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Common Stock Returns and the Business Cycle[†]

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Common Stock Returns and the Business Cycle

ABSTRACT

Abel (1988) intertemporal asset pricing model implies that the autocorrelation pattern in expected returns reflects that observed in output growth rates. Consequently, by using the observed autocorrelation properties of macroeconomic data, we are able to provide univariate tests with power to detect deviations from the stationary random walk model over the post-World War II sample period. After regressing excess returns against industrial production's cyclical component, these univariate tests provide little evidence of serial correlation in the resultant residuals, confirming the presence of a business cycle effect in excess returns. However, our multivariate analysis concludes that while the business cycle contributes to these deviations from the stationary random walk model, predictable long term swings in expected returns arising from variable trends in macroeconomic data still remain.

1 Introduction

Early tests of the efficient markets hypothesis, summarized in Fama (1970), found no economically significant evidence of serial correlation in stock returns[1] However, Summers (1986) suggested that this was because these tests lacked power: Summers suggested a model of "fads" in which stock prices take long swings away from their fundamental values, and showed that even if a fads component such as this accounted for a large fraction of the variance of returns, the fads behavior might be difficult to detect by looking at short horizon autocorrelations of returns as these early tests had done. Several attempts were made to develop tests which would have greater power against "fads" hypotheses such as Summers'. Fama and French (1988b) used a long-horizon regression of multi-year returns on past multi-year returns, and Poterba and Summers (1988) used a variance-ratio test to look for fads-type behavior in stock-index returns in the 1926-1987 period. While both these tests find evidence of "fads" type behavior in returns, the evidence turns out to be rather weak. First, as Kim, Nelson, and Startz (1988) point out, neither test rejects the stationary random walk model over the post-World War II sample period.[2]

Also, Fama and French (1988b) suggest that the evidence of long-horizon autocorrelations should not necessarily be interpred as evidence of fads or of market inefficiency: slow, mean-reverting expected return variation could also induce such long horizon autocorrelations. And, indeed, the evidence for such variation in expected returns is strong. Numerous studies have documented the relation between the dividend-yield, term-spread and default spread (see, for example, Keim and Stambaugh (1986), Campbell (1987), Fama and French(1988a, 1989).) The Fama and French papers, in particular, tie movements in these variables to the business cycle by relating them to NBER datings. Chen (1991) takes this one step further by showing that these variables are closely related to past and future growth rates in production.

Indeed, it is important to determine whether these variations are tied to changing economic conditions: in an efficient markets model expected return variation must in the end be tied

[1]The evidence that short-horizon autocorrelations may be economically significant is now somewhat stronger (see Lo and MacKinlay (1988)).

[2]Also, the statistical significance of these tests is questioned by Richardson (1993), who uses joint χ^2 test proceedures developed in Richardson and Smith (1991) to show that a joint test of the Fama and French (1988b) or Poterba and Summers (1988) results does not reject the null of constant expected returns. Also, Richardson and Stock (1989) suggest that the significance of the Fama and French (1988b) results is due to biased T-statistics.

to the covariation of returns with investors' intertemporal marginal rates of substitution. Indeed, there are now a number of models in the finance literature tying together output and expected returns. Balvers, Cosimano, and McDonald (1990) present a general equilibrium model in which aggregate output is serially correlated, and hence agents attempts to smooth consumption affects the required rate of return on financial assets. Cochrane (1991) and Restoy and Rockinger (1994) present partial equilibrium models that tie togeter the return on investment and the return to financial assets. Kandel and Stambaugh (1990) study the moments of consumption how these relate to the moments of asset return; they find some evidence that the market price of risk is higher in recessions (consistent with Harvey (1989a) and Harvey (1989b)).

The

We fill two gaps in this literature. First, we link

In light of this multivariate evidence, it is surprising that univariate tests remain inconclusive by not taking advantage of the economic explanations offered for multivariate predictability. Of course, even if expected returns do vary with prevailing economic conditions, excess returns need not exhibit univariate predictability if changes in economic conditions themselves are serially uncorrelated. However, the observed characteristics of such economic aggregates as GDP and unemployment suggest that this is not the case. As noted by Zarnowitz (1992), notes that "business cycles are characteristically persistent and pervasive." (p. *xv*) Appealing to Abel's model, expected returns should exhibit this same persistence and, as a result, we can exploit the observed autocorrelation properties of macroeconomic data to design univariate tests which reliably reject the stationary random walk model over the post-World War II sample period. By contrast, we demonstrate that previous univariate tests lack power to detect deviations brought about by business cycle related variation in expected returns.

Abel's model further implies that any univariate predictability in excess returns should be explained by corresponding univariate predictability in output growth and its volatility. Thus, the component of current and past output which predicts future growth should also predict future excess returns. However, predicting future output growth from current and past data is complicated by the fact that output, proxied in this paper by industrial production, is an integrated process ($I(1)$). Econometrically, we overcome this problem by decomposing this time series into its permanent and temporary components. Beveridge and Nelson (1981) establish that any integrated series can be decomposed into a pure random walk with drift, interpreted as its trend component, and a stationary component, interpreted as its cyclical component. Consistent with Lucas (1977), this specification views the business cycle as stationary movements about a stochastic trend.[3] To the extent that production's cyclical component provides a good proxy for future production growth, Abel's model suggests that, after controlling for their cyclical component, excess returns should be serially uncorrelated.

However, errors can arise if this cyclical component is estimated by the residuals of a fitted linear trend (Nelson and Kang (1981) and Nelson and Plosser (1982)). First differencing a time series with both growth (non-stationary) and cyclical (stationary) components is also inappropriate as this simply confounds the contribution of each component Stock and Watson (1988)). We avoid these difficulties by using the Watson (1986) unobserved components ARIMA (*UC-ARIMA*) method as well as a one-sided version of the Hodrick and Prescott (1980) filter to stochastically detrend post-World War II industrial production data. The robustness of our results are also verified using spectral band-pass filters (Baxter and King 1994).

We confirm, using long-horizon regressions, that industrial production's cyclical component is inversely related to excess returns. Furthermore, after regressing excess returns against production's estimated cyclical component, we find that, consistent with Abel's model, our univariate test procedures provide little evidence against the null hypothesis that the resultant residuals are serially uncorrelated. This result complements the Ferson and Harvey (1991) conclusion that most of the time variation in excess returns may be attributed to a single factor. However, we find that these residuals are themselves predictable using the default and term spreads. According to Abel's model, these non-production variables can forecast excess returns *only* if they provide information about future production growth or production volatility. Consistent with this, we provide evidence that the term spread is primarily informative about future growth prospects while additional information about future production volatility

[3]We use the terms *trend* and *cycle* only to conform to their usage in the economics literature and not to suggest the presence of a linear trend nor of an autoregressive component possessing complex roots.

is contained in the default spread.

The plan of this paper is as follows. We begin by discussing Abel's intertemporal asset pricing model and highlight how this framework motivates our subsequent empirical analyses. In Section 3 we develop our univariate test procedures. Asymptotically and in small samples, these tests have significantly more statistical power than previous tests in detecting business cycle deviations from the stationary random walk model. In Section 4 we characterize the comovement of excess returns with the cyclical component of industrial production as well as its stochastic trend. We demonstrate that the rejection of the stationary random walk hypothesis in post-World War II data is, to a large extent, attributable to countercyclical movements in excess returns. We also use our time series decomposition of industrial production into its trend and cycle components to further investigate the relation between excess returns and business cycle indicators, such as the term and default spreads. Section 5 provides a summary and conclusions.

2 Expected Return Variation Over the Business Cycle

Abel (1988) provides a multiperiod general equilibrium asset pricing model in which dividend growth and volatility evolve stochastically over time. For a log utility representative individual (see also Chen (1991)), Abel shows that the risk free rate and the expected market risk premium are given by

$$R^f_{t+1} = \beta^{-1}\left(\frac{\mu_t}{y_t}\right)\cdot\frac{1}{1+\nu_t^2} \tag{1}$$

and

$$E_t\{R^e_t\} = E_t\{R_{t+1} - R^f_{t+1}\} = \beta^{-1}\left(\frac{\mu_t}{y_t}\right)\frac{\nu_t^2}{1+\nu_t^2} \tag{2}$$

where

β	$\equiv$	time invariant discount factor
y_t	$\equiv$	the current level of output
μ_t	$\equiv$	$E_t[y_{t+1}] \equiv$ the expected level of future output
ν_t	$\equiv$	$var_t(y_{t+1})/\mu_t^2 \equiv$ the conditional coefficient of variation of future output.

Notice from (1) and (2) that the risk free rate and the expected market risk premium are countercyclical. That is, both are decreasing in the current level of production y_t for a *given* level of future production, μ.[4] Intuitively, in an expansion (recession) when income is temporarily high (low) relative to wealth, the representative individual is more (less) willing to substitute current consumption for future consumption and, all else equal, returns are correspondingly low (high). According to (2), the expected risk premium is also increasing in the volatility of production, ν^2.

Abel's model implies that excess returns are predictable only to the extent that future production growth and production volatility are themselves predictable. For example, if we assume that production volatility is constant, then persistence in excess returns requires persistence in production growth.

To further understand the implications of Abel's model for the time series behavior of excess returns, we follow, among others, Beveridge and Nelson (1981) and Watson (1986) and decompose the log of production into a permanent or *stochastic trend* component (τ_t) and a temporary or *cyclical* component (c_t)[5]:

$$\ln y_t = \tilde{\tau}_t + \tilde{c}_t. \tag{3}$$

The trend component $\tilde{\tau}_t$ is modeled as a random walk with drift,

$$\tilde{\tau}_t = \delta + \tilde{\tau}_{t-1} + \tilde{e}^{\tau}_t, \qquad var(\tilde{e}^{\tau}_t) = \sigma^2_{\tau}, \tag{4}$$

while the temporary or cyclical component, $\tilde{c}_t$ is characterized by a stationary ARMA process

$$\phi(L)\tilde{c}_t = \theta(L)\tilde{e}^c_t, \qquad var(\tilde{e}^c_t) = \sigma^2_c, \tag{5}$$

where $\phi(L)$ and $\theta(L)$ denote finite order polynomials in the lag operator L, with stationarity requiring that $\theta(L)/\phi(L)$ have roots outside the unit circle.[6]

Innovations in production's trend, $\tilde{e}^{\tau}_t$, are, by construction, unforecastable using current and past production data, while future changes in the stationary component of production, Δc_{t+j}, are forecastable using current and past production data. Innovations in both the trend

[4] Production is equivalent to dividends as well as to consumption in Abel's representative investor setting. In a related model of the production sector, Cochrane (1991) also derives an inverse relationship between the level of production and equilibrium rates of return.

[5] This decomposition is always possible if production is an $I(1)$ process.

[6] Note that we are assuming, for the moment, that production volatility is constant.

and cycle ($\tilde{e}_t^{\tau}$ and $\tilde{e}_t^{c}$), however, may be forecastable if we expand our information set to include non-production data, for example, the default spread or the term spread. Abel's model implies that these variables can forecast excess returns *only* if they provide information about future production growth or production volatility.

If production is a pure trend (*i.e.*, a random walk), then future production growth will be uncorrelated with current and past production growth, and, from (2), the expected (log of the) market risk premium will be unrelated to past and current economic conditions. However, if, as is more likely, production is characterized by a persistent cyclical component, then expected future growth will, on average, be high (low) when this temporary component is relatively low (high), implying that the expected market risk premium will be correspondingly high (low).

Abel's model also has implications for the serial correlation properties of excess returns. Again, if production follows a random walk, then, since production growth is uncorrelated, excess returns will also be serially uncorrelated. Alternatively, the presence of a persistent cyclical component in production implies that past and future production growth will be correlated, and, as a result, excess returns will now be serially correlated. In addition, Abel's model implies that the pattern of serial correlation in excess returns should be closely related to the pattern of serial correlation in production growth.

We make use of these implications of Abel's model in several ways. First, since extant empirical evidence confirms the presence of a cyclical component in production, Abel's model implies that excess returns should also be serially correlated. Furthermore, since the autocorrelation pattern in expected returns should be closely related to that observed in production growth rates, this allows us to design univariate tests which have power to detect deviations from a stationary random walk model for stock prices based upon the observed autocorrelation properties of production data. Additionally, if we can identify production's cyclical component then it should predict future excess returns. To the extent that production's cyclical component is a good proxy for future production growth, the component of returns that remains once we control for its cyclical component should be serially uncorrelated, although it may very well be predictable using other variables in the available information set.

3 Univariate Tests

From Abel's model, risk premia vary counter-cyclically with the business cycle, implying that the time series behavior of production growth rates should be reflected in the stochastic properties of excess returns. In this section, we develop univariate test procedures which have statistical power, both asymptotically and in small samples, against this alternative hypothesis.

To develop such tests requires that we exploit the known properties of the business cycle. While many alternative definitions of the business cycle are available (for example, see Sargent (1987), especially pages 279-283), an exact characterization is, unfortunately, difficult. Furthermore, misspecifying the alternative may result in a less powerful test.

One business cycle restriction which may reasonably be imposed is that movements in economic aggregates are persistent, or more formally, that their spectral density at high frequencies is low. Intuitively, persistence implies that if we are in an expansion (or recession) today, we are likely to still be in an expansion (or recession) six months from today. For example, Zarnowitz (1992), p. 22, writes

> The observed fluctuations vary greatly in amplitude and scope as well as duration, yet they also have much in common. First, they are national, often international, in scope, showing up in a multitude of processes, not just in total output, employment and unemployment. Second, they are persistent - lasting, as a rule several years, that is, long enough to permit the development of cumulative movements in the downward as well as upward direction.

The persistence of the business cycle motivates our univariate test procedures. Abel's model implies that returns and, as we demonstrate in Appendix Appendix A, return autocorrelations should exhibit this same persistence. However, this persistence will typically be obscured by noise in the underlying data. From spectral techniques, we diminish the effects of this noise by applying a moving average filter to return autocorrelations. By doing so, we reduce this noise without significantly altering the business cycle induced pattern of persistent autocorrelations.[7]

[7] Additional statistical tests which directly exploit the persistence of returns have been suggested to us. We have subsequently implemented these tests to investigate the robustness of our results. Both of these additional tests also find statistically significant evidence of serial correlation in excess returns.

The first test calculates the first order serial correlation in monthly return autocorrelations over the 1947-92 sample period. Under the stationary random walk hypothesis, this serial correlation should

3.1 The Power of the Fama and French Regression Test

We first provide intuition why previous tests lack power to detect persistence in stock return autocorrelations. For expositional purposes, we couch our analysis in the context of the Fama and French (1988b) regression test.[8]

The Fama and French test examines whether $\beta(\tau) = 0$ in the following regression:

$$R(t, t+\tau) = \alpha(\tau) + \beta(\tau) \cdot R(t-\tau, t) + \epsilon(t, t+\tau)$$

where $R(t, t+\tau)$ represents the stock's return from t to $t+\tau$. Their ordinary least squares slope estimator is:

$$\hat{\beta} = \frac{\frac{1}{T}\sum_t r(t, t+\tau) r(t-\tau, t)}{\frac{1}{T}\sum_t r^2(t-\tau, t)},$$

where r denotes corresponding demeaned returns. The asymptotic power of the Fama and French regression test may be analytically derived for a local alternative hypothesis using the arguments of Davidson and MacKinnon (1987).[9] Recall that for a sufficiently large sample size, $(T \to \infty)$, we can reject a null hypothesis with certainty for any fixed alternative hypothesis. Therefore, to properly evaluate the asymptotic power of the Fama and French test, we consider the limit of a Pitman sequence of return series for which the distance between the alternative and null hypotheses becomes infinitesimal as the sample size goes to infinity. The rate at which the alternative converges towards the null is such that in the limit the probability of rejecting the null, when the alternative is true, lies in the interval $(0, 1)$ as $T \to \infty$. This requires that the variance of the temporary component of common stock prices goes to zero as $T \to \infty$. It is clear that for the limit of this sequence, the probability limit of the denominator will be:

$$\frac{1}{T}\sum_t r^2(t-\tau, t) = \frac{1}{T}\sum_t \sum_{s=-\tau}^{s=\tau} |s-\tau| r_t r_{t-s} = \frac{\tau}{T}\sum_t r_t^2.$$

be statistically indistinguishable from zero. However, for excess returns to the EW, VW, and size decile portfolios 3-10, these autocorrelations are found to be statistically different from zero at a 1% significance level.

The second test is nonparametric and investigates whether sample return autocorrelations of the same sign tend to cluster. Under the stationary random walk hypothesis, sample autocorrelations of non-overlapping returns at different lags will be uncorrelated. However, this is rejected over the 1947-92 sample period by a runs test at a 5.61% significance level for excess returns to decile 5-9 portfolios (maximum length run of 11), and at a 10.15% significance level for excess returns to decile 1-4 and 10 portfolios (maximum length run of 10).

[8] An investigation of variance ratio tests, not presented here, shows that these tests also suffer from a lack of power against business cycle induced persistence in return autocorrelations.

[9] This is formally demonstrated in Daniel (1996).

Similarly, the probability limit of the numerator will be:

$$\begin{aligned}\frac{1}{T}\sum_t r(t,t+\tau)r(t-\tau,t) &= \frac{1}{T}\sum_t \left(\sum_{u=t}^{t+\tau-1} r_u\right)\left(\sum_{u=t-\tau}^{t-1} r_u\right)\\ &= \frac{1}{T}\sum_t \sum_{s=1}^{2\tau-1} min(s,2\tau-s) r_t r_{t+s}\\ &= \sum_{s=1}^{2\tau-1} min(s,2\tau-s)\frac{1}{T}\sum_t r_t r_{t+s}.\end{aligned}$$

Therefore, the *plim* of the slope estimator will be

$$\hat{\beta} = \frac{1}{\tau}\sum_{s=1}^{2\tau-1} min(s,2\tau-s), \hat{\rho}_s \tag{6}$$

showing that the Fama and French regression test at return horizon τ is asymptotically equivalent to a test of the hypothesis that a weighted sum of return autocorrelations between lags 1 and $2\tau-1$ is equal to zero.

Notice that Fama and French's regression test implicitly assumes a triangular weighing function of return autocorrelations. Whether this provides a powerful test of the random walk hypothesis depends upon the pattern of return autocorrelations expected under the alternative hypothesis. We show in Section 3.2 that under the null and local alternative hypotheses, autocorrelation estimators at different lags are uncorrelated and have approximately the same standard error. Given this, the most powerful test statistic will weight sample autocorrelations so that the weight at a particular lag length will be proportional to the corresponding autocorrelation coefficient expected under the alternative hypothesis. As a result, the Fama and French regression test is likely to have little power against reasonable alternative hypotheses positing slow variation in expected returns over the business cycle.

Since a test's power depends critically on the nature of the alternative hypothesis, a powerful test must impose *a priori* reasonable restrictions on the behavior of expected returns over the business cycle. A general test, such as the Box and Pierce (1970) portmanteau or Q test, will lack power precisely because it imposes little or no such restrictions.[10] On the other hand, it may also be inappropriate to rely on a test positing an exact parameterization of returns over the business cycle, for example, an $AR(p)$ specification. While such a test will more likely reject the stationary random walk model if such a specification actually characterizes the expected

[10]The Box-Pierce test is only optimal if we believe that return autocorrelations are different from zero but we have no a priori information about *how* they should differ from zero.

return generating process, it may have little or no power if expected returns follow some other equally reasonable alternative.[11]

3.2 Powerful Autocorrelation Based Tests

Consider a demeaned stationary time series $\{r_t\}_{t=1}^T$ and define its autocorrelogram by

$$\rho_\tau = \frac{Cov(r_t, r_{t+\tau})}{Var(r_t)} \qquad \text{for } \tau > 0. \tag{7}$$

The autocorrelogram summarizes the autocorrelations of a stationary time series as a function of lag length τ.

We estimate the autocorrelation coefficient at lag length τ by

$$\hat{\rho}_\tau = \frac{T \sum_{j=1}^{T-\tau} r_j r_{j+\tau}}{(T-\tau) \sum_{j=1}^{T} r_j^2}. \tag{8}$$

However, to minimize the effects of any noise in the data, we consider the averaged autocorrelogram estimated by

$$\hat{\rho}_\tau^* = \frac{1}{2\delta + 1} \sum_{i=\tau-\delta}^{\tau+\delta} \hat{\rho}_i. \tag{9}$$

That is, the averaged autocorrelation at τ is estimated by the arithmetic average of the corresponding $2\delta + 1$ sample autocorrelation coefficients centered at lag length τ. Under the null hypothesis that $\{r_t\}_{t=1}^T$ is serially uncorrelated, it follows that

$$\sqrt{(2\delta+1) \cdot (T-\tau)} \cdot \hat{\rho}_\tau^* \sim \mathcal{N}(0, 1). \tag{10}$$

The motivation for this averaging is similar to that of smoothing or windowing in spectral analysis.[12] However, if δ is chosen too large, the resultant over-averaging will eliminate any long-term persistence. Alternatively, a too small δ value will not minimize the effects of any noise. We use $\delta = 3, 4$, and 5. Our choice follows directly from the properties of the business cycle tabulated by macroeconomists. In particular, peacetime expansions (from trough to

[11] For example, Jacquier and Nanda (1990) assume that stock returns explicitly follow an AR(2) specification with complex roots.

[12] In spectral analysis the problem is more severe since if the spectrum is not smoothed the resultant periodigram estimator will be inconsistent. Note that the implicit assumption which justifies the spectral windowing operation in small samples is that the true spectrum is 'smooth' or persistent; that is, adjacent periodigram estimates are close in value. This is precisely the reasoning we use here.

peak) in the United States over the period 1933 to 1982 have an average duration of 37 months with a standard deviation of 15 months, but peacetime contractions (from peak to trough) have only an average duration of 11 months with a standard deviation of 3 months (see Zarnowitz (1992) p. 23, Table 2.1). As a result, by choosing $\delta = 3, 4$, and 5, the averaging window's width is approximately 11 months, ensuring that we do not average over more than one contraction.

To assess whether sampled averaged autocorrelations provide statistical evidence against the stationary random walk hypothesis, we provide two univariate test procedures to detect business cycle induced deviations. The first, the *Sparse* χ^2 or χ^2_S test statistic,

$$\chi^2_S = (2\delta + 1) \sum_{j=1}^{N} (T - (\tau_j + \delta))\, \hat{\rho}^{*2}_{\tau_j} \tag{11}$$

where $\tau_j = \delta + (j-1)(2\delta + 1)$, directly tests the joint restriction imposed by the stationary random walk model across the *averaged* autocorrelogram

$$H_0 : \qquad \rho^*_{\tau_1} = \ldots = \rho^*_{\tau_N} = 0.$$

The derivation of the χ^2_S test statistic and its small sample properties are detailed in Appendix Appendix B.1.

A potential shortcoming of the χ^2_S statistic is that its realized value may be sensitive to the particular averaging interval chosen. In other words, since the averaged autocorrelogram is infrequently (or sparsely) sampled via expression (11), significant departures from the stationary random walk model evidenced, for example, by a peak in the averaged autocorrelogram, may not be detected.

Consequently, we also rely on a second univariate test procedure, the Bonferroni test statistic, which is not subject to this potential shortcoming. In particular, consider the set of averaged autocorrelations coefficients $\{\hat{\rho}^*_\tau\}$ generated by expression (9).[13] Using the Bonferroni inequality, we can calculate an upper bound for the probability, under the null hypothesis H_0, of an averaged autocorrelation being at least as extreme as the most extreme of the observed averaged autocorrelations, $\max_\tau |\hat{\rho}^*_\tau|$. This upper bound is independent of the correlation structure of $\{\hat{\rho}^*_\tau\}$. If this probability is less than conventional significance levels, we may confidently reject H_0.

[13] In our actual calculations, we adjusted this expression for small sample bias as explained in footnote 25.

The derivation of the Bonferroni test statistic and its small sample properties are detailed in Appendix Appendix B.2. Appendix Appendix B.3 investigates the empirical power of both of our univariate tests and demonstrates their power in small samples to detect business cycle deviations from the stationary random walk model.

3.3 Univariate Test Results

We apply our test procedures to monthly excess returns over the post-World War II sample period, 1947:1 - 1992:12. The results are tabulated in Table 1.

Notice that in the absence of averaging, $\delta = 0$, both the χ^2_S (Panel A) and Bonferroni tests (Panel B) reject the random walk model for the small firm portfolio, decile 1. Given the relative importance of these small stocks to the equal-weighted (EW) CRSP portfolio, we see that for $\delta = 0$ the χ^2_S statistic also rejects the random walk model for EW excess returns.[14] However, without averaging, we cannot reject the random walk model for excess returns to either the value-weighted (VW) CRSP portfolio or the large firm portfolio, decile 10.

With averaging, both the χ^2_s and Bonferroni tests now provide evidence against excess returns of the EW and VW portfolios following a random walk. But as suggested earlier, the performance of the χ^2_S test appears sensitive to the choice of δ and the width of the resultant averaging window. In particular, while the Bonferroni test rejects EW and VW excess returns following a random walk for each of $\delta = 3, 4$, and 5, the χ^2_S test only rejects for $\delta = 4$. In addition, both tests reject the null hypothesis with greater significance for the VW portfolio. This result may reflect the greater volatility of excess returns to small firm portfolios. Similar conclusions hold for the decile portfolios where, in particular, the Bonferroni test allows us to reject the random walk hypothesis for the large firm portfolio.[15]

[14]These rejections are due to large autocorrelations at lags which are exact multiples of one year suggesting that this result is due to the January effect Banz (1981) and Keim (1983)).

[15]These results also allow us to reject the $AR(1)$ fads model for stock prices. Recall that any $AR(1)$ fads model implies negative return autocorrelations at all lags. Since applying the Bonferroni inequality to the largest positive averaged autocorrelation rejects the random walk model, for which all autocorrelations are assumed equal to zero, it also rejects the $AR(1)$ fads model. Alternatively, we can also assume a particular specification for the $AR(1)$ fads model and then transform the return series so that the resultant autocorrelations *would* all be zero if this specification held. We then can apply our test to the averaged autocorrelations of the transformed series. Doing so, in unreported results, we strongly reject the specifications of the $AR(1)$ fads model suggested by Poterba and Summers (1988). Also, in unreported results, we find that our evidence against the stationary random walk model is not due to

4 Multivariate Tests

Our preceding empirical analysis demonstrates that excess returns do not follow a stationary random walk. Since our univariate test procedures, motivated by Abel's model, are designed to exploit the persistence which characterizes the business cycle, this suggests the presence of a business cycle effect in excess returns. To statistically confirm and characterize this effect, we now provide a multivariate empirical analysis of excess returns and the business cycle.

Our multivariate analysis is related to that of Chen (1991) who investigates whether the ability of the default and term spreads, as well as other variables including the market dividend yield, to forecast excess returns is due to their power to forecast future output growth and output volatility. However, we extend Chen's analysis in several ways.

First, Chen confirms that these forecasting variables are indicators of current and future economic prospects and can indeed forecast excess returns. Yet it may very well be the case that a different component of these variables is forecasting excess returns than is forecasting output growth or volatility. Therefore, it is important to investigate whether there exists a *direct* link between output and excess returns. To do so, however, is complicated by the fact that measures of output, such as industrial production, are integrated variables, requiring use of stochastic detrending methods to properly obtain their stationary component.

Secondly, motivated by the Fama and French (1989) finding that the default spread and the market dividend yield appear to track longer-run variability in economic conditions than does the term spread, we also investigate the temporal characteristics of these forecasting relationships. We do so by using spectral techniques, as discussed by Baxter and King (1994), to decompose excess returns, the forecasting variables, and production growth and its volatility into their respective trend, cycle, and high frequency components.

The sample period used in our multivariate tests begins in 1953:01. Industrial production data is available on a monthly basis from CITIBASE beginning in 1947:01, but six years of monthly data (72 observations) are used to initialize our stochastic detrending methods.

unconditional nor conditional heteroskedasticity in excess returns.

4.1 Stochastic Detrending of Industrial Production

We use two stochastic detrending methods to empirically estimate the temporary component of post-Korean War industrial production: The Watson (1986) Unobserved Components ARIMA (*UC-ARIMA*) method and the Hodrick and Prescott (1980) filter.

4.1.1 The *UC-ARIMA* Method

The *UC-ARIMA* method recognizes that while the log of industrial production, lny_t, is itself observable, its additive components, τ_t and c_t, are individually unobservable. More significantly, to identify parameters, the *UC-ARIMA* method decomposes the observed series assuming that the trend and stationary innovations are uncorrelated:

$$cov(e_t^{\tau}, e_{t-k}^{c}) = 0 \qquad \forall\ k.$$

That is, the economic factors giving rise to trend innovations are assumed to be unrelated to the economic sources of business cycle movements.

Maximum likelihood estimation of the *UC-ARIMA* model is carried out by casting the model into state-space form and using the Kalman filter initialized at a vague prior Harvey (1981)). Given the maximum likelihood parameter estimates, the Kalman filter also yields corresponding estimates of the unobservable state variables (τ_t, c_t). The maximum likelihood estimation results for the 1953:1 to 1992:12 sample period are as follows (with asymptotic standard errors in parentheses)

$$\begin{array}{rllll}
\ln y_t = & \tau_t + c_t & & & \\
\Delta\tau_t = & .00315 \ + e_t^{\tau} & & \sigma_{\tau} = & .00608 \\
 & (.00031) & & & (.00058) \\
c_t = & 1.664 \ \cdot c_{t-1} - & 0.6848 \ \cdot c_{t-2} + e_t^{c} & \sigma_c = & 0.00652 \\
 & (0.014) & (0.014) & & (0.00060).
\end{array}$$

These results are consistent with an average monthly growth rate of 0.32% in industrial production over our sample period. Industrial production's temporary component is estimated by an AR(2) specification; higher order autoregressive coefficients were found to be statistically insignificant.[16]

[16] We fit the *UC-ARIMA* model with AR(p) specifications for p= 1, 2, 3, and 4. The Akaike information criterion (AIC) was computed for each - for p = 1, AIC = 4311.4; for p = 2, AIC = 4408.8; for p = 3, AIC = 4406.8; for p =4, AIC = 4405.6 - and is largest for p = 2.

4.1.2 The Hodrick-Prescott Filter

To ensure that our subsequent empirical results are not specific to a particular stochastic detrending method, we also apply the Hodrick-Prescott filter to our industrial production data. The Hodrick-Prescott filter uses spline smoothing Reinsch (1967)) to stochastically detrend macroeconomic data. We modify their procedure to utilize only past data (through time t) to estimate industrial production's stochastic trend at time t. This one-sided version of the Hodrick-Prescott filter ensures that any empirically observed relationship between realized returns and the estimated cyclical component does not simply reflect the empirical fact that stock returns forecast future changes in industrial production (Fama (1981, 1990)).

Our one-sided version of the Hodrick-Prescott filter uses the previous $n = 120$ monthly observations of industrial production to estimate τ_t. For each t we determine the function $\{\hat{\tau}_s\}_{s=t-n}^{t}$ which for a given λ minimizes

$$\sum_{s=t-n}^{t} (\ln y_s - \hat{\tau}_s)^2 + \lambda \sum_{s=t-n+1}^{t-1} \left[(\hat{\tau}_{s+1} - \hat{\tau}_s) - (\hat{\tau}_s - \hat{\tau}_{s-1})\right]^2 . \tag{12}$$

The trend at time t is then estimated by $\hat{\tau}_t$ and the estimate of the cyclical component is given by $\hat{c}_t = \ln y_t - \hat{\tau}_t$.

Here λ represents the trade-off between closeness of fit, measured by the residual sum of squares (the first portion of expression (12)), and the smoothness of τ_t, measured by the integrated squared second derivative of the trend (the second portion of expression (12)).

As noted by King and Rebelo (1993), this stochastic detrending method can also be interpreted as a moving average filter which for appropriate λ values removes low frequency movements in the underlying data. We chose that value of λ (3×10^6) which removes fluctuations having periodicity of greater than 8 years in monthly industrial production data. Recall that according to NBER calculations, the business cycle in post-World War II macroeconomic data has periodicity of between approximately two and eight years. This also corresponds to the stochastic characteristics of the Hodrick-Prescott filter implemented by Kydland and Prescott (1990), as well as by Hodrick and Prescott (1980) themselves.

4.1.3 Industrial Production's Estimated Temporary Component

In Figure 1 we plot the estimated temporary component obtained by applying our one-sided Hodrick-Prescott filter to industrial production data over the 1953:01 to 1992:12 sample period. For comparison purposes, we also plot the corresponding temporary component estimated by the *UC-ARIMA* method as well as the NBER datings of business cycle peaks and troughs.[17] Notice that regardless of the stochastic detrending method used, there appears to be broad correspondence between our estimates and the NBER's peak to trough business cycle periods.

4.2 Excess Returns and Industrial Production's Temporary Component

According to Abel's model and our time series specification of industrial production dynamics, we should observe an inverse relationship between excess returns and industrial production's temporary component. Furthermore, if the previously documented deviations from the stationary random walk model are due to business cycle related movements in expected returns, then once we control for industrial production's cyclical component, our univariate tests should provide little, if any, evidence against the null hypothesis that the resultant residuals are serially uncorrelated. Table 2 presents the results of regressing excess returns to the EW, VW, and size decile portfolios against industrial production's temporary component estimated by the UC-ARIMA method (Panel A) and the Hodrick-Prescott filter (Panel B). Consistent with countercyclical movements in expected returns, notice that the regression slope coefficients are significantly negative throughout. The smaller firm portfolios appear to be more sensitive to business cycle movements than the larger firm portfolios. However, the explanatory power of these regressions, as measured by their adjusted R^2s, is low. Assuming that all of the business cycle variation in expected returns has been captured, these results suggest that this business cycle variation is small when compared to the total variation observed in realized monthly returns. To determine whether the previously documented deviations from the stationary random walk model are attributable to business cycle related movements in expected returns, we investigate the stochastic behavior of these excess returns once the estimated cyclical effect is controlled for. We do so by subjecting the residuals of Table 2's regressions to our univariate

[17] The estimate of industrial production's temporary component obtained using spectral band-pass filtering is also presented. See Appendix C for further details.

test procedures. The results are presented in Table 3 where it is evident that the null hypothesis of serially uncorrelated residuals is rejected less frequently than the corresponding null hypothesis for excess returns. In fact, the tests provide no evidence of persistence in the EW and VW residuals at conventional significance levels.[18] This result compliments the Ferson and Harvey (1991) conclusion that most of the time variation in returns may be attributed to a single factor.

Unfortunately, this analysis ignores the fact that stochastic detrending methods estimate industrial production's temporary component with error. Consequently, an errors-in-variable problem may arise. To ensure the robustness of the results presented in Table 3, we generalize our UC-ARIMA framework as follows:

$$\begin{aligned} r_t &= \alpha + \beta c_t + \epsilon_t^r \\ \ln(y_t) &= \tau_t + c_t \\ \tau_t &= \delta + \tau_{t-1} + \epsilon_t^\tau \\ c_t &= \rho_1 c_{t-1} + \rho_2 c_{t-1} + \epsilon_t^c \end{aligned} \tag{13}$$

where, in addition, we assume that

$$cov(e_t^r, e_{t-k}^c) = cov(e_t^r, e_{t-k}^\tau) = cov(e_t^c, e_{t-k}^\tau) = 0 \;\; \forall \;\; k.$$

This joint estimation allows us to investigate the relationship between excess returns and industrial production's temporary component while explicitly recognizing that this cyclical component is estimated with error. Table 4 presents the results of applying our univariate tests to the residuals for the EW, VW, and size decile 1 and 10 portfolios. As in Table 3, we still see little evidence of persistence in these residuals.[19]

[18]We further investigate the robustness of these conclusions to the choice of stochastic detrending method as well as the choice of output series in Appendix Appendix C. There we apply a bandpass filter to GDP growth rates to estimate GDP's cyclical component. The Bonferroni test provides little evidence of serial correlation in the residuals obtained from regressing excess returns against this estimate of GDP's cyclical component.

[19]These results should still be interpreted with some caution since we have not formally accounted for the fact that the residuals are estimated in a separate step.

4.2.1 Business Cycle Indicators and the Predictability of Excess Returns

The preceding analysis provides evidence that the temporary component of industrial production contributes directly to the deviations from the stationary random walk model detected by our univariate test procedures. This conclusion is consistent with the evidence of Fama and French (1989) and others that the default and term spreads can reliably forecast excess returns, especially at long horizons. Default and term spreads are business cycle indicators, with both spreads being low around peaks and high around troughs. If expected returns also have a business cycle component, high returns when business conditions are poor and low returns when business conditions are good, then the default and term spreads are tracking this predictable variation in expected returns.

The estimated cyclical component of industrial production also reliably forecasts excess returns. This can be seen in Table 5 where long-horizon regressions are used to investigate the predictability of excess EW (Panel A) and excess VW (Panel B) returns using the UC-ARIMA estimated cyclical component as well as the default and term spreads.[20] Like the term spread, the estimated cyclical component only forecasts over approximately the next 12 months, with excess VW returns being more predictable than excess EW returns. This latter result is consistent with our univariate test procedures providing stronger evidence against the random walk hypothesis for excess VW returns. In contrast, the default spread forecasts excess returns over longer return horizons. The explanatory power of the default spread is particularly impressive for long horizon excess VW returns; for example, the default spread alone explains approximately 30% of the variation in 48 month excess VW returns.

If this evidence of predictability is consistent with the term spread and the default spread tracking the business cycle variation in excess returns, then these spreads should track industrial production's cyclical component itself. Table 6 directly investigates this by using the UC-ARIMA estimated cyclical component and regressing its changes over successive past and future quarters against the default and term spreads. The countercyclical behavior of both

[20]The default and term spreads are calculated as in Fama and French (1989). We do not include the market dividend yield in our analysis because Fama and French show that it is significantly correlated with the default spread and so moves in a similar way with business conditions. Industrial production's temporary component estimated by the more *ad-hoc* Hodrick-Prescott filter is not separately analyzed but provides similar results.

these spreads is readily apparent. For example, the term spread is significantly related to both past and future changes in the estimated cyclical component of industrial production. As measured by the regressions' R^2s, the term spread is particularly informative about future cyclical changes (up to four quarters). In comparison, while the default spread is also significantly related to both past and future changes in the estimated cyclical component, it appears to provide only a modest amount of information about these changes (up to four quarters in either direction).

However, by construction, changes in production's cyclical component (Δc) do not reflect changes in its trend component ($\Delta \tau$) which also contribute to future production growth (Δlny). To capture this, we regress changes in the log of industrial production over successive past and future quarters against the term and default spreads as well as its estimated cyclical component (Table 7). To ensure the robustness of our results, we also use gross domestic product (GDP) (Table 8).

Like Chen (1991), we find that the default spread is only correlated with immediate past growth rates in industrial production and GDP, although the informativeness of these regressions, as measured by their corresponding $R^2 s$, is minimal. In contrast, the term spread is correlated, in a countercyclical fashion, with both future and, unlike Chen, past growth rates.[21] These regressions are particularly informative about the future growth of the economy (up to four quarters). Similar to the default spread, the estimated cyclical component is only correlated with past growth rates in industrial production and GDP. However, unlike the default spread regressions, these regressions are quite informative about these past growth rates. That the cyclical component provides little information about the economy's future prospects is not surprising since it is estimated on the basis of current and past industrial production data. We also use long horizon regressions to investigate whether the residuals from regressing excess VW returns on the UC-ARIMA estimated cyclical component are themselves predictable using the default and term spreads as well as the estimated cyclical component (Table 9). Like the long horizon excess return regressions, we find that the term spread is significant in forecasting these residuals out to a 12 month horizon, while the default spread is significant out to a 48 month horizon. Also, the explanatory power of the default spread in these regressions signifi-

[21] This latter result may simply reflect the fact that Chen goes back only 4 quarters in his analysis.

cantly exceeds that of the term spread. The estimated cyclical component, as expected, is not found to be significant throughout.

While the default spread can reliably forecast excess returns (Table 5), it says little about the current health of the economy or its future growth prospects (Table 6, 7, and 8). Appealing to Abel's model, this suggests that the default spread provides information about production's volatility. Following Chen (1991), we proxy this volatility by the absolute value of the residuals obtained from regressing changes in the log of industrial production against the average of the default spread over the preceding three months as well as last month's term spread and cyclical estimate[22]:

$$\Delta \log(IP_t + j) = \alpha + \beta_1 \sum_{i=1}^{3} \text{DEF}_{t-i} + \beta_2 \text{TERM}_{t-1} + \beta_3 \text{Cycle}_{t-1} + \epsilon_t + j$$

and our proxy for volatility is[23]:

$$\hat{\sigma}_{IP} = |\epsilon_t|.$$

We then regress changes in production volatility over successive past and future quarters against the term spread and the default spread. The results are tabulated in Table 10. Notice that the default spread and, to a lesser extent, the term spread are correlated with future changes in production volatility. In particular, a high (low) default spread today is associated with an increase (decrease) in future production volatility, while a high (low) term spread today implies a decrease (increase) in future production volatility.

Consistent with Chen (1991), we conclude that the term spread provides information about the economy's future growth prospects. However, while Chen attributes the default spread's ability to forecast excess returns to its informativeness regarding the economy's current health, our results, in contrast, demonstrate that the default spread's forecasting ability arises primarily from its informativeness regarding future production volatility. We explore the macroeconomic determinants of this predictive ability in the next section.

[22] We use the average of the default spread because this provides more forecast power for future IP growth and a corresponding higher R^2 for the regression.

[23] Similar results are obtained if we proxy production volatility by the square of these residuals.

4.2.2 Frequency Band Correlations

The first differencing of macroeconomic variables, such as production or its volatility, potentially obscures any long term dependence which may exist between these variables and excess returns by removing much of this data's low frequency component. Such long term dependence has previously been suggested by Fama and French (1989) who argue, using long horizon regressions and by visual inspection of the data, that long-run variation in expected returns is captured by the default spread, while the term spread forecasts expected returns' shorter-run variation.

In this section, we directly investigate this hypothesis by separately correlating movements in excess returns with movements in default and term spreads at frequencies corresponding to trend movements, business cycle movements, as well as the remaining high-frequency movements in the data. To do so, we filter these variables to isolate their (i) fluctuations which exceed 32 quarters in length (trend component); (ii) fluctuations between 6 and 32 quarters in length (business cycle component); and (iii) fluctuations less than 6 quarters in length (high-frequency component). As noted by Baxter and King (1994), this specification of frequency bands is consistent with Burns and Mitchell (1946) finding that business cycles tend to be no less than 6 quarters in length but typically last fewer than 32 quarters.[24]

Table 11 presents these frequency band correlations for excess EW VW returns. Notice that excess returns are significantly positively correlated with the default and term spreads at the business cycle frequencies. In other words, consistent with the previous multivariate empirical evidence of Keim and Stambaugh (1986) and Fama and French (1989) and others, these spread variables *do* capture the business cycle component of excess returns, with high (low) default and term spreads being significantly associated with high (low) excess returns at these frequencies. However, excess returns are correlated with the default and term spreads at other frequencies. At high frequencies we see a significant positive correlation only between excess returns and the term spread. In contrast, at the trend frequencies, a significant positive correlation is found only between the default spread and excess returns. Therefore, consistent

[24]This particular specification is also used by Baxter (1994) who finds that the correlation between real exchange rates and real interest rate differentials is strongest at these trend and business cycle frequencies. We filter our variables using approximate band-pass filters. Further details are provided in Appendix Appendix C.

with Fama and French's claim, the default spread's trend or low frequency component reliably tracks excess returns' low frequency component, while high frequency movements in excess returns are captured by the term spread's high frequency component.

To better understand the macroeconomic determinants of their predictive ability, Table 11 also gives the correlations of the filtered components of the term and default spreads with production growth rates and production volatility. Production growth rates are significantly positively correlated with the term and default spreads at the business cycle frequencies, with the term spread's correlation being slightly higher. However, these spreads are only marginally correlated with extremely short run variation in production growth rates, and appear to provide no information about the long run variation in production growth rates. Alternatively, we see that production volatility appears to be significantly and positively correlated with the default spread at all frequency bands. In particular, a positive correlation obtains between production volatility and the default spread at the trend frequencies.[25]

The preceding spectral analysis provides an interesting perspective on the relationship between stock returns and the macroeconomy. The dynamics of macroeconomic variables, such as production or its volatility, are characterized by both a stochastic trend component

[25]This spectral analysis suggests an alternative univariate test procedure to exploit the persistence which characterizes the business cycle. Recall that our χ^2_S and Bonferroni test statistics are designed explicitly to take advantage of this characteristic of the business cycle. Alternatively, if excess returns are independently distributed, then the variance of excess returns should be randomly distributed across all frequencies. However, if excess returns exhibit a business cycle induced persistence, then relatively more of this variance should be concentrated at the business cycle frequencies. Hence a most powerful test is obtained by taking the ratio of the variance of the excess return series at the business cycle frequencies to its total variance (see Daniel (1996) for further detail).

More formally, let $A(r_t) = b_t * r_t$ denote the excess return series filtered, as before, to retain only business cycle fluctuations between 6 and 32 quarters in length. The optimal test statistic is of the form

$$\frac{\hat{\sigma}^2(A(r_t))}{\hat{\sigma}^2(r_t)}$$

where $\hat{\sigma}^2$ denotes the sample variance. Notice that this test statistic is like a standard variance-ratio test statistic (Cochrane (1988)) except that for the standard variance-ratio test b is simply a moving average filter.

Under the null hypothesis that excess returns are independently distributed, this test statistic will be asymptotically F distributed. However, to take account of any small sample bias, Monte Carlo methods should be used to determine corresponding empirical cut-off values. When applying this test to excess returns over the 1947:01-1993:12 sample period, we reject the null hypothesis at better than the 1% significance level for the EW, VW and all size decile portfolios save for decile 1 returns where the null is rejected at better than the 5% significance level. This latter result is probably due to the presence of the January seasonal.

as well as a business cycle component. Appealing to Abel's model, excess returns will also be characterized by stochastic trend and business cycle components; it is this latter component which is detected by our univariate test procedures as business cycle deviations from the stationary random walk model. However, the default and term spreads provide additional information about excess returns beyond that contained at business cycle frequencies. In particular, long swings in excess returns, attributable to changes in the macroeconomy's trend, are captured by the default spread whose long run predictive ability arises from the fact that it contains information about corresponding long swings in production volatility.

5 Conclusions

Multivariate tests of market efficiency, for example, Keim and Stambaugh (1986) and Fama and French (1989), conclude that business cycle indicators, such as the default spread and the term spread, reliably forecast stock returns. This result is generally attributed to the systematic variation in expected returns over the business cycle.

Since the distinguishing characteristic of the business cycle is its persistence, the Abel (1988) intertemporal asset pricing model implies that this same persistence will also be evident in the time series behavior of expected returns. Unfortunately, extant univariate tests of market efficiency provide little power against reasonable alternative hypotheses positing slow variation in expected returns over the business cycle. By contrast, this paper's univariate test procedures, motivated by Abel's model and based on a weighted autocorrelogram of returns, allow us to reject, with a high degree of statistical confidence, the null hypothesis that expected returns are constant over the business cycle.

We confirm that industrial production growth rates and excess returns exhibit similar autocorrelation patterns in the post-World War II sample period, suggesting that the business cycle may explain these deviations from the stationary random walk model. We directly measure the business cycle by the stochastically detrended level of industrial production. Regressing excess returns against this estimate of industrial production's cyclical component, our univariate test procedures provide little evidence that the resultant residuals exhibit persistence.

Of course, we cannot design a single univariate test which is most powerful against *all* alternatives. It is quite likely then that our χ_s^2 and Bonferroni test statistics will not be able to detect potentially more complicated autocorrelation patterns present in the data once we have removed industrial production's cyclical component. That the default and term spreads can forecast these residuals implies that these market based variables provide information about excess returns beyond that contained in production's cyclical component and suggests that the business cycle itself does not explain all of the predictability in excess returns.

To more fully characterize the relationship between financial markets and the macroeconomy, this paper recognizes that macroeconomic time series are characterized by variable trends as well as recurrent cyclical fluctuations around this growth path. Our resultant multivariate analysis concludes that while the business cycle contributes to the deviations from the stationary random walk model that we have documented for stock prices, predictable long term swings in expected returns arising from these variable trends remain.

Appendix A Demonstration that the autocorrelogram of a persistent series will itself be autocorrelated

This Appendix formally demonstrates that if a series is persistent, its autocorrelations will be serially correlated.

Consider the real valued, square-summable series $\{x_t\}$ whose Fourier transforms is given by $x(\omega)$, where the Fourier transform is defined by:

$$x(\omega) = \sum_{k=-\infty}^{\infty} x_t e^{i\omega t}.$$

Given Parseval's relation, we have that $x(\omega)$ is in $L_2[-\pi, \pi]$. Consider a second series $\{z_t\}$ which is defined by the relation of its Fourier transform to that of $\{x_t\}$:

$$z(\omega) = y(\omega) \cdot x(\omega)$$

where

$$y(\omega) = \begin{cases} 1 & |\omega| < \omega_0 \\ 0 & \omega_0 \leq |\omega| \leq \pi \end{cases} \tag{14}$$

That is, we are defining $\{z_t\}$ to be just $\{x_t\}$ with its high frequency components attenuated.

The spectrum of $\{z_t\}$ is given by the product of $z(\omega)$ and its complex conjugate:

$$g_z(e^{-i\omega}) = z(\omega) \cdot z(-\omega) = x(\omega) \cdot x(-\omega) \cdot y(\omega) \cdot y(-\omega) = g_x(e^{-i\omega}) \cdot g_y(e^{-i\omega})$$

Inverse Fourier transforming the above relationship gives the autocovariogram of the transformed series:

$$c_z(k) = \frac{1}{2\pi} \int_{-\pi}^{\pi} g_z(e^{-i\omega}) e^{i\omega k} d\omega = \frac{1}{2\pi} \int_{-\pi}^{\pi} g_x(e^{-i\omega}) \cdot g_y(e^{-i\omega}) e^{i\omega k} d\omega = \left(c_x \star c_y(k)\right)_k.$$

where the $\star$ denotes the convolution operation which is defined by:

$$\left(c_x \star c_y(k)\right)_k = \sum_{s=-\infty}^{\infty} c_x(s) c_y(k-s) = \sum_{s=-\infty}^{\infty} c_x(k-s) c_y(s)$$

Since $g_x(e^{-i\omega})$ and $g_y(e^{-i\omega})$ are real-valued, and $c_x(-k) = c_x(k)$ and $c_y(-k) = c_y(k)$, we have that

$$c_y(k) = \frac{1}{2\pi} \int_{-\pi}^{\pi} g_y(e^{-i\omega}) e^{i\omega k} d\omega = \frac{1}{2\pi} \int_{-\pi}^{\pi} \left[y(\omega) \cdot y(-\omega)\right] e^{i\omega k} \, d\omega.$$

$c_y(k)$ can then be solved for directly using the definition of $y(\omega)$ given in equation (14).

$$c_y(k) = \frac{1}{2\pi} \int_{-\omega_0}^{\omega_0} e^{i\omega k} d\omega = \left(\frac{1}{2\pi}\right) \frac{e^{i\omega k}}{ik}\Bigg|_{-\omega_0}^{\omega_0} = \left(\frac{1}{2\pi}\right) \frac{e^{i\omega_0 k} - e^{-i\omega_0 k}}{ik} = \frac{\sin(\omega_0 k)}{\pi k} \tag{15}$$

Also, note that the value of the integral is defined at $k = 0$ and is equal to $\frac{\omega_0}{\pi}$. For large values of k, the value of $c_y(k)$ will be small.

Thus we see that the autocovariogram of $\{z_t\}$ is what is obtained when the autocovariogram of $\{x_t\}$ is smoothed using the smoothing kernel given in equation (15). The smaller the value of ω_0 (the more the high frequencies are attenuated) the more the autocovariogram will be smoothed.

Appendix B Derivation of the Properties of the Univariate Test Statistics

Appendix B.1 Derivation of the χ_S^2 Test statistic and Its Small Sample Properties

Consider the averaged autocorrelation estimator

$$\hat{\rho}_\tau^* = \frac{1}{(2\delta+1)} \sum_{i=\tau-\delta}^{\tau+\delta} \hat{\rho}_i \tag{16}$$

where $\hat{\rho}_i$ is now defined by

$$\hat{\rho}_i = \frac{\sum_{j=1}^{T-(\tau+\delta)} r_j r_{j+i}}{\sum_{j=1}^{T-(\tau+\delta)} r_j^2}. \tag{17}$$

To derive the asymptotic sampling properties of $\hat{\rho}_\tau^*$, note that expressions (16) and (17) imply the following set of orthogonality conditions

$$\frac{1}{T-(\tau+\delta)} \sum_{j=1}^{T-(\tau+\delta)} (r_j r_{j+\tau-\delta} + \ldots + r_j r_{j+\tau+\delta} - (2\delta+1)\hat{\rho}_\tau^* r_j^2) = 0 \qquad \tau = \tau_1, \ldots, \tau_N. \tag{18}$$

From Hansen (1982), $\hat{\rho}_\tau^*$ will be asymptotically normally distributed about its true mean, and, furthermore, under the null hypothesis that returns are serially uncorrelated, its corresponding analytical variance-covariance matrix is given by $\mathbf{V} = [v_{\tau_i\tau_j}]$ where

$$v_{\tau_i\tau_j} = \frac{max[(2\delta+1) - |\tau_i - \tau_j|, 0]}{(2\delta+1)^2}. \tag{19}$$

To test the null hypothesis

$$H_0: \qquad \rho_{\tau_1}^* = \ldots = \rho_{\tau_N}^* = 0,$$

we consider the following test statistic

$$\chi^2 = \left(\sqrt{T-(\tau_1+\delta)}\hat{\rho}_{\tau_1}^* \ldots \sqrt{T-(\tau_N+\delta)}\right) \hat{\rho}_{\tau_N}^* \mathbf{V}^{-1} \begin{pmatrix} \sqrt{T-(\tau_1+\delta)}\hat{\rho}_{\tau_1}^* \\ \vdots \\ \sqrt{T-(\tau_N+\delta)}\hat{\rho}_{\tau_N}^* \end{pmatrix}. \tag{20}$$

Under H_0, this test statistic is asymptotically distributed $\chi_(^2 N)$ where N represents the number of restrictions imposed. To implement this test procedure the following should be noted:

1. Our joint test applied to an unaveraged autocorrelogram ($\delta = 0$) will have little statistical power to detect business cycle induced deviations from the stationary random walk model. Recall that return autocorrelations will themselves be correlated in the presence of the business cycle. Though the induced correlations may be small in magnitude, autocorrelations of the same sign will tend to cluster. However, the χ^2 statistic in the absence

of averaging ($\delta = 0$) in expression (20) is invariant to the ordering of autocorrelations and, as such, the clustering evident in the returns autocorrelogram has no effect on its value.

2. The joint test applied across an averaged autocorrelogram can be based on either overlapping averaging intervals, $(\tau_{i+1} - \tau_i) < (2\delta + 1)$, or non-overlapping averaging intervals, $(\tau_{i+1} - \tau_i) = (2\delta + 1)$. For example, we could apply our test statistic, expression (20), to *all* averaged autocorrelations between lags τ_1 through τ_N as a test of the joint restriction

$$\rho^*_{\tau_1} = \rho^*_{\tau_1+1} = \cdots = \rho^*_{\tau_N-1} = \rho^*_{\tau_N} = 0 \tag{21}$$

where the two adjacent averaged autocorrelations $\rho^*_{\tau_i}$ and $\rho^*_{\tau_i+1}$ share 2δ autocorrelations $\{\rho_{\tau_i-\delta+1}, \cdots, \rho_{\tau_i+\delta}\}$. However, if the following 2δ restrictions are additionally imposed

$$\rho_{\tau_1-\delta} = \rho_{\tau_1-\delta+1} = \cdots = \rho_{\tau_1+\delta-2} = \rho_{\tau_1+\delta-1} = 0$$

then taken together these restrictions yield

$$\rho_{\tau_1-\delta} = \rho_{\tau_1-\delta+1} = \cdots = \rho_{\tau_N+\delta-1} = \rho_{\tau_N+\delta} = 0, \tag{22}$$

precisely the joint restriction tested by applying our test statistic to the unaveraged autocorrelogram between lags $\tau_1 - \delta$ and $\tau_N + \delta$. Intuitively, the independent restrictions implied by expression (21) correspond approximately to the restrictions implied by expression (22). from Morrison (1976), it follows that the value of the χ^2 statistic testing expression (21) will be approximately equal to the value of the χ^2 statistic testing expression (22).[26] Therefore this joint test will have little power to detect cyclical deviations from the null hypothesis.

Consequently, we restrict our attention to the test statistic based on averaged autocorrelations with non-overlapping averaging intervals $(\tau_{i+1} - \tau_i) = (2\delta + 1)$, as applied to equation 11.

We assess the empirical performance of the χ^2_S statistic by conducting the following Monte Carlo simulation.[27] To reflect monthly observations over the 1947:1 to 1992:12 sample period, 552 observations are drawn independently from a $\mathcal{N}(\mu, \sigma^{\in})$ distribution with parameters chosen to match the corresponding mean and the variance of the CRSP VW index.[28] Subsequently,

[26] More precisely, Morrison shows that if two restrictions are equivalent (*i.e.* linear combinations of one another), the corresponding χ^2 statistics will be identical.

[27] Since the autocorrelation estimator, expression (16), exhibits small sample bias under the null hypothesis, we correct for this by using the following autocorrelation estimator:

$$\hat{\rho}_i = \frac{\sum_{j=1}^{T-(\tau+\delta)} r_j r_{j+i}}{\sum_{j=1}^{T-(\tau+\delta)} r_j^2} + \frac{1}{T-(\tau+\delta)}.$$

We use this estimator in all our analyses.

[28] The sampling results are invariant with respect to the particular choice of mean and variance. Intuitively, varying these parameters does not affect the maintained assumption that monthly return observations are uncorrelated. In particular, changing the assumed mean simply shifts the simulated return series up or down, the effect of which is removed by demeaning, and therefore does not affect return autocorrelations. Similarly, multiplying the simulated returns by a constant increases the series' variance, but does not affect sample autocorrelations.

for each of $\delta = 0, 3, 4$, and 5, we choose non-overlapping lag lengths, $\tau_1, \ldots, \tau_N$, spanning 109 months from a minimum of 12 months to a maximum of 120 months. For example, for $\delta = 3$ we have 15 non-overlapping averaging intervals of length 7 months centered at $\tau_1 = 15$ months, $\tau_2 = 22$ months, $\ldots, \tau_{14} = 106$ months, and $\tau_{15} = 113$ months. By considering lags of between 12 and 120 months, we include holding periods considered by Fama and French (1988b) (one to ten years) and Poterba and Summers (1988) (two to eight years), as well as the periodicity of the NBER minor business cycle (two to four years) and the NBER major business cycle (eight years). The χ^2_S statistic is calculated according to expression (11) for each of $\delta = 0, 3, 4$, and 5. We repeat this procedure 100,000 times and tabulate the resultant sampling distributions in Table 12.

Notice that for each δ, the empirical distribution is shifted out relative to the tails of the corresponding χ^2 distribution. Furthermore, this rejection bias appears to be more severe the smaller the assumed value of δ. Given that our test is biased toward rejection when using tabulated χ^2 values, we rely exclusively on the corresponding empirical distributions.

Appendix B.2 Derivation of the Bonferroni Joint Z Test Statistic

Assume H_0 imposes N restrictions on the averaged autocorrelogram. In particular, for each of the lag lengths $\tau_1, \ldots, \tau_N$, we calculate from expression (10) corresponding test statistics $\{Z_{\tau_1}, \ldots, Z_{\tau_N}\}$. Of the N available test statistics, let

$$Z^{max} = \max_{\tau}\{|Z_\tau|\}$$

with a corresponding marginal significance level of α^* where

$$1 - \Phi(Z^{max}) = \alpha^*/2$$

and $\Phi(\cdot)$ represents the standard normal cumulative distribution function. In other words,

$$P\{|Z_\tau| > Z^{max}\} = \alpha^* \text{ for all } \tau.$$

An upper bound on the probability of rejecting H_0 is given by $N\alpha^*$ since by the Bonferroni inequality (see Miller (1966), especially page 8) it follows that

$$P\{\cup_\tau[|Z_\tau| \geq Z^{\alpha/2N}]\} = 1 - P\{\cap_\tau[|Z_\tau| < Z^{max}]\} \leq \sum_\tau P\{|Z_\tau| > Z^{max}\} = N\alpha^*.$$

Alternatively, for a given significance level α, we can determine the critical test statistic value Z^* such that

$$1 - \Phi(Z^*) = \alpha/2N \tag{23}$$

which allows rejection of H_0 with probability not exceeding α. Intuitively, ignoring the potential dependence between test statistics across different holding periods will, in general, overstate the joint probability of rejecting H_0.

We also summarize the empirical performance of the Bonferroni test in Table 12. As before, 554 observations are independently drawn from a $N(\mu, \sigma^2)$ distribution with parameters chosen to match the mean and variance of the CRSP VW index over the sample period 1947:1 to

1992:12. Repeating this procedure 100,000 times, we calculate empirical cutoff values for the Bonferroni test statistic, for each of $\delta = 0, 3, 4$ and 5, under the assumption that the stationary random walk model implies the following $N = 109 - 2\delta$ restrictions:

$$H_0 : \rho^*_{12+\delta} = \rho^*_{12+\delta+1} = \cdots = \rho^*_{120-\delta-1} = \rho^*_{120-\delta} = 0.$$

For comparison purposes, expression (23) is used to calculate corresponding theoretical cutoff values.

Whether we average or not, we see from Table 12 that the empirical cutoff values are in broad agreement with their theoretical counterparts. However, with averaging the empirical distribution is shifted out slightly relative to the tails of the theoretical distribution. As in the case of the χ^2_S statistic, we subsequently rely on the empirical distribution of the Bonferroni test statistic.

Appendix B.3 Empirical Power of the χ^2_s and Bonferroni Tests

We now investigate the power of the χ^2_S and Bonferroni tests in small samples. The particular alternative hypothesis, H_A, assumed is that returns are generated by an AR(2) process with complex roots (see Jacquier and Nanda (1990)). This parsimonious specification allows us to vary expected returns in a smooth cyclical fashion. We emphasize, however, that the AR(2) specification is chosen only for illustrative purposes. As noted earlier, we expect our univariate tests to exhibit power against *any* alternative characterized by slow variation in expected returns.

We assume that realized returns (r_t) are composed of expected return (μ_t) and idiosyncratic (ν_t) components. The idiosyncratic component is assumed normally distributed, while expected returns follow a second order process. More formally,

$$\begin{array}{ll} \tilde{r}_t = \tilde{\mu}_t + \tilde{\nu}_t & \tilde{\nu}_t \sim \mathcal{N}(0, \sigma^2_\nu) \\ (1 - \lambda_1 \mathbf{L})(1 - \lambda_2 \mathbf{L})\tilde{\mu}_t = \tilde{\epsilon}_t & \tilde{\epsilon}_t \sim \mathcal{N}(130581)(0, \sigma^2_\epsilon) \\ \lambda_1 = e^{-\rho} e^{i\omega}, \quad \lambda_2 = e^{-\rho} e^{-i\omega} & \end{array}$$

According to this specification, the autocorrelogram for realized returns exhibits damped oscillations (for $\rho > 0$) with periodicity of $2\pi/\omega$.

Our sampling experiments assume that the periodicity of movements in expected returns corresponds to a business cycle periodicity of 48 months by setting $\omega = 2\pi/48$. According to Zarnowitz (1992), peacetime business cycles in the United States have an average duration of 48 months over the period 1933 to 1982. We also set $\rho = 0.01$ as well as $\rho = 0.03$; the larger the value of ρ, the more damped expected return oscillations. Finally, without loss of generality, we assume $\sigma^2_\nu = 1$ and vary the proportion, γ, of the total variance of the realized return series attributable to time varying expected returns between $\gamma = 0.001$ and $\gamma = .2$. The larger γ, the more important expected return variation is to the behavior of realized returns.

For a given specification of the alternative hypothesis, we generate a realized return series of length 554 months. We then use the corresponding empirical cutoff values of the χ^2_S and Bonferroni joint Z test statistics to determine whether to reject the null hypothesis, H_0, of a stationary random walk model. We also investigate the empirical power of Fama and French's long-horizon regression test by using the empirical cutoff values of the Richardson and Smith (1991) Wald test of whether the eight Fama and French regression coefficients are jointly equal to zero. We generate 100,000 realized return series and calculate the empirical power of a particular test as the proportion of times it rejects H_0 at a given significance level.

The results are tabulated in Table 13 assuming a 5% significance level. As expected, for the smallest value of γ, each test rejects H_0 approximately 5% of the time. However, as γ increases, that is, as the proportion of the variance attributable to time varying expected returns increases, both the χ^2_S and Bonferroni joint Z tests reject H_0 far more frequently. For example, for $\gamma = 0.20$ and $\rho = 0.03$, the percentage rejection levels for the χ^2_S and Bonferroni joint Z tests are 98%, yet only 19% for the long-horizon regression test. The empirical power gains of the χ^2_S and Bonferroni joint Z tests appear to be larger for $\rho = 0.03$ than $\rho = 0.01$, suggesting that the more damped expected return oscillations are, the greater the deterioration in the performance of the long-horizon regression test.

Appendix C   Frequency Band Correlation Analysis

From Baxter and King (1994), we adapt the Burns and Mitchell (1946) specification that the business cycle, on average, lasts no less than six quarters or eighteen months, and typically lasts fewer than thirty-two quarters or eight years.

By specifying the business cycle as fluctuations within this particular range or band of periodicities necessitates that we eliminate very slow moving components in the data (having periodicities greater than eight years) as well as rapidly varying seasonal and irregular components (having periodicities less than eighteen months), while retaining, or passing through, the remaining intermediate components.

The resultant ideal band-pass filter requires a symmetric two-sided moving-average filter of, unfortunately, infinite order. We approximate this filter by a finite-order two-sided moving average with maximum lag length K, implying that we lose $2K$ observations (K lags and K leads). So while increasing K improves this approximation, it results in more lost observations. We chose $K = 30$ months for our post-World War II monthly time series, implying that our spectral analysis covers the 1949:07 to 1990:06 sample period.[29]. We then determine the resultant moving average weights which minimize the distance, in a weighted least squares sense, between the ideal and actual frequency responses using MATLAB's FIRLS (finite impulse response least squares) function. Similarly, we construct low-pass and high-pass filters which, respectively, only pass through movements in the data of more than eight years and less than eighteen months. The frequency responses of the resultant filters are plotted in Figure 2. Notice that the responses of the high-pass and band-pass filters are both zero at zero frequency meaning that both will remove any $I(1)$ or unit root component present in the data. This is not the case for the low-pass filter.

To investigate the robustness of our univariate conclusions, we apply this band-pass filter to GDP growth rates and regress excess returns against GDP's resultant cyclical component.

[29]For further discussion on the choice of K, see Baxter and King (1994), especially Section 2.6, pages 8-9.

By using GDP rather than industrial production, we ensure that our results are not particular to industrial production data. The Bonferroni test once again reveals little evidence of serial correlation in the resultant residuals:

	$\delta = 3$	$\delta = 4$	$\delta = 5$
VW	-2.77	-2.47	-2.37
EW	$3.25^{\dagger}$	2.58	2.23

where † denotes significance at a 10% level.

We calculate frequency band correlations between two filtered time series as follows. We lag one of the series by between -12 and +12 months and calculate the correlation between the two series at each of these twenty-five lags. The correlation that we actually report at a particular frequency is the maximum of these twenty-five correlations since it is unlikely that the strongest relationship between the two filtered series occurs when the two series are coincident. This procedure does not introduce a bias when assessing the statistical significance of our results because we take this maximization into account when calculating the reported correlation coefficients' p-values.

Because filtering introduces serial dependence in the resultant time series, standard measures of the statistical significance of autocorrelations are inappropriate. We therefore use Monte Carlo methods to properly assess this statistical significance. In particular, we perform a frequency band correlation analysis, exactly as above, for a sequence of *i.i.d.* normal random numbers with either the default spread or the term spread. This analysis is repeated 50,000 times. The p-values reported are the fraction of these 50,000 correlation coefficients which are higher than the corresponding coefficient obtained with actual data. Thus the p-values represent the probability of obtaining correlation coefficients at least as large as observed if returns or industrial production growth rates are *i.i.d.* normal and distributed independently of the default and term spreads. However, this distributional assumption may not be appropriate for the industrial production series and, as a result, may introduce a bias in the corresponding p-values.

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Table 1: χ_S^2 **and Bonferroni Statistics -** *Stationary Random Walk Model*

This table presents the results of applying the univariate test statistics to monthly portfolio excess returns. The portfolio returns are the log returns of the VW, EW, and the NYSE/CRSP size decile portfolios 1 and 10 (1 is smallest), net of the 1-month T-Bill rate from the CRSP RISKFREE file. The statistics for the χ_S^2 (Panel A) and Bonferroni (Panel B) tests are for autocorrelogram smoothing parameters of $\delta = 0, 3, 4$, and 5. Significance levels are indicated below. The sample period is 1947:01 to 1992:12.

	Panel A: χ_S^2 Statistic				Panel B: Bonferroni Statistics			
index	$\delta = 0$	$\delta = 3$	$\delta = 4$	$\delta = 5$	$\delta = 0$	$\delta = 3$	$\delta = 4$	$\delta = 5$
EW	152.81*	19.69†	18.01†	11.21	2.70	3.92*	4.07*	4.14*
VW	111.93	17.88	23.68*	11.26	-3.04	3.40*	3.26†	-3.09†
D1	321.59*	52.14*	28.58*	20.72*	6.92*	-4.20*	-4.41*	-4.55*
D10	110.63	20.05†	23.58*	12.51†	2.76	3.94 *	4.17*	4.24*

† denotes significance at a 10% level, and * at a 5% level.

Table 2: **Regression of Excess Portfolio Returns on Stochastically Detrended Industrial Production**

This table presents slope coefficients with Hansen-Hodrick corrected t-statistics and R^2s of univariate regressions of excess portfolio returns on stochastically detrended industrial production. The independent variables are log returns of the VW, EW, and the NYSE/CRSP size decile portfolios 1 and 10 (1 is smallest) net of the 1-month T-bill rate from the CRSP RISKFREE file. The dependent variable is the total US industrial production series (seasonally adjusted) from CITIBASE (Series IP) stochastically detrended using the $UC - ARIMA$ method (Panel A) and a one-side version of the Hodrick-Prescott filter (Panel B). Significance levels are indicated below. The sample period is 1953:01 to 1992:12.

	A: UC-ARIMA			B: Hodrick-Prescott		
	β	$T(\beta)$	$R^2(\%)$	β	$T(\beta)$	$R^2(\%)$
VW	-0.21	-3.14*	2.4	-0.0059	-2.88*	2.0
EW	-0.28	-3.16*	2.4	-0.0078	-2.92*	2.0
D1	-0.30	-2.41*	1.4	-0.0076	-2.06*	1.0
D10	-0.19	-2.90*	2.0	-0.0053	-2.67*	1.7

† denotes significance at a 10% level, and * at a 5% level.

Table 3: **Univariate Test Statistics of Residuals from Regressions of Excess Portfolio Returns on Stochastically Detrended Industrial Production**

This table presents the results of applying the univariate test statistics to the residuals obtained from the regression of portfolio excess returns on stochastically detrended industrial production. The Bonferroni and χ^2_S statistics are for autocorrelogram smoothing parameters of $\delta = 0, 3, 4$, and 5. Significance levels are indicated below. Panel A presents the results for the regression of excess returns on Hodrick-Prescott detrended industrial production, and Panel B for *UC-ARIMA* detrended industrial production. The sample period is 1953:01 to 1992:12.

Panel A: **Residuals from Regression on HP Detrended Production**

	χ^2_s statistic				Bonferroni statistics			
index	$\delta = 0$	$\delta = 3$	$\delta = 4$	$\delta = 5$	$\delta = 0$	$\delta = 3$	$\delta = 4$	$\delta = 5$
EW	140.35†	24.28†	17.29	12.94	-2.99	2.79	-3.53	-2.84
VW	110.17	20.00	14.39	13.78	-2.63	3.41*	2.73	2.88
D1	200.48*	22.05	15.49	8.97	4.64*	-3.01	-2.86	-2.53
D10	108.80	19.20	12.45	11.68	-2.63	3.52*	2.73	2.68

Panel B: **Residuals from Regression on** *UC-ARIMA* **Detrended Production**

	χ^2_s statistic				Bonferroni statistics			
index	$\delta = 0$	$\delta = 3$	$\delta = 4$	$\delta = 5$	$\delta = 0$	$\delta = 3$	$\delta = 4$	$\delta = 5$
EW	140.60†	23.19	16.80	12.10	3.02	2.85	-3.51	-2.83
VW	110.49	19.44	14.36	13.30	2.66	3.39*	2.70	2.94
D1	199.99*	20.85	14.48	8.27	4.56*	-2.94	-2.82	-2.45
D10	108.77	18.60	12.23	11.19	-2.61	3.47*	2.68	2.71

† denotes significance at a 10% level, and * at a 5% level.

Table 4: **Univariate test statistics of excess return residuals obtained from the Bivariate Kalman filter.**

This table presents the the results of applying the univariate test statistics to the return residuals (e_t^r) obtained from the maximum likelihood estimation of the system of equations in expression (13). The Bonferroni and χ_S^2 statistics are calculated for autocorrelogram smoothing parameters of $\delta = 0, 3, 4$, and 5. Significance levels are indicated below. The sample period is 1953:01 to 1992:12.

	χ_S^2 Statistic				Bonferroni Statistics			
index	$\delta = 0$	$\delta = 3$	$\delta = 4$	$\delta = 5$	$\delta = 0$	$\delta = 3$	$\delta = 4$	$\delta = 5$
EW	141.86*	16.24	7.54	7.09	3.43*	2.71	2.72	2.41
VW	112.72	21.12	13.20	13.91	-2.72	3.31†	2.59	2.96
DEC1	164.04*	15.39	8.27	6.49	-3.77*	2.49	2.57	-2.55
DEC10	114.66	25.45†	16.01	16.25†	-2.67	3.98*	3.18†	3.06†

† denotes significance at a 10% level, and * at a 5% level.

Table 5: **Long-horizon Univariate Regressions of Excess Portfolio Returns on State Variables**

This table presents slope coefficients with Hansen-Hodrick corrected t-statistics and R^2s of univariate regressions of long-horizon excess returns on state variables. Results for excess EW returns are in Panel A while results for excess VW returns are in Panel B. The state variables used are the default spread, the term spread, and industrial production's temporary component estimated using the $UC-ARIMA$ method. Significance levels are indicated below. The sample period is 1953:01 to 1992:12.

Panel A - Excess EW Returns

Horizon	Default Spread			Term Spread			Estimated Cycle		
(months)	Coeff	T-stat	R^2(%)	Coeff	T-stat	R^2(%)	Coeff	T-stat	R^2(%)
1	3.2720	2.54*	1.33	0.6099	3.41*	2.37	-0.2758	3.17*	2.06
3	11.2104	3.22*	4.22	1.2884	2.74*	2.84	-0.7522	3.20*	4.13
6	21.3773	3.56*	7.33	1.7803	2.22*	2.57	-1.2920	3.14*	5.81
12	34.6346	3.44*	10.41	2.5479	1.81†	2.78	-1.7575	2.36*	5.76
24	40.3681	2.26*	8.19	-2.9122	1.35	2.08	-0.2209	0.18	0.05
36	17.4934	0.80	1.29	-4.0713	1.51	3.43	0.3795	0.26	0.13
48	3.1555	0.12	0.04	-3.7638	1.09	2.40	0.0260	1.56	0.00

Panel B - Excess VW Returns

Horizon	Default Spread			Term Spread			Estimated Cycle		
(months)	Coeff	T-stat	R^2(%)	Coeff	T-stat	R^2(%)	Coeff	T-stat	R^2(%)
1	2.7158	2.73*	1.53	0.5532	3.97*	3.23	-0.2092	3.11*	1.97
3	8.8182	3.55*	5.03	1.2153	3.64*	5.39	-0.5919	3.50*	4.93
6	18.1011	4.26*	9.93	1.9421	3.40*	6.48	-1.0630	3.56*	7.43
12	32.8702	5.35*	16.89	3.0442	3.11*	7.28	-1.5548	2.95*	8.12
24	50.2398	5.32*	25.02	0.6514	0.46	2.08	-0.9379	0.02	1.81
36	50.7771	4.35*	23.34	0.9140	0.57	0.81	-0.9219	0.02	3.87
48	58.6367	4.26*	28.68	1.6875	0.92	1.44	-1.4940	1.48	3.84

† denotes significance at a 10% level, and * at a 5% level.

Table 6: **Univariate Regressions of Quarterly Changes in Industrial Production's Estimated Temporary Component on State Variables**

This table presents slope coefficients with Hansen-Hodrick corrected t-statistics and R^2s of univariate regressions of the form $\Delta c_{t+lag} = a + b \cdot \text{state variable}_t + e_t$ where Δc_{t+lag} is the change in industrial production's temporary component from quarter $t + lag - 1$ to $t + lag$. The temporary component is estimated using the $UC - ARIMA$ method. The state variables used are the default spread, the term spread, and industrial production's temporary component itself. Significance levels are indicated below. The sample period is 1953:01 to 1992:12.

Lag	Default Spread			Term Spread			Estimated Cycle		
	coeff	T-stat	R^2(%)	coeff	T-stat	R^2(%)	coeff	T-stat	R^2(%)
-16	0.5150	0.8894	0.54	-0.0076	0.1028	0.01	-0.0221	0.5639	0.22
-15	0.9421	1.6431	1.82	-0.0274	0.3736	0.10	-0.0315	0.8090	0.45
-14	0.7796	1.3605	1.24	-0.0221	0.3025	0.06	-0.0215	0.5548	0.21
-13	0.7680	1.3413	1.20	-0.0690	0.9455	0.60	-0.0236	0.6092	0.25
-12	0.5499	0.9599	0.61	-0.1352	1.8793†	2.30	-0.0097	0.2522	0.04
-11	0.3552	0.6227	0.26	-0.1810	2.5418*	4.13	-0.0027	0.0692	0.00
-10	-0.2592	0.4577	0.14	-0.1419	1.9835*	2.54	-0.0093	0.2457	0.04
-9	-0.2791	0.4967	0.16	-0.1062	1.4803	1.42	0.0096	0.2552	0.04
-8	-0.3221	0.5790	0.22	-0.0643	0.8954	0.52	0.0588	1.5778	1.60
-7	-0.3770	0.6819	0.30	-0.0532	0.7398	0.35	0.0846	2.2931*	3.30
-6	-0.4819	0.8773	0.49	-0.0643	0.8971	0.52	0.0941	2.5735*	4.10
-5	-0.7842	1.4413	1.31	-0.0356	0.4972	0.16	0.1381	3.8937*	8.86
-4	-1.2095	2.2569*	3.14	-0.0072	0.1010	0.01	0.1813	5.3399*	15.37
-3	-1.4428	2.7336*	4.52	0.0188	0.2648	0.04	0.1885	5.6216*	16.67
-2	-1.4791	2.8263*	4.78	0.0160	0.2250	0.03	0.1833	5.4552*	15.77
-1	-1.1993	2.2934*	3.18	0.0053	0.0755	0.00	0.1080	3.0445*	5.48
0	-0.7578	1.4495	1.29	0.1890	2.7440*	4.47	-0.1055	2.9817*	5.23
1	-0.0799	0.1513	0.01	0.3293	4.9840*	13.44	-0.1813	5.3946*	15.39
2	1.3732	2.6950*	4.37	0.2901	4.3684*	10.72	-0.1832	5.5496*	16.23
3	1.5238	3.0883*	5.69	0.2690	4.1160*	9.68	-0.1801	5.5826*	16.48
4	1.4820	2.9966*	5.41	0.2096	3.1343*	5.89	-0.1369	4.0617*	9.51
5	1.0805	2.1493*	2.88	0.0885	1.2859	1.05	-0.0913	2.6145*	4.20
6	0.4986	0.9775	0.61	0.0337	0.4848	0.15	-0.0832	2.3497*	3.44
7	0.5794	1.1405	0.84	-0.0796	1.1465	0.85	-0.0579	1.6172	1.67
8	0.9327	1.8838†	2.27	-0.2032	3.0674*	5.79	-0.0058	0.1633	0.02
9	0.5371	1.0744	0.75	-0.2179	3.2995*	6.68	0.0143	0.4027	0.11
10	0.0941	0.1867	0.02	-0.1922	2.8794*	5.20	0.0071	0.1986	0.03
11	-0.0311	0.0614	0.00	-0.1497	2.2120*	3.16	0.0138	0.3866	0.10
12	-0.4907	0.9803	0.64	-0.0547	0.8030	0.43	0.0250	0.7042	0.33
13	-0.3150	0.6322	0.27	-0.0258	0.3800	0.10	0.0196	0.5547	0.21
14	-0.1443	0.2888	0.06	-0.0496	0.7292	0.36	0.0284	0.8060	0.44
15	-0.2126	0.4242	0.12	-0.0272	0.3977	0.11	0.0191	0.5376	0.20
16	-0.3757	0.7481	0.38	-0.0108	0.1572	0.02	-0.0148	0.4168	0.12

† denotes significance at a 10% level, and * at a 5% level.

Table 7: **Univariate Regressions of Quarterly Growth Rates in Industrial Production on State Variables**

This table presents slope coefficients with Hansen-Hodrick corrected t-statistics and R^2s of univariate regressions of the form growth $\text{rate}_{t+lag} = a + b \cdot \text{state variable}_t + e_t$ where growth rate_{t+lag} is the growth in industrial production from quarter $t + lag - 1$ to $t + lag$. The state variables used are the default spread, the term spread, and industrial production's temporary component estimated by the $UC - ARIMA$ method. Significance levels are indicated below. The sample period is 1953:01 to 1992:12.

Lag	Default Spread			Term Spread			Estimated Cycle		
	coeff	T-stat	R^2(%)	coeff	T-stat	R^2(%)	coeff	T-stat	R^2(%)
-16	0.7241	0.7648	0.40	-0.0149	0.1236	0.01	-0.0286	0.4457	0.14
-15	1.1613	1.2347	1.03	-0.0350	0.2914	0.06	-0.0375	0.5888	0.24
-14	0.9483	1.0096	0.69	-0.0342	0.2861	0.06	-0.0328	0.5183	0.18
-13	1.1602	1.2380	1.02	-0.1541	1.2955	1.12	-0.0316	0.5003	0.17
-12	0.8466	0.9038	0.55	-0.2658	2.2664*	3.33	-0.0123	0.1952	0.03
-11	0.3532	0.3785	0.10	-0.3329	2.8758*	5.23	-0.0193	0.3085	0.06
-10	-0.2895	0.3125	0.06	-0.2877	2.4764*	3.90	-0.0353	0.5678	0.21
-9	-0.1525	0.1658	0.02	-0.2299	1.9712*	2.49	0.0193	0.3127	0.06
-8	-0.3441	0.3771	0.09	-0.1959	1.6738†	1.80	0.0976	1.5985	1.64
-7	-0.3802	0.4183	0.11	-0.2334	1.9990*	2.53	0.1390	2.2933*	3.30
-6	-0.8966	0.9522	0.63	-0.2509	2.1591*	2.92	0.1978	3.3414*	6.72
-5	-1.7287	1.9488†	2.38	-0.2051	1.7627†	1.95	0.3212	5.8172*	17.83
-4	-2.4919	2.8635*	4.96	-0.1904	1.6409	1.69	0.4047	7.9114*	28.50
-3	-3.1505	3.7089*	8.01	-0.1353	1.1654	0.85	0.4476	9.2115*	34.94
-2	-3.2141	3.8225*	8.42	-0.1839	1.5959	1.58	0.4490	9.3028*	35.25
-1	-2.9475	3.5127*	7.16	-0.0883	0.7639	0.36	0.2355	4.1464*	9.70
0	-2.2621	2.6814*	4.27	0.2694	2.3735*	3.38	-0.0677	1.1413	0.80
1	-0.5939	0.6894	0.30	0.4438	4.0145*	9.15	-0.1438	2.4543*	3.63
2	1.2568	1.4642	1.33	0.3893	3.4628*	7.01	-0.1712	2.9389*	5.15
3	1.2674	1.5097	1.42	0.4495	4.1343*	9.76	-0.1787	3.1355*	5.86
4	1.3118	1.5595	1.53	0.3278	2.9305*	5.19	-0.1154	1.9780*	2.43
5	0.7093	0.8362	0.45	0.2073	1.8167†	2.07	-0.0957	1.6228	1.66
6	0.1153	0.1352	0.01	0.1041	0.8995	0.52	-0.0966	1.6282	1.67
7	0.9577	1.1501	0.85	-0.0996	0.8742	0.49	-0.0539	0.9127	0.54
8	1.2155	1.4738	1.40	-0.2739	2.4674*	3.83	0.0161	0.2747	0.05
9	0.5329	0.6408	0.27	-0.2938	2.6495*	4.41	0.0322	0.5465	0.20
10	0.0087	0.0103	0.00	-0.2830	2.5393*	4.10	0.0183	0.3092	0.06
11	-0.2790	0.3333	0.07	-0.2058	1.8279†	2.18	0.0446	0.7554	0.38
12	-0.9118	1.1066	0.82	-0.1025	0.9138	0.56	0.0504	0.8640	0.50
13	-0.5062	0.6164	0.26	-0.1067	0.9566	0.61	0.0494	0.8521	0.49
14	-0.4203	0.5100	0.18	-0.1314	1.1739	0.93	0.0660	1.1367	0.87
15	-0.6911	0.8383	0.48	-0.1003	0.8930	0.54	0.0374	0.6407	0.28
16	-0.8236	0.9968	0.68	-0.0900	0.7982	0.44	-0.0145	0.2471	0.04

† denotes significance at a 10% level, and * at a 5% level.

Table 8: **Univariate Regressions of Quarterly Growth Rates in GDP on State Variables**

This table presents slope coefficients with Hansen-Hodrick corrected t-statistics and R^2s of univariate regressions of the form growth rate$_{t+lag}$ $= a + b \cdot$ state variable$_t$ $+ e_t$ where growth rate$_{t+lag}$ is the growth rate in GDP from quarter $t+lag-1$ to $t+lag$. The state variables used are the default spread, the term spread, and industrial production's temporary component estimated by the $UC-ARIMA$ method. Significance levels are indicated below. The sample period is 1953:01 to 1992:12.

Lag	Default Spread			Term Spread			Estimated Cycle		
	coeff	T-stat	R^2(%)	coeff	T-stat	R^2(%)	coeff	T-stat	R^2(%)
-16	0.2244	0.5382	0.20	-0.0348	0.6569	0.30	-0.0079	0.2797	0.05
-15	0.3218	0.7754	0.41	-0.0407	0.7729	0.41	-0.0173	0.6171	0.26
-14	0.3072	0.7424	0.37	-0.0343	0.6534	0.29	-0.0097	0.3487	0.08
-13	0.1512	0.3657	0.09	-0.0839	1.6110	1.72	-0.0007	0.0264	0.00
-12	0.1173	0.2845	0.05	-0.1500	2.9451*	5.50	0.0080	0.2898	0.06
-11	-0.0136	0.0332	0.00	-0.1884	3.7757*	8.68	0.0066	0.2389	0.04
-10	-0.3584	0.8822	0.51	-0.1190	2.3251*	3.46	0.0096	0.3506	0.08
-9	-0.4874	1.2068	0.95	-0.0860	1.6652†	1.79	0.0370	1.3652	1.21
-8	-0.3793	0.9401	0.57	-0.1091	2.1143*	2.84	0.0781	2.9427*	5.36
-7	-0.4494	1.1160	0.80	-0.1277	2.4764*	3.83	0.0992	3.7845*	8.51
-6	-0.8224	2.0743*	2.70	-0.1471	2.8795*	5.08	0.1246	4.9155*	13.49
-5	-1.1171	2.8692*	5.01	-0.0588	1.1298	0.81	0.1641	6.9213*	23.49
-4	-1.3500	3.5277*	7.34	-0.0860	1.6637†	1.73	0.1927	8.7096*	32.58
-3	-1.5061	4.0086*	9.23	-0.0623	1.2044	0.91	0.1963	8.9996*	33.89
-2	-1.5326	4.1176*	9.63	-0.0474	0.9176	0.53	0.1719	7.4772*	26.02
-1	-1.4529	3.9192*	8.76	0.0041	0.0804	0.00	0.0895	3.4875*	7.06
0	-0.9411	2.4963*	3.73	0.1657	3.3281*	6.44	-0.0208	0.7854	0.38
1	-0.2449	0.6361	0.25	0.2453	5.1030*	14.00	-0.0529	2.0083*	2.46
2	0.493	1.2795	1.02	0.2224	4.5217*	11.39	-0.0548	2.0724*	2.63
3	0.3545	0.9217	0.53	0.2052	4.1382*	9.78	-0.0523	1.9760*	2.41
4	0.4689	1.2218	0.94	0.1686	3.3398*	6.63	-0.0378	1.4163	1.26
5	0.2881	0.7461	0.36	0.0840	1.6153	1.65	-0.0292	1.0829	0.75
6	0.2304	0.5973	0.23	0.0539	1.0290	0.68	-0.0328	1.2122	0.94
7	0.2639	0.6887	0.31	-0.0416	0.7956	0.41	-0.0297	1.0971	0.78
8	0.4391	1.1496	0.86	-0.0825	1.5913	1.63	-0.0142	0.5250	0.18
9	0.2068	0.5389	0.19	-0.1194	2.3229*	3.43	-0.0135	0.4975	0.16
10	-0.0077	0.0201	0.00	-0.0822	1.5806	1.63	-0.0222	0.8156	0.44
11	-0.0631	0.1631	0.02	-0.0529	1.0093	0.67	-0.0154	0.5623	0.21
12	-0.1452	0.3794	0.10	-0.0610	1.1761	0.92	0.0016	0.0602	0.00
13	-0.1447	0.3766	0.10	-0.0663	1.2745	1.09	0.0151	0.5551	0.21
14	-0.1605	0.4166	0.12	-0.0794	1.5242	1.56	0.0263	0.9672	0.63
15	-0.1869	0.4835	0.16	-0.0959	1.8409†	2.27	0.0227	0.8300	0.47
16	-0.246	0.6371	0.28	-0.0839	1.6072	1.75	-0.0002	0.0083	0.00

† denotes significance at a 10% level, and * at a 5% level.

Table 9: **Long-Horizon Univariate Regressions of Excess Returns Controlled for Industrial Production's Estimated Temporary Component on State Variables**

This table presents slope coefficients with Hansen-Hodrick corrected t-statistics and R^2s of univariate long-horizon regressions of residuals obtained from regressing excess VW returns on the $UC-ARIMA$ estimated temporary component of industrial production on state variables. The state variables used are the default spread, the term spread, and industrial production's estimated temporary component. Significance levels are indicated below. The sample period is 1953:01 to 1992:12.

Horizon	Default Spread			Term Spread			Estimated Cycle		
(months)	Coeff	T-stat	$R^2(\%)$	Coeff	T-stat	$R^2(\%)$	Coeff	T-stat	$R^2(\%)$
1	1.42	1.41	0.41	0.4081	2.93^*	1.75	0.0070	0.10	0.00
3	4.81	$1.85^\dagger$	1.46	0.8086	2.34^*	2.10	0.0381	0.21	0.02
6	9.79	2.00^*	2.85	1.2938	2.06^*	2.50	0.1022	0.30	0.07
12	17.60	$1.87^\dagger$	4.49	2.5040	2.12^*	4.46	0.3184	0.50	0.32
24	32.99	$1.88^\dagger$	7.39	1.7248	0.87	0.98	1.2832	1.17	2.32
36	38.79	1.60	6.73	2.3383	0.92	1.20	1.2101	0.85	1.36
48	49.42	$1.65^\dagger$	8.44	2.0601	0.69	0.71	0.8401	0.49	0.51

† denotes significance at a 10% level, and * at a 5% level.

Table 10: **Multivariate Regressions of Quarterly Changes in Estimated Production Volatility Against the Term and Default Spreads**

This table presents slope coefficients with Hansen-Hodrick corrected t-statistics and R^2's of multivariate regressions of the form $\hat{\sigma}_{IP,t+lag} = a + b \cdot \text{TERM}_t + c \cdot \text{DEF} + e_t$ where $\hat{\sigma}_{IP,t+lag}$ is the change in the estimated production volatility from quarter $t + lag - 1$ to $t + lag$. Significance levels are indicated below. The sample period is 1953:01 to 1992:12.

Lag	Default Spread		Term Spread		
	coeff	T-stat	coeff	T-stat	$R^2(\%)$
-16	-0.162	-0.23	-0.129	-1.42	1.8
-15	-0.579	-0.83	-0.036	-0.40	0.8
-14	-0.892	-1.28	0.044	0.50	1.4
-13	-0.434	-0.61	0.063	0.70	0.6
-12	0.200	0.29	0.045	0.50	0.3
-11	0.467	0.69	0.103	1.17	1.6
-10	0.169	0.26	0.12	1.42	1.7
-9	0.387	0.57	0.087	0.97	1.1
-8	0.909	1.34	0.095	1.06	2.5
-7	1.228	1.85†	0.156	1.78†	5.4
-6	1.198	1.80†	0.135	1.53	4.6
-5	1.401	2.24*	0.039	0.47	4.0
-4	1.807	3.29*	0.007	0.10	7.7
-3	1.515	2.91*	-0.052	-0.75	6.1
-2	1.504	3.06*	0.082	1.24	8.0
-1	2.595	4.26*	0.056	0.68	12.5
0	3.354	6.15*	-0.128	-1.72	22.4
1	2.656	4.61*	-0.13	-1.65†	14.5
2	2.102	3.48*	-0.194	-2.35*	11.0
3	1.832	3.16*	-0.191	-2.41*	10.0
4	2.239	3.80*	-0.204	-2.54*	12.9
5	2.304	3.90*	-0.227	-2.81*	14.2
6	1.518	2.47*	-0.188	-2.21*	7.3
7	1.118	1.83†	-0.142	-1.66†	4.3
8	0.669	1.11	-0.078	-0.92	1.5
9	1.202	1.96*	-0.029	-0.33	3.0
10	0.621	0.99	0.015	0.17	0.8
11	0.651	1.02	0.087	0.95	1.6
12	1.042	1.66	0.042	0.46	2.4
13	0.945	1.52	0.033	0.37	2.0
14	0.475	0.76	0.078	0.87	1.1
15	0.526	0.84	0.063	0.69	1.0
16	0.856	1.39	0.096	1.06	2.5

† denotes significance at a 10% level, and * at a 5% level.

Table 11: **Frequency Band Correlations**

This table presents frequency band correlations of the default and term spreads with excess VW and EW returns, as well as the growth in industrial production and the estimated volatility of industrial production. The trend component is given by fluctuations which exceed 32 quarters in length, the business cycle component is given by fluctuations between 6 and 32 quarters in length, while the high-frequency component is given by fluctuation less than 6 quarters in length. This filtering is accomplished using an approximate band-pass filter as detailed in Appendix C. The sample period is 1949:07 to 1990:06. To calculate frequency band correlations between any two filtered series we lag one of the series by between -12 and +12 months and calculate the correlation between the two series at each of these twenty-five lags. The reported correlation coefficient is the maximum of these twenty-five correlations.

	Trend		Bus. Cycle		High Freq.	
Series	DEF	TERM	DEF	TERM	DEF	TERM
VW	0.8917*	-0.0832	0.6411**	0.6715**	0.1166	0.1560†
EW	0.4787	-0.3122	0.7128**	0.6774**	0.1392†	0.1775*
IP Growth	0.0039	-0.3180	0.6151**	0.7042**	0.1311†	0.1055
IP Volatility	0.7187†	-0.1782	0.6276**	0.3990†	0.1993**	0.1270

† denotes significance at a 10% level, * at a 1% level, and ** at a 0.1% level.

Table 12: **Theoretical and Monte Carlo Determined Significance Levels of χ^2_S and Bonferroni Statistics**

This table presents the theoretically and Monte-Carlo calculated cutoff levels of the χ^2_S (Panel A) and Bonferroni (Panel B) test statistics for autocorrelogram smoothing parameters of $\delta = 0$, 3, 4, and 5 and a horizon of $\tau = 120$ months. The empirical cutoffs are calculated using 100,000 simulated returns series with 544 returns in each. The simulated series were demeaned and the univariate statistics (based on bias-adjusted sample autocorrelations) were calculated and compiled.

Panel A: χ^2_S **Statistic**

significance	$\delta = 0$ d.f.=109		$\delta = 3$ d.f.=15		$\delta = 4$ d.f.=12		$\delta = 5$ d.f.=9	
level	theoretical	empirical	theoretical	empirical	theoretical	empirical	theoretical	empirical
10%	128.4	122.8	22.3	19.3	18.5	15.5	14.7	11.8
5%	134.4	131.2	25.0	23.2	21.0	19.2	16.9	15.1
2%	141.3	139.2	28.5	27.2	24.3	22.9	19.9	18.4
1%	146.4	149.0	30.6	32.6	26.2	28.0	21.7	22.8
0.5%	151.0	156.2	32.8	36.6	28.3	31.8	23.6	26.3
0.2%	158.1	163.5	35.7	40.5	31.0	35.9	26.0	30.2
0.1%	160.4	172.2	37.7	45.8	32.9	41.4	27.9	35.0

Panel B: **Bonferroni Statistic**

significance	$\delta = 0$		$\delta = 3$		$\delta = 4$		$\delta = 5$	
level	theoretical	empirical	theoretical	empirical	theoretical	empirical	theoretical	empirical
10%	3.31	3.28	3.30	3.14	3.29	3.08	3.28	3.03
5%	3.50	3.48	3.49	3.38	3.48	3.35	3.47	3.31
2%	3.74	3.72	3.73	3.69	3.72	3.66	3.71	3.64
1%	3.91	3.90	3.90	3.90	3.89	3.88	3.89	3.87
0.5%	4.07	4.07	4.06	4.13	4.06	4.12	4.05	4.08
0.2%	4.28	4.29	4.27	4.36	4.26	4.39	4.26	4.37
0.1%	4.44	4.45	4.42	4.52	4.42	4.60	4.41	4.61

Table 13: **Monte Carlo calculated Power values for χ^2_S, Bonferroni and Long-Horizon Regression Tests**

This table presents the Monte-Carlo power (defined as 1 minus the Type I error rate) for the χ^2_S, Bonferroni and Long-Horizon tests against a specific $AR(2)$ alternative (described in the text) for reversion parameters of $\rho = 0.01$ and $\rho = 0.03$. The Bonferroni test statistic is the maximum absolute value of the averaged-autocorrelogram between lags of zero and 120 months while the χ^2_S is the value of a χ^2 test of whether the averaged autocorrelogram is everywhere zero (described in more detail in the text). Both tests use $\delta = 4$. The long-horizon regression test is the Wald test of whether the eight Fama-French regression coefficients are jointly equal to zero. The significance level for each test is empricically determined to be that which yields a type II error rate of 5%.

Monte-Carlo Determined Power Values for $\rho = 0.01$

	γ							
Test Type	0.001	0.002	0.005	0.01	0.02	0.05	0.1	0.2
χ^2_S	0.0526	0.0604	0.0691	0.1112	0.2203	0.5573	0.8437	0.9806
Bonferroni	0.0539	0.0597	0.0716	0.1116	0.2128	0.5405	0.8323	0.9768
Long-Horizon	0.0497	0.0508	0.0530	0.0606	0.0845	0.1733	0.3137	0.5085

Monte-Carlo Determined Power Values for $\rho = 0.03$

	γ							
Test Type	0.001	0.002	0.005	0.01	0.02	0.05	0.1	0.2
χ^2_S	0.0529	0.0601	0.0671	0.0980	0.1699	0.4582	0.8117	0.9844
Bonferroni	0.0537	0.0589	0.0696	0.0983	0.1653	0.4338	0.7807	0.9740
Long-Horizon	0.0500	0.0492	0.0518	0.0546	0.0638	0.0829	0.1287	0.1879

Figure 1: **Stochastically Detrended Production and NBER Turning Points, 1952-1993**

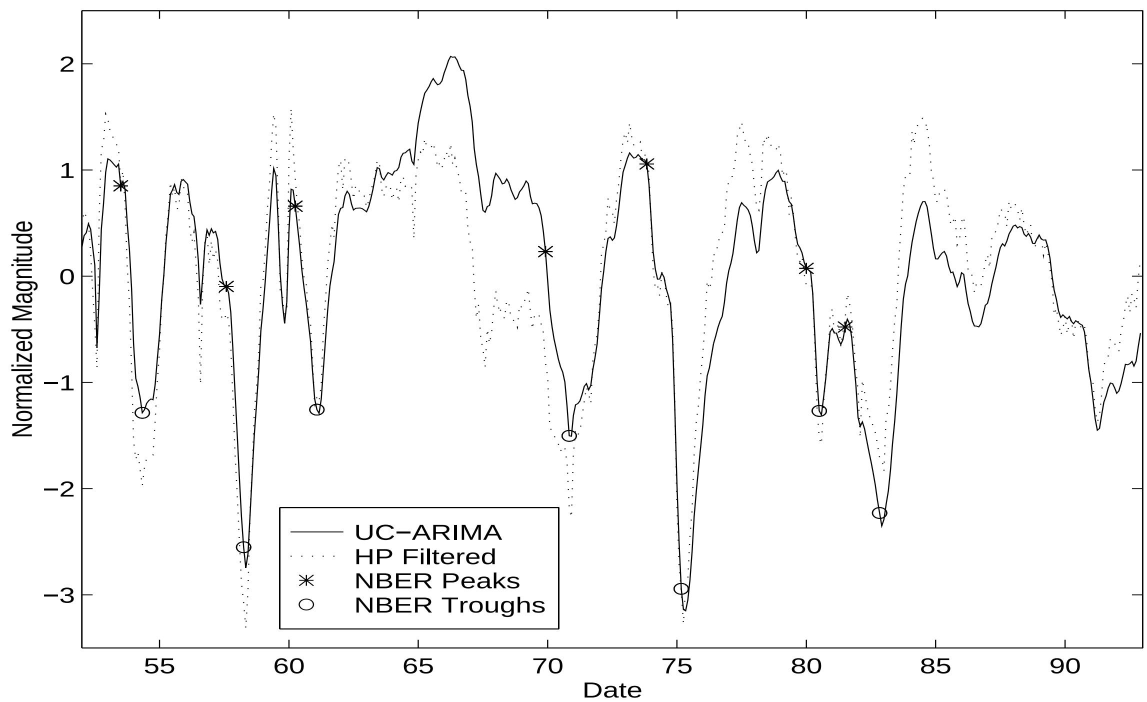

Figure 2: **Frequency Responses of Trend, Business Cycle and high-pass filters**