</td>
<td>----------</td>
</tr>
<tr>
<td>Agricult</td>
<td></td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
<td>0.052</td>
<td>0.056</td>
</tr>
<tr>
<td>Mining</td>
<td></td>
<td>0.004</td>
<td>0.004</td>
<td>0.004</td>
<td>0.004</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td>Manufact</td>
<td></td>
<td>0.009</td>
<td>0.009</td>
<td>0.009</td>
<td>0.009</td>
<td>0.009</td>
<td>0.009</td>
</tr>
<tr>
<td>Energy</td>
<td></td>
<td>0.548</td>
<td>0.548</td>
<td>0.557</td>
<td>0.559</td>
<td>0.564</td>
<td>0.622</td>
</tr>
<tr>
<td>Construc</td>
<td></td>
<td>0.029</td>
<td>0.029</td>
<td>0.029</td>
<td>0.029</td>
<td>0.029</td>
<td>0.030</td>
</tr>
<tr>
<td>Transprt</td>
<td></td>
<td>0.052</td>
<td>0.052</td>
<td>0.053</td>
<td>0.052</td>
<td>0.053</td>
<td>0.055</td>
</tr>
<tr>
<td>Communuc</td>
<td></td>
<td>0.057</td>
<td>0.057</td>
<td>0.057</td>
<td>0.057</td>
<td>0.057</td>
<td>0.059</td>
</tr>
<tr>
<td>Oth Serv</td>
<td></td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
<td>0.013</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>0.095</td>
<td>0.095</td>
<td>0.097</td>
<td>0.097</td>
<td>0.098</td>
<td>0.106</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Unb</th>
<th>ApprUnb</th>
<th>$Y_{T} \hat{G}_{h,T}$</th>
<th>Naive</th>
<th>Consist1</th>
<th>Consist2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricult</td>
<td>*</td>
<td>0.000</td>
<td>1.170</td>
<td>1.631</td>
<td>2.217</td>
<td>10.902</td>
</tr>
<tr>
<td>Mining</td>
<td>*</td>
<td>0.000</td>
<td>0.744</td>
<td>1.221</td>
<td>1.513</td>
<td>8.187</td>
</tr>
<tr>
<td>Manufact</td>
<td>*</td>
<td>0.000</td>
<td>0.289</td>
<td>0.500</td>
<td>0.601</td>
<td>3.343</td>
</tr>
<tr>
<td>Energy</td>
<td>*</td>
<td>0.000</td>
<td>1.607</td>
<td>1.949</td>
<td>2.901</td>
<td>13.452</td>
</tr>
<tr>
<td>Construc</td>
<td>*</td>
<td>0.000</td>
<td>1.207</td>
<td>0.849</td>
<td>1.803</td>
<td>5.989</td>
</tr>
<tr>
<td>Transprt</td>
<td>*</td>
<td>0.001</td>
<td>2.122</td>
<td>0.838</td>
<td>2.738</td>
<td>6.590</td>
</tr>
<tr>
<td>Communuc</td>
<td>*</td>
<td>0.000</td>
<td>0.454</td>
<td>0.623</td>
<td>0.850</td>
<td>4.041</td>
</tr>
<tr>
<td>Oth Serv</td>
<td>*</td>
<td>0.000</td>
<td>0.244</td>
<td>0.428</td>
<td>0.509</td>
<td>2.804</td>
</tr>
<tr>
<td>Average</td>
<td>*</td>
<td>0.000</td>
<td>0.980</td>
<td>1.005</td>
<td>1.641</td>
<td>6.913</td>
</tr>
</tbody>
</table>

1956 - 2005: $T = 50$, Forecasting horizon $h = 10$, nr simulations = 100,000.
### Sectoral Parameter Estimates

<table>
<thead>
<tr>
<th></th>
<th>incpt</th>
<th>dd72</th>
<th>d74</th>
<th>dd75</th>
<th>dd76</th>
<th>d80</th>
<th>dd84</th>
<th>dll</th>
<th>dllk</th>
<th>(\hat{\sigma})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricult</td>
<td>0.021</td>
<td>-0.068</td>
<td>-0.138</td>
<td>0.120</td>
<td>-0.031</td>
<td>0.177</td>
<td>0.042</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mining</td>
<td>0.014</td>
<td>-0.117</td>
<td>-0.111</td>
<td>-0.467</td>
<td>0.491</td>
<td>-0.019</td>
<td>0.064</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manufact</td>
<td>0.017</td>
<td></td>
<td></td>
<td>-0.030</td>
<td>0.490</td>
<td>0.515</td>
<td>0.020</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Energy</td>
<td>0.036</td>
<td></td>
<td></td>
<td>-0.205</td>
<td>0.096</td>
<td>0.801</td>
<td>0.047</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construc</td>
<td>0.015</td>
<td>-0.125</td>
<td></td>
<td>-0.068</td>
<td>0.679</td>
<td>0.266</td>
<td>0.032</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transprt</td>
<td>0.023</td>
<td></td>
<td></td>
<td>-0.060</td>
<td>0.337</td>
<td>0.103</td>
<td>0.032</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Communic</td>
<td>0.042</td>
<td></td>
<td></td>
<td></td>
<td>0.375</td>
<td>0.099</td>
<td>0.025</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oth Serv</td>
<td>0.023</td>
<td></td>
<td></td>
<td>-0.051</td>
<td>0.545</td>
<td>0.123</td>
<td>0.023</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>0.024</td>
<td>-0.015</td>
<td>-0.016</td>
<td>-0.014</td>
<td>-0.008</td>
<td>-0.017</td>
<td>-0.022</td>
<td>-0.073</td>
<td>0.373</td>
<td>0.258</td>
</tr>
</tbody>
</table>

### Growth: Average Actual and predicted

<table>
<thead>
<tr>
<th></th>
<th>Actual</th>
<th>Unb</th>
<th>ApprUnb</th>
<th>Naive</th>
<th>Consist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufact</td>
<td>27.918</td>
<td>27.937</td>
<td>27.937</td>
<td>27.735</td>
<td>27.994</td>
</tr>
<tr>
<td>Energy</td>
<td>76.283</td>
<td>76.318</td>
<td>76.318</td>
<td>74.890</td>
<td>76.843</td>
</tr>
<tr>
<td>Construc</td>
<td>8.933</td>
<td>8.940</td>
<td>8.940</td>
<td>8.613</td>
<td>9.164</td>
</tr>
<tr>
<td>Transprt</td>
<td>32.767</td>
<td>32.713</td>
<td>32.714</td>
<td>32.317</td>
<td>32.979</td>
</tr>
<tr>
<td>Communic</td>
<td>54.868</td>
<td>54.927</td>
<td>54.928</td>
<td>54.542</td>
<td>55.034</td>
</tr>
<tr>
<td>Oth Serv</td>
<td>40.697</td>
<td>40.736</td>
<td>40.736</td>
<td>40.434</td>
<td>40.821</td>
</tr>
<tr>
<td>Average</td>
<td>31.860</td>
<td>31.885</td>
<td>31.885</td>
<td>31.224</td>
<td>32.126</td>
</tr>
</tbody>
</table>
## Growth: Bias

<table>
<thead>
<tr>
<th>1956-2005</th>
<th>Unb</th>
<th>ApprUnb</th>
<th>Naive</th>
<th>Consist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricult</td>
<td>0.033</td>
<td>0.033</td>
<td>-0.814</td>
<td>0.262</td>
</tr>
<tr>
<td>Mining</td>
<td>-0.034</td>
<td>-0.033</td>
<td>-1.429</td>
<td>0.406</td>
</tr>
<tr>
<td>Manufact</td>
<td>0.019</td>
<td>0.019</td>
<td>-0.184</td>
<td>0.076</td>
</tr>
<tr>
<td>Energy</td>
<td>0.035</td>
<td>0.035</td>
<td>-1.392</td>
<td>0.560</td>
</tr>
<tr>
<td>Construc</td>
<td>0.006</td>
<td>0.006</td>
<td>-0.321</td>
<td>0.231</td>
</tr>
<tr>
<td>Transprt</td>
<td>0.037</td>
<td>0.037</td>
<td>-0.359</td>
<td>0.303</td>
</tr>
<tr>
<td>Communic</td>
<td>0.060</td>
<td>0.060</td>
<td>-0.325</td>
<td>0.166</td>
</tr>
<tr>
<td>Oth Serv</td>
<td>0.039</td>
<td>0.039</td>
<td>-0.263</td>
<td>0.124</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>0.024</td>
<td>0.025</td>
<td>-0.636</td>
<td>0.266</td>
</tr>
</tbody>
</table>

## Growth: MSE

<table>
<thead>
<tr>
<th>Sector</th>
<th>Unb</th>
<th>ApprUnb</th>
<th>Naive</th>
<th>Consist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricult</td>
<td>57.225</td>
<td>57.225</td>
<td>57.129</td>
<td>57.509</td>
</tr>
<tr>
<td>Mining</td>
<td>78.427</td>
<td>78.428</td>
<td>77.885</td>
<td>79.452</td>
</tr>
<tr>
<td>Energy</td>
<td>185.455</td>
<td>185.456</td>
<td>184.374</td>
<td>186.929</td>
</tr>
<tr>
<td>Construc</td>
<td>48.750</td>
<td>48.750</td>
<td>48.545</td>
<td>49.021</td>
</tr>
<tr>
<td>Transprt</td>
<td>70.251</td>
<td>70.251</td>
<td>69.955</td>
<td>70.634</td>
</tr>
<tr>
<td>Communic</td>
<td>32.854</td>
<td>32.854</td>
<td>32.818</td>
<td>32.919</td>
</tr>
<tr>
<td>Oth Serv</td>
<td>24.006</td>
<td>24.006</td>
<td>23.984</td>
<td>24.047</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>63.936</td>
<td>63.936</td>
<td>63.651</td>
<td>64.381</td>
</tr>
</tbody>
</table>
### Growth: relative deficiency MSE vs best in perc

<table>
<thead>
<tr>
<th>1956-2005</th>
<th>Unb</th>
<th>ApprUnb</th>
<th>Naive</th>
<th>Consist</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricult</td>
<td>0.167</td>
<td>0.168</td>
<td>*</td>
<td>0.665</td>
</tr>
<tr>
<td>Mining</td>
<td>0.695</td>
<td>0.696</td>
<td>*</td>
<td>2.012</td>
</tr>
<tr>
<td>Manufact</td>
<td>0.017</td>
<td>0.017</td>
<td>*</td>
<td>0.128</td>
</tr>
<tr>
<td>Energy</td>
<td>0.586</td>
<td>0.586</td>
<td>*</td>
<td>1.386</td>
</tr>
<tr>
<td>Construc</td>
<td>0.423</td>
<td>0.423</td>
<td>*</td>
<td>0.980</td>
</tr>
<tr>
<td>Transprt</td>
<td>0.423</td>
<td>0.423</td>
<td>*</td>
<td>0.970</td>
</tr>
<tr>
<td>Communic</td>
<td>0.112</td>
<td>0.112</td>
<td>*</td>
<td>0.308</td>
</tr>
<tr>
<td>Oth Serv</td>
<td>0.091</td>
<td>0.091</td>
<td>*</td>
<td>0.260</td>
</tr>
<tr>
<td>Average</td>
<td>0.314</td>
<td>0.314</td>
<td>*</td>
<td>0.839</td>
</tr>
</tbody>
</table>

### Level : Average Actual and predicted

<table>
<thead>
<tr>
<th>1956-2005</th>
<th>Actual</th>
<th>Unb</th>
<th>ApprUnb</th>
<th>Y_\hat{T}G^\hat{h}_{h,T}</th>
<th>Naive</th>
<th>Consist1</th>
<th>Consist2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mining</td>
<td>0.278</td>
<td>0.278</td>
<td>0.278</td>
<td>0.285</td>
<td>0.290</td>
<td>0.291</td>
<td>0.323</td>
</tr>
<tr>
<td>Construc</td>
<td>1.979</td>
<td>1.979</td>
<td>1.979</td>
<td>1.993</td>
<td>1.999</td>
<td>2.003</td>
<td>2.054</td>
</tr>
<tr>
<td>Transprt</td>
<td>3.582</td>
<td>3.584</td>
<td>3.584</td>
<td>3.609</td>
<td>3.620</td>
<td>3.627</td>
<td>3.718</td>
</tr>
<tr>
<td>Communic</td>
<td>15.659</td>
<td>15.666</td>
<td>15.666</td>
<td>15.727</td>
<td>15.766</td>
<td>15.777</td>
<td>16.029</td>
</tr>
<tr>
<td>Average</td>
<td>7.583</td>
<td>7.585</td>
<td>7.585</td>
<td>7.649</td>
<td>7.688</td>
<td>7.701</td>
<td>7.968</td>
</tr>
</tbody>
</table>
### Level : Bias

<table>
<thead>
<tr>
<th>1956-2005</th>
<th>Unb</th>
<th>ApprUnb</th>
<th>$Y_T\hat{G}_{h,T}$</th>
<th>Naive</th>
<th>Consist1</th>
<th>Consist2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricult</td>
<td>0.002</td>
<td>0.002</td>
<td>0.044</td>
<td>0.071</td>
<td>0.079</td>
<td>0.257</td>
</tr>
<tr>
<td>Mining</td>
<td>0.000</td>
<td>0.000</td>
<td>0.007</td>
<td>0.012</td>
<td>0.013</td>
<td>0.045</td>
</tr>
<tr>
<td>Manufact</td>
<td>0.001</td>
<td>0.001</td>
<td>0.011</td>
<td>0.018</td>
<td>0.020</td>
<td>0.064</td>
</tr>
<tr>
<td>Energy</td>
<td>0.003</td>
<td>0.003</td>
<td>0.337</td>
<td>0.532</td>
<td>0.603</td>
<td>1.984</td>
</tr>
<tr>
<td>Construc</td>
<td>0.000</td>
<td>0.000</td>
<td>0.014</td>
<td>0.020</td>
<td>0.024</td>
<td>0.075</td>
</tr>
<tr>
<td>Transprt</td>
<td>0.001</td>
<td>0.001</td>
<td>0.027</td>
<td>0.037</td>
<td>0.045</td>
<td>0.136</td>
</tr>
<tr>
<td>Communic</td>
<td>0.007</td>
<td>0.007</td>
<td>0.068</td>
<td>0.107</td>
<td>0.118</td>
<td>0.370</td>
</tr>
<tr>
<td>Oth Serv</td>
<td>0.002</td>
<td>0.002</td>
<td>0.027</td>
<td>0.043</td>
<td>0.047</td>
<td>0.150</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>0.002</td>
<td>0.002</td>
<td>0.067</td>
<td>0.105</td>
<td>0.119</td>
<td>0.385</td>
</tr>
</tbody>
</table>

### Level : MSFE

<table>
<thead>
<tr>
<th>1956-2005</th>
<th>Unb</th>
<th>ApprUnb</th>
<th>$Y_T\hat{G}_{h,T}$</th>
<th>Naive</th>
<th>Consist1</th>
<th>Consist2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricult</td>
<td>0.368</td>
<td>0.368</td>
<td>0.378</td>
<td>0.386</td>
<td>0.389</td>
<td>0.493</td>
</tr>
<tr>
<td>Mining</td>
<td>0.005</td>
<td>0.005</td>
<td>0.006</td>
<td>0.006</td>
<td>0.006</td>
<td>0.010</td>
</tr>
<tr>
<td>Manufact</td>
<td>0.094</td>
<td>0.094</td>
<td>0.094</td>
<td>0.095</td>
<td>0.095</td>
<td>0.101</td>
</tr>
<tr>
<td>Construc</td>
<td>0.059</td>
<td>0.059</td>
<td>0.060</td>
<td>0.061</td>
<td>0.061</td>
<td>0.070</td>
</tr>
<tr>
<td>Transprt</td>
<td>0.193</td>
<td>0.193</td>
<td>0.197</td>
<td>0.199</td>
<td>0.200</td>
<td>0.228</td>
</tr>
<tr>
<td>Communic</td>
<td>1.983</td>
<td>1.983</td>
<td>2.003</td>
<td>2.020</td>
<td>2.026</td>
<td>2.223</td>
</tr>
<tr>
<td>Oth Serv</td>
<td>0.379</td>
<td>0.379</td>
<td>0.382</td>
<td>0.385</td>
<td>0.386</td>
<td>0.418</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>2.635</td>
<td>2.635</td>
<td>2.720</td>
<td>2.787</td>
<td>2.814</td>
<td>3.670</td>
</tr>
<tr>
<td>1956-2005</td>
<td>Unb</td>
<td>ApprUnb</td>
<td>$Y_T\hat{G}_{h,T}$</td>
<td>Naive</td>
<td>Consist1</td>
<td>Consist2</td>
</tr>
<tr>
<td>-----------</td>
<td>-----</td>
<td>---------</td>
<td>-------------------</td>
<td>-------</td>
<td>----------</td>
<td>---------</td>
</tr>
<tr>
<td>Agricult</td>
<td>*</td>
<td>0.001</td>
<td>2.711</td>
<td>5.100</td>
<td>5.827</td>
<td>34.170</td>
</tr>
<tr>
<td>Mining</td>
<td>*</td>
<td>0.003</td>
<td>6.414</td>
<td>11.895</td>
<td>13.856</td>
<td>86.535</td>
</tr>
<tr>
<td>Manufact</td>
<td>*</td>
<td>0.000</td>
<td>0.631</td>
<td>1.174</td>
<td>1.345</td>
<td>7.593</td>
</tr>
<tr>
<td>Energy</td>
<td>*</td>
<td>0.001</td>
<td>3.568</td>
<td>6.353</td>
<td>7.508</td>
<td>43.437</td>
</tr>
<tr>
<td>Construc</td>
<td>*</td>
<td>0.000</td>
<td>1.761</td>
<td>2.737</td>
<td>3.486</td>
<td>18.255</td>
</tr>
<tr>
<td>Transprt</td>
<td>*</td>
<td>0.000</td>
<td>1.779</td>
<td>2.770</td>
<td>3.510</td>
<td>18.162</td>
</tr>
<tr>
<td>Communic</td>
<td>*</td>
<td>0.000</td>
<td>1.012</td>
<td>1.881</td>
<td>2.151</td>
<td>12.102</td>
</tr>
<tr>
<td>Oth Serv</td>
<td>*</td>
<td>0.000</td>
<td>0.855</td>
<td>1.590</td>
<td>1.822</td>
<td>10.345</td>
</tr>
<tr>
<td>Average</td>
<td>*</td>
<td>0.001</td>
<td>2.341</td>
<td>4.187</td>
<td>4.938</td>
<td>28.825</td>
</tr>
</tbody>
</table>