Low-Frequency Econometrics

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Abstract

Many questions in economics involve long-run or “trend” variation and covariation in time series. Yet, time series of typical lengths contain only limited information about this long-run variation. This paper suggests that long-run sample information can be isolated using a small number of low-frequency trigonometric weighted averages, which in turn can be used to conduct inference about long-run variability and covariability. An advantage of this approach is that, because the low-frequency weighted averages have large-sample normal distributions, large sample valid inference can often be conducted using familiar small sample normal inference procedures. Moreover, the general approach is applicable for a wide range of persistent stochastic processes that go beyond the familiar I(0) and I(1) models.

JEL classification: C22, C32, C12

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1 Introduction

This paper discusses inference about trends in economic time series. By “trend” we mean the low-frequency variability evident in a time series after forming moving averages such as low-pass (cf. Baxter and King (1999)) or Hodrick and Prescott (1997) filters. To measure this low-frequency variability we rely on projections of the series onto a small number of trigonometric functions (e.g., discrete Fourier, sine, or cosine transforms). The fact that a small number of projection coefficients capture low-frequency variability reflects the scarcity of low-frequency information in the data, leading to what is effectively a “small-sample” econometric problem. As we show, it is still relatively straightforward to conduct statistical inference using the small sample of low-frequency data summaries. Moreover, these low-frequency methods are appropriate for both weakly and highly persistent processes. Before getting into the details, it is useful to fix ideas by looking at some data.

Figure 1 plots the value of per-capita GDP growth rates (panel A) and price inflation (panel B) for the United States using quarterly data from 1947 through 2014, and where both are expressed in percentage points at an annual rate.\(^1\) The plots show the raw series and two “trends”. The first trend was constructed using a band-pass moving average filter designed to pass cyclical components with periods longer than $T/6 \approx 11$ years, and the second is the full-sample projection of the series onto a constant and twelve cosine functions with periods $2T/j$ for $j = 1, \ldots, 12$, also designed to capture variability for periods longer than 11 years.\(^2\) A glance at the figure shows that the band-pass and projection trends essentially coincide both for GDP, for which there is only moderate trend variability, and inflation, for which there is substantial trend variability. This paper focuses on trends computed by projection methods because, as we will see, they give rise to simple methods for statistical inference.

Figure 1 also suggests several empirical questions. For example, the trend in GDP growth

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\(^1\)Three data series are used in this paper. All are quarterly series from 1947:Q1 to 2014:Q4 for the United States. Per capita gross domestic product is available from FRED as series A939RC0Q052SBEA. Inflation is measured using the price deflator for personal consumption expenditures (FRED series PCECTPI). Total factor productivity is from Fernald (2014) and is available at http://www.frbsf.org/economic-research/economists/john-fernald/.

\(^2\)The low-pass values were computed using an ideal low-pass filter truncated after $T/2$ terms applied to the padded series using forecasts/backcasts constructed from an $AR(4)$ model. The cosine projections are the fitted values from the regression of the series onto a constant term and $\sqrt{2} \cos \left( j \left( t - \frac{1}{2} \right) / T \right)$ for $j = 1, \ldots, 12$. 
Figure 1: Trends in U.S. Time Series

Panel (A)

Panel (B)
has been low for the last decade. Does this portend low average growth over the next decade? Or, is there mean reversion in the trend so that the next decade is more likely to exhibit faster than average growth? And, what is the value of the population mean growth rate of GDP? The plot for inflation shows large persistent variation in its trends over the past sixty years. Does this suggest that the inflation process is $I(1)$? Or is this behavior consistent with an $I(0)$ process? Alternatively, what about something “between” the $I(0)$ and $I(1)$ processes? More generally, the average value of inflation varies considerably over non-overlapping 10- or 25-year time periods; average GDP growth rates show less, but still substantial variability. How much variability should we expect to see in future 10- and 25-year samples? Section 3 takes up these questions, along with several other questions that can be answered using univariate time series methods.

Figure 2 plots both total factor productivity (TFP) and GDP growth rates. The trend components of the series move together, suggesting (for good reason) that long-run variation in GDP and TFP growth rates are closely related. But, exactly how closely are they related, and by how much is the trend growth rate in GDP predicted to increase if the trend growth rate of TFP increases by, say, 10 basis points? Section 4 takes questions like these that involve multiple (here two) time series.

The paper begins, in Section 2, with notation and (finite and large-sample) properties of
discrete “cosine transforms,” the trigonometric projections used in our analysis. Sections 3 and 4 show how these cosine transforms can be used to answer trend-related inference questions. “Low-frequency” variability conjures up spectral analysis, and Section 5 uses frequency-domain concepts to explain several facets of the analysis. To keep the focus on key ideas and concepts, the analysis in the body of the paper uses relatively simple stochastic processes, and Section 6 briefly discusses some extensions and concludes.

2 Some properties of low-frequency weighted averages

Let \( x_t \) denote a scalar time series that is observed for \( t = 1, \ldots, T \), and let \( \Psi_j(s) = \sqrt{2} \cos(js\pi), \) so that \( \Psi_j(t/T) \) has period \( 2T/j \). Let \( \Psi(s) = [\Psi_1(s), \Psi_2(s), \ldots, \Psi_q(s)]' \), a \( \mathbb{R}^q \) valued function, and let \( \Psi_T = [\Psi((1-1/2)/T), \Psi((2-1/2)/T), \ldots, \Psi((T-1/2)/T)]' \) be the \( T \times q \) matrix obtained by evaluating \( \Psi(\cdot) \) at \( s = (t - \frac{1}{2})/T, \ t = 1, \ldots, T \). The low-frequency projections shown in Figures 1 and 2 are the fitted values from the OLS regression of \( [x_1, x_2, \ldots, x_T] \) onto a constant and \( \Psi_T \); that is, \( \hat{x}_t = \bar{x} + \Psi((t - 1/2)/T)'X_T, \) where \( \bar{x} = T^{-1} \sum_{t=1}^{T} x_t \) and \( X_T \) are the OLS regression coefficients. Because the columns of \( \Psi_T \) are orthogonal, sum to zero, and have length \( T \) (that is, \( T^{-1}\Psi_T'\Psi_T = I_q \) and \( \Psi_T'\ell_T = 0, \) where \( \ell_T \) denotes a \( T \times 1 \) vector of 1s), the OLS regression coefficients have a simple form

\[
X_T = T^{-1} \sum_{t=1}^{T} \Psi((t - 1/2)/T)x_t.
\]

The \( j^{th} \) regression coefficient, \( X_{jT} \), is called the \( j^{th} \) cosine transform of \( [x_1, x_2, \ldots, x_T]' \).

2.1 Large-sample properties of \( X_T \)

Suppose that \( x_t \) can be represented as \( x_t = \mu + u_t, \) where \( \mu \) is the mean of \( x \) and \( u_t \) is a zero mean stochastic process. Because the cosine weights sum to zero, the value of \( \mu \) has no effect on \( X_T, \) so cosine weighted averages of \( x_t \) and \( u_t \) coincide \( (T^{-1} \sum_{t=1}^{T} \Psi((t-1/2)/T)x_t = T^{-1} \sum_{t=1}^{T} \Psi((t-1/2)/T)u_t). \) Scaled versions of these weighted averages are normally distributed in large samples if \( u_t \) satisfies certain moment and persistence properties. In Section 5.3 we present a central limit theorem that relies on the assumption that the first difference

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3As discussed below, analogous properties hold for other transforms such as discrete Fourier or sine transforms.
of $u_t$ has a spectral density. Here we use a simpler argument from Müller and Watson (2008) that relies on the assumption that suitably scaled partial sums of $u_t$ behave like a Gaussian process in large samples.

Specifically, suppose that for some number $\alpha$, $T^{-\alpha} \sum_{t=1}^{[T]} u_t = G_T(\cdot) \Rightarrow G(\cdot)$, where $G$ is a Gaussian process. Using an identity for the cosine weights $\int_{(t-1)/T}^{t/T} \Psi_j(s) ds = l_{jT}^{-1} T^{-1} \Psi_j((t-1/2)/T)$ with $l_{jT} = \sin(j\pi/(2T))/(j\pi/2T)$, the following representation for the $j^{th}$ cosine transform follows directly

$$T^{1-\alpha} x_{jT} = T^{-\alpha} \sum_{t=1}^{T} \Psi_j((t-1/2)/T) u_t$$

$$= l_{jT} T^{-\alpha} \int_{0}^{1} \Psi_j(s) u_{[sT]+1} ds$$

$$= l_{jT} [\Psi_j(1) G_T(1) - \int_{0}^{1} \psi_j(s) G_T(s) ds]$$

$$\Rightarrow \Psi_j(1) G(1) - \int_{0}^{1} \psi_j(s) G(s) ds$$

$$= \int_{0}^{1} \Psi_j(s) dG(s)$$

where the first two lines use the properties of $\Psi_j$, the third uses the definition of $G_T$ and integration by parts with $\psi_j(s) = d\Psi_j(s)/ds$, the fourth uses the continuous mapping theorem and $l_{jT} \to 1$, and the final line uses the stochastic calculus version of integration by parts. This representation holds jointly for the elements of $X_T$, so

$$T^{1-\alpha} X_T \Rightarrow X = \int_{0}^{1} \Psi(s) dG(s) \sim \mathcal{N}(0, \Sigma).$$

(2)

The elements of the covariance matrix $\Sigma$ follow directly from the covariance kernel of $G$ and the cosine weights (see Müller and Watson (2008)). The key idea of our approach to low-frequency econometrics is to conduct inference based on the large sample approximation (2), $T^{1-\alpha} X_T \sim \mathcal{N}(0, \Sigma)$.

Figure 3 plots the first 12 cosine transforms for GDP growth rates and inflation. Roughly speaking, the cosine transforms for GDP growth rates look like a sample of i.i.d. random variables, while the cosine transforms for inflation appear to be heteroskedastic, with larger variance for the first few cosine transforms. The value of the covariance matrix $\Sigma$ in the $I(0)$ and $I(1)$ models help explain these differences. In the $I(0)$ model $T^{-1/2} \sum_{t=1}^{[T]} u_t \Rightarrow
Figure 3: Cosine Transforms of GDP Growth and Inflation

Panel (A): GDP Growth

Panel (B): Inflation
$\omega W(\cdot)$ with $W$ a standard Wiener process and $\omega^2 > 0$ the long-run variance, $\Sigma = \omega^2 I_q$, so $X_j$ is i.i.d.$\mathcal{N}(0, \omega^2)$. In the $I(1)$ model $T^{-2/2} \sum_{t=1}^{[T]} u_t \Rightarrow \omega \int_0^T W(s)ds$, $\Sigma = \omega^2 D$, where $D$ is a diagonal matrix with elements $D_{jj} = 1/(j\pi)^2$, so the $X_j$'s are independent but heteroskedastic.\(^4\) In the following section we present tests for both the $I(0)$ and $I(1)$ null hypotheses. Given these scatter plots, it is not too surprising that the $I(0)$ null is not rejected for GDP growth, but the $I(1)$ null is rejected, and just the opposite result obtains for inflation.

While $\Sigma$ has a simple form for the $I(0)$ and $I(1)$ models, it can be more complicated for other stochastic processes, so it is useful to have a simple numerical method for obtaining accurate approximations for $\Sigma$. As representation (1) suggests, $\Sigma$ can be approximated by the large-$T$ finite sample covariance matrix $\text{Var}[T^{1-\alpha} X_T] = T^{2-2\alpha} \Psi_T' \Xi_T \Psi_T$ where $\Xi_T$ is the $T \times T$ covariance matrix of $[u_1, u_2, \ldots, u_T]'$ under any (not too heavy-tailed) process for $u_t$ that induces the same Gaussian process limit of its partial sums. For example, if $u_t$ is $I(0)$, then $\Sigma$ can be approximated using the large-$T$ finite-sample covariance matrix of the cosine transform of an i.i.d. process with variance $\omega^2$, $\Sigma \approx \omega^2 T \Psi_T' \Psi_T = \omega^2 I_q$. Indeed, because $\Sigma = \omega^2 I_q$ for the $I(0)$ model, this approximation is exact. When $u_t$ is $I(1)$ $\Sigma$ can be approximated using the large-$T$ finite sample covariance matrix of the cosine transforms of a random walk process, $\Sigma \approx \omega^2 \Psi_T' \Xi_T \Psi_T$, where $\Xi_T$ has $(i, j)$th element $\min(i, j)$. In Section 3, we consider the local-to-unity AR model and fractional $I(d)$ model, and the covariance matrices for these processes can be approximated in analogous fashion.

While this discussion has focused on discrete cosine transforms, the representation in (1) is seen to hold for any set of smooth set of weights, $\Psi(s)$. Because our interest is focused on trends, it is important that the weighted averages extract low-frequency variability from the data, and Figure 1 shows that the cosine transforms do just that (also see Section 5.1 below). But, low-frequency Fourier or sine transforms are equally well-suited and can be used instead of the cosine transforms after appropriate modification of the covariance matrix $\Sigma$.\(^5\)

And finally, it is worth stressing that in the asymptotic analysis presented in this section the dimension of $X_T$, which we have denoted by $q$, is held fixed as $T$ grows large. Such

\(^4\)The asymptotic covariance matrix $\Sigma$ is diagonal in both the $I(0)$ and $I(1)$ models because the cosine functions are the eigenfunctions of the covariance kernel of a demeaned Wiener process; cf. Phillips (1998).

\(^5\)For example, while the cosine transforms of an $I(1)$ process have the diagonal covariance matrix discussed in the last paragraph, the covariance matrix of Fourier transforms is somewhat more complicated (cf. Akdi and Dickey (1998)).
asymptotics reflect the notion that there is only a relatively modest amount of information about low-frequency phenomena in, say, 65-year realizations of macro time series. In practice, this translates into using a relatively small number of low-frequency averages from a long time series. Our empirical analysis uses \( q = 12 \) from \( T = 272 \) quarterly observations because, from Figures 1 and 2, this produces a sensible notion of the “trend” in inflation and growth rates in GDP and TFP, corresponding the periodicities longer than 11 years. The econometric challenge then is to draw valid conclusions from these \( q \) observations. Further discussion of the choice of \( q \) may be found in Section 5.

3 Inference examples: univariate time series

This section takes up five examples of statistical inference involving the low-frequency properties of a univariate stochastic process. In each case, the normal limit for \( X_T \) discussed in the last section yields a simple, and standard, small-sample inference problem involving a normal random vector.

3.1 I(0) inference

The first two examples assume the I(0) model and concern inference about the long-run variance \( (\omega^2) \) and mean \( (\mu) \) of \( x \). These problems are related as both involve \( \omega^2 \), in the first instance because it is the parameter of interest, and in the second because it characterizes the variability of the sample mean. There is a large literature on consistent estimation of \( \omega^2 \), including the important contributions of Newey and West (1987) and others, and earlier work on spectral estimation (see Priestley (1981) for a classic textbook treatment). As is now widely understood, consistent long-run variance estimators can perform poorly in finite samples even for only moderately persistent series. Motivated by these poor finite-sample properties, a burgeoning literature studies inconsistent long-run variance estimators (see Kiefer, Vogelsang, and Bunzel (2000) and Kiefer and Vogelsang (2002, 2005), Jansson (2004), Phillips (2005), Sun, Phillips, and Jin (2008), Phillips, Sun and Jin (2006, 2007) and Gonçalves and Vogelsang (2011), and Müller (2014) for a recent survey), and estimators constructed from the cosine transforms as suggested by Müller (2004, 2007) provide a leading example.

Thus, consider using \( X_T \) to learn about the value of \( \omega^2 \). Because \( \sqrt{T}X_T \Rightarrow X \sim \)
Figure 4: Low-Frequency Log-Likelihood for the Long-Run Standard Deviation of GDP Growth

Table 1: Descriptive statistics for GDP growth rates and Inflation: 1947:Q2 - 2014:Q4

<table>
<thead>
<tr>
<th></th>
<th>GDP</th>
<th>Inflation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample Mean ( \bar{x} )</td>
<td>1.96</td>
<td>3.13</td>
</tr>
<tr>
<td>Sample long-run standard deviation ( \hat{\omega}_T )</td>
<td>4.78</td>
<td>9.24</td>
</tr>
<tr>
<td>90% Confidence interval for ( \omega ) in I(0) model</td>
<td>[3.61;7.24]</td>
<td>[6.98;14.00]</td>
</tr>
<tr>
<td>90% Confidence interval for ( \mu ) in I(0) model</td>
<td>[1.44;2.47]</td>
<td>[2.13;4.13]</td>
</tr>
</tbody>
</table>
\( \mathcal{N}(0, \omega^2 I_q) \), asymptotically justified inference proceeds as in the familiar small sample \( i.i.d. \) normal model. Letting \( SSX_T = TX'X_T \Rightarrow SSX = X'X \) denote the (scaled) sum of squares, the large-sample log-likelihood is proportional to \(-\frac{1}{2} \ln (\omega^2) + SSX / \omega^2 \) and the corresponding maximum likelihood estimator (MLE) for \( \omega^2 \) is \( \hat{\omega}_T^2 = SSX_T / q \). Because \( \hat{\omega}_T^2 \) is computed using only \( q \) observations (and in the asymptotics \( q \) is held fixed as \( T \to \infty \)), \( \hat{\omega}_T^2 \) is not consistent. Indeed, using \( q = 12 \), \( X_T \) contains limited information about \( \omega^2 \), so there is considerable uncertainty about its value. Figure 4 shows the log-likelihood for \( \omega \) constructed using \( X_T \) for real GDP growth rates. The MLE is \( \hat{\omega}_T = 4.8 \), but the plot shows that likelihood for values of \( \omega \) as small as 3.5 and as large as 6.5 are within one log-point of the maximum. Because \( X'X / \omega^2 \sim \chi^2_q \) confidence intervals for \( \omega \) are readily constructed \((P(SSX_T / \chi^2_{q,1-\alpha/2} \leq \omega^2 \leq SSX_T / \chi^2_{q,\alpha/2}) \to 1 - \alpha, \) with \( \chi^2_{q,p} \) the \( p \)th quantile of the Chi-squared distribution with \( q \) degrees of freedom), and the resulting confidence intervals for the long-run standard deviation of GDP growth rates and inflation are shown in Table 1.

Next, consider inference about \( \mu \), the mean of \( x_t \). Using the same arguments as Section 2 shows that \( \sqrt{T}[(\bar{x} - \mu), X_T'] \Rightarrow (X_0, X')' \sim \mathcal{N}(0, \omega^2 I_{q+1}) \), so inference about \( \mu \) can be obtained as in the standard small-sample normal problem. In particular, \( \sqrt{T}(\bar{x} - \mu) / \hat{\omega}_T \Rightarrow t_q \) (the Student-\( t \) distribution with \( q \) degrees of freedom), so inference about \( \mu \) follows directly. Table 1 shows 90% confidence intervals for the mean GDP growth rate and the mean inflation rate constructed as \( \bar{x} \pm 1.78\hat{\omega}_T / \sqrt{T} \), where 1.78 is the 95\(^{th} \) percentile of the \( t_{12} \) distribution.

These confidence intervals for \( \omega^2 \) and \( \mu \) are predicated on the assumption that \( x_t \sim I(0) \) and, particularly for inflation, this assumption is suspect. The next inference examples concern the persistence of the \( x_t \) process.

### 3.2 Inference about persistence parameters

As discussed in Section 2, the normal limit for \( X_T \) holds under conditions more general than the \( I(0) \) model, and the parameters characterizing the persistence of \( x_t \) determine the covariance matrix \( \Sigma \). Thus, inference about these parameters can be conducted using methods for inference about the covariance matrix of a multivariate normal random variable. This section discusses three classes of examples. First a few preliminaries.

Some parametric models of persistence. Section 2 discussed the covariance matrix \( \Sigma \) for \( I(0) \) and \( I(1) \) processes. Here we describe three other widely used parametric models for persistence in economic time series. The first is a sum of \( I(0) \) and \( I(1) \) processes: with
appropriate scaling for the components this is a version of Harvey’s (1989) ‘local-level-model’ (LLM) \( x_t = v_{1t} + (b/T) \sum_{s=1}^{t} v_{2s} \) where \((v_{1t}, v_{2t})\) is bivariate \( I(0) \) with long-run covariance matrix \( \omega^2 I_2 \). Another is the ‘local-to-unity AR’ model (LTUM) in which \( u_t = \rho_T u_{t-1} + v_t \), with AR coefficient \( \rho_T = 1 - c/T \) and \( v_t \) an \( I(0) \) process, as introduced by Cavanagh (1985), Chan and Wei (1987) and Phillips (1987). A third is the ‘fractional’ model (FRM) \((1-L)^d x_t = v_t\) where \( v_t \) is \( I(0) \) with \(-\frac{1}{2} < d < \frac{3}{2}\) (cf. Baillie (1996) and Robinson (2003) for surveys). Each of these processes exhibits different degrees of persistence that depend on the value of the model’s parameter value. For example, \( I(0) \) behavior follows when \( b = 0 \) in LLM, \( d = 0 \) in FRM, and \( c \) very large in LTUM. The processes exhibit \( I(1) \) persistence when \( c = 0 \) (LTUM), \( d = 1 \) (FRM), and \( b \) very large (LLM). Alternative parameter values yield persistence between \( I(0) \) and \( I(1) \), and the FRM with \( d < 0 \) or \( d > 1 \) allows for persistence beyond these extremes. Excluding their \( I(0) \) and \( I(1) \) parameterizations, the models yield subtly different low-frequency behavior as evidenced by their (pseudo-) spectra discussed in Section 5.2. For now we simply note that this behavior results in different values of the covariance matrix \( \Sigma \).

Scale invariance/equivariance. In many inference problems, interest is focused on the persistence of the process (say \( b, c, \) or \( d \)) and not on the scale of the process (\( \omega \)). This motivates basing inference on statistics that are invariant to scale transformations, which in our setting corresponds to basing inference on \( X_T^a = X_T / \sqrt{X_T'X_T} \). The continuous mapping theorem implies that \( X_T^a \Rightarrow X^a = X / \sqrt{X'X} \), and the density \( f_{X^a}(x^a|\Sigma) \) of \( X^a \) is explicitly computed in King (1980) and proportional to \( f_{X^a}(x^a|\Sigma) \propto |\Sigma|^{-1/2}(x^a\Sigma^{-1}x^a)^{-q/2} \).

Armed with these preliminaries we are now ready to tackle inference about persistence parameters. We will construct hypothesis tests, and in some cases invert these tests to

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The scaling factor for \( X_T \) is \( T^{1/2} \) for LLM, \( T^{-1/2} \) for LTUM, and \( T^{1/2-d} \) for FRM. The covariance matrix \( \Sigma \) for each of these models is given in Müller and Watson (2008), and can be approximated using the appropriate choice of \( \Xi_T \) for the finite-sample methods in Section 2: the covariance matrix for the LTUM can be approximated using the autocovariances of a stationary AR(1) process with coefficient \((1-c/T)\); and the covariance matrix for the LLM is the sum of the \( I(0) \) covariance matrix and \( b^2 \) times the \( I(1) \) covariance matrix. The covariance matrix for FRM with \(-1/2 < d < 1/2\) can be approximated using the autocovariances for \((1-L)^d u_t = \epsilon_t \) where \( \epsilon_t \) is white noise with variance \( \sigma^2 \) and the autocovariances for \( u_t \) are given, for example, in Baillie (1996); for \( 1/2 < d < 3/2 \), \( \Sigma \) can be approximated using the autocovariances of \( \sum_{s=0}^{t} u_s \), where \((1-L)^{d-1} u_t = \epsilon_t \). Müller and Watson (2008) show that the resulting limiting covariance matrix \( \Sigma \) is continuous at \( d = 1/2 \) in the FRM.

Note that the \( T^{1-\alpha} \) scale factor cancels in \( X_T^a \), so \( \alpha \) disappears from the analysis.
construct confidence sets. We focus on three classes of efficient tests: (i) point-optimal, (ii) weighted average power (WAP) optimal and (iii) approximately optimal tests constructed using numerical approximations to least favorable distributions. Each is discussed in the context of a specific testing problem.

Point-optimal tests. Let $\theta$ denote the value of a persistence parameter (say $b$, $c$, or $d$ in the models described above), so that $\Sigma = \Sigma(\theta)$, and the scale of $\Sigma$ does not matter because of the form of the density for $X^*$. Several problems of interest follow the classic Neyman-Pearson setup with a simple null and simple alternative, $H_0 : \theta = \theta_0$ versus $H_a : \theta = \theta_a$, so the likelihood ratio statistic yields the most powerful test. Given the form of the density $f_{X^*}$, this means rejecting the null for large values of the ratio of generalized sums of squares: $(X'_T \Sigma(\theta_0)^{-1} X_T)/(X'_T \Sigma(\theta_a)^{-1} X_T)$. Such tests are “point-optimal” in the sense of having best power against the $\theta = \theta_a$ alternative.\(^8\) Two examples are low-frequency ‘unit-root’ (LFUR) and ‘stationarity’ (LFST) tests, which respectively test the $I(1)$ and $I(0)$ null hypotheses, as previously derived in Müller and Watson (2008). We discuss them in turn.

Dufour and King (1991), Elliott, Rothenberg, and Stock (1996) and Elliott (1999) derive efficient Neyman-Pearson tests in the AR(1) Gaussian model with AR coefficient $\rho = 1$ and $\rho = \rho_a$ under the alternative, and the latter two references extend these tests to more general settings using asymptotic approximations for LTUM where the unit root null corresponds to $c_0 = 0$ and the alternative to $c = c_a$. While a uniformly most powerful test does not

\(^8\)Müller (2011) shows that these point optimal tests, viewed as a function of $X_T$, are asymptotically point optimal in the class of all tests that control size for all processes satisfying (2).
exist, Elliott, Rothenberg, and Stock (1996) show that the point optimal test associated with a particular value of \( c_0 \) exhibits near optimality for a wide range of values of \( c \) under the alternative. The low frequency version of the point-optimal unit root test rejects for large values of

\[
LFUR = \frac{X_T^2 \Sigma(c_0)^{-1} X_T}{X_T^2 \Sigma(c_0)^{-1} X_T}
\]

where \( \Sigma(c_0) \) is the covariance matrix under the null (the I(1) model with \( c_0 = 0 \)) and \( \Sigma(c_a) \) is the covariance matrix using \( c_a \). Table 2 shows the \( p \)-value of this LFUR test for GDP growth rates and inflation using Elliott’s (1999) choice of \( c_a = 10 \). The I(1) model is not rejected for inflation (\( p \)-value = 0.16), but is rejected for GDP growth rates (\( p \)-value = 0.00).

Nyblom (1989) and Kwiatkowski, Phillips, Schmidt, and Shin (1992) develop tests for the null of an I(0) model versus an alternative in which the process exhibits I(1) behavior by nesting the processes in the LLM.\(^9\) Under the null \( b = 0 \), and under the alternative \( b > 0 \). As in the unit root problem, a uniformly most powerful test does not exist, but a Neyman-Pearson point-optimal test using \( b = b_a \) follows directly. Given the special structure of the I(0) and I(1) \( \Sigma \) matrices, the point-optimal test has a particularly simple form:

\[
LFST = \frac{\sum_{i=1}^{q} X_{iT}^2}{\sum_{i=1}^{q} X_{iT}^2 (1 + b_a/(i\pi)^2)^{-1}}
\]

Müller and Watson (2013) tabulate critical value for this test using \( b_a = 10 \), and show that the test has power close to optimal power for a wide range of values of \( b \). Table 2 shows the \( p \)-values of this test for GDP growth rates (\( p \)-value = 0.62) and for inflation (\( p \)-value = 0.03).

**Weighted average power (WAP) tests.** LFST and LFUR test the I(\( d \)) model for \( d = 0 \) and \( d = 1 \), but what about other value of \( d \), and how can the tests be inverted to form a confidence set for the true value of \( d \)? One approach is to use point-optimal tests for the null and alternative \( H_0 : d = d_0 \) versus \( H_a : d = d_a \) for various value of \( d_0 \); the collection of values of \( d_0 \) that are not rejected form a confidence set. But an immediate problem arises: what value of \( d_a \) should be used? A desirable test should have good power for a wide range of values of \( d_a \), both larger and smaller than \( d_0 \), so that point-optimal tests (which specify a single value of \( d_a \)) are not appealing. A useful framework in these situations is to consider tests with best “weighted average power” (WAP), where the weights put mass on different values of \( d_a \). As explained in Andrews and Ploberger (1994), for example, optimal WAP

\(^9\)See Stock (1994) for a survey and additional references.
tests are easy to construct. The logic is as follows: Consider an alternative in which \( d \) is a random variable with distribution function \( F_a \). This is a simple alternative \( H_{a,F_a}: X^s \) has mixture density \( \int f_{X^s}(x^s, \Sigma(d)) dF_a(d) \), and the optimal test of \( H_0 \) versus \( H_{a,F_a} \) is the Neyman-Pearson likelihood ratio test. Rearranging the power expression for this test shows that it has greatest WAP for \( H_a: d = d_a \) using \( F_a \) as the weight function.\(^{10}\)

Figure 5 shows the large-sample log likelihood for \( d \) using \( X_d^n \) for real GDP growth rates and inflation. The MLE of \( d \) is near zero (\( \hat{d} = -0.11 \)) for GDP, but much larger (\( \hat{d} = 0.77 \)) for inflation. But the plots indicate substantial uncertainty about the value of \( d \). Using a weighting function \( F_a \) that is uniform on \(-0.5 < d < 1.5\), we constructed WAP tests for fine grid of values of \( d_0 \). Inverting these tests, yields a confidence set for \( d \), and these are shown in Table 2. For GDP, the 67\% confidence sets for \( d \) ranges from -0.29 to 0.22, and for inflation it ranges from 0.45 to 0.99. 90\% confidence sets are, of course, wider.

**Least Favorable Distributions.** Our final example considers the following question: How much should we expect the sample average value of \( x_t \) (GDP growth rates or inflation) to vary over long periods of time, say a decade or a quarter of century? To be specific, let \( \overline{x}_{1:h} \) denote the sample mean constructed using observations 1 through \( h \) and consider the variance \( \sigma_{\Delta X}^2(h) = \text{Var}[\overline{x}_{h+1:2h} - \overline{x}_{1:h}] \), for large values of \( h \). The parameter \( \sigma_{\Delta X}(h) \) is the standard deviation of the change in the sample mean over adjacent non-overlapping sample periods of length \( h \).\(^{11}\) In the large sample framework, let \( r = h/T \) and consider asymptotic approximations constructed with \( r \) held fixed as \( T \to \infty \). To conduct inference about \( \sigma_{\Delta X}^2(rT) \) using \( X_T \), we must determine how \( \sigma_{\Delta X}^2(rT) \) relates to the value of \( \Sigma \), the limiting covariance matrix for \( X_T \) (appropriately scaled). This is straightforward: first an extension of the central limit result discussed in Section 2 yields

\[
T^{1-\alpha} \left( \frac{\overline{x}_{rT+1:2rT} - \overline{x}_{1:rT}}{X_T} \right) \Rightarrow \left( \begin{array}{c} Y \\ X \end{array} \right) \sim \mathcal{N} \left( 0, \left( \begin{array}{cc} \Sigma_{YY} & \Sigma_{YX} \\ \Sigma_{XY} & \Sigma_{XX} \end{array} \right) \right).
\]

Second, because \( \text{Var}[\overline{x}_{h+1:2h} - \overline{x}_{1:h}]/\sigma_{\Delta X}(rT) = 1 \), \( X_T/\sigma_{\Delta X}(rT) \Rightarrow \mathcal{N}(0, \Gamma) \) where \( \Gamma = \Sigma_{XX}/\Sigma_{YY} \). A test of \( H_0 : \sigma_{\Delta X}(rT) = \sigma_{\Delta X,0}(rT) \) against \( H_a : \sigma_{\Delta X}(rT) \neq \sigma_{\Delta X,0}(rT) \) may thus be based on the statistic \( X_a = X_T/\sigma_{\Delta X,0}(rT) \). Under \( H_0 \), \( X_a \Rightarrow \mathcal{N}(0, \Gamma) \), and under \( H_1 \),

\(^{10}\)As pointed out by Pratt (1961), the resulting confidence set \( \text{CS}(X) \subset \mathbb{R} \) for \( d \) has minimal expected weighted average length \( E[\int 1_{d \in \text{CS}(X)}|dF_a(d)|] \) among all confidence sets of the prespecified level.

\(^{11}\)Note that \( \sigma_{\Delta X} \) is well defined even for some infinite variance processes, such as the FRM with \( 1/2 < d < 3/2 \).
Figure 5: Low-Frequency Log-Likelihood in Fractional Model

Panel (A): GDP Growth

Panel (B): Inflation
\[ X_\sigma \Rightarrow \mathcal{N}(0, (\sigma_{\Delta x_0}^2)\Gamma^2), \] so the problem again reduces to an inference problem about the covariance matrix of a multivariate normal.

The alternative can be reduced to a single alternative \( H_{a,F_a} \) by maximizing a weighted average power criterion, as above. The problem is still more challenging than the previous example, however, because the (large sample) null distribution of \( X_\sigma \Rightarrow \mathcal{N}(0, \Gamma) \) depends on nuisance parameters that describe the persistence of the \( x_t \) process. In the FRM, for example, \( \Gamma = \Gamma(d) \) with \( d \in D \) for some range of values \( D \). In the jargon of hypothesis testing the null hypothesis is composite, because it contains a set of probability distributions for \( X_\sigma \) indexed by the value of \( d \). The challenge is to find a powerful test of \( H_0 \) that controls size under all values of \( d \in D \).

One general solution to this type of problem uses the same simplification that was used to solve the weighted average power problem: introduce a weighting function, say \( \Lambda(d) \) for the values of \( d \in D \) and use the mixture density \( H_{0,\Lambda} : X_\sigma \sim \int f_{X_\sigma}(x_\sigma, \Gamma(d))d\Lambda(d) \) as the density under the null. This yields a simple null hypothesis (that is, a single probability density for the data), so the best test is again given by the likelihood ratio. However, while the resulting test will control the probability of a false null rejection on average over the values of \( d \) with \( d \) drawn from \( \Lambda \), it won’t necessarily control the rejection probability for all values of \( d \) allowed under \( H_0 \); that is, the test may not have the correct size. But, because any test that controls the null rejection probability for all values of \( d \) automatically controls the rejection frequency on average over \( d \), any test with size \( \alpha \) under \( H_0 \) is also a feasible size \( \alpha \) under under \( H_{0,\Lambda} \), so it must have power less than or equal to power-maximizing test for \( H_{0,\Lambda} \). Thus, if a distribution \( \Lambda \) can be found that does control size for all \( d \), the resulting likelihood ratio test for \( H_{0,\Lambda} \) is guaranteed to be the optimal test for \( H_0 \). Such a \( \Lambda \) is called a “least favorable distribution” (LFD). In some problems, least favorable distributions can be found by clever reasoning (see Lehmann and Romano (2005) for examples), but this is the exception rather than the rule. Numerical methods can alternatively be used to approximate the LFD (see Elliott, Müller, and Watson (2015) for discussion and examples), and we will utilize that approach here.

With this background out of the way, we can now return to the problem of determining the value of \( \sigma_{\Delta \bar{x}}^2(h) \). We do this allowing for \( I(d) \) persistence, and allow \( d \) to take on any value between -0.4 to 1.4. The weighting in the WAP criterion is uniform on \( d \), and, conditional on \( d \), sets the alternative covariance matrix equal to \( \Gamma_a = \Gamma(d)e^U \) where \( U \) is uniformly distributed.
Figure 6: 90% Confidence Sets for Standard Deviation of $\bar{x}_{h+1:2h} - \bar{x}_{1:h}$ as a function of $h$

Panel (A): GDP Growth

Panel (B): Inflation
distributed on \((-5,5)\).\(^{12}\) Figure 6 summarizes the resulting (pointwise in \(h\)) 90\% confidence sets for \(\sigma_{\Delta \tau} (h)\) for \(h\) ranging from 15 to 70 years. For averages computed over 20-years, the 90\% confidence confidence interval for \(\sigma_{\Delta \tau}\) ranges from approximately 0.5 to 1.3 percentage points, and the range shifts down somewhat (to 0.25 to 1.2 percentage points) for averages computed over 60 years. The lower range of the confidence set essentially coincides with the corresponding \(I(0)\) confidence set (which only reflects uncertainty about the value of the long-run variance of GDP growth), but the upper range is substantially larger than its \(I(0)\) counterpart, reflecting the allowance for more persistence than \(I(0)\) model. The confidence intervals for inflation indicate both large and uncertain values for \(\sigma_{\Delta \tau}\), reflecting the larger persistence in the series. The uncertainty about persistence in inflation leads to very wide confidence intervals for averages computed over long samples.

4 Inference examples: multiple time series

In this section we use the same structure and tools discussed in the last section to study some inference problems involving multiple time series. Thus, now let \(x_t\) denote an \(n \times 1\) vector of time series and \(X_{jT}\) denote the \(n \times 1\) vector composed of the \(j^{th}\) cosine transform for each of the \(n\) variables. Let \(X_T\) denote a \(q \times n\) matrix with \(j^{th}\) row given by \(X_{jT}\). In the multivariate model, the assumption of Section 2 about the large sample behavior of the partial sum process becomes \(\Upsilon_T \sum_{t=1}^{\lfloor T \rfloor} u_t \to \Gamma(\cdot)\), where \(\Gamma\) is now an \(n \times 1\) Gaussian process and \(\Upsilon_T\) is an \(n \times n\) scaling matrix.\(^{13}\) Using the argument from Section 2, this implies \(T \Upsilon_T X_T \Rightarrow X\) with vec\((X) \sim \mathcal{N}(0, \Sigma)\). In this section we discuss inference problems in the context of this limiting distribution. We first consider the multivariate \(I(0)\) model and inference about its key parameters. We then relate these parameters to population properties of the trend projections, and return to the empirical question of the relationship between the trend in GDP and TFP growth rates discussed in the introduction. We end this section with a discussion of inference in cointegrated models; these are characterized by linear combinations of the data that are \(I(0)\) and other linear combinations that are \(I(1)\).

\(^{12}\)The numerical work uses fine discrete grids for the \(F_a\) and the approximate LFD.

\(^{13}\)The scaling matrix \(\Upsilon_T\) replaces the scale factor \(T^{1-\alpha}\) of Section 2 to allow the partial sum of linear combination of \(u_t\) to converge at different rates, which occurs, for example, if the elements of \(u_t\) are cointegrated.
4.1 Inference in the I(0) Model

In the multivariate I(0) model $x_t = \mu + u_t$, we set $Y_T = T^{-1/2}I_q$ and assume $T^{-1/2} \sum_{t=1}^{\lfloor T \rfloor} u_t \Rightarrow \Omega^{1/2}W(\cdot)$, where $\Omega$ is the $n \times n$ long-run covariance matrix of $u_t$ and $W$ is a $n \times 1$ multivariate standard Wiener process. The covariance matrix of $\text{vec}(X)$ then becomes $\Sigma = \Omega \otimes I_q$, so that $X_j \sim iid\mathcal{N}(0, \Omega)$, where $X_j'$ is the $j^{th}$ row of $X$.

Inference about $\Omega$. With $\sqrt{T}X_{jT}$ approximately iid$\mathcal{N}(0, \Omega)$, standard methods for i.i.d. multivariate normal samples (see, for instance, Anderson (1984)) can be used to obtain inference. In particular, the limiting distribution of the multivariate sum of squares is Wishart: $\text{SSX}_T = TX_T'X_T \Rightarrow \text{SSX} = X'X \sim W_n(\Omega, q)$, and $\hat{\Omega} = \text{SSX}_T / q$ is the (low-frequency) MLE of $\Omega$. This can be used directly for inference about the $n \times n$ parameter $\Omega$. Often it will be more interesting to conduct inference about the scalar correlation parameters $\rho_{ij} = \Omega_{ij}/\sqrt{\Omega_{ii}\Omega_{jj}}$.

By the continuous mapping theorem, $\hat{\rho}_{ij} = \hat{\Omega}_{ij}/\sqrt{\hat{\Omega}_{ii}\hat{\Omega}_{jj}} \Rightarrow \text{SSX}_{ij}/\sqrt{\text{SSX}_{ii}\text{SSX}_{jj}}$. This limiting distribution is known and is a function only of $\rho_{ij}$ and $q$ (see Anderson’s (1984) Theorem 4.2.2), allowing the ready construction of confidence intervals for $\rho_{ij}$ based on $\hat{\rho}_{ij}$. For example, for the GDP and TFP growth rates, we obtain a 90% confidence interval for the low-frequency correlation of $[0.28; 0.86]$.

Now let $x_t = (y_t, z_t)'$, where $y_t$ is scalar and $z_t$ is $(n - 1) \times 1$, with corresponding cosine transforms $X_{jT} = (Y_{Tj}, Z_{Tj})'$ and

$$
\sqrt{T} \begin{pmatrix} Y_{Tj} \\ Z_{Tj} \end{pmatrix} \Rightarrow \begin{pmatrix} Y_j \\ Z_j \end{pmatrix} \sim \mathcal{N} \left( 0, \begin{pmatrix} \Omega_{yy} & \Omega_{yz} \\ \Omega_{zy} & \Omega_{zz} \end{pmatrix} \right).
$$

A function of $\Omega$ of potential interest is the $(n - 1) \times 1$ vector $\beta = \Omega_{zz}^{-1}\Omega_{zy}$. Since conditional on $Z = (Z_1, \ldots, Z_q)$, $\varepsilon_j = Y_j - Z_j'\beta$ is iid$\mathcal{N}(0, \sigma^2)$ with $\sigma^2 = \Omega_{yy} - \Omega_{yz}\Omega_{zz}^{-1}\Omega_{zy}$, $\beta$ is the population regression coefficient in a regression of $Y_j$ on $Z_j$, $j = 1, \ldots, q$. Substantively, $Z_j'\beta$ provides the best predictor of $Y_j$ given $Z$, so it gauges how low-frequency variability in $z_t$ predicts corresponding low-frequency variability of $y_t$. The population $R^2$ of this regression (that is, the square of the multiple correlation coefficient) is $\rho^2 = 1 - \sigma^2/\Omega_{yy}$ and measures the fraction of the low-frequency variability in $y_t$ that can be explained by the low-frequency variability in $z_t$.$^{14}$

$^{14}$Regressions like these using discrete Fourier transforms are familiar the literature on band-spectral regression (e.g., Engle (1974)). Much of the analysis presented here can be viewed as version of these methods for a narrow frequency band in the $1/T$ neighborhood of zero.
As long as \( n \leq q \), inference about these regression parameters follow immediately from standard small sample results for a linear regression with i.i.d. normal errors:

\[
\hat{\beta}_T = \left( \sum_{j=1}^{q} Z_{Tj}Z_{Tj}' \right)^{-1} \left( \sum_{j=1}^{q} Z_{jT}Y_{jT} \right) \Rightarrow \hat{\beta} = \left( \sum_{j=1}^{q} Z_jZ_j' \right)^{-1} \left( \sum_{j=1}^{q} Z_jY_j \right)
\]

\[
\text{RSS}_T = T \sum_{j=1}^{q} (Y_{jT} - Z_{jT}'\hat{\beta}_T)^2 \Rightarrow \text{RSS} = \sum_{j=1}^{q} (Y_j - Z_j'\hat{\beta})^2
\]

with \( \text{RSS} \sim \chi^2_{q-n} \), the standard error of the regression is \( \hat{\sigma}^2 = \text{RSS}_T / (q - n) \Rightarrow \hat{\sigma}^2 = \text{RSS} / (q - n) \), the total sum of squares is \( \text{TSS}_T = T \sum_{j=1}^{q} Y_{jT}^2 \Rightarrow \text{TSS} = \sum_{j=1}^{q} Y_j^2 \) and the regression \( R^2 \) is \( R^2_T = 1 - \text{RSS}_T / \text{TSS}_T \Rightarrow R^2 = 1 - \text{RSS} / \text{TSS} \). By standard arguments (e.g. Anderson (1984) section 4.4.3), the distribution of \( R^2 \) depends only on \( \rho^2 \) and \( q \), so that a confidence set for \( \rho^2 \) is readily computed from \( R^2 \). Furthermore, with \( \hat{S}_T = \hat{\sigma}^2_T (q^{-1} T \sum_{j=1}^{q} Z_{Tj}Z_{Tj}')^{-1} \Rightarrow \hat{S} = \sigma^2 (q^{-1} \sum_{j=1}^{q} Z_jZ_j')^{-1} \), inference about \( \beta \) can be performed by the usual F-statistic \( F = q(\hat{\beta}_T - \beta)'\hat{S}_T^{-1}(\hat{\beta}_T - \beta) / \sigma^2_T \Rightarrow F_{n-1,q-n+1} \) (with \( F_{n,m} \) the central F-distribution with \( n \) and \( m \) degrees of freedom in the numerator and denominator, respectively). For scalar elements of \( \beta, \beta_i \), usual t-statistic inference is applicable: \( \sqrt{q}(\hat{\beta}_{Ti} - \beta) / \sqrt{S_{Ti}} \Rightarrow \sqrt{q}(\hat{\beta}_i - \beta) / \sqrt{S_{ii}} \sim \text{Student-}t_{q-n+1} \).

Inference about \( \mu \). Let \( \bar{x} = (\bar{x}_1, \ldots, \bar{x}_n)' \) be the \( n \times 1 \) vector of sample means. In exact
analogy to the derivations of Section 3.1, we now have

$$\sqrt{T} \operatorname{vec} \left( \begin{array}{c} (\bar{x} - \mu)' \\ X_T \end{array} \right) \Rightarrow N(0, \Omega \otimes I_{q+1})$$

so that in large samples, $\sqrt{T}((\bar{x} - \mu), X_{1T}, X_{2T}, \ldots, X_{qT})' \sim \text{iid} N(0, \Omega)$. Thus, as previously suggested by Müller (2004), Hotelling’s (1931)-$T^2$ statistic $T(\bar{x} - \mu)'\hat{\Omega}_T^{-1}(\bar{x} - \mu) \Rightarrow \frac{nq}{q+1-n} F_{n, q+1-n}$ provides a basis for inference about $\mu = (\mu_x, \mu_y)'$. Figure 7 shows 67% and 90% confidence ellipses for the average growth rates of TFP and GDP based on the $T^2$-statistic.

**Interpreting elements of $\Omega$ in terms of time-domain projections:** Figure 2 plotted low-frequency trends for GDP and TFP growth rates, and the two series appear to be highly correlated. Figure 8 plots the cosine transforms of the two series which are also highly correlated. These correlations are closely related. Denoting the two series by $y_t$ (GDP) and $z_t$ (TFP), the projections are $\hat{y}_t = \bar{y} + Y_t'\Psi((t - 1/2)/T$ and $\hat{z}_t = \bar{z} + Z_t'\Psi((t - 1/2)/T$ so $T^{-1}\sum_{t=1}^T (\hat{y}_t - \bar{y})(\hat{z}_t - \bar{z}) = Y_T'Z_T$. Thus, the variability and covariability of the projection sample paths, $(\hat{y}_t, \hat{z}_t)$, are determined by the cosine transforms $(Y_T, Z_T)$ and the sample means $(\bar{y}, \bar{z})$. Consider the projection sample path of $y_t$, centered at $\mu_y$ and expressed as a fraction $s$ of the sample, $\hat{y}_{[sT]} - \mu_y$. Then, from Section 2, $T^{1/2}(\hat{y}_{[sT]} - \mu_y) \Rightarrow p_y(\cdot) = Y_0 + Y'\Psi(\cdot)$, and similarly for $z_t$. Thus, the large-sample variability and covariability of the projections correspond to the variability and covariability of $\bar{X} = (X_0, X')'$ and $\bar{Y} = (Y_0, Y')'$. For
Table 3: OLS regression of cosine transform of GDP growth rates on TFP growth rates

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Sample size (q)</th>
<th>( \hat{\beta} )</th>
<th>se(( \hat{\beta} ))</th>
<th>t-statistic</th>
<th>90% confidence interval for ( \beta )</th>
<th>Standard error (( \hat{\sigma} ))</th>
<th>( R^2 )</th>
<th>90% confidence interval for ( \rho^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>12</td>
<td>0.87</td>
<td>0.29</td>
<td>3.04</td>
<td>([0.36;1.39])</td>
<td>0.22</td>
<td>0.46</td>
<td>([0.08;0.74])</td>
</tr>
</tbody>
</table>

Notes: The 90% confidence interval for \( \beta \) is computed using the Student-\( t \) distribution with 11 degrees of freedom. The 90% confidence interval for \( \rho^2 \) is based on the 90% confidence interval for \( \rho \), which in turn is computed from the exact distribution of the sample correlation coefficient \( \hat{\rho} \) as explained in the text.

Table 3 shows the results from the OLS regression of the cosine transforms of the growth rate of GDP onto the growth rate of TFP. The OLS estimate of \( \hat{\beta} \) is 0.87, suggesting that a trend increase in the TFP growth rate of 1% leads to a 0.86% increase in the trend growth rate of GDP. However, this estimate is based on only 12 observations, and the 90% confidence interval for \( \beta \) ranges from 0.36 to 1.39.\(^{15}\) The regression \( R^2 \) is roughly 50%, and the 90% confidence interval for \( \rho^2 \) is \([0.08;0.74]\).

\(^{15}\)To put these values in perspective, recall that the standard neoclassical model, which exhibits balanced growth, implies that a permanent one percentage point increase in TFP leads to a \( \beta = (1 - \alpha)^{-1} \) percentage increase.
confidence interval for the correlation of the GDP and TFP trends ranges from 0.29 to 0.86, suggesting that variations in TFP are important, but not the sole factor, behind variation in trend per-capita GDP growth rates. Figure 9 plots the historical trend growth of GDP, \( \hat{y}_t \), along with the predicted values \( \hat{\alpha} + \hat{\beta} \hat{z}_t \) from the low-frequency linear regression. TFP explained slightly more than half of the above average trend GDP growth in the 1960s and nearly all of the below and then above average growth in 1990s, but explains little of low growth in the late 1950s. More recently, the plot indicates that TFP growth played only a small role in the slower than average growth in GDP over the past decade.

4.2 Cointegration

In the general cointegration model there are \( n \) variables with different linear combinations of the variables being integrated of different orders. The notation for the general model can be taxing, but many of the insights can be gleaned from a bivariate model with \( x_t = [y_t, z_t]' \), where \( y_t \) and \( z_t \) are scalar, \( z_t \sim I(1) \) and \( v_t = y_t - \beta z_t \sim I(0) \). Denoting the corresponding elements of \( u_t \) as \( u_t = [u_{y,t}, u_{z,t}]' \), the partial sum process of \( u_t \) satisfies

\[
\left( T^{-1/2} \sum_{t=1}^{T} (u_{y,t} - \beta u_{z,t}) \right) \Rightarrow \left( \omega_1 W_1(\cdot) \right)
\]

\[
\left( T^{-3/2} \sum_{t=1}^{T} u_{z,t} \right) \Rightarrow \left( \omega_2 J_0^{[\cdot]} (\rho^{1/2} W_1(s) + (1 - \rho^2)^{1/2} W_2(s)) ds \right)
\]

point long-run increase in GDP, where \( \alpha \) denotes the elasticity of output with respect to capital. Thus \( \beta = 1.5 \) if \( \alpha = 2/3 \).
where $W_1$ and $W_2$ are independent Wiener processes and the parameter $\rho$ denotes the long-run correlation between the $I(0)$ and $I(1)$ components. Thus, letting $V_T = Y_T - \beta Z_T$, 
$[T^{1/2}V_T, T^{-1/2}Z_T] \Rightarrow [V, Z]$ with $[V', Z']^{\prime} \sim \mathcal{N}(0, \Sigma)$. Because $v_t \sim I(0)$ and $z_t \sim I(1)$, the covariance matrix $\Sigma$ has the partitioned form: $\Sigma_{VV} = \omega_1^2 I$, $\Sigma_{ZZ} = \omega_2^2 D$, and $\Sigma_{VZ} = \omega_1 \omega_2 \rho D^{1/2}$, where $D$ is the $I(1)$ covariance matrix defined in Section 2.

There are a variety of inference questions that arise in the cointegration model, and several of these are straightforward to address using the low-frequency transforms of the data.\footnote{Also see Bierens and Ploberger (1997) for a related approach.} For example, one question asks whether the cointegrating coefficient takes on a specific value, that is whether $\beta = \beta_0$. Müller and Watson (2013) take up this question using the low-frequency framework. The idea is straightforward. Write $Y_T - \beta_0 Z_T = V_T - (\beta - \beta_0)Z_T$. If $\beta = \beta_0$, then the term involving $Z_T$ is absent, but otherwise this component is present. Thus, $[T^{1/2}(Y_T - \beta_0 Z_T), T^{-1/2}Z_T] \Rightarrow [V + b_0 Z, Z]$ where $b_0 = T(\beta_0 - \beta)$. The covariance matrix of $[(V + b_0 Z)', Z']^{\prime}$ is readily computed and depends on $b_0$. Thus, a hypothesis about the value of the cointegrating coefficient, say $\beta = \beta_0$ or equivalently $b = b_0$, can be tested as a restriction on the covariance matrix. After imposing invariance restrictions, Müller and Watson (2013) show that the scales $\omega_1$ and $\omega_2$ can be set to unity, so that $\rho$ is the only remaining parameter, and develop an optimal test for $\beta = \beta_0$ using a numerical approximation to the LFD as discussed in the last section. Thus, as in the other inference examples in the low frequency setting, optimal inference about cointegrating coefficients becomes a standard problem involving the covariance matrix of normal random vector.

Perhaps a more interesting question involves the cointegration model’s assumption that $z_t$ follows an $I(1)$ process. What if $z_t$ followed another persistent process, perhaps one of the parametric processes described in the last section? In the context of “efficient” regression inferences about $\beta$, Elliott (1998) showed that the $I(1)$ assumption was crucial in the sense that large size distortions could arise if $z_t$ followed a LTUM instead of an exact $I(1)$ process. The low-frequency analysis outlined in the last paragraph is not immune from Elliott’s critique: it uses the full covariance matrix for $[(V + b_0 Z)', Z']^{\prime}$, and therefore utilizes the $I(1)$ property of $z_t$ (through the $I(1)$ covariance matrix $D$ that appears in $\Sigma_{ZZ}$ and $\Sigma_{VZ}$). Müller and Watson (2013) study optimal tests for $\beta = \beta_0$ under alternative assumptions about the trend process. In particular, they show that if the $z_t$ process is unrestricted, then the (essentially) most powerful test simply involves testing whether $y_t - \beta_0 z_t$ is $I(0)$ using the LFST test in (4), a solution to the Elliott critique originally proposed by Wright (2000),
although not in the low-frequency setting.\textsuperscript{17}

5 Relationship to Spectral Analysis

This section relates our method to spectral analysis. A first subsection discusses why one cannot simply use traditional spectral analysis inference tools to answer questions about low-frequency variability. A second subsection derives the limiting covariance matrix of the cosine transforms in terms of the spectral density of the underlying time series. A calculation shows that the covariance matrix is fully determined by the shape of the spectral density close to the origin, a function we call the “local-to-zero spectrum.”\textsuperscript{18} In the third subsection, we present a central limit theorem for low frequency transforms under general forms of the local-to-zero spectrum.
5.1 Scarcity of low-frequency information and its extraction using cosine transforms

Scarcity of low-frequency information. In traditional spectral analysis (see, for instance, Priestley (1981) or Brockwell and Davis (1991)), the periodogram is the starting point to learn about the spectral properties of a time series. Figure 10 plots the periodogram for quarterly GDP growth rates. The shaded portion of the figure shows the frequencies corresponding to periods of 11 years or longer. A mere six periodogram ordinates fall into this low-frequency region, and this count would remain unaltered if GDP growth was instead sampled at the monthly or even weekly frequency. Intuitively, 67 years of data contain only limited information about components with periods of 11 years or longer.

Traditional inference about the shape and value of the spectral density is based on averaging periodogram ordinates. The asymptotics are driven by an assumption that the spectrum is locally flat (that is, the spectrum is fixed and continuous), so that as the sample size grows, eventually there will be more and more relevant periodogram ordinates to estimate the value of the spectral density at any given point. Under such asymptotics, Laws of Large Numbers and Central Limit Theorems are applicable and enable asymptotically normal inference.

But with the relevant number of periodogram ordinates as small as six, such asymptotics do not provide good approximations. What is more, in any non-$I(0)$ model, the spectrum has non-negligible curvature even within a $O(T^{-1})$ band around zero, and this band contains a fixed number of periodogram ordinates. For these reasons, the traditional inference tools of spectral analysis are not directly applicable.

Extracting low-frequency information using cosine transforms. Do a small number of cosine transforms do a good job at extracting the low-frequency information that is contained in the sample data? One useful way to answer this question is to consider the case that the time series is a perfectly periodic and of frequency $\phi$, say $x_t = \sin(\phi t + \delta)$ with phase shift $\delta \in [0, \pi]$. Ideally, the low-frequency cosine transforms $X_T$ would capture the entire variation of $x_t$ for $0 \leq \phi \leq \bar{\phi}$ for small values of $\bar{\phi}$ and none of the variation if $\phi > \bar{\phi}$. In large samples, with $\bar{\phi} = \bar{\lambda}/T$ for fixed $\bar{\lambda}$, the corresponding $R_T^2$ of a regression of $x_t$ on $\Psi_T$ is well approximated by the $R^2$ of a continuous time regression of $\sin(\lambda s + \phi)$ on the $q \times 1$

\footnote{The Müller and Watson (2013) result on the near-optimality of the LFST test holds in the cointegration model with a single cointegrating vector. If there are multiple cointegration vectors then it is possible to obtain more powerful tests even absent assumptions on the process for the common stochastic trends.}

\footnote{This subsection largely follows the development in Müller and Watson (2014).}
cosine functions $\Psi(s)$ and a constant for $s \in [0, 1]$. Figure 11 plots this continuous time $R^2$ as a function of $\lambda$ for $\lambda = q\pi$. While the $R^2$ plot does not follow the ideal step function form, it still provides evidence that the low-frequency cosine transforms do a reasonably good job at extracting the low-frequency information of interest.$^{19}$

### 5.2 Local-to-Zero Spectra

Because $\Sigma$ is the limiting covariance matrix of the cosine transforms, which in turn are weighted averages of the underlying series $x_t$, the elements of $\Sigma$ depend on the autocovariances of the $x$-process. These, in turn, are linked to spectrum of the process, and this makes it possible to express $\Sigma$ as a function of the spectrum. Because the cosine transforms extract low-frequency information in $x$, it should not be surprising that it is the low-frequency spectrum that determines $\Sigma$. The remainder of this subsection makes this explicit by showing that $\Sigma$ can expressed as a function of the spectrum evaluated at frequencies in a $O(T^{-1})$ neighborhood of frequency zero, a function we call the local-to-zero spectrum.

*Local-to-zero spectrum for a stationary process.* Suppose that $x_t$ is a stationary process with spectral density $f_T(\phi).^{20}$ Suppose that in the $O(T^{-1})$ neighborhood of the origin, the suitably scaled spectral density converges (in an $L_1$ sense)

$$T^{1-2\alpha} f_T(\lambda/T) \to S(\lambda).$$

\text{Figure 11: $R^2$ Plot of Generic Trigonometric Series on Cosine Transforms}

---

$^{19}$Low-frequency Fourier transforms perform similarly well for extracting low-frequency variations. See Müller and Watson (2008) for the corresponding $R^2$ plot.

$^{20}$The $T$ subscript on $f_T$ accomodates "double-array" processes such as the LTUM in which the AR(1) coefficient depends on $T$. 

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For example, the FRM is traditionally defined by the assumption that \( f_T(\phi) \) is proportional to \(|\phi|^{-2d}\) for small \( \phi \), so that (5) holds with \( \alpha = \frac{1}{2} - d \). More generally, the function \( S(\lambda) \) is the large sample limit of the shape of the original spectrum \( f_T \) close to the origin, and we correspondingly refer to it as the "local-to-zero" spectrum.

Now consider a weighted average of \( x_t \),

\[
\eta_T = \int_0^1 g(s)x_{\lfloor sT \rfloor + 1}ds = T^{-1} \sum_{t=1}^T \tilde{g}_{T,t}x_t
\]

for some Riemann integrable function \( g \) and \( \tilde{g}_{T,t} = T \int_{(t-1)/T}^{t/T} g(s)ds \). In light of (1), the cosine transforms are an example of \( \eta_T \). Recalling that the \( \phi \)th autocovariance of \( x_t \) is given by

\[
\rho_{-\phi} = \int_{-\pi}^{\pi} f_T(\phi) e^{-i\phi \lambda} d\phi,
\]

we obtain for the covariance between two such weighted averages, \( \eta_T \) and \( \eta_T^2 \):

\[
T^{2(1-\alpha)}E[\eta_T^1 \eta_T^2] = T^{-2\alpha} E \left[ \left( \sum_{s=1}^T \tilde{g}_{T,s}^1 x_s \right) \left( \sum_{t=1}^T \tilde{g}_{T,t}^2 x_t \right) \right]
\]

\[
= T^{-2\alpha} \sum_{s=1}^T \sum_{t=1}^T \tilde{g}_{T,s}^1 \tilde{g}_{T,t}^2 E[x_s x_t]
\]

\[
= T^{-2\alpha} \sum_{s=1}^T \sum_{t=1}^T \tilde{g}_{T,s}^1 \tilde{g}_{T,t}^2 \int_{-\pi}^{\pi} f_T(\phi) e^{-i\phi (s-t)} d\phi
\]

\[
= T^{-2\alpha} \int_{-\pi}^{\pi} f_T(\phi) \left( \sum_{s=1}^T \tilde{g}_{T,s}^1 e^{i\phi s} \right) \left( \sum_{t=1}^T \tilde{g}_{T,t}^2 e^{-i\phi t} \right) d\phi
\]

\[
= T^{1-2\alpha} \int_{-\pi T}^{\pi T} f_T(\lambda/T) \left( T^{-1} \sum_{s=1}^T \tilde{g}_{T,s}^1 e^{i\lambda s/T} \right) \left( T^{-1} \sum_{t=1}^T \tilde{g}_{T,t}^2 e^{-i\lambda t/T} \right) d\lambda
\]

\[
\rightarrow \int_{-\infty}^{\infty} S(\lambda) \left( \int_0^1 g^1(s)e^{i\lambda s} ds \right) \left( \int_0^1 g^2(s)e^{-i\lambda s} ds \right) d\lambda
\]

Thus the limiting covariance matrix \( \Sigma \) depends on \( f_T \) only through \( S \) (albeit for \( -\infty < \lambda < \infty \), a point we return to below).

**Local-to-zero pseudo-spectrum.** This calculation requires the spectral density of \( x_t \) to exist. For some models, such as the \( I(1) \) model, only the spectral density of \( \Delta x_t \) is well defined, so a generalization of (6) to this more general case is required. This is possible when the \( g \)-weights add to zero, that is when \( \int_0^1 g(s)ds = 0 \) (otherwise, if \( \bar{x} \) doesn’t have a finite second moment, then neither does \( \eta_T \)).
Let $f_{\Delta,T}(\phi)$ denote the spectral density of $\Delta x_t$, and assume it has a local-to-zero spectrum defined as

$$T^{3-2\alpha} f_{\Delta,T}(\lambda/T) \to S_{\Delta}(\lambda).$$

(7)

With $\tilde{g}_{T,t} = T \int_{(t-1)T}^{tT} g(s)ds$ and $\tilde{G}_{T,t} = T^{-1} \sum_{s=1}^{t-1} \tilde{g}_{T,t}$, summation by parts yields $T^{-1} \sum_{t=1}^{T} \tilde{g}_{T,t} x_{T,t} = -T^{-1} \sum_{t=1}^{T} \tilde{G}_{T,t} \Delta x_{T,t},$ since $\tilde{G}_{T,T+1} = 0$. Thus

$$T^{2(1-\alpha)} E[\eta_1^2 \eta_T^2] = T^{2(1-\alpha)} E \left[ \left( \sum_{s=1}^{T} G_{T,s}^1 \Delta x_s \right) \left( \sum_{t=1}^{T} \tilde{G}_{T,t}^2 \Delta x_t \right) \right]$$

$$= T^{3-2\alpha} \int_{-\pi T}^{\pi T} f_{\Delta,T}(\lambda/T) \left( T^{-1} \sum_{s=1}^{T} \tilde{G}_{T,s}^1 e^{i\lambda s/T} \right) \left( T^{-1} \sum_{t=1}^{T} \tilde{G}_{T,t}^2 e^{-i\lambda \lambda/T} \right) d\lambda$$

$$\to \int_{-\infty}^{\infty} S_{\Delta}(\lambda) \left( \int_{0}^{1} G^1(s) e^{i\lambda s} ds \right) \left( \int_{0}^{1} G^2(s) e^{-i\lambda \lambda s} ds \right) d\lambda = \gamma^{12}$$

where $G(s) = \int_{0}^{s} g(r) dr$. Furthermore, by integration by parts and $G(1) = 0$, $\int_{0}^{1} G(s) e^{i\lambda s} ds = -\int_{0}^{1} g(s) \frac{e^{i\lambda s}}{i\lambda} ds$, so that

$$\gamma^{12} = \int_{-\infty}^{\infty} \frac{S_{\Delta}(\lambda)}{\lambda^2} \left( \int_{0}^{1} g^1(s) e^{i\lambda s} ds \right) \left( \int_{0}^{1} g^2(s) e^{-i\lambda \lambda s} ds \right) d\lambda. \tag{8}$$

Thus, when $\int_{0}^{1} g^1(s) ds = \int_{0}^{1} g^2(s) ds = 0$, equation (8) generalizes (6): If the spectral density of $x_t$ is well defined, then $f_T(\phi)|1 - e^{-i\phi}|^2 = f_{T,\Delta}(\phi)$, and (5) and (7) are equivalent, since $T^2|1 - e^{-i\lambda/T}|^2 \to \lambda^2$, so that $S_{\Delta}(\lambda) = S(\lambda)\lambda^2$. On the other hand, if the spectral density of $x_t$ does not exist, then $f_T(\phi) = f_{T,\Delta}(\phi)/|1 - e^{-i\phi}|^2$ suitably defines a “pseudo spectrum” of $x_t$ with local-to-zero limit $S(\lambda) = S_{\Delta}(\lambda)/\lambda^2$, so (8) still applies.

$\Sigma$ as a weighted average of $S(\lambda)$. Several features of $\Sigma$ follow from the representation (8). Since $S$ is an even function and $g^1$ and $g^2$ are real valued, $\gamma^{12}$ can be rewritten as $\gamma^{12} = 2 \int_{0}^{\infty} S(\lambda) w^{12}(\lambda) d\lambda$, where $w^{12}(\lambda) = \Re \left[ \left( \int_{0}^{1} g^1(s) e^{i\lambda s} ds \right) \left( \int_{0}^{1} g^2(s) e^{-i\lambda \lambda s} ds \right) \right]$. Elements of $\Sigma$ are thus equal to a weighted average of the local-to-zero spectrum $S$. With $g^1 = \sqrt{2} \cos(\pi j s)$ and $g^2 = \sqrt{2} \cos(\pi k s)$, a calculation shows that $w^{12}(\lambda) = w_{j,k}(\lambda) = 0$ for $1 \leq j, k \leq q$ and $j + k$ odd, so that $E[X_j X_k] = 0$ for all odd $j + k$, independent of the local-to-zero spectrum $S$. With $X_0$ the suitably scaled limit of the sample mean $\bar{x}$ (so that $g(s) = 1$), this holds for all $j, k = 0, 1, 2 \ldots$

Figure 11 plots $w_{j,k}(\cdot)$ for selected values of $j$ and $k$. The figure displays the weights $w_{j,k}$ corresponding to the covariance matrix of the vector $(X_0, X_1, X_2, X_3, X_{10}, X_{11}, X_{12})'$, organized into a symmetric matrix of 9 panels corresponding to $X_0$, $(X_1, X_2, X_3)'$ and
Figure 12: Weights on Local-to-Zero Spectrum for Covariance Matrix of $(X_0, X_1, X_2, X_3, X_{10}, X_{11}, X_{12})'$
The weights for the variances $w_{j,j}$ are shown in bold and the weights for the covariances $w_{j,k}, j \neq k$ are shown as thin curves. A calculation shows that covariance weights $w_{j,k}, j \neq k$, integrate to zero, which implies that for a flat local-to-zero spectrum $S$, $\Sigma$ is diagonal. As can be seen from the panels on the diagonal, the variance of $X_j$ is mostly determined by the values of $\Sigma$ in the interval $\pi j \pm 2\pi$. Further, as long as $S$ is somewhat smooth, the correlation between $X_j$ and $X_k$ is very close to zero for $|j - k|$ large. For $X_j, j > 0$, the weights $w_{j,j}$ put zero mass on $\lambda = 0$; it is this feature that makes it possible for $\Sigma$ to be well defined even if $S(\lambda)$ is not integrable, as is the case if $f_T$ is only a “pseudo-spectrum”. In contrast, because $\int_0^1 g(s)ds \neq 0$ for $X_0$, there is positive weight placed on $\lambda = 0$, so the variance of $X_0$ will not exist for processes such as the $I(1)$ model.

Since the local-to-zero spectrum determines $\Sigma$, $S$ is the key property of the underlying process $x_t$ for the purposes of “low frequency econometrics.” It is instructive to revisit the three benchmark models LTUM, LLM and FRM introduced in Section 3.2 from this perspective. As already noted above, the FRM model has a (pseudo-) spectrum proportional to $|\phi|^{-2d}$ for $\phi$ close to zero, so that $S(\lambda) \propto |\lambda|^{-2d}, -1/2 < d < 3/2$. In particular $S$ is constant for the $I(0)$ model and it is proportional to $\lambda^{-2}$ for the $I(1)$ model. This implies that the local-to-zero spectrum of the LLM satisfies $S(\lambda) \propto b^{-2} + \lambda^{-2}$. Finally, in the LTUM, a straightforward calculation shows that $S(\lambda) \propto 1/(\lambda^2 + c^2)$. (Note that $(b, c) \rightarrow (0, \infty)$ and $(b, c) \rightarrow (\infty, 0)$ recover the $I(0)$ and $I(1)$ model, respectively). Figure 13 plots the logarithm of the local-to-zero spectra of the three benchmark models for selected values of $b, c$ and $d$.

The $x$-axes in Figures 12 and 13 are usefully thought of as focusing on the shaded area in the periodogram plot of Figure 10: In terms of the original time series, local-to-zero frequencies of, say, $|\omega| < 12\pi$ correspond to cycles of periodicity $T/6$. Thus, with 66 years worth of data (of any sampling frequency), the shape of the spectrum for frequencies below 11 year cycles more or less determines the properties of the cosine transforms for $q = 12$. In the context of a specific model of low-frequency variability, such as the $I(0)$ or $I(1)$ model, or parametric families such as the FRM, LLM or LTUM, the choice of $q$ then governs the frequencies for which the model’s implications are exploited for inference. For instance, conducting inference about $\mu$ in the context of the $I(0)$ model with $q = 12$ and 66 years of data implicitly assumes that the spectrum is approximately flat over all frequencies corresponding to cycles of 11 years or more. In practice, the choice of $q$ is a trade-off between robustness and efficiency: a large $q$ enables more powerful inference, as more cosine transforms are used to learn about model parameters of interest, but a large $q$ also increases the danger of rely-
Figure 13: Local-to-Zero Log-Spectra of some Benchmark Models of Low-Frequency Variability

Panel (A): $I(0)$ and $I(1)$ model

Panel (B): Local-level model

Panel (C): Local-to-Unity AR(1) model

Panel (D): Fractional model
ing on a misspecified model for this inference, as the low frequency model must accurately describe the spectrum over a wider frequency band.

**Multivariate local-to-zero spectra.** As a final generalization of the connection between the second moments of weighted averages and the spectrum of the underlying series, consider now the case where \( x_t \) is a \( n \times 1 \) vector. Its spectral density then is a \( n \times n \) Hermitian matrix valued function \( f_T(\phi) \). Assume that for some \( n \times n \) matrix \( \Upsilon_T \), \( T \Upsilon_T f_T(\lambda/T) \Upsilon_T' \rightarrow S(\lambda) \). Let \( \eta^i_T = v^i \Upsilon_T \sum_{t=1}^{T} \bar{g}^i_{T,t} x_t \) for \( i = 1, 2 \). Then proceeding as for (6) yields

\[
E[\eta^1_T \eta^2_T] \rightarrow \int_{-\infty}^{\infty} v^1 S(\lambda) v^2 \left( \int_{0}^{1} g^1(s)e^{i\lambda s} ds \right) \left( \int_{0}^{1} g^2(s)e^{-i\lambda s} ds \right) d\lambda,
\]

and if \( T^3 \Upsilon_T f_{\Delta,T}(\lambda/T) \Upsilon'_T \rightarrow S_{\Delta}(\lambda) \) and \( \int_{0}^{1} g^1(s) ds = \int_{0}^{1} g^2(s) ds = 0 \), then also

\[
E[\eta^1_T \eta^2_T] \rightarrow \int_{-\infty}^{\infty} v^1 S_{\Delta}(\lambda) v^2 \left( \int_{0}^{1} g^1(s)e^{i\lambda s} ds \right) \left( \int_{0}^{1} g^2(s)e^{-i\lambda s} ds \right) d\lambda.
\]

### 5.3 A Central Limit Theorem

The inference results presented in Sections 3 and 4 all depend crucially on the large sample *Gaussianity* of the suitably scaled cosine transform \( X_T \), and not just on the value of the limiting covariance matrix \( \Sigma \). In Section 2, we provided an argument for this asymptotic normality based on existing results about the large sample behavior of the partial sum process for some benchmark models. The last subsection identified the local-to-zero spectrum \( S \) as the key feature of \( x_t \) that determines the asymptotic covariance matrix. We now present a corresponding central limit theorem that takes the local-to-zero behavior of the spectral density function as its starting point and is applicable to general weighted averages \( T^{1/2} \int_{0}^{1} g(s) x_{T,[sT]_+} ds \). Müller and Watson (2014) derive a corresponding CLT for weighted averages with weights that add to zero, \( \int_{0}^{1} g(s) ds = 0 \), which allows for more persistent processes \( x_t \) (as discussed in the last subsection).

**Theorem 1** Let \( x_{T,t} = \sum_{s=-\infty}^{\infty} c_{T,s} \varepsilon_{t-s} \). Suppose that

(i) \( \{ \varepsilon_t, \mathcal{F}_t \} \) is a martingale difference sequence with \( E(\varepsilon_t^2) = 1 \), \( \sup_t E(|\varepsilon_t|^{2+\delta}) < \infty \) for some \( \delta > 0 \), and

\[
E(\varepsilon_t^2 - 1|\mathcal{F}_{t-m}) \leq \xi_m \quad (9)
\]

for some sequence \( \xi_m \rightarrow 0 \).
(ii) For every \( \epsilon > 0 \) the exists an integer \( L_\epsilon > 0 \) such that
\[
\limsup_{T \to \infty} T^{-1} \sum_{t=L_\epsilon T+1}^{\infty} (T \sup_{|s| \geq t} |c_{T,s}|)^2 < \epsilon.
\]

(iii) \( \sum_{s=-\infty}^{\infty} c_{T,s}^2 < \infty \) (but not necessarily uniformly in \( T \)). The spectral density of \( x_{T,t} \) thus exists; denote it by \( f_T : [-\pi, \pi] \mapsto \mathbb{R} \).

(iii.a) Assume that there exists a function \( S : \mathbb{R} \mapsto \mathbb{R} \) such that \( \lambda \mapsto S(\lambda) \) is integrable, and for all fixed \( K \),
\[
\int_0^K |f_T(\frac{\lambda}{T}) - S(\lambda)|d\lambda \to 0. \tag{10}
\]

(iii.b) For every diverging sequence \( K_T \to \infty \)
\[
T^{-1} \int_{K_T/T}^{\pi} f_T(\phi)\phi^{-2}d\phi = \int_{K_T}^{\pi T} f_T(\lambda/T)\lambda^{-2}d\lambda \to 0. \tag{11}
\]

(iii.c)
\[
T^{-1/2} \int_{1/T}^{\pi} f_T(\phi)^{1/2}\phi^{-1}d\phi = T^{-1/2} \int_1^{\pi T} f_T(\lambda/T)^{1/2}\lambda^{-1}d\lambda \to 0. \tag{12}
\]

(iv) The function \( g : [0, 1] \mapsto \mathbb{R} \) is of bounded variation.

Then
\[
T^{-1/2} \sum_{t=1}^{T} g(\frac{t-1}{T})x_{T,t} \Rightarrow N(0, \int_{-\infty}^{\infty} S(\lambda) \left| \int_0^1 e^{-i\lambda s}g(s)ds \right|^2 d\lambda). \tag{13}
\]

The proof of Theorem 1 is in Appendix A.

To better understand the role of assumptions (ii) and (iii), consider some leading examples. Suppose first that \( x_{T,t} \) is causal and weakly dependent with exponentially decaying \( c_{T,s} \), \( |c_{T,s}| \leq C_0e^{-C_1s} \) for some \( C_0, C_1 > 0 \), as would arise in causal and invertible ARMA models of any fixed and finite order. Then \( T^{-1} \sum_{t=L}^{\infty} (T \sup_{|s| \geq t} |c_{T,s}|)^2 \to 0 \) for any \( L > 0 \), \( S(\lambda) \) is constant and equal to the long-run variance of \( x_{T,t} \), and (11) and (12) hold, since \( f_T \) is bounded, \( \int_{K_T}^{\infty} \lambda^{-2}d\lambda \to 0 \) for any \( K_T \to \infty \) and \( T^{-1/2} \int_1^{\pi T} \lambda^{-1}d\lambda = T^{-1/2}\ln(\pi T) \to 0 \).

Second, suppose \( x_{T,t} \) is fractionally integrated with parameter \( d \in (-1/2, 1/2) \). With \( x_{T,t} \) scaled by \( T^{-d} \), \( c_{T,s} \approx C_0 T^{-d}s^{-1} \), so that \( T^{-1} \sum_{t=L}^{\infty} (T \sup_{|s| \geq t} |c_{T,s}|)^2 \to 0 \) for any \( L > 0 \), \( S(\lambda) = C_0\lambda^{-2d} \). Under suitable assumptions about about higher frequency properties of \( x_{T,t} \), (11) and (12) hold, since \( T^{-1} \int_{K_T/T}^{\pi} (\phi T)^{-2d}\phi^{-2}d\phi = \int_{K_T}^{\pi T} \lambda^{-2d-2}d\lambda \to 0 \) and \( T^{-1/2} \int_1^{\pi T} (\phi T)^{-d}\phi^{-1}d\phi = T^{-1/2} \int_1^{\pi T} \lambda^{-d-1}d\lambda = T^{-1/2}d^{-1}(1 - (\pi T)^{-d}) \to 0 \). For instance, even integrable poles in \( f_T \) at frequencies other than zero can be accommodated.
Third, suppose \( x_{T,t} \) is an AR(1) process with local-to-unity coefficient \( \rho_T = 1 - c/T \) and innovation variance equal to \( T^{-1} \). Then \( c_{T,s} = T^{-1} \rho_T^s, \ s \geq 0 \). Thus \( T^{-1} \sum_{t=L+1}^{T} (T \sup|s| \geq |c_{T,s}|)^2 \to \int_0^\infty e^{-2cs}ds \), which can be made arbitrarily small by choosing \( L \) large. Further, \( f_T(\phi) = T^{-2}/|1 - \rho_T e^{-i\phi}|^2 \), which is seen to satisfy (10) with \( S(\lambda) = 1/(\lambda^2 + c^2) \). Conditions (11) and (12) also hold in this example, since \( f_T(\phi) \leq 1 \).

Corresponding central limit theorems for a vector of weighted averages of one or multiple time series follow readily by invoking the Cramer-Wold device.

6 Concluding remarks

Inference about low-frequency phenomena is challenging because of the scarcity of corresponding sampling information. We suggest extracting this information by computing \( q \) trigonometrically weighted averages of the time series of interest. We then apply an asymptotic framework that explicitly accounts for the scarcity by keeping the number \( q \) fixed, so that in the limit, the inference problem becomes a small sample problem involving \( q \) Gaussian variables. In many instances, this small sample problem is readily solved by classic results about inference in small Gaussian samples. In other cases, one can apply analytical or numerical approaches to derive powerful inference from first principles.

The results presented here did not allow for a deterministic time trend in the \( x_t \) process. One approach to dealing with deterministic trends is to use inference methods that are unaffected by their presence. Alternatively, for example in the context of measuring the covariability of multiple time series, one might model the presence of common time trends. In either case, it is straightforward to isolate the deterministic trend component by using a suitable set of \( q \) weight functions, where one is equal to the (demeaned) trend (and whose value is potentially ignored in the subsequent analysis), and the other \( q - 1 \) trigonometric weights are orthogonal to both a constant and a time trend. One such set of weights is derived in Müller and Watson (2008).

The results presented here were also based on the large sample Gaussianity of the \( q \) weighted averages due to a central limit theorem. The key mechanisms of the approach, however, would go still through even for a non-Gaussian limit distribution after suitably adjusting the solution of the now non-Gaussian limit problem. For example, consider a stochastic volatility model for the scalar series \( x_t \), where the volatility process is, say, local-to-unity. Conditional on the volatility path, the cosine transforms have a Gaussian limit, with
a covariance matrix that depends on the realization of the volatility path. The unconditional distribution thus becomes a mixture of normals, and the corresponding small sample problem becomes inference about the parameters of this normal mixture.

More generally, we believe our general approach to low-frequency econometrics to be useful for issues beyond those discussed here. For instance, in Müller and Watson (2014), we use this framework to derive predictive sets for very long-run predictions that are valid for a wide range of persistent processes. We are currently working on inference about the degree of covariability of potentially non-\( I(0) \) series. And it would also be of great interest to connect the low-frequency econometrics approach more directly with structural economic models, such as asset pricing models that stress long-run uncertainty.

A Proof of Theorem 1

The proof of Theorem 1 is based on the following Lemmas.

**Lemma 1** Under assumption (iv) of Theorem 1, there exists \( C < \infty \) such that \( \sup_{0 \leq \xi \leq \pi} \sum_{t=1}^{T} e^{-i\lambda t} g(t/T) \leq C \lambda^{-1} \).

**Proof.** Let \( r_t = \sum_{s=1}^{t} e^{i\lambda s} = e^{i\lambda}(1 - e^{i\lambda})^{-1}(e^{i\lambda t} - 1) \). By summation by parts,

\[
\sum_{t=1}^{T} e^{-i\lambda t} g(t/T) = r_T g(1) - \sum_{t=1}^{T} r_t (g(t/T) - g(t-1/T)) = \frac{e^{i\lambda}}{1 - e^{i\lambda}} \left( (e^{i\lambda T} - 1) g(1) - \sum_{t=1}^{T} (e^{i\lambda t} - 1)(g(t/T) - g(t-1/T)) \right).
\]

For \( 0 \leq \lambda \leq \pi \), \(|e^{i\lambda}(1 - e^{i\lambda})^{-1}| = (2 \sin(\lambda/2))^{-1} \leq 2\lambda \). Furthermore, \( \limsup_{T \to \infty} \sum_{t=1}^{T} |g(t/T) - g(t-1/T)| < \infty \), since \( g \) is of bounded variation.

**Lemma 2** \( \sigma_T^2 = \text{Var}[T^{-1/2} \sum_{t=1}^{T} g(t/T) x_{T,t}] \to \sigma^2 = \int_{-\infty}^{\infty} S(\omega) \left| \int_{0}^{1} e^{-i\omega s} g(s) ds \right|^2 d\omega \).

**Proof.** Let \( \gamma_T \) be the autocovariances of \( x_{T,t} \). We find

\[
\text{Var}[T^{-1/2} \sum_{t=1}^{T} g(t/T) x_{T,t}] = T^{-1} \sum_{j,k=1}^{T} \gamma_T(k-j) g(k-1/T) g(j-1/T) = T^{-1} \sum_{j,k=1}^{T} \left( \int_{-\pi}^{\pi} e^{i\lambda(k-j)} F_T(\lambda) d\lambda \right) g(k-1/T) g(j-1/T) = T^{-1} \int_{-\pi}^{\pi} F_T(\lambda) \left| \sum_{t=1}^{T} e^{i\lambda t} g(t-1/T) \right|^2 d\lambda.
\]
Now for any fixed $K$, we will show

$$ T^{-1} \int_{-K/T}^{K/T} F_T(\lambda) \left| \sum_{t=1}^{T} e^{i\lambda t} g(t - 1) \right|^2 d\lambda = \int_{-K}^{K} F_T(\omega) \left| \sum_{t=1}^{T} e^{i\omega t/T} g(t - 1) \right|^2 d\omega 
$$

$$ \rightarrow \int_{-K}^{K} S(\omega) \left| \int_{0}^{1} e^{i\omega g(s)} ds \right|^2 d\omega. \quad (14) $$

First note that for any two complex numbers $a, b$, $|a - b| \geq |a| - |b|$, so that $|a|^2 - |b|^2 = |(|a| + |b|)(|a| - |b|)| \leq (|a| + |b|)|a - b|$. Thus,

$$ \left| \int_{0}^{1} e^{i\omega g(s)} ds \right|^2 - T^{-1} \sum_{t=1}^{T} e^{i\omega t/T} g(t - 1) \right|^2 \leq 2 \sup_s |g(s)| \left| T^{-1} \sum_{t=1}^{T} e^{i\omega t/T} g(t - 1) - \int_{0}^{1} e^{i\omega g(s)} ds \right| $$

and

$$ \left| T^{-1} \sum_{t=1}^{T} e^{i\omega t/T} g(t - 1) - \int_{0}^{1} e^{i\omega g(s)} ds \right| $$

$$ \leq \int_{0}^{1} \left| e^{i\omega} g(s) - e^{i\omega |sT|/T} g(|sT|/T) \right| ds $$

$$ = \int_{0}^{1} \left| e^{i\omega} (g(s) - g(|sT|/T)) + g(|sT|/T)(e^{i\omega} - e^{i\omega |sT|/T}) \right| ds $$

$$ \leq \int_{0}^{1} |g(s) - g(|sT|/T)| ds + \sup_s |g(s)| \int_{0}^{1} \left| 1 - e^{i\omega (|sT|/T - s)} \right| ds. $$

The first term converges to zero since $g$ is assumed to be of bounded variation. For the second term, note that for any real $\alpha$, $|1 - e^{i\alpha}| < |\alpha|$, so that $\sup_{|\omega| \leq K} |1 - e^{i\omega (|sT|/T - s)}| \leq K/T \rightarrow 0$. Thus,

$$ \sup_{|\omega| \leq K} \left| T^{-1} \sum_{t=1}^{T} e^{i\omega t/T} g(t - 1) \right|^2 \rightarrow 0 $$

and (14) follows from assumption (iii.a) by straightforward arguments.

Thus, for any fixed $K$,

$$ \delta_K(T) = T^{-1} \int_{-K/T}^{K/T} F_T(\lambda) \left| \sum_{t=1}^{T} e^{i\lambda t} g(t - 1) \right|^2 d\lambda - \int_{-K}^{K} S(\omega) \left| \int_{0}^{1} e^{i\omega g(s)} ds \right|^2 d\omega \rightarrow 0. $$

Now for each $T$, define $K_T$ as the largest integer $K \leq T$ for which $\sup_{T \geq T} |\delta_K(T')| \leq 1/K$ (and zero if no such $K$ exists). Note that $\delta_K(T) \rightarrow 0$ for all fixed $K$ implies that $K_T \rightarrow \infty$, and by
construction, also \( \delta_{K_T}(T) \to 0 \). The result now follows from

\[
T^{-1} \int_{K_T/T}^{\pi} F_T(\lambda) \left| \sum_{t=1}^{T} e^{i\lambda g(t/T-1)} \right|^2 d\lambda \leq C^2 T^{-1} \int_{K_T/T}^{\pi} F_T(\lambda) \lambda^{-2} d\lambda \to 0
\]

by assumptions (iii.b) and Lemma 1. ■

**Lemma 3** Let \( T \to 1/2 \) \( \sup_{t,T} |\sum_{j=1}^{T} g(\frac{j-1}{T})c_{T,j-t}| \to 0 \).

**Proof.** Recall that for any two real, square integrable sequences \( \{a_j\}_{j=-\infty}^{\infty} \) and \( \{b_j\}_{j=-\infty}^{\infty} \),

\[
\sum_{j=-\infty}^{\infty} a_j b_j = \frac{1}{2\pi} \int_{-\pi}^{\pi} \hat{A}(\lambda) \hat{B}(\lambda) d\lambda,
\]

where \( \hat{A}(\lambda) = \sum_{j=-\infty}^{\infty} a_j e^{-i\lambda j} \) and \( \hat{B}(\lambda) = \sum_{j=-\infty}^{\infty} b_j e^{i\lambda j} \). Thus

\[
\sum_{j=1}^{T} g(\frac{j-1}{T})c_{T,j-t} = \sum_{j=1}^{T-t} g(\frac{t+j-1}{T})c_{T,j} = \frac{1}{2\pi} \int_{-\pi}^{\pi} e^{i\lambda T} \hat{G}_T(\lambda) \hat{C}_T^*(\lambda) d\lambda
\]

where \( \hat{C}_T(\lambda) = \sum_{j=-\infty}^{\infty} c_{T,j} e^{-i\lambda j} \) and \( \hat{G}_T(\lambda) = \sum_{j=1}^{T} e^{-i\lambda j} g(\frac{j-1}{T}) \), so that \( e^{i\lambda T} \hat{G}_T(\lambda) = \sum_{j=1}^{T} e^{-i\lambda (j-t)} g(\frac{j-t-1}{T}) = \sum_{j=1-t}^{T} e^{-i\lambda j} g(\frac{j-t-1}{T}) \), and \( \hat{C}_T^* \) is the complex conjugate of \( \hat{C}_T \). Now since

\[
F_T(\lambda) = \frac{1}{2\pi} |\hat{C}_T(\lambda)|^2
\]

we find

\[
2\pi \sum_{j=1}^{T} g(\frac{j-1}{T})c_{T,j-t} = \left| \int_{-\pi}^{\pi} e^{i\lambda T} \hat{G}_T(\lambda) \hat{C}_T^*(\lambda) d\lambda \right| \leq \sqrt{2\pi} \int_{-\pi}^{\pi} |\hat{G}_T(\lambda)||F_T(\lambda)|^{1/2} d\lambda.
\]

Also, using \( |\hat{G}_T(\lambda)| \leq \sum_{j=1}^{T} |g(\frac{j-1}{T})| \), we have

\[
\int_{0}^{1/T} |\hat{G}_T(\lambda)||F_T(\lambda)|^{1/2} d\lambda \leq T^{-1} \sum_{j=1}^{T} |g(\frac{j-1}{T})| \cdot \int_{0}^{1} F_T(\omega/T)^{1/2} d\omega
\]

\[
\leq T^{-1} \sum_{j=1}^{T} |g(\frac{j-1}{T})| \cdot \left( \int_{0}^{1} F_T(\omega/T) d\omega \right)^{1/2}
\]

\[
\to \int_{0}^{1} |g(s)| ds \cdot \left( \int_{0}^{1} S(\omega) d\omega \right)^{1/2} < \infty
\]

where the convergence follows from assumption (iii.a). Furthermore, by Lemma 1,

\[
\int_{1/T}^{\pi} |\hat{G}_T(\lambda)||F_T(\lambda)|^{1/2} d\lambda \leq C \int_{1/T}^{\pi} F_T(\lambda)^{1/2} \lambda^{-1} d\lambda.
\]

The result follows by assumption (iii.c). ■

**Lemma 4** For every \( \epsilon > 0 \) there exists a \( M > 0 \) such that

\[
\lim_{T \to \infty} \sup \text{Var} \left[ T^{-1/2} \sum_{t=1}^{T} g(\frac{t-1}{T}) \xi_{T,t} - T^{-1/2} \sum_{t=-MT}^{MT} \left( \sum_{j=1}^{T} g(\frac{j-1}{T})c_{T,j-t} \right) \epsilon_t \right] < \epsilon.
\]

For this \( M \), \( \sigma_{T,M}^2 = \text{Var} \left[ T^{-1/2} \sum_{t=-MT}^{MT} \left( \sum_{j=1}^{T} g(\frac{j-1}{T})c_{T,j-t} \right) \epsilon_t \right] \) satisfies \( \lim_{T \to \infty} |\sigma_{T,M}^2 - \sigma^2| < \epsilon \).
Proof. We have

\[ T^{-1/2} \sum_{t=1}^{T} g(t-1) x_{T,t} = \sum_{t=-\infty}^{\infty} \left( \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right) c_{T,j-t} \right) \varepsilon_t \]

so that, with \( \bar{g} = \sup_{0 \leq s < 1} |g(s)| < \infty \) (bounded variation implies boundedness)

\[ \text{Var}[T^{-1/2} \sum_{t=1}^{T} g(t-1) x_{T,t} - T^{-1/2} \sum_{t=-MT}^{MT} \left( \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right) c_{T,j-t} \right) \varepsilon_t] \]

\[ = T^{-1} \sum_{t=-\infty}^{-MT-1} \left( \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right) c_{T,j-t} \right)^2 + T^{-1} \sum_{t=MT+1}^{\infty} \left( \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right) c_{T,j-t} \right)^2 \]

\[ \leq \bar{g}^2 T^{-1} \sum_{t=MT+1}^{\infty} \left( \sum_{j=1}^{T} (|c_{T,j-t}| + |c_{T,j+t}|) \right)^2 \]

\[ \leq 4 \bar{g}^2 T^{-1} \sum_{t=MT+1}^{\infty} \left( T \sup_{|s| \geq t-T} |c_{T,s}| \right)^2 \]

\[ = 4 \bar{g}^2 T^{-1} \sum_{t=(M-1)T+1}^{\infty} \left( T \sup_{|s| \geq t} |c_{T,s}| \right)^2 \]

which can be made arbitrarily small by choosing \( M \) large enough via assumption (ii).

The second claim follows directly from Lemma 2. \( \blacksquare \)

Lemma 5 For any large enough integer \( M > 0 \), \( \sigma_{M,T}^{-1} T^{-1/2} \sum_{t=-MT}^{MT} \left( \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right) c_{T,j-t} \right) \varepsilon_t \Rightarrow \mathcal{N}(0,1) \).

Proof. By the second claim in Lemma 4 and Lemma 2, \( \sigma_{M,T}^{-1} = O(1) \) and \( \sigma_{M,T}^{-1} = O(1) \). By Theorem 24.3 in Davidson (1994), it thus suffices to show (a) \( T^{-1/2} \sum_{1 \leq t \leq T} |\sum_{j=1}^{T} g\left(\frac{j-1}{T}\right) c_{T,j-t} \varepsilon_t| \overset{p}{\rightarrow} 0 \) and (b) \( T^{-1} \sum_{t=-MT}^{MT} \left( \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right) c_{T,j-t} \right)^2 (\varepsilon_t^2 - 1) \overset{p}{\rightarrow} 0 \).

(a) is implied by the Lyapunov condition via Davidson’s (1994) Theorems 23.16 and 23.11. Thus, it suffices to show that

\[ \sum_{t=-MT}^{MT} E \left[ |T^{-1/2} \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right) c_{T,j-t} \varepsilon_t|^{2+\delta} \right] \rightarrow 0. \]

Now

\[ \sum_{t=-MT}^{MT} E \left[ \left| T^{-1/2} \left( \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right) c_{T,j-t} \right) \varepsilon_t \right|^{2+\delta} \right] \]
\[ \begin{align*}
\leq & \ T^{-1-\delta/2} \sum_{t=-MT}^{MT} \left| \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right)c_{T,j-t} \right|^{2+\delta} E(|\varepsilon_t|^{2+\delta}) \\
\leq & \ (\sup_t E(|\varepsilon_t|^{2+\delta})) \cdot T^{-\delta/2} \sup_t \left| \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right)c_{T,j-t} \right|^{\delta} \cdot T^{-1} \sum_{t=-MT}^{MT} \left| \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right)c_{T,j-t} \right|^{2} \\
= & \ (\sup_t E(|\varepsilon_t|^{2+\delta})) \cdot \left( T^{-1/2} \sup_t \left| \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right)c_{T,j-t} \right| \right)^{\delta} \cdot \sigma_{M,T}^2 \to 0
\end{align*} \]

where the convergence follows from Lemma 3.

For (b), we apply Theorem 19.11 of Davidson (1994) with Davidson’s \( X \) and \( c \) chosen as \( X_{T,t}^D = c_{T,t}^D (\varepsilon_t^2 - 1) \) and \( c_{T,t}^D = T^{-1} \left( \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right)c_{T,j-t} \right)^2 \). Then \( X_{T,t}^D/c_{T,t}^D = \varepsilon_t^2 - 1 \) is uniformly integrable, since \( \sup_t E(|\varepsilon_t|^{2+\delta}) < \infty \). Further,

\[ \sum_{t=-MT}^{MT} c_{T,t}^D = T^{-1} \sum_{t=-MT}^{MT} \left( \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right)c_{T,j-t} \right)^2 = \sigma_{M,T}^2 = O(1) \]

and

\[ \sum_{t=-MT}^{MT} (c_{T,t}^D)^2 \leq T^{-2} \sum_{t=-MT}^{MT} \left( \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right)c_{T,j-t} \right)^4 \]

\[ \leq \sup_{-MT \leq t \leq MT} \left| T^{-1/2} \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right)c_{T,j-t} \right|^{2} \cdot T^{-1} \sum_{t=-MT}^{MT} \left( \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right)c_{T,j-t} \right)^2 \]

\[ = \sup_{-MT \leq t \leq MT} \left| T^{-1/2} \sum_{j=1}^{T} g\left(\frac{j-1}{T}\right)c_{T,j-t} \right|^{2} \cdot \sigma_{M,T}^2 \to 0 \]

where the convergence follows from Lemma 3.

**Proof of Theorem 1:**

By Lemmas 2, 4 and 5, for large enough \( M \),

\[ \sigma^{-1}T^{-1/2} \sum_{t=1}^{T} g\left(\frac{t-1}{T}\right)x_{T,t} = \frac{\sigma_{M,T}}{\sigma} A_T + \frac{\sigma_{M,T}}{\sigma} B_T \]

where \( A_T \Rightarrow N(0, 1) \), \( \lim sup_{T \to \infty} E(B_T^2) < \epsilon \) and \( \lim sup_{T \to \infty} |\sigma_{M,T}^2 - \sigma^2| < \epsilon \). Thus, by Slutzky’s Theorem, as \( \epsilon \to 0 \), the desired convergence in distribution follows. But \( \epsilon \) was arbitrary, which proves the Theorem.
References


