



Department of Economics

Business Cycle Volatility and Economic Growth

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Business Cycle Volatility and Economic Growth: A Reassessment

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1. INTRODUCTION

One of the important implications of real business cycle theory is that there should be a positive relationship between economic fluctuations and economic growth, or, to be more specific, that the growth of real gross domestic product per capita should fall as the business cycle becomes less volatile. This is, of course, a conjecture that is open to empirical verification, at least in principle, but there are a variety of approaches that may be taken which will not necessarily yield consistent sets of findings. Altman (1995), for example, uses primarily the Maddison (1991) data set of some 13 countries from 1870 to 1986 and detrends using log-linear trend lines across benchmark years to obtain the cyclical component of output. He then uses rank and linear correlation techniques to assess the strength of a possible positive relationship between cyclical volatility, measured as the standard deviation of the cyclical component, and output growth across a variety of sub-periods.

Altman finds little evidence in favour of this implication of real business cycles models, but it may be argued that his conclusion relies heavily on two questionable features of his empirical approach. Both the method used to construct the cyclical components and the correlation techniques employed to assess the strength of any relationship between cyclical volatility and growth may be criticised as being less than statistical 'best practice'. We therefore aim to reassess this evidence by extending Altman's analysis in three directions. The first is to use a more extensive output per capita data set - we employ Maddison's (1995) updated set of 22 countries, which now ends in 1994. We then employ several statistical techniques that are explicitly designed to extract business cycle components from annual economic time series and, finally, we use robust non-parametric methods to investigate the relationship between cyclical volatility and growth.

2. THE DATA

The 22 countries for which output per capita are available on a reasonably long time span are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, the Netherlands, Italy, New Zealand, Norway, Sweden, the U.K. and the U.S., all with dates beginning in 1870, Japan, with start date 1885, Switzerland (1899), Argentina, Brazil and Spain (all 1900), Taiwan (1903), and Korea (1911). They thus represent a wider and longer selection than that used by Altman, and are not all restricted to being developed market economies. The data set has been used by Mills and Crafts (2000) to study trend growth patterns and issues of convergence within the context of the endogenous growth debate, and this reference may be consulted for extensive evidence on the time series properties of the series under consideration.

3. CONSTRUCTING CYCLICAL COMPONENTS

The method used by Altman to compute the cyclical component of output is to choose a sub-period of data, say from T_a to T_b , and estimate the semi-logarithmic regression

$$y_t = \mathbf{a} + \mathbf{b}t + u_t, \quad t = T_a, \dots, T_b \quad (1)$$

where y_t is the logarithm of output per capita and u_t is an error *assumed* to satisfy the classical assumptions of regression. Unfortunately, there are several difficulties with this approach. As discussed in Mills (1992), for example, it assumes that for every sub-period that the linear trend (1) is fitted, the underlying process generating y_t must be trend stationary and, further, that the trend function is discontinuous across sub-periods. Even if we are prepared to make these heroic assumptions, estimation of (1) by OLS is a badly flawed procedure if u_t is, in fact, highly autocorrelated, as it is likely to be. See on this Canjels and Watson (1997), who also show that the standard correction used in these circumstances, Cochrane-Orcutt estimation, does not improve the situation and should not be used.

Although Mills and Crafts (2000) find that segmented linear trends can often be useful when modelling this data set, their focus was primarily on questions of long run growth rather than on extracting cyclical components. In this latter context, two approaches have typically been followed in the modern business cycle literature. The first is to estimate a *structural* model, where the observed series y_t is assumed to be decomposed into three mutually uncorrelated unobservable components, a trend, \mathbf{m}_t , a cycle, \mathbf{y}_t , and an irregular, \mathbf{e}_t , such that

$$y_t = \mathbf{m}_t + \mathbf{y}_t + \mathbf{e}_t \quad (2)$$

First introduced by Harvey (1985), the structural model has a stochastic trend component that is specified as a random walk with a drift that is itself a random walk. This allows the trend to be stochastic, with both its level and slope able to change. The linear trend results as a limiting case when the innovations driving the two random walks have zero variances, i.e., disappear from the specification.

The cyclical component is specified as a set of sinusoidal functions (a mixture of sine and cosine waves), whose weights evolve over time, thus allowing the cycle to be stochastic. The irregular component is assumed to be white noise. Full details of the specification and of the methods used for the estimation of (2) may be found in Koopman, Harvey, Doornik and Shephard (1995), which provides documentation for

the software package *STAMP 5.0*, which we use to obtain estimates of the cyclical component, $\hat{\mathbf{y}}_t$.

An alternative, nonparametric, approach to estimating the cyclical component is to employ a linear filter (a two-sided moving average) that is explicitly designed to capture movements in a time series that correspond to business cycle fluctuations. Baxter and King (1995) develop a band-pass filter that extracts such components while removing components at higher (i.e., trend) and lower (irregular) frequencies. For annual data, the filter that passes components with frequencies of between two and eight years is defined as

$$y_t^* = 0.7741y_t - 0.2010(y_{t-1} + y_{t+1}) - 0.1351(y_{t-2} + y_{t+2}) - 0.0501(y_{t-3} + y_{t+3}) \quad (3)$$

Studies that have used this filter to extract cyclical components include, in the historical context, Basu and Taylor (1999), and, using its quarterly variant, Stock and Watson (1998). The band-pass filter is close to being the ideal filter for passing only components with business cycle frequencies, its sub-optimality being a consequence of having to use a finite, rather than an infinite, time series for y_t .

A filter that is similar to the band-pass, and which has been widely used in business cycle research, is that proposed by Hodrick and Prescott (1997): see also King and Rebelo (1993). The Hodrick-Prescott (H-P) filter has a tendency to pass high-frequency noise outside the business cycle frequency band but judicious setting of the ‘smoothing parameter’, \mathbf{I} , which penalises variation in trend, enables the H-P filter to closely approximate the band-pass. Although the H-P filter can be written as a two-sided moving average, similar to (3) above, the moving average weights are extremely complicated, although general expressions are given in King and Rebelo (1993). Fortunately, the cyclical component, denoted y_t^{HP} , can be constructed by a simple computational algorithm that is widely available in econometric packages. It is therefore also used here with the smoothing parameter set at $\mathbf{I} = 7$, which has been found to be a sensible choice for annual data.

For each series, three cyclical components are therefore computed: $\hat{\mathbf{y}}_t$, y_t^* and y_t^{HP} . For each of the cycles, standard deviations are calculated for the complete sample 1870-1994 and for the sub-periods 1870-1908, 1870-1928, 1947-1994 and 1954-1972, these corresponding to the periods selected by Altman (for the first sub-period several standard deviations could not be calculated because of lack of data). For comparison, we also calculated the volatility measure used by Altman – the standard deviation of the residuals from the linear trend (1) fitted to the various sample periods. Figure 1 shows the four alternative cycles, $\hat{\mathbf{y}}_t$, y_t^* and y_t^{HP} plus \hat{u}_t from the regression of (1) with $T_a = 1870$ and $T_b = 1994$, for the U.S. The two linear

filters are very similar, but the Hodrick-Prescott cycle has a slightly larger amplitude than the band-pass cycle (the standard deviations are 3.86% and 3.63% respectively), since the former passes more ‘non-business cycle frequency’ variation. The structural and linear cycles are very different from these, however, being dominated by the behaviour during the 1935-1950 period – these methods treat the large fluctuations in the series during these years as primarily cyclical movements, whereas the linear filters classify them more as part of the trend and irregular components. In any case, it is clear that alternative methods of decomposition can lead to markedly different estimates of cyclical volatility, particularly across specific sub-periods of the data.

4. VISUALISING THE VOLATILITY-GROWTH RELATIONSHIP

Altman considers both the relationship between annual output per capita growth and volatility in each of the sub-periods and the relationship between the growth and volatility *ratios* calculated by dividing the estimates from the period 1947-1994 by those from 1870-1928 (and also between 1954-1972 and 1870-1908). The statistical techniques used are graphical, linear regression and rank correlation, and the general conclusion is that there is little evidence of a positive relationship between growth and volatility - if anything, his results suggest a weak negative relationship.

Since there is no theory to suggest the form of the relationship between growth and volatility, we should be wary of making formal probabilistic inferences, particularly as the volatility measures are themselves *derived* from the observed data. An alternative approach to investigating the interaction between growth and volatility is ‘visualisation’, a set of tools, often referred to as ‘exploratory data analysis’, that may reveal intricate structure in data that cannot be absorbed in any other way and which does not rest on the foundations of probabilistic inference. Cleveland (1993) is an excellent handbook on visualisation techniques, while Mills (1990, chapters 2-4) discusses basic techniques within an economic context.

Since we are interested in examining the bivariate relationship between growth and volatility, but have little or no prior knowledge as to the functional form of this relationship, we shall use scatterplots (as does Altman), but with robust non-parametric curves superimposed. These curves are *loess* fits, which is a local regression technique originally introduced by Cleveland (1979) and discussed in detail in Cleveland (1993, chapter 3). Such a technique is known to have some highly desirable statistical properties (see, for example, Fan, 1992).

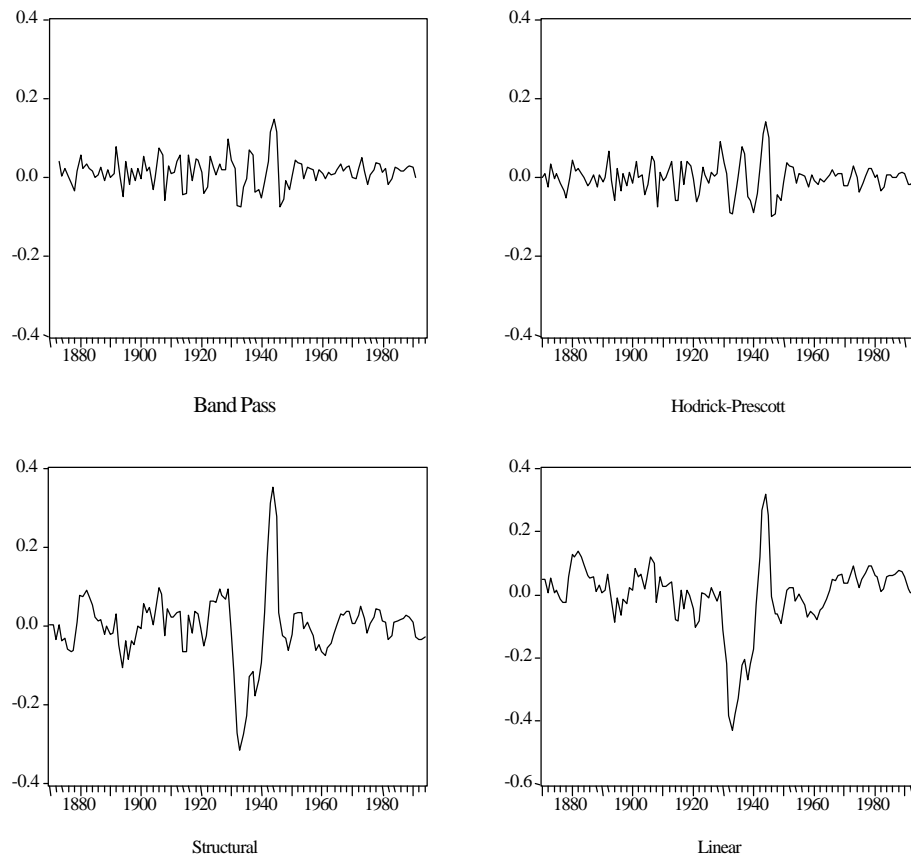


Figure 1: Alternative Estimates of the U.S. Business Cycle

Since for each sample period we have a maximum of 22 matched pairs of growth and volatility observations, we choose to report local linear loess fits (local quadratic fits produced almost identical curves) with the smoothing parameter set at unity. This controls the proportion of the sample size that is used in computing the local regression fit at each point – with such a small sample, setting this parameter to unity, so that all the data is used, enables a smooth fit to be obtained. Experiments with smaller values produced ‘wiggly’ fits that did not look sensible.

Figures 2 to 6 present loess fits to scatterplots of the growth-volatility relationship for the five sample periods and four volatility estimates. For the complete period 1870-1994 (Figure 2), all but the structural volatility estimate show a nonlinear but positive relationship between growth and volatility, although this is undoubtedly driven by three high volatility-growth countries, which are the Asian economies of Japan, Korea and Taiwan. Without these observations, there would be little relationship between growth and volatility using any of the four methods.

Figure 3 shows the relationships for the period 1870-1908. For all but the linear trend estimate of volatility, the relationship is essentially flat for low levels of volatility, but is positive for those countries with the highest cyclical volatility. The linear trend measure, on the other hand, indicates a positive relationship for low levels of volatility but a negative relationship for high levels. When the sample period is extended to 1928 (Figure 4), all estimates suggest no relationship for low levels of volatility, but the two linear filter estimates produce a positive relationship for high levels. The ‘Golden Age’ of economic growth, 1954-1972, shown in Figure 5, seems to have low levels of volatility positively associated with growth for all measures, but only for the linear trend measure is this association continued at higher volatility levels. Finally, Figure 6 shows the entire post-war period, 1947-1994. It is only here that a reasonably consistent positive relationship is observed, although it is still flat for low volatility levels when the linear filter measures are used. We should emphasise, however, that none of these loess fits may be regarded as ‘tight’ – any relationship between growth and volatility is without doubt a loose one, no matter how volatility is estimated.

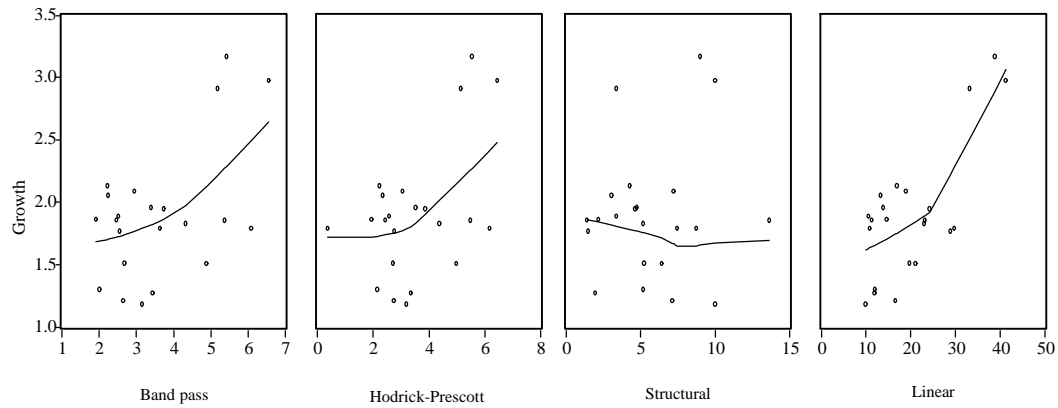
Figure 7 shows growth-volatility ratios for 1947-1994 compared to 1870-1908. In each case there is a positive relationship, although all the scatterplots split into two groups – a ‘high’ ratio group containing the majority of the countries, and a ‘low’ ratio group comprising Canada, Denmark, New Zealand, Sweden and the U.S. Figure 8 presents scatterplots for these two groups separately. For the group with high growth and volatility ratios there is little relationship, but for the low ratio group the relationship is clearly positive, i.e., those countries for which there has only been a small increase in growth rates and volatility show a positive association between the two ratios, although with such a small sample we should be wary of making too much of this.

5. CONCLUSIONS

Using a more limited data set, an arguably inappropriate measure of business cycle volatility and simple correlation techniques, Altman (1995) found little evidence of a relationship between economic growth and cyclical volatility. As his results could be criticised on all three counts, we have reworked the analysis using several techniques aimed at rebutting such criticisms. It is clear from our results that a tight relationship between growth and volatility certainly has not existed over the complete run of 20th century data, for only the Asian economies of Japan, Korea and Taiwan clearly exhibit such a trade-off.

Figure 2

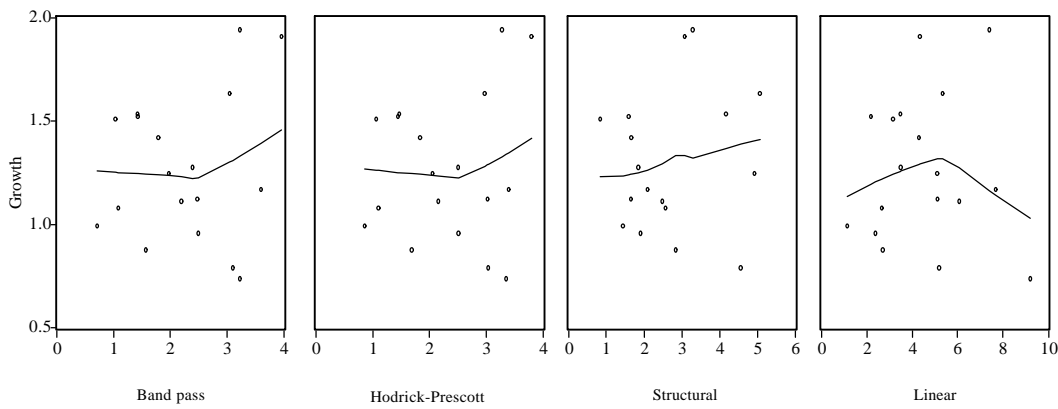
Growth - Volatility Relationships: 1870 - 1994



Robust Local Linear LOESS Fits

Figure 3

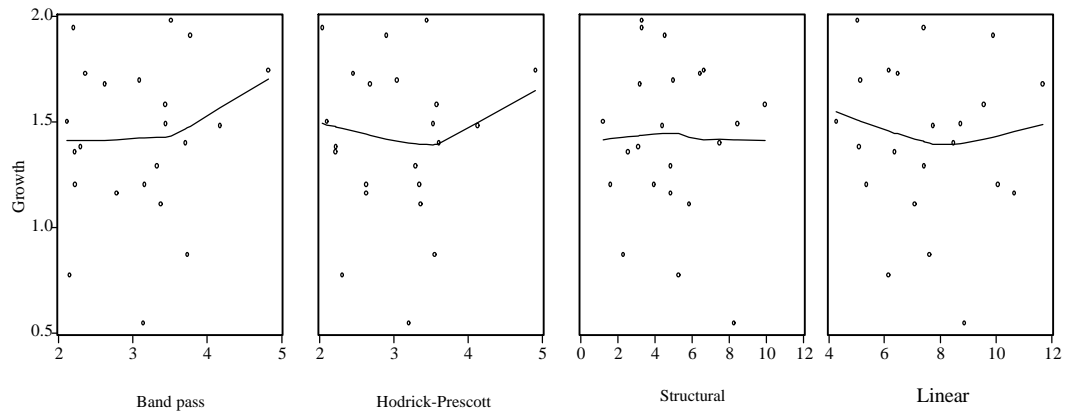
Growth - Volatility Relationships: 1870-1908



Robust Local Linear LOESS Fits

Figure 4

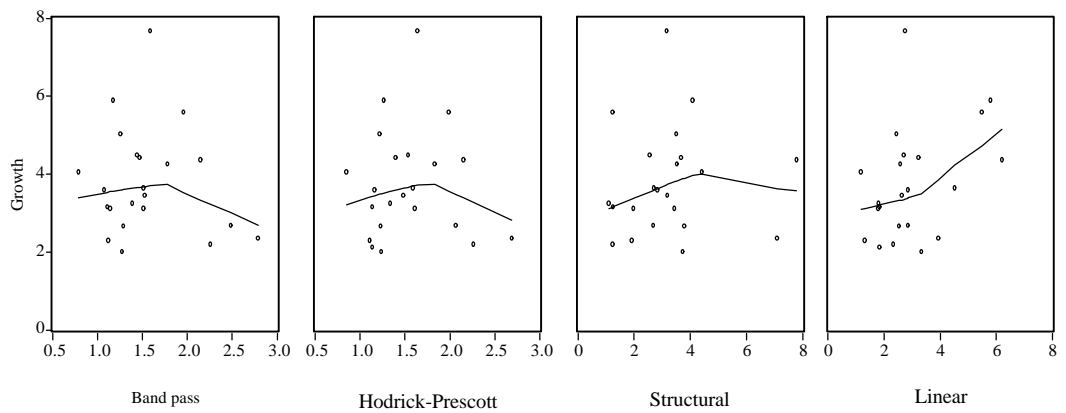
Growth - Volatility Relationships: 1870 - 1928



Robust Local Linear LOESS Fits

Figure 5

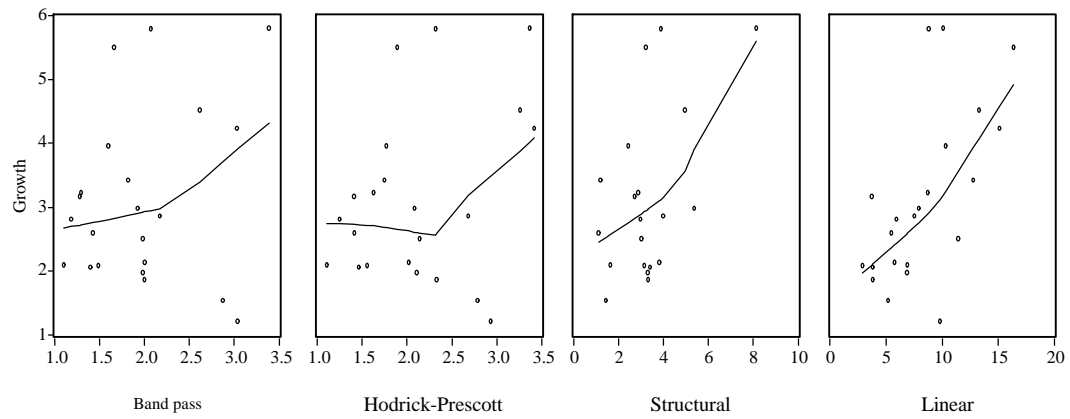
Growth - Volatility Relationships: 1954 - 1972



Robust Local Linear LOESS Fits

Figure 6

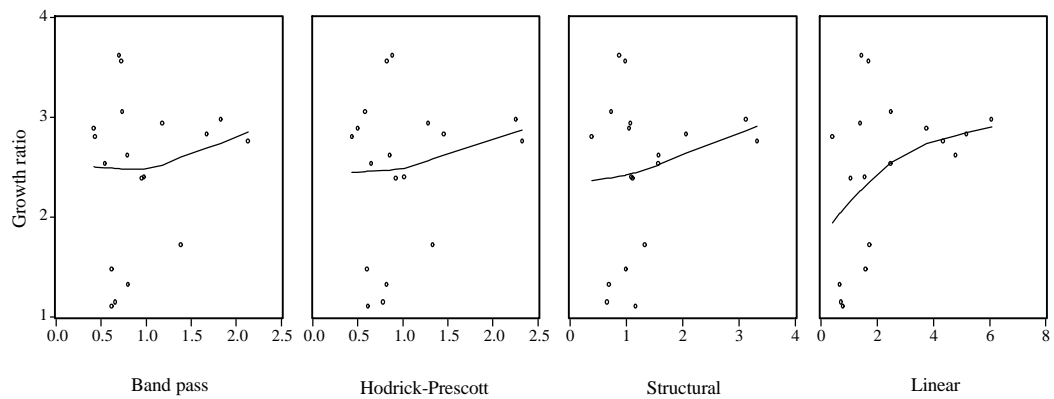
Growth - Volatility Relationships: 1946 - 1994



Robust Local Linear LOESS Fits

Figure 7

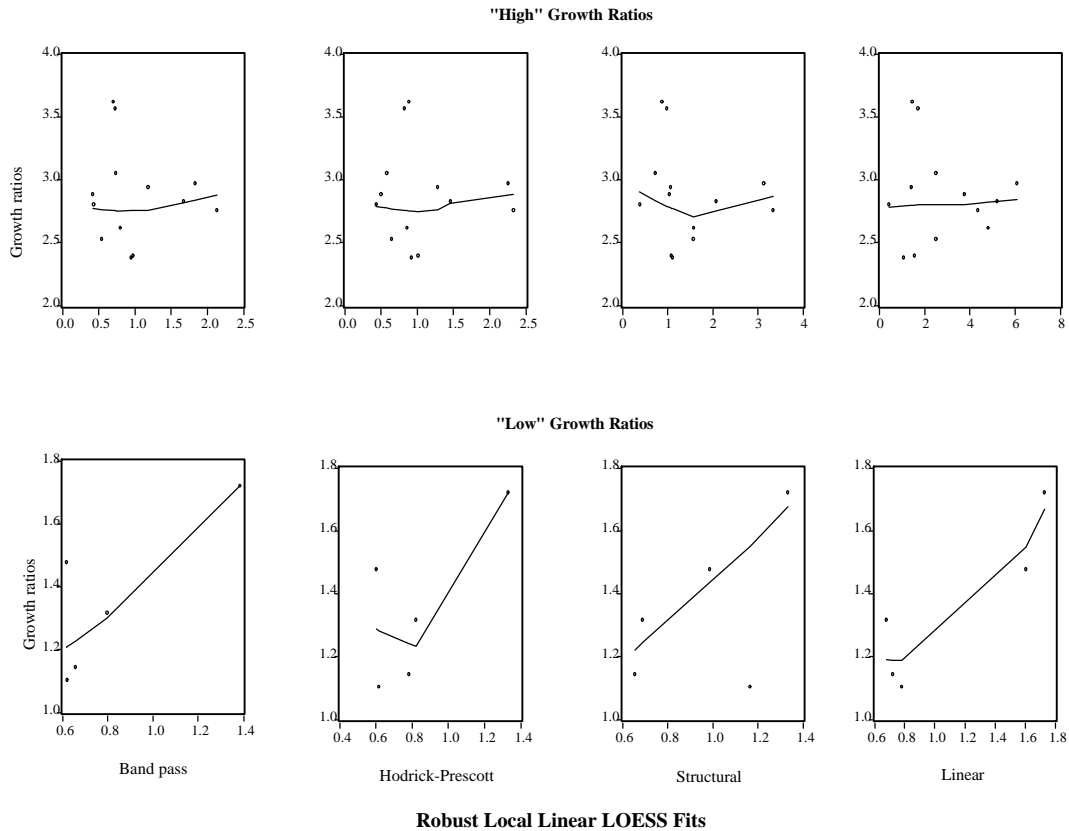
**Growth - Volatility Ratios:
1946 - 1994 relative to 1870 -1908**



Robust Local Linear LOESS Fits

Figure 8

**Growth - Volatility Ratios:
1946 - 1994 relative to 1870 - 1908**



There is, however, stronger evidence that such a tradeoff has existed for the post-war period: for all measures of cyclical volatility, the loess fits indicate that higher levels of volatility do appear to be associated with higher levels of growth. Nevertheless, the underlying scatterplots still reveal a diversity of growth and volatility performances amongst these 22 economies, and it is therefore difficult to disagree with Altman's conclusion that efforts to reduce cyclical volatility need not interfere with efforts to improve an economy's growth performance. Rapid growth and economic stability are indeed compatible and credible objectives of government policy.

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