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ESSAYS IN HONOR OF SUBAL KUMBHAKAR

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This book is dedicated to the memory of Mike Tsionas who passed away shortly after the completion of this volume. He was an amazing colleague and brilliant thinker.

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CHAPTER 1

EDITORS' INTRODUCTION

Christopher F. Parmeter[a], Mike G. Tsionas[b] and Hung-Jen Wang[c]

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Deciding to put together this special issue in honor of Subal Kumbhakar was easy. Subal has been, and remains, a great colleague, mentor, friend, and coauthor to all of us. His influence on the applied productivity and efficiency profession is legion, as evidenced by the attendance of sessions where he is presenting (or most usually his coauthors are presenting, since despite all of Subal's many gifts, he still cannot be in two places at the same time). Subal's oeuvre continues to grow, his ability to move the applied econometric and productivity literature forward never stalling, and his charismatic smile always there to cheer up colleagues and friends on a gloomy day. It is our distinct honor to have put together this collection of research that honors Subal's many accomplishments and draws further attention to the various areas of scholarship that he has touched. We hope this volume will be useful for future researchers and serve as a beacon of respect and admiration for Subal.

The present volume is composed of 14 chapters, many of which are from Subal's peers and coauthors. The contributions cover a wide array of applied econometric domains, from model averaging to panel data methods, stochastic frontier analysis to productivity decompositions and ending on the two-tier frontier. The applied topics also cover a broad range: homelessness, underreporting of satisfaction, production, cryptocurrency and healthcare to name a few. This vast array of topics speaks to the impact that Subal continues to have. We thank all of the contributors for putting up with us as we went through the review process

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and asked for countless changes. But when the honoree has such high standards, we had quite a lot to live up to as editors. We would also like to thank those contributors who participated in a special session at the recent North American Productivity Workshop at the Miami Herbert Business School[1] in honor of Subal. Nearly half of the contributors to this volume were in attendance and it was moving to see Subal honored with such a large audience present.

We would also like to thank all of the external reviewers who took time away from their schedules to rigorously peer review all of the submissions to ensure the highest quality. Referees are routinely overlooked and underappreciated, but play a critical role in affecting the quality and clarity of submissions. To them, we offer our thanks and perhaps a beer or coffee at the next conference (on Subal of course). We would also like to thank the editorial team at *Advances in Econometrics* for entertaining our proposal and enthusiastically giving us the go-ahead with this project.

We have ordered the contributions in this volume by those who are closest to Subal, followed by those chapters that tie in closely to his various treks into productivity, ending on an area that has always interested Subal, the two-tier frontier. Here, our goal is to simply highlight the individual contributions, hoping to draw distinct interest in them but still leaving the desire for the reader to dig into the meat of each chapter on their own.

When we started putting together this special volume in honor of Subal, we reached out to his dissertation adviser, Dennis Aigner, who had moved from the University of Southern California (where Subal received his PhD) to the University of California at Irvine, to see if he could provide some remarks on Subal, the graduate student. We were delighted that he took us up on our offer and has provided some fantastic insight into the younger version of Subal that we all know now. We also found it fascinating that Subal and Dennis had not seen each other in over 35 years until this past June at the University of Southern California for the First USC PhD Alumni Conference (a photo of the two of them at the conference appears in Fig. 1.1). Fitting, in our opinion, that this volume is coming out after this event.

Baltagi's "Hausman's Specification Test for Panel Data: Practical Tips" discusses the case of interpreting the Hausman test when faced with a rejection of the null hypothesis. It is well known that Hausman's (1978) test is a general specification test and a rejection does not necessarily imply what is wrong, only that something is wrong. In the panel data case, this test is most commonly deployed to assess whether a fixed effects or a random effects framework is adequate for the data at hand. But when one rejects the null hypothesis of the random effects framework, what is the implication? Baltagi's work is a step in this direction, highlighting various deficiencies that might arise for which practitioners should be aware of.

An interesting point which Baltagi draws attention to is that if the random effects framework is rejected (thereby throwing support toward a fixed effects framework) one can test the restrictions that are inherent in the fixed effects framework. This can be done following Chamberlain (1982), for example, but as Baltagi rightly notes, it is rarely taken up in practice. A key takeaway from

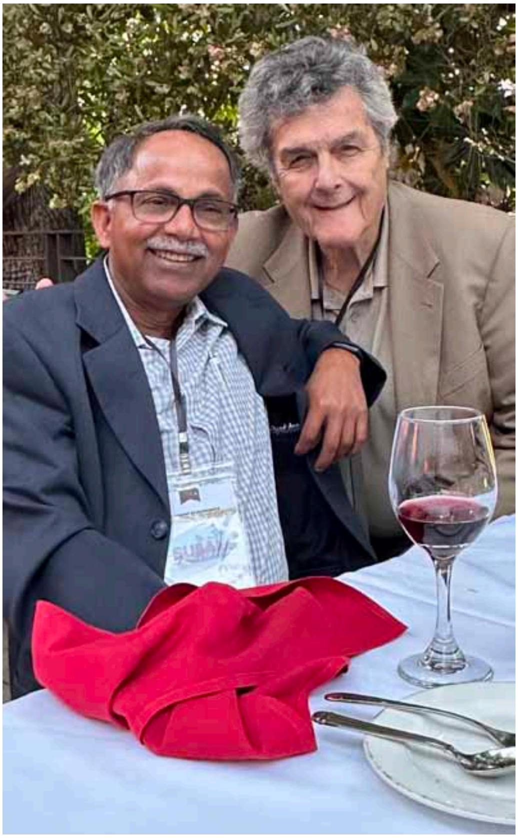

Fig. 1.1. Subal and Dennis, Together Again.

Baltagi's contribution is that a rejection of the random effects estimator using the Hausman (1978) test does not automatically imply that the fixed effects estimator is correct. While this seems simple to write and state, it occurs so frequently in practice that it is useful to have these reminders.

Lahiri and Noroski's "Do Federal Disability Insurance Participants Exaggerate Their Health Problems? A Study Using Anchoring Vignettes" uses anchoring vignettes to examine whether or not applicants and recipients of federal disability insurance inflate their self-assessed health problems relative to others. This is a self-styled measurement error study, which has deep connections to the composite error structure of the stochastic frontier model, as recently described in Millimet and Parmeter (2022). Generally, survey data are used in place of revealed preference data, but concerns exist over respondents' ability to accurately convey the information being asked of them. This is especially important when designing policies where the survey answers are used to justify moving forward (or holding back) on a given agenda.

For Social Security Administration survey data, no consensus exists in the academic literature on the truthfulness of self-reports of disability. Anchoring vignettes, developed by King, Murray, Salomon, and Tandon (2004), provide a way of examining whether recipients of federal disability treat health-related survey questions any differently than non-recipients. Lahiri and Noroski use a parametric form of this approach to estimate a model of self-reported disability that is free of differential item functioning. A key finding is that reporting heterogeneity has the potential to affect the magnitude and significance of various components of self-reported disability.

Fuller and Sickles' "Homelessness on the West Coast and the Role of Health: Inefficiency and Productivity Loss in American Society" tackles a difficult empirical problem, homelessness. Homelessness is a stark example of the inefficient use of resources, which exemplifies nearly all of Subal's research. Homelessness is hard to address for many reasons, but one is the lack of data on the exact number of individuals who are homeless. Among the homeless, the prevalence of substance abuse and/or mental health disorders is significantly higher than those that live in a place fit for habitation. A lack of adequate habitation can negatively impact an individual's health, having the potential to create a negative feedback loop that can make exiting homelessness arduous. This suggests that a simple empirical model to unravel these effects is likely to be limited and a more formal approach is needed.

The model that Fuller and Sickles work with includes the potential consequences of poor health and healthcare access on homelessness within a two-period consumption framework developed originally by Glomm and John (2002). An individual's health is integrated directly into the model through an assumption that health directly impacts the skills a worker brings into the labor market. These skills in turn affect their earnings potential. The theoretical predictions of this model are then tested econometrically using an array of data from West Coast states.

As anyone who has met (or knows) Subal can attest, he has developed a lot of models. So many models in fact that it is difficult to know which model Subal might prefer. So what can be done when confronted with a multitude of models? Two competing approaches to adjudicate across models are model selection and model averaging. Since the seminal work of Hansen (2007), a large literature on model averaging has cropped up to combat the issues associated with model selection. They range from simple applications of regression models to more sophisticated frameworks in nonparametric settings (Henderson & Parmeter, 2016) and the full distribution theory (Liu, 2015).

In this volume, we are fortunate to have two contributions associated with model averaging. First, Hansen and Racine's "Bootstrap Model Averaging Unit Root Inference" provides a model averaging procedure to deal with model uncertainty when one is interested in testing for the presence of a unit root. These methods are preferable to inference based on model selection where a hard thresholding rule creates an inherently discontinuous choice of the selected model, and hence a discontinuous change in the test statistic. Beyond the construction of a model average test statistic, Hansen and Racine also deploy a model-free, automatic, time series bootstrap procedure which avoids issues with the selection of a model from which to bootstrap from. From the extensive Monte Carlo simulations provided, the proposed bootstrap model average approach emerges as the procedure of choice. We certainly believe that practitioners will find it a useful addition to their toolkit.

Our second model averaging piece is Gao, Lehrer, Xie, and Zhang's "Averaging Heterogeneous Autoregression Models with Heteroskedastic Errors: Theory and an Application to Cryptocurrency Volatility Forecasting." This chapter complements nicely with Hansen and Racine's, focusing on model averaging in a time series setting, but here with an eye on estimation rather than inference. They propose a heteroskedastic model averaging heterogeneous autoregressive (H-MAHAR) estimator to develop a forecasting strategy that can account for both model uncertainty and heteroskedasticity of unknown form. This estimator is studied theoretically and also applied to learn about realized volatility in the cryptocurrency arena.

Yao, Lu, Sun, and Zhang's "Efficient Estimation in Varying Coefficient Panel Data Model with Different Smoothing Variables and Fixed Effects" proposes a semiparametric smooth coefficient panel data model that allows for different smoothing variables across the various smooth coefficients. Smooth coefficient models are crafty modeling devices as, conditional on a given set of covariates, they can be interpreted as linear in parameter models (Hartarska, Parmeter, & Nadolnyak, 2011). Traditionally, varying coefficient models restrict the smooth coefficients to depend on the same smoothing variables, but in Yao et al.'s application, they have different variables which influence production and technical efficiency, making a model of this ilk necessary to modify. Naturally, the presence of fixed effects stemming from the panel data framework makes estimation more challenging than in a cross-sectional setup, but Yao et al. deploy a two-stage estimator, beginning first with a series based profile least squares estimator (Su & Ullah, 2006) and then use backfitting in a second stage to recover the smooth coefficients.

The approach of Yao et al. follows a recent set of work by Subal (Parmeter, Wang, & Kumbhakar, 2017; Zhou, Parmeter, & Kumbhakar, 2020) that seeks to allow determinants of inefficiency to enter into a panel data stochastic frontier model in a fully nonparametric setup. The difference however is the earlier papers that Subal coauthored always modeled the production technology in a parametric framework. Yao et al. further relax this assumption by allowing the production frontier to be semiparametric in nature, which has obvious appeal.

Next, a collection of the chapters focuses on some of Subal's recent contributions related to the difference between structural models of productivity (such as Gandhi, Navarro, & Rivers, 2020; Levinsohn & Petrin, 2003) and the stochastic frontier model (Aigner, Lovell, & Schmidt, 1977). This is highlighted by Tsionas and Kumbhakar (2023) and Subal's keynote address at the recent New York Camp Econometrics XVII in Bolton's Landing.[2] This line of research seeks to bridge the gap between these two styles of models (unobserved inefficiency vs unobserved productivity).

Tsionas' "The Role of Management in Efficient Production: Theoretical and Statistical Implications" attempts to understand how a simple model of production with managerial inefficiency can lead to statistical insights that link to the stochastic production frontier model. More specifically, Tsionas constructs a dynamic model of the firm under the assumption that managerial skill contributes to technical efficiency. There are several important implications from Tsionas' contribution. First, it turns out that it is not optimal for the firm to be fully efficient (in the information-processing sense) even if this possibility is an option. Second, his model shows that it is not optimal for the firm to be efficient even in the long-run. Beyond these theoretical insights, an econometric model of the inefficiency–management nexus is proposed that is nonparametric in nature and is applied to the well-known Bloom and Van Reenen (2007) dataset on managerial practice. A key finding is a nonlinear but positive relationship between estimated managerial compensation and effort. The relationship is concave, suggesting a turning point, where additional effort actually leads to reduced compensation, further evincing the lack of optimality of becoming fully efficient (at least by management standards).

Malikov, Zhao, and Zhang's "A System Approach to Structural Identification of Production Functions with Multi-Dimensional Productivity" extends Gandhi et al.'s (2020) proxy variable framework for structurally identifying production functions to a more general case when latent firm productivity is multi-dimensional, with both factor-neutral and (biased) factor-augmenting components. A novelty of their model is that it can be identified under weaker data requirements than are commonly required, eschewing reliance on cross-sectional variation in input prices, which are typically unavailable for a large swath of datasets. This identification comes at the expense of migrating from a fully nonparametric framework to a parametric framework. However, this setup also produces the identification of key model parameters that only depend on the cost-to-revenue ratio, which is typically observable in micro level.

A further benefit of Malikov et al.'s approach is that it is robust to the critique of Ackerberg, Caves, and Frazer (2015). Specifically, this critique draws into question the ability of a common class of structural "proxy" estimators to identify both the production function itself and a Hicksian productivity component, given the additive nature that arises in the construction of the model. The model proposed here does not fall under this critique since no endogenous variable input appears on the right-hand side of their final estimating equation, having been removed at an earlier stage. This new model, and subsequent estimation approach, are then demonstrated using both simulated data and an application to Chinese manufacturing firms. In their simulations, with a modestly large sample size, their methodology recovers the true parameters fairly well, however, those in the third stage are estimated the least precisely, which is to be expected.

Orea, Álvarez-Ayuso, and Servén's "The Structural and Productivity Effects of Infrastructure Provision in Developed and Developing Countries" provides evidence on the effects of infrastructure provision on aggregate productivity using industry-level data across a group of developed and developing countries. They do this by deploying a two-level decomposition of aggregate productivity.

First, the approach of Diewert (2015) is leveraged, (which breaks total factor productivity (TFP) into its constituent pieces) and then measures aggregate TFP improvements directly attributable to infrastructure provision (and other productivity drivers as well). That such a decomposition is feasible hinges on the two different channels through which infrastructure provision may promote aggregate productivity gains: a within effect and a reallocation effect.

Their decomposition has important implications for policy. A key finding from the empirical analysis is that public infrastructure capital improves within-firm productivity while also facilitating the efficient reallocation of inputs across both firms and industries. This suggests that the promotion of enhanced infrastructure investments should be a public policy priority in developing countries.

Our last set of chapters are perhaps the most apt to honor Subal, focusing on various aspects of the stochastic frontier model proposed by Aigner et al. (1977). It is this specific class of models that has served as the backbone of Subal's research agenda over the past four decades. Subal has made far too many contributions here to successfully highlight all of them, but each of the chapter in this area that appear here is predicated on insights that Subal has made. These chapters span the spectrum from predicting efficiency to new estimators and novel applications related to healthcare.

Amsler, James, Prokhorov, and Schmidt's "Improving Predictions of Technical Inefficiency" considers the classic Jondrow, Lovell, Materov, and Schmidt's (1982) estimator of technical efficiency and asks if this measure can be improved. In essence, Amsler et al. argue that what helps to improve the prediction of technical inefficiency is enlarging the conditioning set. This stems from the well-known decomposition of the variance of a random variable into distinct explained and unexplained components. In the most basic version of the prediction of inefficiency, only the residuals from maximum likelihood estimation enter the conditioning set. However, there typically arise many empirical settings where more information is available: a cost function with share equations (Schmidt & Lovell, 1979, 1980), panel data (Amsler, Prokhorov, & Schmidt, 2014), or endogeneity (Amsler, Prokhorov, & Schmidt, 2016), for example.

Here the authors go a step further and examine the impact that estimated objects entering the conditioning set have on the overall predictive power of the estimator. They suggest two alternative nonparametric estimators for this endeavor (the textbook local constant estimator and a local linear random forest). Their simulations reveal that, in the panel data setting, conditioning on all of the errors, not just the contemporaneous error, leads to reductions for the local linear random forest estimator.

That the local constant estimator does not result in improvements is due to the curse of dimensionality; as the number of time periods goes up, the size of the conditioning set increases and the finite sample bias dwarfs the reduction in variance, leading to increases in mean squared error.[3] A similar story emerges from their simulations incorporating cost shares. Conditioning on allocative inefficiency dramatically improves the estimation of technical inefficiency as the correlation between these two increases. Interestingly, reductions in mean square error are similar regardless of the number of inputs in the production function;

this suggests that even conditioning on a single allocative inefficiency term has the potential to substantially improve estimates of technical inefficiency scores.

Wang and Henderson's "A Semiparametric Constant Elasticity of Substitution Stochastic Frontier Model for Panel Data" begins with a classical constant elasticity of substitution (CES) production frontier, but proposes estimation of the model without resorting to log-linearization, which is known to induce substantial finite sample biases (Santos Silva & Tenreyro, 2006). They further enhance the model by allowing a set of covariates to impact efficiency levels and do so in a nonparametric fashion. Lastly, their model allows the technological shift parameter in the traditional CES model to depend on a set of covariates as well, and in a single index fashion. This model is then extended to the panel data setting to allow for unobserved firm level heterogeneity. They propose a two-step estimation procedure to estimate all the constituent components of the model. They provide theoretical results establishing identification as well as a set of high level assumptions that are conjectured to lead to the overall consistency of the estimator.

Beyond their theory, Wang and Henderson showcase their estimator using both simulations and an interesting empirical application. Their simulations reveal that their estimator can recover all of the primitives of the model with little concern over accuracy. The application focuses on the impact that trade has on cross-country productive efficiency levels. To facilitate comparisons, Wang and Henderson estimate four benchmark parametric stochastic frontier panel data models with different structures. The estimate of ρ, which measures elasticity of substitution, across the three different CES specifications, is statistically significant at the 1% level, casting some doubt on the Cobb–Douglas specification that is more common in applied frontier studies. Their proposed model reveals a significant nonlinear structure of the technology function, clearly deviating from the commonly assumed exponential functional form. As a result of this finding, the impact of the share of merchandising exports that a country has on technology deviates substantially from the proposed CES model compared to more rigid parametric frameworks. As Wang and Henderson note, for this finding the ability to model technology nonparametrically is vital to avoid misleading inferences on the effect of environment variables stemming from model misspecification.

Wang and Zelenyuk's "Random Versus Explained Inefficiency in Stochastic Frontier Analysis: The Case of Queensland Hospitals" is a *ne plus ultra* application of stochastic frontier methods. They apply several of the most well-known models to learn about hospital efficiency in Queensland, Australia. This analysis is then sistered with an array of model selection devices to help understand some of the interesting divergences that arise between models. Specifically, using a classic cross-sectional stochastic frontier model, Queensland hospitals are found to be nearly fully efficient, yet, accounting for a range of determinants (such as if it is a teaching hospital, located in a rural area, the occupancy rate and the number of beds), these high efficiency levels fade away.

To facilitate further confidence in their model selection findings, Wang and Zelenyuk use a novel approach: designing a recovery test based on their preferred model findings. The idea is to take the parameter estimates from a previously estimated model, use the actual data, and take random draws from the error terms to