Peter C.B. Phillips' Contributions to Panel Data Methods

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Abstract

This paper discusses Peter Phillips' contributions to panel data methods. These include contributions in the areas of seemingly unrelated regressions, nonstationary panel data, dynamic panels, and the development of multiple index asymptotic theory. We also discuss his empirical contributions in the area of economic growth and

convergence that use macro panel data.

1 Introduction

Panel data is available when we can observe the same cross-sectional units such as individuals, industries, firms, and countries at different points in time. We use the double-indexed notation z_{it} to denote the observation on the random vector Z for cross-sectional unit i at time t. We suppose that such observations are available for $i = 1, ..., n$ and $t = 1, ..., T$.

Traditionally, most panels had the characteristic of having a large cross-sectional dimension n but a small time-series dimension T. This type of panel was widely used in microeconometrics with applications in, for example, labor economics, public economics, and industrial organization. The asymptotic analysis of such panels was then naturally carried out based on n going to infinity while keeping T fixed. The dynamic properties of the data was not specifically modelled. It is therefore not surprising that for this type of panel data, the issue of the stationarity or not of the data in the time dimension was not often addressed.

This situation has changed dramatically in the last 15 years or so with the wider availability of panels with relatively large time series dimensions. Examples of such macro panels are the Penn-World Table, International Financial Statistics or even the Panel for the Study of Income Dynamics which now has a span of about 30 years. The availability of such macro panels called for a reconsideration of the methods used to analyze them. In particular, more careful analysis of the time series properties of the data is possible and required. This has been a very active area of research for the past 10-15 years, and Peter Phillips has played a crucial role in these developments.

One important contribution has been the development of new types of asymptotic analysis. The assumption of a fixed T is no longer satisfactory. In such settings, approximations where both dimensions diverge to infinity are likely to be a more reliable guide to what happens in finite samples. Phillips and Moon (1999) provided a rigorous foundation for the asymptotic analysis of such double-indexed processes.

A second important contribution is the estimation of dynamic panel models with nonstationary or asymptotically nonstationary data. In such settings, traditional IV estimators may lead to a weak instrument problem, making the estimator severely biased with non-normal distributions in finite samples. Phillips contributed to the analysis of this bias in Moon and Phillips

(1999, 2000) and Phillips and Sul (2003, 2007a). Some solutions have been suggested in these papers as well as in Moon and Phillips (2004), Gourieroux, Phillips, and Yu (2010) and Han and Phillips (2010).

One application of the above estimation is in testing for a panel unit root. Phillips has had an important impact on this literature both directly through his writing, but also indirectly through the adaptation to a panel context of many of his numerous contributions in the analysis of univariate time series with unit roots. A noticeable contribution to this literature is concerned with the modelling of cross-sectional dependence in Phillips and Sul (2003) and the analysis of power and development of optimal tests in Ploberger and Phillips (2002) and Moon, Perron, and Phillips (2006, 2007).

This survey is organized as follows. The next section summarizes Phillips's contribution to the seemingly unrelated regression literature. These can be viewed as panel models where the number of cross-sections or number of equations is fixed. Then, section 3 discusses the framework for double-indexed processes in Phillips and Moon (1999) . Section 4 introduces the nonstationary panel regression. Section 5 discusses contributions in the estimation and testing of dynamic panels. Finally, section 6 discusses applications of these methods, while section 7 concludes.

2 Seemingly Unrelated Regression

Phillips made early contributions to panel data analysis in the context of the seemingly unrelated regression (SUR) model. We will use SUR to refer to the case where panel data is available but the cross-sectional dimension n is small while the time series dimension is relatively large. Suppose that Y_{it} is a dependent variable, $X_{it} = (1, X_{it,1}, X_{it,2}, ..., X_{it,K_i-1})'$ is a K_i-vector of explanatory variables for observational unit i, and U_{it} is an unobservable error term. A classical linear SUR model is a system of linear regression equations,

$$
\begin{aligned}
Y_{1t} &= \beta_1' X_{1t} + U_{1t} \\
&\vdots \\
Y_{nt} &= \beta_n' X_{nt} + U_{nt}
\end{aligned}
$$

where $i = 1, \cdots, n$, and $t = 1, ..., T$. These n equations can be estimated one at a time using the observations for each cross-sectional unit. However, the famous Zellner (1962) result shows that one can get efficiency gains by adopting a system approach and applying GLS to this system of equations. The efficiency gains come from the correlation among the error terms of the equations.

Practical application of the Zellner estimator has shown that, in many cases, it can behave in ways that are quite different from those predicted by the usual normal asymptotic results. Phillips' contributions to this area (Phillips, 1977, 1985) were to improve on these normal asymptotics. These two contributions were made in the more general framework of a multivariate regression model, of which SUR is a special case. Phillips (1977) used an Edgeworth expansion to obtain an approximation of the feasible (two-step) GLS estimator for the multivariate regression model with exogenous regressors. This allowed a characterization of the gains, in finite samples, of using feasible GLS over system OLS. Later, Phillips (1985) characterized the *exact* distribution of the two-step estimator in a multivariate regression model, possibly with constraints. Here again, SUR is a special case. This was made possible by the development of matrix fractional calculus.

3 Asymptotic Theories for Large n, T Panels

This section summarizes the contributions made in Phillips and Moon (1999). As mentioned in the introduction, since the early 1960s, panel data studies focused on the case of panel data with large n but small T. The main reason was that in these early days of data collection, data was only available over short time periods. With the advent of panels with longer time spans in the 1990s, the literature started paying more attention to long-span panel data (for example, the Penn World Table). When analyzing such data sets, one faces estimators and test statistics that depend on both n and T, where both of these quantities are large. A typical form is $X_{nT} = \frac{1}{k_n} \sum_{i=1}^{n} \frac{1}{k_T} \sum_{t=1}^{T} W_{it}$ where k_n and k_T are normalizing factors that depend on the properties of the data, for example $k_n = \sqrt{n}$ and $k_T = \sqrt{T}$ for data that is weakly correlated in both the cross-sectional and time dimensions and $\{W_{it}\}$ satisfies regularity conditions for a central limit theorem. To approximate such processes, one needs new theories for multiple indices, in this case n and T, tending to infinity.

In dealing with multiple indices, one can distinguish different limit concepts: (i) sequential limit by letting $T \rightarrow \infty$ for fixed n, and then letting $n \rightarrow \infty$ (or vice versa), (ii) diagonal path limit by letting $n \rightarrow \infty$, $T \rightarrow \infty$ along a particular path $T(n)$ or $n(T)$, and (iii) joint limit by letting $n, T \rightarrow \infty$ without restricting the order in which they do so. In the early literature on long-span panel data, researchers did not distinguish these different limit concepts rigorously and chose an approximation theory in a rather ad-hoc way. For example, Quah (1994) and Levin and Lin (1993a,b) derived limiting results following a diagonal path, $T = T(n) \to \infty$, while Pedroni (1995), Maddala and Wu (1999), Choi (2001) and many others considered a sequential approach whereby $T \to \infty$ for fixed n, followed by $n \to \infty$. There was no paper that adopted the joint limit.

One of the important contributions of Phillips and Moon (1999) to the long-span panel literature[1] is that it rigorously distinguishes the different limit concepts and clarifies relationships among them. Most importantly, it finds sufficient conditions under which the sequential limit and the joint limit coincide. These conditions require certain uniformity conditions and sometimes restrictions on the relative speed that n and T increase to infinity. It also finds regularity conditions for the central limit theorem of double index process of $X_{nT} = \frac{1}{k_n}\sum_{i=1}^{n}\frac{1}{k_T}\sum_{t=1}^{T} W_{it}$, where W_{it} are cross sectionally independent but not necessarily identically distributed across i. As an application, the paper studies linear nonstationary panel regression models, which will be discussed in the following section.

[1] Phillips and Moon (2000) surveys Moon and Phillips (1999) and some of the aforementioned papers.

4 General Analysis of Linear Nonstationary Panel Regression Models

When two variables, say Y_{it} and X_{it}, are integrated over t and there is no cointegrating relation between them, it is well known in the nonstationary time series literature (Granger and Newbold, 1974, and Phillips, 1986) that a time series regression for given i becomes spurious and yields an estimator that has a nondegenerate limit distribution. Phillips and Moon (1999) observed that when panel observations of Y_{it} and X_{it} are available, a regression on the pooled cross section and time series data uncovers a certain relationship between Y_{it} and X_{it}[2]. Another important contribution of Phillips and Moon (1999) is to show the existence of an interesting long-run relation between panel vectors like Y_{it} and X_{it} even if no individual time series cointegrating relation exists and to develop a limit theory that is helpful in understanding and interpreting regressions of this type.

To be more specific, suppose that we have nonstationary data $Z_{it} =$

[2] This was also found independently by Kao (1999).

$(Y_{it}', X_{it}')'$ and $\Delta Z_{it} = U_{it} = \left(U_{y,it}', U_{x,it}'\right)'$, with

$$\Omega_i = \begin{pmatrix} \Omega_{i,yy} & \Omega_{i,xy} \\ \Omega_{i,yx} & \Omega_{i,xx} \end{pmatrix} : \text{ long run covariance matrix of } U_{it}$$

The new relation concept in Phillips and Moon (1999) is a long-run average relationship over the cross sections. Let the cross-sectional average long-run covariance matrices be $\Omega_{yx} = \lim_{n\to\infty} \frac{1}{n} \sum_{i=1}^{n} \Omega_{i,yx}$ and $\Omega_{xx} = \lim_{n\to\infty} \frac{1}{n} \sum_{i=1}^{n} \Omega_{i,xx}$. Then, the long-run average relationship is parametrized as [3] $\beta = \Omega_{yx}\Omega_{xx}^{-1}$. Phillips and Moon (1999) consider four possible panel structures for Y_{it} and X_{it}:

(i) no cointegrating relation, $Y_{it} = \beta X_{it} + E_{it}$, where $E_{it} = I(1)$;

(ii) a heterogeneous cointegrating relation, $Y_{it} = \beta_i X_{it} + E_{it}$, where $E_{it} = I(0)$ and $\beta_i = \Omega_{i,yx}\Omega_{i,xx}^{-1}$;

(iii) a homogeneous cointegrating relation, $Y_{it} = \beta X_{it} + E_{it}$, where $E_{it} = I(0)$ and $\beta = \Omega_{yx}\Omega_{xx}^{-1}$;

(iv) a near-homogeneous relation, $Y_{it} = \left(\beta + \frac{\theta_i}{\sqrt{nT}}\right) X_{it} + E_{it}$, where $E_{it} =$

[3]Notice that the long-run average relation in Pesaran and Smith (1995) is $\lim_n \frac{1}{n} \sum_{i=1}^{n} \Omega_{i,yx}\Omega_{i,xx}^{-1}$, which is different from the long-run average parameter here in general.

$I(0)$ and $\beta = \Omega_{yx}\Omega_{xx}^{-1}$.

Then, they show that in all four cases the pooled ordinary least squares estimator $(\hat{\beta})$ is consistent as $n, T \to \infty$ jointly. In the cases of no cointegration and heterogenous cointegration, $\sqrt{n}\left(\hat{\beta} - \beta\right)$ has a normal limit distribution as $n, T \to \infty$ with $\frac{n}{T} \to 0$. In the cases of homogenous cointegration and near homogenous cointegration, they also construct a pooled fully modified estimator of β, say $\hat{\beta}_{PFM}$, that converges faster and show that $\sqrt{n}T\left(\hat{\beta}_{PFM} - \beta\right)$ has a normal limit distribution as $n, T \to \infty$ with $\frac{n}{T} \to 0$. They also show how to test restrictions on the long-run average parameters both within and between individuals.

5 Dynamic Panel

The basic model in the dynamic panel literature can be represented by the following form (or its variations):

$$Z_{it} = D_{it} + Y_{it},$$

where

$$\begin{aligned} D_{it} &= \beta_i \text{: time invariant fixed effects} \\ D_{it} &= \beta_{i0} + \beta_{i1} t : \text{ incidental trends} \\ D_{it} &= \beta_i' f_t : \text{ factor model} \end{aligned}$$

and

$$\begin{aligned} Y_{it} &= \rho Y_{it-1} + U_{it} \text{ (homogeneous panel)} \\ \text{or } Y_{it} &= \rho_i Y_{it-1} + U_{it} \text{ (heterogeneous panel)} \end{aligned}$$

The main goal of the literature is to estimate ρ in the presence of incidental (nuisance) parameters D_{it} and test for restrictions on ρ or ρ_i. In particular, testing for $\rho_i = 1$ for all cross-sectional units has attracted special attention in the panel unit root literature. We separate these two issues and discuss each of them in the next two sections.

5.1 Dynamic Panels: Estimation

We start this section by quickly summarizing the dynamic panel literature up to the 1990s, most of which assumes that the individual effects D_{it} are time invariant and the time dimension T is fixed. In this case, one of the most important results is that the (quasi) maximum likelihood estimator (QMLE) of ρ is inconsistent (*e.g.*, Nickel, 1981), which is an "incidental parameter problem" that was originally found by Neyman and Scott (1948). An important issue since Nickell (1981) is to find a consistent estimator of ρ in these conditions and to reduce the bias of the estimator of ρ. Early contributors suggested the use of IV or GMM methods. These include Anderson and Hsiao (1982), Arellano and Bond (1991), Arellano and Bover (1995), and Ahn and Schmidt (1995), for example. More recently, Hahn and Kuersteiner (2002) characterize the asymptotic bias of the QMLE due to the incidental parameters using an alternative asymptotics where $n, T \to \infty$ with $\frac{n}{T} \to \pi$. This allows them to suggest a bias-corrected estimator.

Another important issue is that it is well known in the time series literature that the OLS estimator of the AR(1) coefficient has a large downward bias, especially if the coefficient is close to one and an intercept term is included. Hence, it is important in the dynamic panel literature to understand the bias of the various estimators of ρ, in particular, in the presence of incidental parameters.

In this section we discuss the contributions of Phillips to the estimation of dynamic panels with a focus on the issues mentioned above. The relevant papers are Moon and Phillips (1999, 2000, 2004), Phillips and Sul (2003, 2007a), Gourieroux, Phillips, and Yu (2010), and Han and Phillips (2010).

The main issue in Moon and Phillips (1999, 2000, 2004) is the accurate estimation of ρ when ρ is close to one, in particular in the presence of heterogeneous trends. In other words, they focus on a homogeneous panel with a near unit root as in $\rho = 1 - \frac{c}{T}$ and aim to estimate the local parameter c consistently in the presence of $D_{it} = \beta_{i0} + \beta_{i1}t$ as $n, T \to \infty$.

Moon and Phillips (1999) find that with known D_{it} the QMLE of c is consistent when $n, T \to \infty$. However, when the individual-specific trends $D_{it} = \beta_{i0} + \beta_{i1}t$ are not known, the QMLE of c becomes inconsistent even if $n, T \to \infty$. They call this an "incidental trend problem".

In Moon and Phillips (2000) the parameter set for c is restricted to be $[c_{\min,} c_{\max}]$, where $0 < c_{\min} < c_{\max} < \infty$ and various methods to correct for the incidental trend problems are considered. These include an iterative ordinary least squares (OLS) procedure and a double bias-corrected estimator. They show that these estimators are $\sqrt{n}-$consistent and asymptotically normal. However, the interesting case of a unit root, that is, $c = 0$ is explicitly ruled out by the assumption on the parameter space of c.

Later, Moon and Phillips (2004) allow the local parameter c to be zero (the unit root case) with parameter set $[0, c_{\max}]$. They notice that when $\rho = 1 - \frac{c}{T}$, the conventional IVs which are further lags of the panel data such as Z_{it-2} become weak instruments, and they suggest the use of modified scores as moment conditions that hold asymptotically as $T \to \infty$ instead. The first moment condition they suggest is a modified score of the OLS-detrended data constructed by subtracting the bias of the OLS score function, and the second moment condition is a modified score of the GLS-detrended data constructed by subtracting the bias of the GLS detrended score function. The main finding is that the GMM estimator based on these two moment conditions is consistent and converges at rate $n^{1/6}$, much slower than the usual $n^{1/2}$. This finding suggests the important implication that the local power of panel unit root tests will be low in the presence of these incidental trends. This was confirmed later by Ploberger and Phillips (2002) and Moon, Perron, and Phillips (2007).

In Phillips and Sul (2003), a dynamic panel model with both incidental trends and factors is considered. The factors play the role of modelling cross-sectional dependence (*e.g.*, Bai and Ng (2004) and Moon and Perron (2004)[4]). First, the authors illustrate the bias in small samples of the pooled panel OLS estimators. Then, they propose new estimators: a pooled feasible generalized median unbiased estimator and a seemingly unrelated median unbiased estimator.

Phillips and Sul (2007a) extend Nickell (1981)'s results by computing the bias of the QMLE of ρ for general cases that include incidental trends, unit root, predetermined and exogenous regressors, and errors that may be cross-sectionally dependent through factors. They find that the bias is large when incidental trends are estimated and T is small. With factors, they find that the conventional QMLE is not consistent and has a random probability limit.

In Gourieroux, Phillips, and Yu (2010), the built-in bias-reduction feature of indirect inference is exploited to reduce the bias of MLE in a dynamic panel model. As opposed to other bias-reduction techniques available in the literature, this does not require complicated analytical expressions for the bias since simulation techniques are used.

Finally, Han and Phillips (2010) propose a simple GMM estimation method

[4] In Moon and Perron (2004)'s model the factor component is defined in Y_{it} instead of in D_{it}.

of ρ with moment conditions based on first differences (when fixed effects are present) or second differences (when incidental trends are present). The moment conditions used do not suffer from the weak IV or identification problem when $\rho \simeq 1$ and $\rho = 1$. They show that the estimator has a normal limit distribution for any $\rho \in (-1, 1]$ as $nT \to \infty$ (any combination of n and T is allowed).

5.2 Dynamic Panels: Testing

In this section we discuss the contributions of Phillips to testing in dynamic panels. The null hypotheses of interest here are either $H_0 : \rho_i = \rho$ (homogeneity) or $H_0 : \rho_i = 1$ (panel unit root). The relevant papers in this section include Ploberger and Phillips (2002), Phillips and Sul (2003), and Moon, Perron, and Phillips (2006, 2007).

We start the section with a short background. Several early papers on panel unit root testing are available. For example, Quah (1994) and Levin, Lin, and Chu (2002) (which was circulated as Levin and Lin, 1993a, 1993b) propose a modified $t-$ ratio type statistic based on the pooled OLS estimator with OLS-detrended data. Im, Pesaran, and Shin (2003) propose a panel unit root test statistic based on a cross-sectional average of the individual time series unit root test statistics (such as the Dickey-Fuller statistic). Maddala and Wu (1999) and Choi (2001) propose a test based on Fisher statistics which are cross-sectional averages of (transformed) p-values.

These papers were classified as first generation panel unit root tests by Breitung and Pesaran (2008). Their common feature is that they assume that cross-sectional units are independent. Also, these papers only analyze the size of the tests by deriving the asymptotic distributions of the tests under the null hypothesis of a panel unit root. In all of these papers, consistency of the test is established under a fixed alternative, and the analysis of power is left to simulation, which is usually suggestive but design-dependent. Two important issues were left to be addressed. The first one is how to test for a panel unit root when the cross-section units are dependent, and the second one is the power properties of the panel unit root tests. The main contributions of Phillips' dynamic panel testing papers provide some answers to these important questions.

Phillips and Sul (2003) consider cross-sectional dependence by allowing for a single factor. The hypothesis they consider is $H_0 : \rho_i = \rho$, homogeneity of the coefficient. A special case of this is when $\rho = 1$ (unit root). In the case of stationarity ($|\rho| < 1$), they propose a modified Hausman test under cross-sectional dependence. The test compares the pooled feasible generalized median unbiased estimator of ρ and a vector of the individual median unbiased estimator of ρ_i. In the case of unit root ($\rho = 1$), they propose a further modified Hausman type test. The test is based on the same type of estimators as in the stationary case. However, the estimators are based on orthogonalized samples where the factor is estimated and the cross-sectional dependence is removed.

The other papers, Ploberger and Phillips (2002) and Moon, Phillips, and Perron (2006, 2007) analyze the power of the panel unit root tests analytically. These papers consider a heterogeneous local alternative:

$$\rho_i = 1 - \frac{c_i}{n^{\kappa} T},$$

where the value of κ determines the size of the neighborhood of significant local alternatives. When the cross-sectional units are independent, it was known that without the incidental parameters D_{it}, local power of the t test based on the pooled OLS estimator exists in a neighborhood of one with $\kappa = 1/2$ (e.g., Breitung (2000), Moon and Perron (2008)).

The main contribution of Ploberger and Phillips (2002) is to propose an optimal invariant test that maximizes power against a weighted average of alternatives. Moreover, they show that with incidental trends, that is with $D_{it} = \beta_{i0} + \beta_{i1}t$, this test has significant power with $\kappa = 1/4$ only rather than 1/2. This means that the rate of definition of local neighborhoods is slower in the presence of incidental trends.

Moon, Phillips, and Perron (2006, 2007) derive the asymptotic power envelope assuming Gaussian innovations. They show that in the case of (i) without fixed effects (D_{it} is known), (ii) with heterogeneous intercepts only ($D_{it} = \beta_i$), or (iii) trends with heterogenous intercepts but homogenous slope ($D_{it} = \beta_{i0} + \beta_1 t$), significant local power exists in neighborhoods with $\kappa = 1/2$, $(n^{-1/2}T^{-1})$. However, with heterogeneous intercepts and trends, they show that significant local power exists in neighborhoods with $\kappa = 1/4$ $\left(n^{-1/4}T^{-1}\right)$, which is wider than $\kappa = 1/2$, $(n^{-1/2}T^{-1})$. They also propose feasible common point-optimal tests and compare their analytical local power with that of other existing tests such as the Levin-Lin-Chu, Ploberger-Phillips, Moon-Phillips, and Breitung tests.

6 Empirical Contributions

In addition to the above theoretical contributions, Phillips has made empirical contributions as well in the area of economic growth and convergence. The two published papers are Phillips and Sul (2007b, 2007c).

The neoclassical growth model implies that poor countries should grow faster (catch up) with larger countries. However, when researchers consider data from a large cross-section of countries (e.g. from the Penn-World Table), the typical finding is that there is overall divergence rather than convergence. Barro and Sala-i-Martin (1992) and Mankiw, Romer and Weil (1992) emphasized that this could be explained by the fact that countries could be converging to different steady states (conditional convergence). In this explanation, heterogeneity plays an important role since it determines the steady state, but there are still homogeneity restrictions, in particular technology.

The contribution of the Phillips and Sul papers is to employ new panel techniques to uncover even more general heterogeneity in the transition dynamics than was allowed before. The idea is to decompose log per capita income (or GDP) as a factor model:

$$\log y_{it} \, (= X_{it}) = \delta_{it} \mu_t$$

where μ_t is a growth path common to all countries. The coefficients δ_{it} measure the response of country i at time t to this common factor. These will reflect the transition path of economy i to the common trend.

Phillips and Sul consider the transition relative to the average as a function of t (called the transition path, or relative transition parameter):

$$h_{it} = \frac{\delta_{it}}{\frac{1}{n}\sum_{j=1}^{n}\delta_{jt}}.$$

The use of the average eliminates the effect of the common factor μ_t. In this context, convergence is defined as:

$$\lim_{t\to\infty} h_{it} = 1 \text{ for all } i.$$

This convergence condition can be tested by parametrizing the evolution of the transition paths. For example, Phillips and Sul (2007c) assume the form:

$$\delta_{it} = \delta_i + \frac{\sigma_i}{L(t)\, t^{\alpha}}\xi_{it}$$

where $L(t)$ is a slowly-varying function at infinity and ξ_{it} is $i.i.d.\,(0,1)$. This parametrization allows the loading coefficients for a given individual to vary over time, but their variance shrinks if $\alpha > 0$. Convergence is characterized by $\delta_i = \delta$ for all i and $\alpha \geq 0$. This can be tested as

$$H_0 : \delta_i = \delta \text{ and } \alpha \geq 0.$$

by considering the so-called $\log t$ regression:

$$\log \left(\frac{H_1}{H_t} \right) - 2 \log L(t) = a + b \log t + u_t$$

where $H_t = \frac{1}{n} \sum_{i=1}^{n} (h_{it} - 1)^2$ and $b = 2\alpha$. The test statistic is just the usual (HAC) t statistic on $\hat{b}$ in this regression.

Rejection of the convergence null does not rule out that some sub-groups converge (these are known as convergence clubs). This type of clustering is allowed for if $\delta_i = \delta$ for some subset of units and $\alpha \geq 0$. Phillips and Sul (2007*c*) propose an algorithm for grouping the data among clusters.

7 Conclusion

Peter Phillips has made important contributions to the analysis of macro-type panel data. The rigorous foundation for the development of double-indexed asymptotics in Phillips and Moon (1999) stands out as the most crucial element. Numerous researchers use these tools routinely to develop methods suited for a very wide class of problems. The impact of these contributions will only grow with time.

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