Non-structural Analysis of Productivity Growth for the Industrialized Countries: A Jackknife Model Averaging Approach

Anders Isaksson
United National Industrial Development Organization, Vienna, Austria
a.isaksson@unido.org
Chenjun Shang
Freddie Mac, McLean VA, USA
chenjun_shang@freddiemac.com
Robin Sickles
Rice University, Houston, TX, USA
rsickles@rice.edu

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Abstract

Various structural and non-structural models of productivity growth have been proposed in the literature. In either class of models, predictive measurements of productivity and efficiency are obtained. This paper examines the model averaging approaches of Hansen and Racine (2012), which can provide a vehicle to weight predictions (in the form of productivity and efficiency measurements) from different non-structural methods. We first describe the jackknife model averaging estimator proposed by Hansen and Racine (2012) and illustrate how to apply the technique to a set of competing stochastic frontier estimators. The derived method is then used to analyze productivity and efficiency dynamics in 25 highly-industrialized countries over the period 1990 to 2014. Through the empirical application, we show that the model averaging method provides relatively stable estimates, in comparison to standard model selection methods that simply select one model with the highest measure of goodness of fit.

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1 Introduction

Understanding how productivity is evolving is crucial for an informed understanding of the health of an economy. It is also crucial that policy makers, industry, and firms have accurate infromation about productivity growth to gauge how stronly they should react to it various cycles, upticks, and downturns. Due to the importance of productivity as a metric to measure economic performance and the growth in the wealth of an economy, numerous approaches to productivity measurement have emerged in the literature. Often, different approaches are not used in concert to assess the range of possible levels and changes in productivity and what is reported is one result based on one chosen method. This paper offers a different and more robust approach that considers different approaches used in concert and which assesses the range of possible levels and changes in productivity.

For example, various structural and non-structural models of productivity growth have been proposed in the literature. The classical structural models, particularly those of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015), have focused on identifying innovation and efficiency within a structural model of the firm. These models typically are estimated using disaggregated plant-level or firm level data and then aggregated up to the country or sector level. Petrin and Levinsohn (2012) and Kim (2018) are but two examples of this approach. Aggregation of the productivity growth measures from these structural models and its decomposition into such factors as efficiency and reallocation effects provides the link between such models and the aggregate measures we will examine in our paper. Such aggregation of productivity measures and its decomposition, but based on non-structural approaches rather than structural models, is discussed extensively in Sickles and Zelenyuk (2018, Chapter 5), building on the work of Blackorby and Russell (1999), Kumar and Russell (2002), and Mayer and Zelenyuk (2014). We do not in this paper pursue such an aggregation exercise but rather focus on the aggregate economy itself.

Non-structural approaches, often stochastic frontier methods, focus on the asymmetry of productivity shocks implied by the presence of a best practice technology. It is well-known that such stochastic frontier approaches may suffer from endogeneity of the inputs that are correlated with unobserved technical inefficiency or productivity. Endogeneity can arise because input choices are determined by some factors that are unobserved to the econometrician but observed by the firm, such as the firm's beliefs about its productivity and efficiency. This in part led Schmidt and Sickles (1984) to utilize fixed effects treatments to address the potential endogeneity issue in production function estimation. In addition to fixed-effects-type estimators that require the assumption that the productivity terms are constant across time, extensions to time varying effects models can be found in Cornwell, Schmidt, and Sickles, (1990) and more recently in general factor model approaches (Kneip, Sickles, and Song, 2012).

Another set of two-step techniques, advocated by Olley and Pakes (1996), used observed investment to control for unobserved productivity shocks (efficiency). Levinsohn and Petrin (2003) expanded on this idea and used intermediate inputs instead of investment to solve the endogeneity issue, which they point out is a data-driven solution owing to issues that often surface when there are many observations with zero investment. This often occurs in data sets at levels of disaggregation that are establishment specific. Ackerberg et al. (2015) also have noted that both approaches suffer from collinearity problems in such two-stage IV-type estimators. Amsler, Prokhorov, and Schmidt (2016) reviewed two-stage IV-type procedures (2SLS) for the stochastic frontier model and pointed out the advantages of their corrected 2SLS (C2SLS) to solve a general endogeneity problem in stochastic frontier analysis wherein the productivity shock may also be correlated with the idiosyncratic disturbance. A somewhat similar two-step procedure was developed by Guan, Kumbhakar, Myers, and Lansink (2009).

In this paper we consider a number of competing models to estimate productivity that deal in various ways with endogeneity of inputs as well as potential endogeneity of unobserved productivity and efficiency effects that may change over time. These methods do not rely on the assumed monotonicity of investment and productivity on which the aforementioned structural models are based. We concentrate on robust methods to identify productivity and its constituent parts of innovation and technical efficiency, without the benefit of the overidentifying restrictions implied by structural approaches in the Olley and Pakes-class of structural models. In either class of models, Olley-Pakes or stochastic frontiers, we typically estimate what amounts to a reduced form-type of measure of productivity and efficiency. For structural models these are based on the implicit restricted reduced form, which is familiar to many productivity researchers as a linear equation with latent unobserved productivity (technical efficiency) assumed to follow a first-order Markov process that is correlated with the variable inputs, usually labor and materials, and typically not correlated with the quasi-fixed capital that provides production services that are assumed to be proportional to its level. It is this maintained structural assumption that motivates the use of investment as a valid instrument.

The specification of the estimating equation for productivity differs marginally from the specification of the estimation equations used in the stochastic frontier literature that began with the works of Aigner, Lovell, and Schmidt (1977) and van den Broeck and Meussen (1977). In that class of models the production function is also a linear equation with latent unobserved productivity (technical efficiency). However, in the stochastic frontier literature the latent technical efficiency term is introduced as a consequence of the implications of classical economic principles first pointed in Debreu (1951) and Farrell (1957). The one-sided nature of latent technical efficiency is based on the definition of production as a maximization operation. This class of stochastic frontier models are used by regulators in Europe and Latin America to establish tariff structures that incentivize enhanced performances of lagging firms while still rewarding frontier firms based on their historical high levels of performance (Agrell and Bogetoft, 2018). Thus we have two rather comparable estimating equations from which to extract technical efficiency measures for the Olley-Pakes and stochastic frontier paradigms. They differ in terms of structural assumptions but they lead to quite similar forms of estimating equations. In one class of models latent technical efficiency is specified as first-order Markov and in the other class is specified simply as nonsymmetric, owing to the implications of economic theory. While these approaches all have their merits, they are also based on various assumptions, which may or may not be supported by the true underlying data generating process (DGP). Thus, selecting an approach over all the alternatives may be fraught with great risk and lead to the wrong policy response. As the DGP process cannot be observed, we consider the model averaging approaches in the stochastic frontier setting, trying to reduce model selection risk and obtain more stable and reliable estimates of efficiency and productivity. We focus in this paper only on model averaging estimates from the stochastic frontier class of productivity model. Although this paper does not pursue model averaging using these two approaches for predicting productivity, such a model averaging exercise in principle can also be carried out.

In the remainder of the paper we first describe how the stochastic frontier model is developed to model productivity and then introduce a set of competing specifications that are widely used in empirical applications. Section 3 then explains the details of the jackknife model averaging technique. Section 4 describes the empirical setting we use for productivity analysis. Section 5 introduces the data and explains different measurements of the variables. Results are discussed in section 6. Section 7 concludes our paper.

2 Productivity Measurement and Stochastic Frontier Models

Productivity is usually measured as a ratio of an output index to an input index, where a higher ratio means more outputs can be produced from a given certain combination of inputs. In a simple one-output production process, total factor productivity (TFP) can be expressed as

$$\mathrm{TFP} = \frac{Y}{\sum a_i X_i} \tag{1}$$

where Y is the output, and X_i's are the inputs. When multiple outputs exist, TFP can be measured as a ratio of an index of aggregated outputs to an index of aggregated inputs. The value and properties of such a TFP measure will then depend on the methods of aggregation and index construction. Taking the log of (1), we can construct a total factor productivity index as the difference between the logged output and logged input indexes (Jorgenson and Griliches, (1972)).

TFP can be decomposed into technical efficiency (TE) and technical innovation. In a specific period, the technology may be regarded as fixed, while firms, or countries, might experience different technical efficiency levels. Denote $0 < \mathrm{TE}_i \leq 1$ to be the technical efficiency level for individual i, and let $f(\cdot)$ be the production function that defines the frontier. The production process for each production unit can be modeled as

$$y_i = f(X_i, \beta) \cdot \mathrm{TE}_i \tag{2}$$

where β is the coefficients vector of inputs X_i. Taking the log of (2) gives the following form,

$$\ln y_i = \ln f(X_i, \beta) + \ln \mathrm{TE}_i = \ln f(X_i, \beta) + u_i \tag{3}$$

where u_i is the logged efficiency level for each unit. Adding the usual disturbance term v_i to (3) to account for random production shocks completes the standard stochastic frontier model proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977). To identify the efficiency term, the stochastic frontier model with cross-sectional data required a distributional assumption on u_i. With panel data, however, one can allow for a non-parametric form of the efficiency term. As shown by Park, Sickles, and Simar (1998) the estimator of efficiency based on the within estimator can be shown to be semi-parametric efficient. In this section, we will focus on panel data models and consider several competing stochastic frontier settings in our study of productivity growth. After introducing each candidate model, we will show how to apply the model averaging technique to compute the optimal weights and obtain the jackknife averaging estimator.

We start with the most standard stochastic frontier models with panel data, which were first proposed in Pitt and Lee (1981) and Schmidt and Sickles (1984):

$$y_{it} = \alpha + X_{it}'\beta + u_i + v_{it} \qquad t = 1, \ldots, T;\ i = 1, \ldots, N \tag{4}$$

Here X_{it} is a vector of input variables, y_{it} is the output variable, v_{it} is the usual disturbance term and is assumed to be independently and identically distributed, possibly with a parameterized distribution such as $N(0, \sigma_v^2)$, and u_i represents the efficiency level of each individual. If we denote $\alpha_i = \alpha + u_i$, the model can be written as

$$y_{it} = \alpha_i + X_{it}'\beta + v_{it} \tag{5}$$

which is just the standard form of the panel data model. The coefficients can be obtained using the within or GLS estimators, depending on whether the error terms are assumed to be correlated with regressors. It is typical in such models to allow for a technology shifter that either is identified by a set of time dummies or by some time trend that is common to all firms or countries. Such a time trend proxies the innovation that shifts the frontier as new technologies diffuse across industries and countries.

In the original formulation of the Pitt and Lee (1981) and Schmidt and Sickles (1984) stochastic panel frontier model, the technical efficiencies were assumed to be fixed over time. However, with changes in possible influencing factors, such as adjustments in input allocation, workers' education levels, firms' administrative systems, and so on, we expect the efficiency levels to also change from period to period. Many researchers have extended the standard setting to model time-varying inefficiencies. One such extension was introduced by Cornwell, Schmidt and Sickles (1990) (Hereafter CSS) who considered a model allowing for time-varying individual effects by allowing for heterogeneous slope coefficients on the model's common time trend variables (t and t^2) that identify the common innovation factors that shift frontier production:

$$y_{it} = X_{it}'\beta + W_{it}'\delta_i + v_{it} \tag{6}$$

where $W_{it}\delta_i$ can be used to model cross-sectional efficiencies, which vary both over time and across sections. Denote $\delta_0 = E(\delta_i)$, then $\delta_i = \delta_0 + u_i$, where u_i is a zero-mean random variable and is independent of v_{it}. The model can be rewritten as

$$\begin{aligned} y_{it} &= X'_{it}\beta + W'_{it}\delta_0 + \epsilon_{it} && (7) \\ \epsilon_{it} &= W'_{it}u_i + v_{it} && (8) \end{aligned}$$

The CSS model can be estimated using extensions of the within and GLS estimators. If the effects u_i are assumed to be correlated with the exogenous regressors (X_{it}, W_{it}), then we can utilize a slight modification of the standard within transformation to estimate 7 - 8.

Another model we can consider is the one proposed by Battese and Coelli (1992). The generic setting is

$$y_{it} = X'_{it}\beta + u_{it} + v_{it} \tag{9}$$

where u_{it} represents the efficiency effects that can vary across both time and cross-section. The time changing path is specified as an exponential function:

$$u_{it} = -\{\exp[-\eta(t - T)]\}u_i. \tag{10}$$

With such a specification, the non-negative individual effects can increase, decrease or remain constant over time, corresponding to $\eta > 0$, $\eta < 0$ or $\eta = 0$. The effects u_i are assumed to be i.i.d. random variables following a non-negative truncation of the normal distribution $N(0, \sigma_u^2)$.

Denote $\epsilon_{it} = u_{it} + v_{it}$ as the composite error. As both u_i and v_{it} are assumed to follow specific distributions, we can derive an explicit expression for the distribution of ϵ_{it}. Parametric MLE can then be used to estimate the parameters. One problem is that the MLE is not linear, while the model averaging method we will employ is proposed for a set of linear estimators. We will show below how the Battese and Coelli (BC) model can be nested in a more general model setting, and thus how estimates of the coefficients from the BC estimator can be approximated with a linear estimator.

The general setting that nests the BC model is the one proposed by Kneip, Sickles, and Song (2012) (KSS) and is specified as

$$y_{it} = \alpha_t + X'_{it}\beta + u_{it} + v_{it} \tag{11}$$

The individual effects u_{it} are assumed to be affected by a set of underlying factors and are formulated by linear combinations of some basis functions:

$$u_{it} = \sum_{r=1}^{L} \delta_{ir} g_r(t) \tag{12}$$

For identifiability, it is assumed that $\sum_i^n u_{it} = 0$, $t = 1, \ldots, T$. The intercept α_t can be eliminated by transforming the model to the centered form,

$$y_{it} - \bar{y}_t = (X_{it} - \bar{X}_t)'^{L}_{r=1}\delta_{ir} g_r(t) + v_{it} - \bar{v}_t \tag{13}$$

where $\bar{y}_t = \frac{1}{n}\sum_i y_{it}$, $\bar{X}_t = \frac{1}{n}\sum_i X_{it}$ and $\bar{v}_i = \frac{1}{n}v_{it}$. Denote $\tilde{y}_{it} = y_{it} - \bar{y}_t$ and $\tilde{X}_{it} =$

$X_{it} - \bar{X}_t$, we return to the basic stochastic frontier setting

$$\tilde{y}_{it} = \tilde{X}_{it}'\beta + \sum_{r=1}^{L} \delta_{ir} g_r(t) + \tilde{v}_{it} \tag{14}$$

We can see that the individual effects u_{it} are assumed to be determined by a finite number of underlying factors, which are represented by a set of basis functions $(g_1(t), \ldots, g_L(t))$. Denote $\mathcal{L} \equiv span\{g_1, \ldots, g_L\}$ to be the space of the underlying factors. A problem is that the set of basis functions is not unique, and thus a normalization is needed for the estimation problem to be well defined. KSS used the following normalization.

(a) $\frac{1}{n}\sum_{i=1}^{n} \delta_{i1}^2 \geq \frac{1}{n}\sum_{i=1}^{n} \delta_{i2}^2 \geq \cdots \geq \frac{1}{n}\sum_{i=1}^{n} \delta_{iL}^2 \geq 0$
(b)$\frac{1}{n}\sum_{i=1}^{n} \delta_{ir} = 0$ and $\frac{1}{n}\sum_{i=1}^{n} \delta_{ir}\delta_{is} = 0$ for all r, $s \in 1, \ldots, L$, $r \neq s$.
(c) $\frac{1}{T}\sum_{t=1}^{T} g_r(t)^2 = 1$ and $\frac{1}{T}\sum_{t=1}^{T} g_r(t) g_s(t) = 0$ for all r, $s \in 1, \ldots, L$, $r \neq s$.

Provided that $n > L$, $T > L$, conditions (a) - (c) do not impose any restrictions, and they introduce a suitable normalization, which ensures identifiability of the components up to sign changes (instead of δ_{it}, g_r , one may use $-\delta_{ir}$, $-g_r$). Note that (a) - (c) lead to orthogonal vectors g_r as well as empirically uncorrelated coefficients δ_i. Bai (2003,2009) uses expectations in (a) and (b), which leads to another standardization and different basis functions, which are determined from the eigenvectors of the (conditional) covariance matrix. With such a normalization, the Battese and Coelli model can be nested after some rescaling. It corresponds to the case that $L = 1$ and $h(t) = exp(-\eta(t-T))/\sqrt{\frac{1}{T}\sum_{s=1}^{T} exp(-\eta(s-T))^2}$, that is, the BC model is equivalent to the following specification under the KSS framework:

$$y_{it} = X_{it}'\beta + u_i h(t) + v_{it} \tag{15}$$

KSS provides a semi-parametric method for estimation. First, it searches for the dimension of underlying factor space, L, through leave-one-out cross-validation. After the dimension number is determined, the set of basis function, $\{g(t)\}_r$ are calculated utilizing the spline theory (Details can be referred to Kneip, Sickles, and Song (2012) Section 2.2 and 3.1). To estimate the BC model as specified in (15), we first use this semi-parametric method to get productivity and efficiency estimate, $\hat{u_{it}} = \sum_r^L \hat{\theta}_r \hat{g_r}(t)$, and then solve for η by numerically minimizing the mean squared error of the difference between $\hat{u}_{it}$ and $u_i h(t)$. Individual factor u_1 is set to 1 for identification.

The KSS model is a very general setting. The CSS specification we described above can also be nested in the KSS model with $L = 3$ and polynomial functions being the basis function for individual effects. Some transformation will be needed for the basis functions to meet the standardization conditions.

3 Model Averaging

Facing a list of competing models, one may wish to know which one can best describe the true data generating process, thus providing a suitable platform on which one can conduct further analysis. This inquiry leads to a general model selection problem. On one hand, we wish to have a model that can explain the relation among variables well, allowing us to identify the influencing factors of certain observed phenomenon or to make predictions about future changes. On the other hand, we want a model that is both parsimonious and simple to implement. The literature discussing model selection is voluminous and various criteria have been proposed, each of which has a different focus. The well-known Akaike information criterion (AIC; Akaike, 1973) and the Schwarz-Bayes information criterion (BIC; Schwarz, 1978) aim to reach a balance between the goodness of fit and the parsimony of the model. A more recent concept, the focused information criterion (Hjort and Claeskens, 2003), considers the estimating quality of the parameters of interest instead of the fit of the entire model. The typical procedure of model selection starts with choosing one such criterion and calculating it for all the candidate models. The model with the best performance will then be selected and treated as the "true" model that is assumed to generate the data. Further analysis, such as making inferences or predictions, will be solely based on this "true" model. One problem with the model selection procedure is that it ignores model uncertainty. That is, we assume that the probability that the chosen model is the "true" data generating process (DGP) is one, while in reality such a procedure leads to over optimistic inferences and higher prediction error. Another problem is that the "true" model can be different based on the criterion employed. Though there can be a general guide directing which criterion to use according to the main interest of the problem, there is no standard and systematic procedure to follow. It is also difficult to evaluate how well these criteria perform.

The difficulty of selecting an optimal or "true" model lies in the fact that the true DGP is unobservable. All that we can do is to approximate the underlying mechanism as accurately as possible based on the observed data. By assigning a set of weights to all the candidate models instead of treating a single model as the "best" or "true" model, model averaging can be seen as an agnostic method. This method has been shown to be a more favorable approach if the goal of econometric analysis is to approximate the underlying DGP rather than to discover it.

As all the candidate models can reflect the underlying DGP to some extent, it is reasonable to assign each one a weight based on its ability to explain the data. The model selection procedure can be seen as a special case of model averaging in which the "best" model receives a probability of one while others receive a zero weight. If reliance on one model is replaced by reliance on many then one must determine how to weight the predictions from the various models under consideration. Like other statistical techniques, model averaging methods can be classified into Frequentist Model Averaging (FMA) and Bayesian Model Averaging (BMA). Early work on model averaging was mainly from the Bayesian perspective, and there has emerged a voluminous literature on both theoretical extensions and empirical applications of BMA. In general, the BMA approach first assigns to each candidate model a prior probability, which is updated through the observed data, and the updated posterior probability is then used as the weight.

Choosing the prior probabilities is the first step in the BMA method. This is problematic because we do not know what priors are the most appropriate, and priors can be in conflict with each other. The FMA approach, on the other hand, does not need such ex ante assumptions of probabilities, and thus avoids finite sample problems associated with the BMA approach. There has been a growing literature discussing FMA methods. Buckland, Burnham and Augustin (1997) proposed to assign weights according to an information criterion of each candidate model m:

$$I_m = -2log(L_m) + l \tag{16}$$

where L_m is the maximized likelihood function of the m-th model, and l is some penalty function. The weights based on this criterion are calculated as

$$w_I = \frac{exp(\frac{1}{2}I_m)}{\sum_{m \in \mathcal{M}} exp(\frac{1}{2}I_m)} \tag{17}$$

in which M is the set of all competing models. If $l = 2k$, where k is the number of parameters in the model, the information criterion I_m is just the AIC score. If $l = k \cdot log(n)$, and n represents the number of observations, I_m becomes the BIC score. It is straightforward to base the weights on such model evaluating criteria, but we lack a method to measure the effectiveness of these weighting schemes. It is also difficult to tell by how much they can improve the quality of the estimators.

Other weighting schemes have been proposed in recent years. Leung and Barron (2006) considered assigning the weights to a set of least squares estimators based on their risk characteristics. Hansen (2007) proposed to select the weights by minimizing a Mallows criterion, which works in a set of nested linear models with homoskedastic errors. Hansen shows that the Mallows model average estimator can asymptotically achieve the lowest squared error among a finite number of model averaging estimators. Based on the work of Hansen (2007), Wan, Zhang and Zou (2010) relaxed the assumptions that candidate models should be nested based on certain ordering of regressors. They also provided a proof of the optimality of Mallows criterion in a continuous weight set. Wang, Zhang and Zou (2009) also reviewed important developments in FMA methods.

Hansen and Racine (2012) considered a more general situation in which the candidate models can be non-nested and have heteroscedastic errors. The proposed estimator is termed "jackknife model averaging" (JMA) estimator. It is obtained by minimizing a leave-one-out cross-validation criterion. This JMA estimator is proved to be asymptotically optimal in the sense that it approaches the lowest possible expected squared errors as the sample size approaches infinity (for a panel data of N individuals and T time periods, the sample size is equal to $N \times T$). We employ this JMA technique in our stochastic frontier analysis as it provides us with a model averaging procedure that has optimal properties for the class of models we consider.

3.1 Jackknife Model Averaging

To illustrate the jackknife model averaging method, we begin with a number of competing models that can be written as

$$y_i = \mu_i + \epsilon_i \qquad i = 1, \ldots, n \tag{18}$$

where $\mu_i = E(y_i|X_i)$, and X_i is the vector of input variables. ϵ_i is the error term with zero mean conditional on X_i. The conditional variance of ϵ_i is allowed to vary across observations. That is,

$$E(\epsilon_i|X_i) = 0 \tag{19}$$
$$E(\epsilon_i^2|X_i) = \sigma_i^2. \tag{20}$$

Suppose we have M candidate models, and for each model m, we have a linear estimator, denoted as $\hat{\mu}^m = P_m y$. The estimator is linear in the sense that P_m is not a function of y. This definition covers a fairly broad class of estimators. As mentioned in Hansen and Racine (2012), the standard OLS, ridge regression, nearest neighbor estimators, series estimators, etc. are all in this class. The jackknife averaging estimator is then calculated as the weighted average of all the candidate models.

For each model m, the jackknife estimator is denoted as $\tilde{\mu}^m = (\tilde{\mu}_1^m, \ldots, \tilde{\mu}_n^m)'$, and $\tilde{\mu}_i^m$ is the estimate of y_i with parameters estimated after the ith observation being deleted (i.e. the leave-one-out cross validation). The jackknife residual is then computed as $\tilde{e}^m = y - \tilde{\mu}^m$. Hansen and Racine (2012) provided a simpler method to calculate the jackknife residual for the standard OLS estimator to avoid n times regressions for each model. However, this particular approach is not applicable for the stochastic frontier models we consider below.

The weights are assumed to be non-negative and sum to one. The weight vector lies on the $\mathbb{R}^M$ unit simplex.

$$\mathcal{H}_M = \Big\{ w \in \mathbb{R}^M : w^m \geq 0, \sum_{m=1}^{M} w^m = 1 \Big\}.$$

Given a specific weight vector w, the averaged estimator is

$$\tilde{\mu}(w) = \sum_{m=1}^{M} w^m \tilde{\mu}^m = \tilde{\mu} w \tag{21}$$

and the averaged residual is

$$\tilde{e}(w) = y - \tilde{\mu}(w) = \tilde{e} w. \tag{22}$$

The jackknife or leave-one-out cross-validation criterion can be expressed in terms of the averaged residuals as

$$CV_n(w) = \frac{1}{n} \tilde{e}(w)' \tilde{e}(w). \tag{23}$$

The jackknife weights can be obtained by minimizing this criterion over the weight space $\mathcal{H}_M$, i.e.

$$w^* = \arg\min_{w \in \mathcal{H}_M} CV_n(w). \tag{24}$$

The jackknife averaging estimator is thus $\hat{\mu}(w^*) = \hat{\mu}w^*$. Depending on different specifications of the model setting, the applicable weight space might be only a subset of $\mathcal{H}_M$.

4 Model Averaging Estimates of Productivity Growth

We assume that technology or technical innovations can be accessed by all countries during the year and thus that technical change is shared by the countries in the sample. The differences in productivity are assumed to be caused by relative efficiencies. Technical innovation change could be proxied by differences in R&D expenditure over time, number of patents appeared, or other similar factors, but such data is not available. However, R&D expenditures and patents are, at best, proxies for invention and not necessarily for innovation. The implicit assumption that innovation is a monotone increasing function of R&D expenditures is simply not empirically valid, especially across nations or industries (within nations). Many factors affect how and how much R&D eventually translates into innovation. When building up the empirical model, we could also use time variables to proxy the technical innovation, such as the time index method proposed in Baltagi and Griffin (1988). In our estimations below we use a standard time trend to proxy technical change, which may be endogenous in that it can be correlated with the efficiency with which different countries utilize it. Endogenous growth is formally addressed via the stochastic frontier specification of the dynamic efficiency terms, which complement growth due to innovation to generate total factor productivity growth, or TFP growth. The technical efficiencies and their changes are estimated by linearized versions of the stochastic frontier models.

In keeping with the growth literature, we specify a Cobb-Douglas production function with inputs capital K and labor L, and output Y, measured by GDP. Technical change that is available to industrialized countries is proxied by t and t^2, leading the basic econometric model

$$lnY_{it} = \alpha_i + \beta_1 lnK_{it} + \beta_2 lnL_{it} + \theta_1 t + \theta_2 t^2 + u_{it} + v_{it}. \tag{25}$$

The candidate estimators are within and GLS estimators from the standard panel data model with no time-varying efficiencies proposed by Pitt and Lee (1981) and Schmidt and Sickles (1984) (denoted as 'Fixed' and 'Random' respectively), the within and GLS estimators from the CSS model (denoted as 'CSSW' and 'CSSG' respectively) with time varying efficiencies, and the BC estimator, whose specification of time varying efficiency scales a common and potentially nonlinear time path with country specific shifters. In subsequent work Battese and Coelli (1995) made these shifters functions of a set of "environmental" factors that not only could change the efficiency level but also its variance. We do not utilize this extension in this study.

As with most aggregate country studies, we assume as steady-state equilibrium for the countries under study and thus that the production function displays constant returns to scale. Thus the empirical model can be written as

$$lnY_{it} = \alpha_i + \beta_1 lnK_{it} + (1 - \beta_1)lnL_{it} + \theta_1 t + \theta_2 t^2 + u_{it} + v_{it}. \tag{26}$$

Denoting $ln\tilde{Y}_{it} = lnY_{it} - lnL_{it}$ and $ln\tilde{K}_{it} = lnK_{it} - lnL_{it}$, the regression function for the CRS case is

$$ln\tilde{Y}_{it} = \alpha_i + \beta_1 ln\tilde{K}_{it} + \theta_1 t + \theta_2 t^2 + u_{it} + v_{it}. \tag{27}$$

Recall that the jackknife model averaging method is applied to the class of linear estimators, which includes, for example, standard linear least-squares, ridge regression, nearest neighbor estimators, and spline estimators. The optimized weights are calculated through leave-one-out cross-validation. In our case, with a panel data of N countries and T periods, the cross-validation means $N \times T$ times estimation for each candidate model, which can be quite time-consuming when the data set gets large. Hansen and Racine (2012) provided an analytical expression of the jackknife residual vector $\tilde{e}$ for least-squares estimators, which can greatly reduce computing time but is not applicable in our case. In our estimation process, we experimented with block cross-validation (treating observations in the same time period as a block, and leaving out one block a time as the validation set) to see how it would affect the optimal weights, and found the results from such a "shortcut" are completed different than those calculated from leave-one-out cross-validation. Zhang, Wan, and Zou (2013) discussed the problem of block cross-validation: the selection of block length is data dependent, which leads to μ being a non-linear function of y. This non-linearity contradicts the assumption of the jackknife method, thus the asymptotic properties cannot be guaranteed. So for all other linear estimators that cannot be expressed in the form of $X(X'^{-1}X'y$, the computing time for leave-one-out cross-validation is inevitable.

5 Data Description

Our calculations are based on data from the United Nation Industrial Development Organization (UNIDO), which provides information on productivity related variables and statistics of 112 countries. Since the World Productivity Database (WPD) contains data only up to year 2000, we have extended the data series to 2014. Different measures of TFP are included in the database, as well as some partial measurements, such as labor productivity.

GDP is our output measure and is a chain-weighted real index that is adjusted for purchasing power parity using constant 1996 prices. When the data for one or more of the end years are missing, the WPD uses the growth rates of real GDP to impute the value. Information about the real GDP growth rates is obtained from World Development Indicators from the World Bank.

The difficulty in measuring capital is largely due to the need to measure the flow of capital services, which cannot be easily measured for a number of countries covered in the WPD. Thus, the WPD assumes that the capital services are proportional to the capital stock and provides several different measurements of capital stock, denoted as K06, K13, Ks, and Keff, respectively. The differences in these measurements are reflected in how the initial capital stock is computed, the depreciation rate, whether the rate is constant or changes over time, and asset lifetime.

Due to limited data, we use K06, K13, and Ks as different measurements of capital in separate estimations using the various estimating models. All three variables are based on the perpetual inventory method and assume a constant depreciation rate. The perpetual inventory method specifies capital stock in any period t as equaling the remaining capital stock from the previous period after depreciation plus the new investment made in the last period. Dated back to the starting period, the capital stock at period t is expressed as a function of the initial capital K_0 and the depreciation rate δ,

$$K_t = (1-\delta)K_{t-1} + I_{t-1} = (1-\delta)^t K_0 + \sum_{i=1}^{t}(1-\delta)^{t-1} I_i \tag{28}$$

where I_t is the investment in each period, which is also provided in the WPD. The three different measures of the capital stock then differ in the methods used to estimate its initial level and the value assumed for the depreciation rate. Both K06 and K13 use ten years of investments as the estimate for the initial capital stock K_0, for example, investments from 1980 to 1989 for the capital series to start from 1990. The only difference between the two is the depreciation rate assumed: 6 percent for K06 and 13.3 percent for K13. The rapid depreciation rate used for K13 means this measure places more emphasis on recent investments and the initial capital stock has relatively less impact. The value assumed for δ matches the double-declining balancing method in accounting, implying an asset lifetime of 15 years. K06, by contrast, is more affected by the initial capital stock.

The initial capital stock for Ks is computed by assuming the country is at its steady state capital-output ratio. The steady-state capital-output ratio is related to the investment ratio, the growth of real GDP, and the rate of depreciation of the capital stock via:

$$k = \frac{i}{g+\delta} \tag{29}$$

where g is the growth rate of real GDP, and i is the investment ratio (I/Y). An estimate of the capital-output ratio of the starting year can be obtained by using equation (29). The estimate of the initial year's output is then calculated by multiplying this ratio by Y_0. Compared with K06 and K13, Ks does not require the extra ten years of data for the calculation of K_0.

For the labor input, the WPD provides five measurements for the labor inputs: labor force, employment (EMP), derived employment (EDMP), hours worked based on employment (HEMP) and hours worked based on derived employment (HDEMP). Employment is obtained by adjusting the labor force for the population that is employed. A direct measure of employment leads to EMP, and the derived value, which is obtained by applying the unemployment rate to labor force data, leads to DEMP. Further adjustment of EMP and DEMP for the numbers in hours worked results in the last two measurement: HEMP and HDEMP. Among all these measurements, labor force is a standard proxy used in the empirical study, and the data usually has better quality compared to its alternatives. On the other hand, the use of labor force may result in underestimation of productivity since not all of the labor force is fully utilized. Considering data quality and accuracy of the measurement, we use labor force and employment as the two labor measurements.

An additional important factor is the schooling levels of labor, which are, in general, measured in two ways: as a separate input or as an increase to labor input. We adopt the latter method in this paper, and the final measurements of labor are schooling-adjusted labor force and schooling-adjusted employment.

The data we use consist of 25 highly-industrialized countries over the period 1990 to 2014. According to World Bank 2016 statistic, this group contributes over 50% of world GDP. The countries are:

Australia, Austria, Belgium, Canada, Cyprus, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and United States.

6 Results

The coefficient estimates of each model are shown in Table 1 and 2. Coefficients of log capital range between 0.3 to 0.7. The estimates obtained from the CSS model are generally lower, around 0.3 to 0.45, and the estimates from the KSS model are higher with all different combinations of input measurements. We see from the tables that, with the same capital measurement, the estimated returns to labor is lower when we use labor force rather than employment as the labor measure, which reflects the general belief that use of labor force may inflate the level of labor input and leads to underestimation of returns to labor. We will see below that productivity estimates obtained using labor force are also lower than those generated using employment.

The weights obtained using the jackknife criterion are reported in Tables 3. For all measurement combinations, most of the weight falls on the CSSW estimator. The BC estimator gets a small weight of around 0.1, and the weights on the standard within estimator, random effects GLS and the extended time varying random effects CSSG estimators are negligible. Based on the weights assigned to within and to the GLS estimators (both standard ones and the extended in CSS setting), the assumptions of the within estimators appear to be consistent with the data as the existence of considerable correlation between the regressors and the effects appears clear. Besides the comparison between the within and GLS estimators, we expect the CSS and BC specifications of cross-sectional and temporal changes differences in productivity to allow for a richer parameterization of heterogeneities in unexplained production dynamics while in a standard panel data setting in which the effects are time invariant the efficiency terms are fixed over time. We can see that the CSSW estimator does receive most of the weight. The BC estimator's performance might be constrained somewhat by the linearized approximation of the exponential function of the efficiency term that we have used. There would be some loss of accuracy when we numerically minimized the difference between the estimated efficiency $\hat{u}_{it}$ and BC specification $u_i h(t)$, especially with our small dataset. We would expect that the data-driven approach used in implementing the BC estimator should perform better on a larger data set that can provide more information about underlying patterns. Among the five candidate estimators, standard within and GLS estimators are relatively more simplified specifications, resulting in less explanatory power. We would expect the weights to be more evenly spread out as we increase the number of competing models.

Technical innovations are proxied by the time variables, t and t^2, and technical efficiencies are estimated using stochastic frontier methods. Combining the two effects, we have the estimates of total factor productivity. Based on the beginning- and ending-period productivity levels, we can calculate the annualized productivity growth rates. The group annualized TFP growth rates are aggregated from each individual country by using 1) equal weights, 2) GDP weights. The results are shown in Table 4 and 5 correspondingly. We can see that, with the same capital measure, productivity estimates are lower when we use labor force. The average annual growth rates of TFP are between 0.7% and 0.8% when we use simple average, and are around 0.4% to 0.55% when we use GDP as weights, which is as expected. Countries with large GDP, like United States and Japan, are highly developed, and are relatively slow in productivity growth.

The estimates of total factor productivity for the entire studied period are plotted in Figures 1 to 3 for simple averaged results, and Figure 4 to 6 for GDP weighted numbers. As we specify a quadratic function to approximate technical changes, most of the plots show concave quadratic curves. We have standardized the productivity estimates so that the series all begin at zero in order to track the relative changes of different countries over the sample period.

As we pointed above, in addition to the stochastic frontier models we discussed here, structural models are an alternative approach that researchers employ in productivity study. One may be able to modify the class of structural models introduced by Olley and Pakes (1996) to describe the country-level productivity growth based on a linearized version of the derived reduced form and thus use it as an additional model in the model averaging exercise. We will leave this for future research.

7 Conclusion

This paper introduces the model averaging method to the analysis of productivity using stochastic frontier models. The optimal weights are calculated by minimizing the jackknife model averaging criterion, which is a leave-one-out cross-validation method. Though each candidate model needs to be estimated $N \times T$ times, the procedure is not complex and the computational burden is moderate in our application.

The SFA methods we have discussed and utilized have been adopted in Europe and Latin America as one of several approaches that must be considered in establishing efficiency benchmarks when setting tariffs in regulated industries (Agrell and Bogetoft, 2018) and such methods as we consider are already used in an ad hoc way by industry regulators. Also, it should not be lost on the policy maker the importance of understanding and accepting that these different methods are fraught with uncertainty and that model averaging allows us to provide an estimate with upper/lower bands (of uncertainty), thus providing a more robust and credible set of statistics that can be developed by the analyst.

In general, the model averaging technique provides us with more stable and reliable estimates of efficiencies and productivities. In our paper, we only analyze a highly industrialized country group. As we have pointed out, model averaging method reduces the risk of wrong specification or wrong assumptions based on only one model. The choice of the frequentist model averaging method in our study avoids the difficulty in choosing proper priors that are required in Bayesian model averaging, and the jackknife model averaging estimator achieves optimality in the sense that it can asymptotically approaches the lowest possible expected squared errors.

Our methods for constructing 'consensus' estimates of productivity growth could/ should be used by for example policymakers and international organizations in their analytical work to lower the impact and risk of using a single approachs assumptions that may not be supported by the true DGP. In addition, international organizations should not take 'academic' positions for methods and thus would be better off averaging across several 'widely acceptable and used' approaches. As such, the proposed averaging method may be viewed as a risk-reducing strategy, which helps avoiding placing too much weight on a certain policy response because of some implicit (strong) assumption in a single measurement method. Likewise, for international organizations assisting countries, putting together a properly weighted package to address challenges is of the essence and to this end productivity is a crucial indicator informing of the proper mix. Again, as accurate as possible measurement of productivity is significantly important to make the best use of scarce resources.

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8 Tables and Figures

	Est.	Std. Err	Est.	Std. Err	Est.	Std. Err
FIX	Ks, Ls		Ks, ES		K06, LS	
lnK	0.452640	0.040638	0.397820	0.038534	0.462480	0.040230
lnL	0.547360		0.602180		0.537520	
t	0.026084	0.001860	0.025213	0.001759	0.025368	0.001865
t^2	-0.000731	0.000066	-0.000666	0.000064	-0.000716	0.000066
FIX	K06, ES		K13, LS		K13, ES	
lnK	0.406980	0.038389	0.465840	0.040061	0.409560	0.038491
lnL	0.593020		0.534160		0.590440	
t	0.024601	0.001764	0.025349	0.001859	0.024597	0.001763
t^2	-0.000654	0.000063	-0.000717	0.000066	-0.000655	0.000063
RND	Ks, Ls		Ks, ES		K06, LS	
lnK	0.481620	0.038517	0.419020	0.036708	0.489820	0.038159
lnL	0.518380		0.580980		0.510180	
t	0.025686	0.001852	0.024979	0.001755	0.024958	0.001855
t^2	-0.000729	0.000066	-0.000667	0.000064	-0.000713	0.000066
RND	K06, ES		K13, LS		K13, ES	
lnK	0.426900	0.036575	0.492690	0.038002	0.429310	0.036656
lnL	0.573100		0.507310		0.570690	
t	0.024356	0.001759	0.024948	0.001850	0.024355	0.001758
t^2	-0.000654	0.000063	-0.000714	0.000066	-0.000655	0.000063
CSSW	Ks, Ls		Ks, ES		K06, LS	
lnK	0.368840	0.063058	0.312160	0.050096	0.376060	0.062807
lnL	0.631160		0.687840		0.623940	
CSSW	K06, ES		K13, LS		K13, ES	
lnK	0.312520	0.050725	0.387660	0.062993	0.320830	0.050787
lnL	0.687480		0.612340		0.679170	

Table 1: Coefficients Estimates

	Est.	Std. Err	Est.	Std. Err	Est.	Std. Err
CSSG	Ks, Ls		Ks, ES		K06, LS	
lnK	0.423620	0.048775	0.361800	0.040391	0.428440	0.048599
lnL	0.576380		0.638200		0.571560	
t	0.026483	0.003651	0.025611	0.003218	0.025879	0.003649
t^2	-0.000733	0.000099	-0.000664	0.000086	-0.000719	0.000099
CSSG	K06, ES		K13, LS		K13, ES	
lnK	0.362570	0.040734	0.439440	0.048523	0.370310	0.040857
lnL	0.637430		0.560560		0.629690	
t	0.025148	0.003211	0.025743	0.003640	0.025077	0.003221
t^2	-0.000653	0.000086	-0.000719	0.000098	-0.000654	0.000086
KSS	Ks, Ls		Ks, ES		K06, LS	
lnK	0.591020	0.044351	0.712660	0.037440	0.570910	0.050488
lnL	0.408980		0.287340		0.429090	
KSS	K06, ES		K13, LS		K13, ES	
lnK	0.741910	0.047111	0.521870	0.050260	0.722030	0.047632
lnL	0.258090		0.478130		0.277970	

Table 2: Coefficients Estimates (Cont.)

	FIX	RND	CSSW	CSSG	BC
Ks, Ls	0.000000	0.000000	0.880577	0.000000	0.119423
Ks, Es	0.000000	0.000000	0.885944	0.000000	0.114056
K06, Ls	0.000000	0.000000	0.877251	0.000000	0.122749
K06, Es	0.000000	0.000000	0.883554	0.000000	0.116446
K13, Ls	0.000000	0.000000	0.922453	0.000000	0.077547
K13, Es	0.000000	0.000000	0.891062	0.000000	0.108938

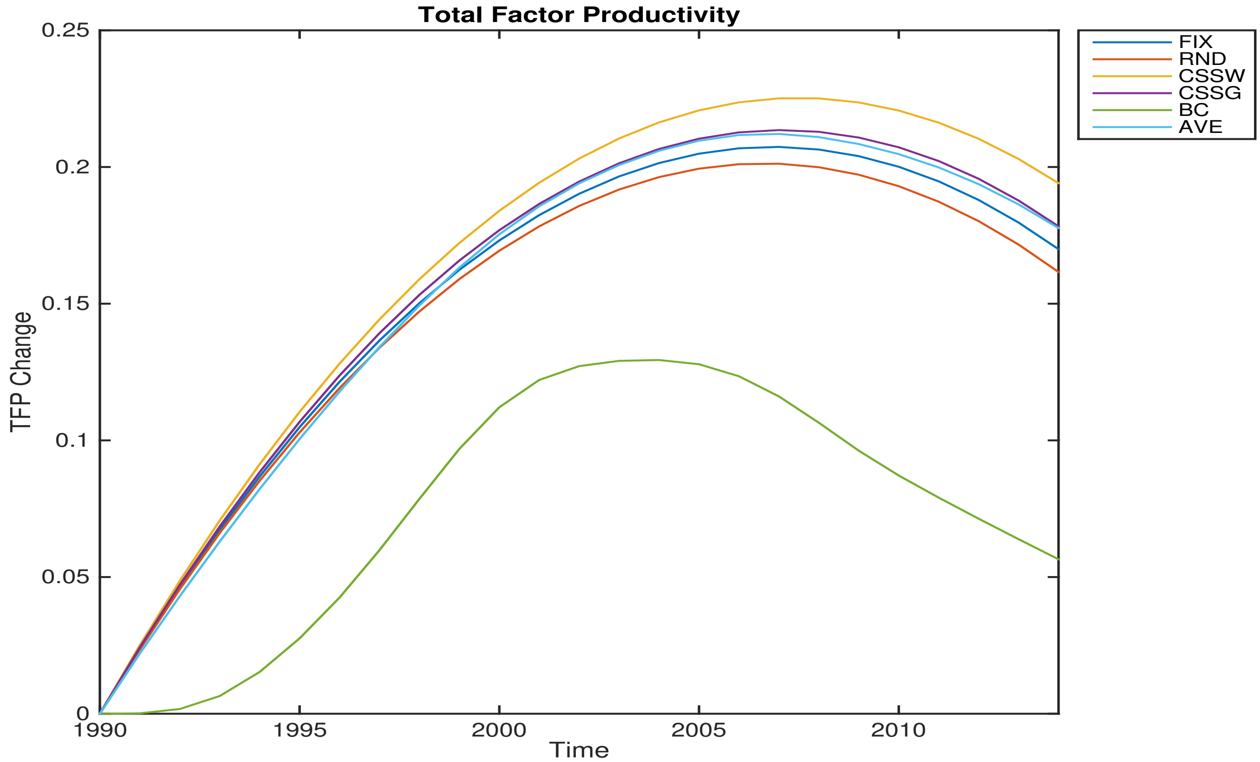
Table 3: Weights on different estimators

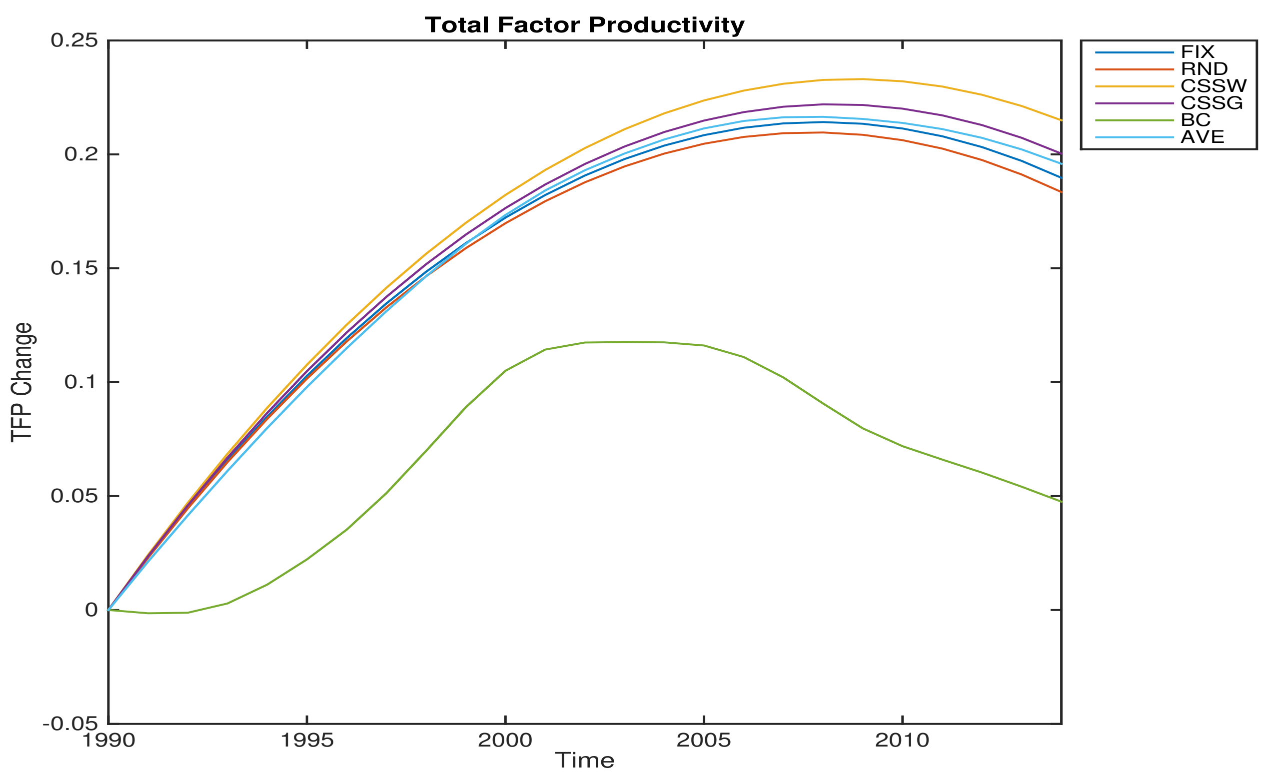
	FIX	RND	CSSW	CSSG	BC	AVE
Ks, LS	0.006798	0.006464	0.007764	0.007132	0.002260	0.007106
Ks, ES	0.007590	0.007340	0.008600	0.008014	0.001902	0.007836
K06, LS	0.006480	0.006153	0.007514	0.006888	0.002518	0.006901
K06, ES	0.007302	0.007058	0.008457	0.007845	0.001087	0.007599
K13, LS	0.006442	0.006122	0.007378	0.006758	0.002210	0.006977
K13, ES	0.007272	0.007031	0.008358	0.007752	0.001391	0.007598

Table 4: Annualized simple average TFP growth rate

	FIX	RND	CSSW	CSSG	BC	AVE
Ks, LS	0.006798	0.006464	0.004942	0.004237	0.002170	0.004740
Ks, ES	0.007590	0.007340	0.005914	0.005258	0.001855	0.005602
K06, LS	0.006480	0.006153	0.004721	0.004029	0.002442	0.004555
K06, ES	0.007302	0.007058	0.005803	0.005124	0.001025	0.005438
K13, LS	0.006442	0.006122	0.004646	0.003972	0.002100	0.004451
K13, ES	0.007272	0.007031	0.005755	0.005094	0.001340	0.005412

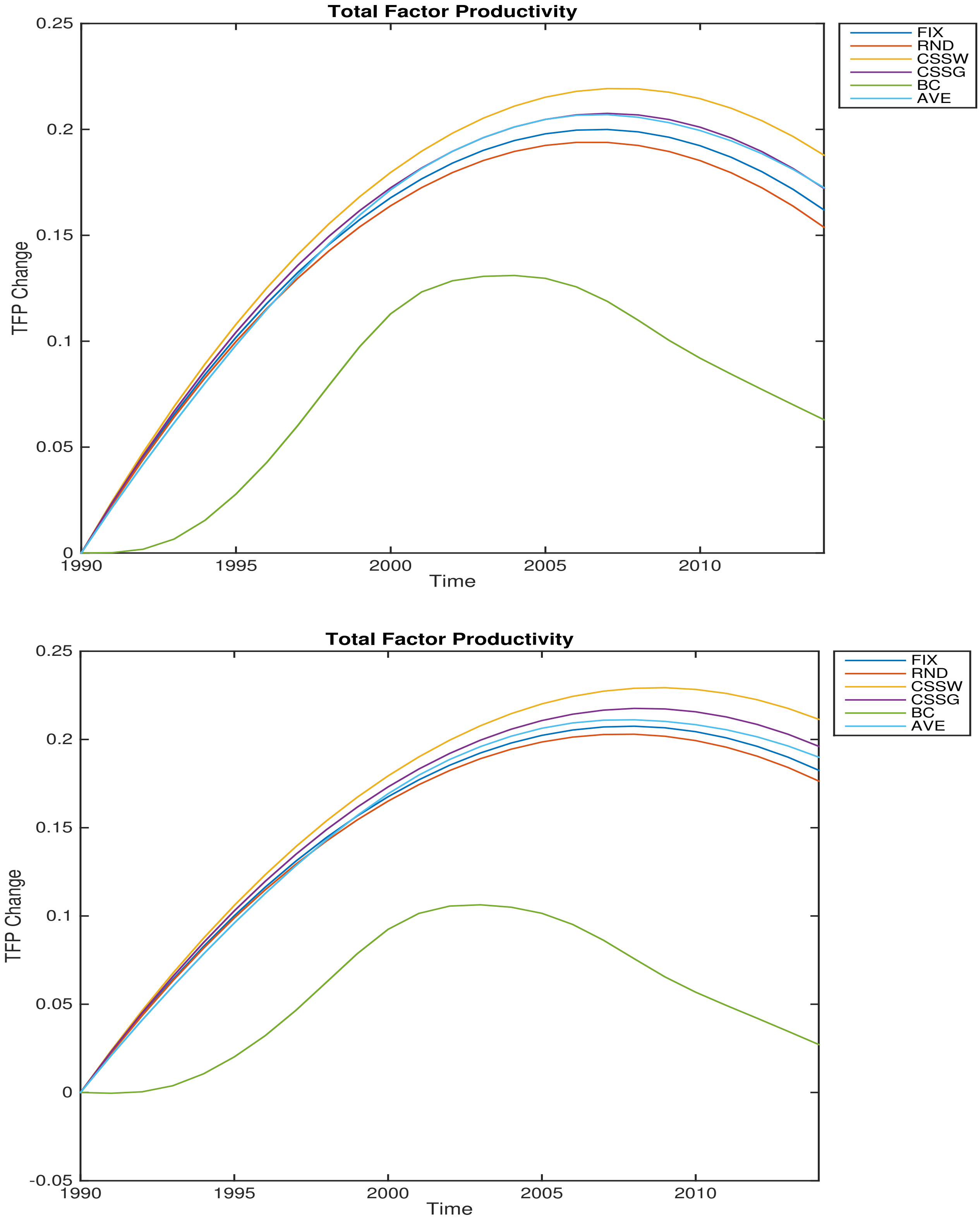
Table 5: Annualized GDP-weighted TFP growth rate





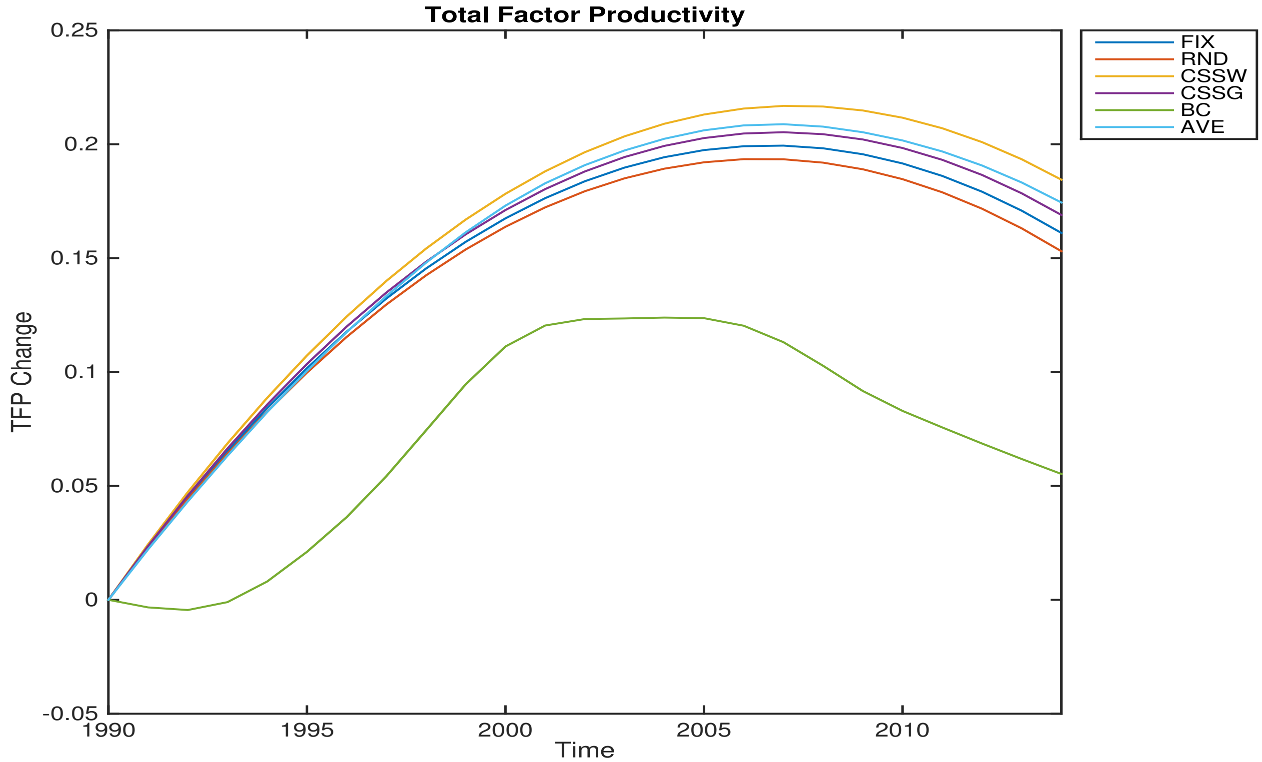
(b) Ks, ES

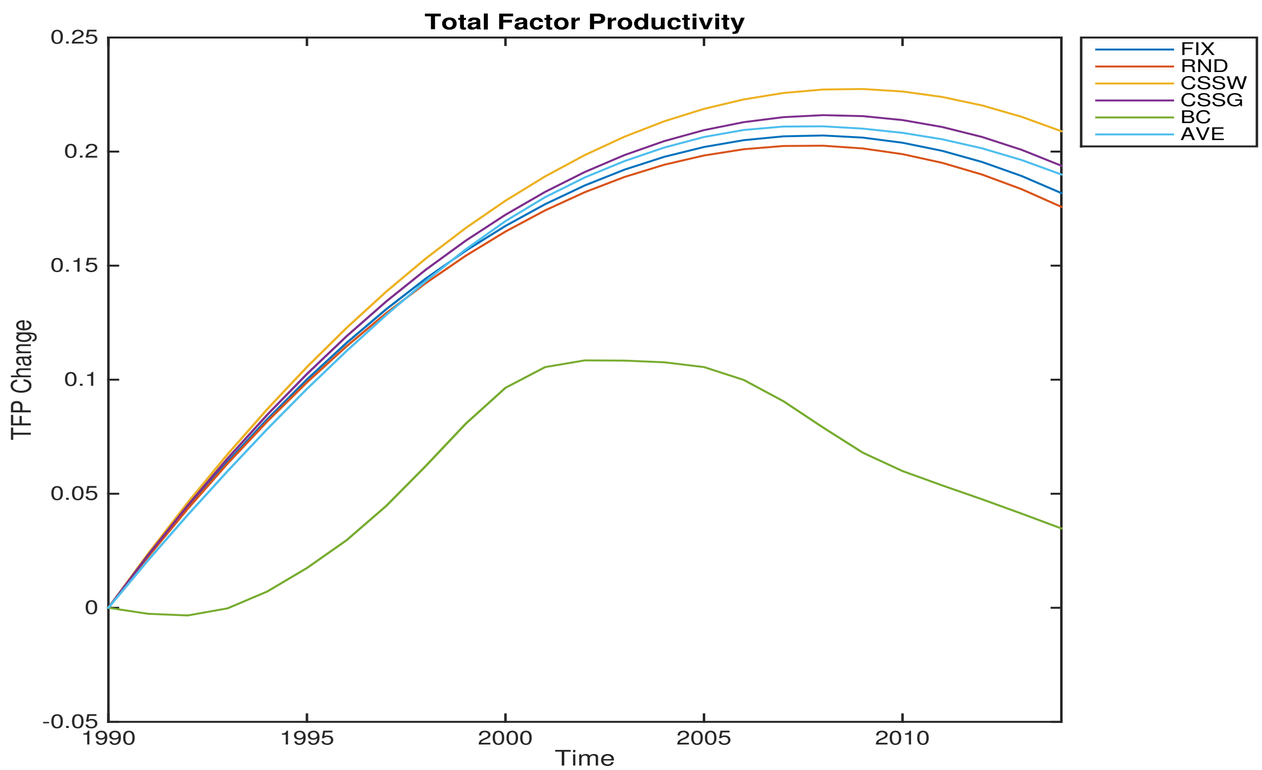
Figure 1: Total Factor Productivity-I



(b) K06, ES

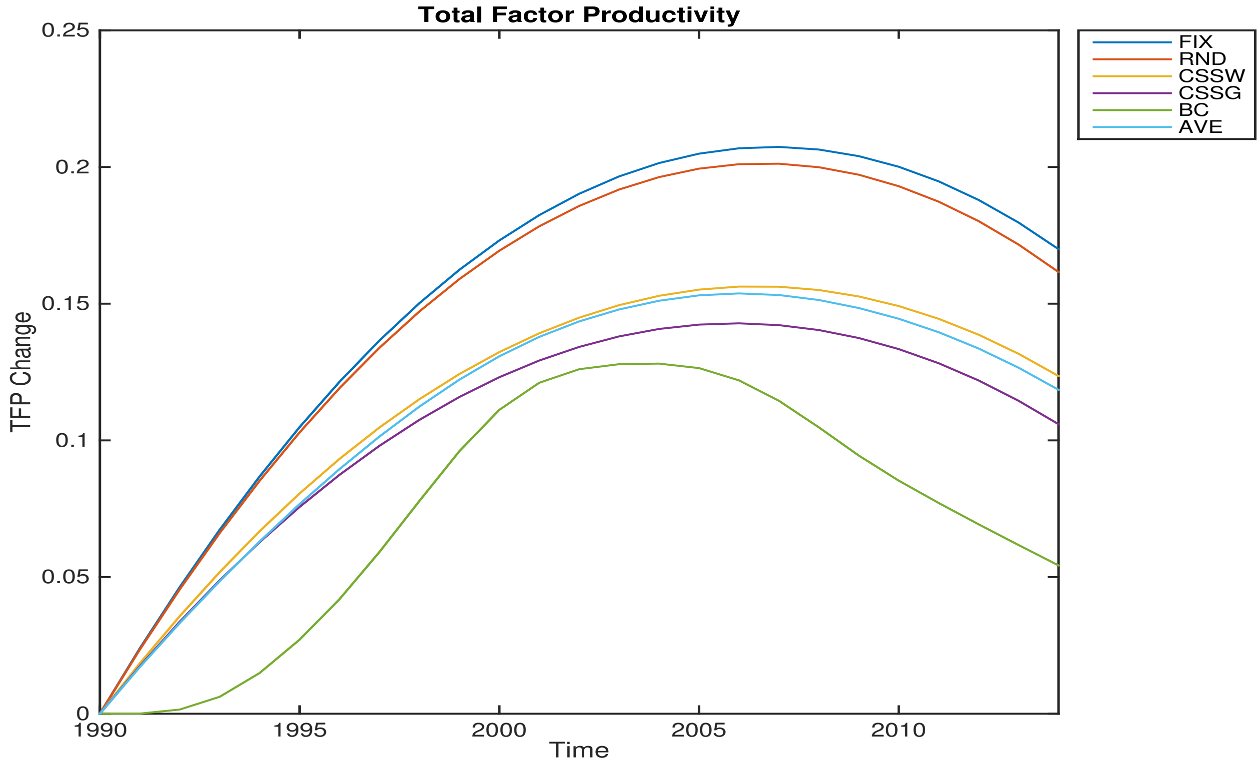
Figure 2: Total Factor Productivity-II

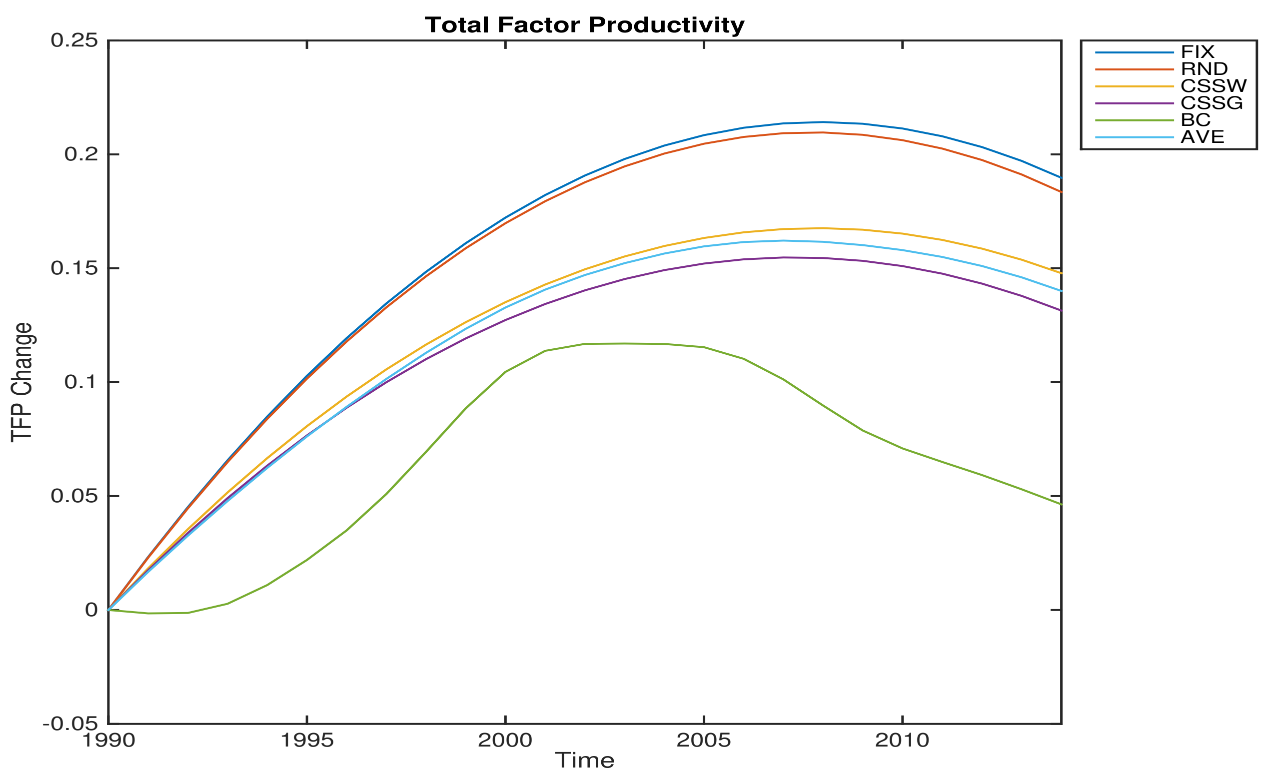




(b) K13, ES

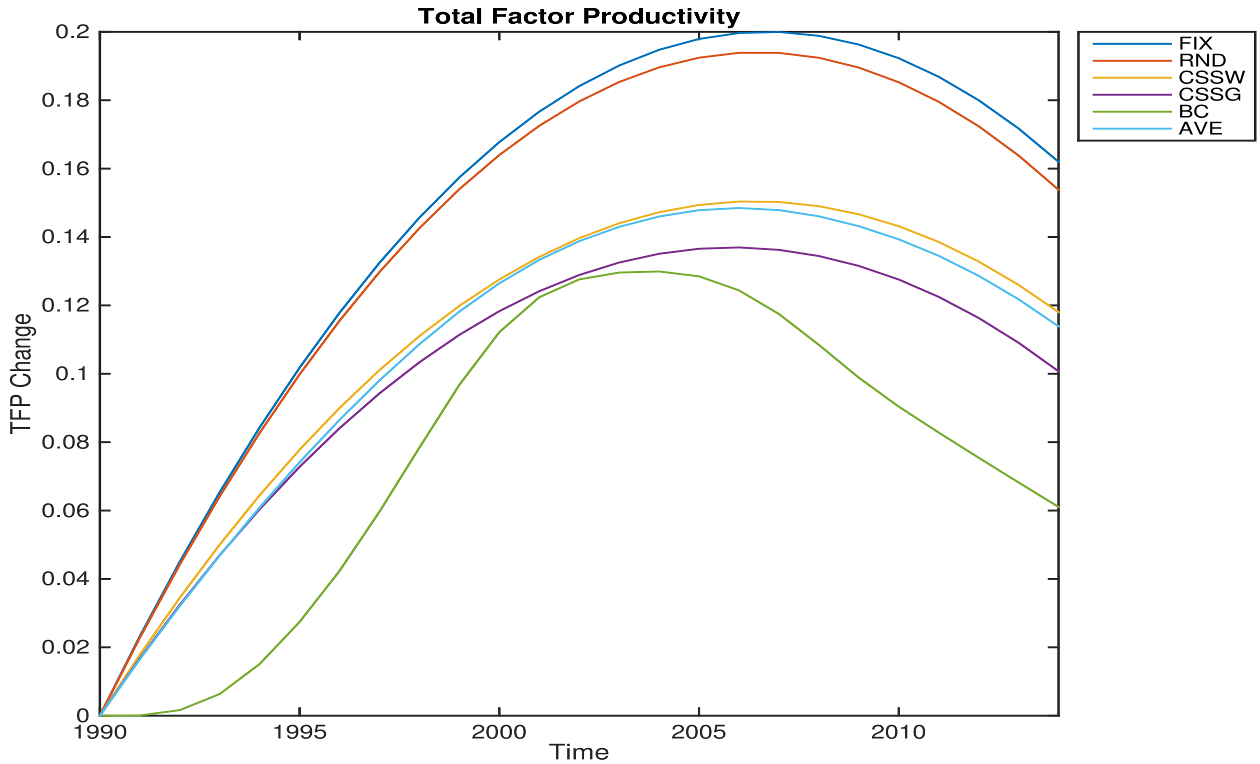
Figure 3: Total Factor Productivity-III

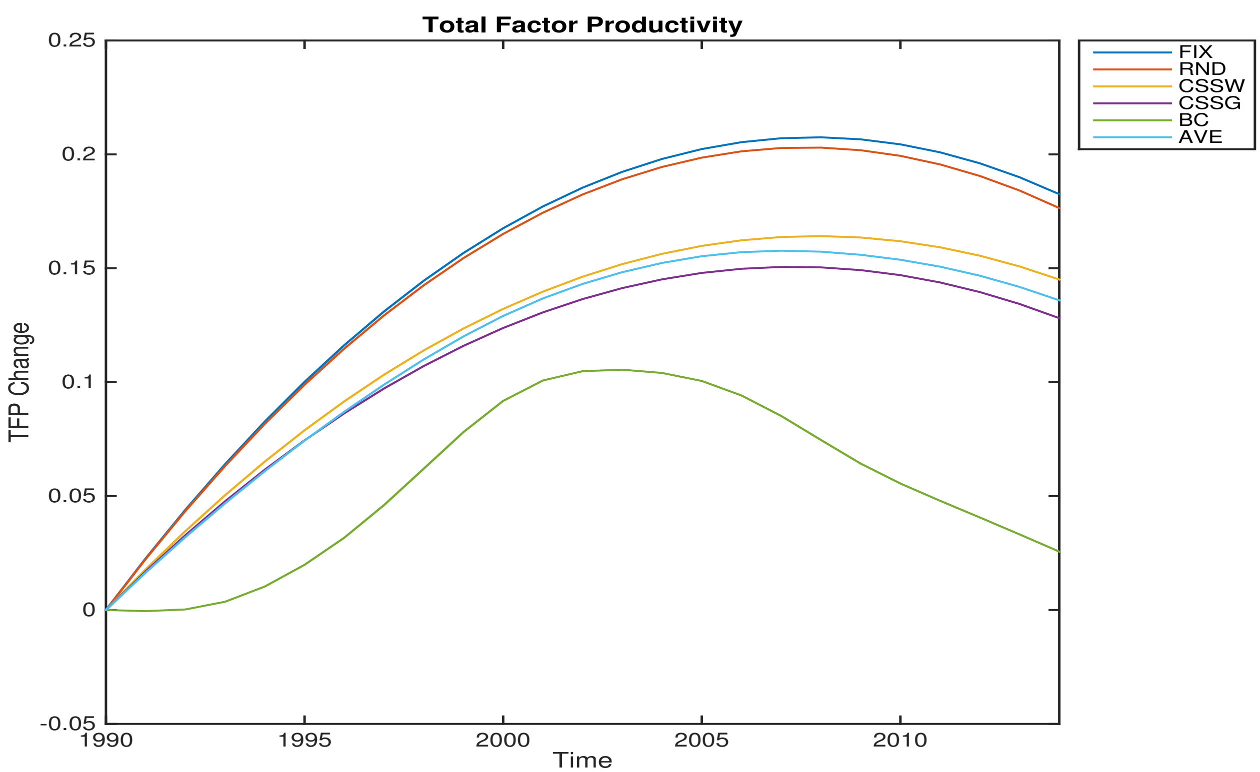




(b) Ks, ES

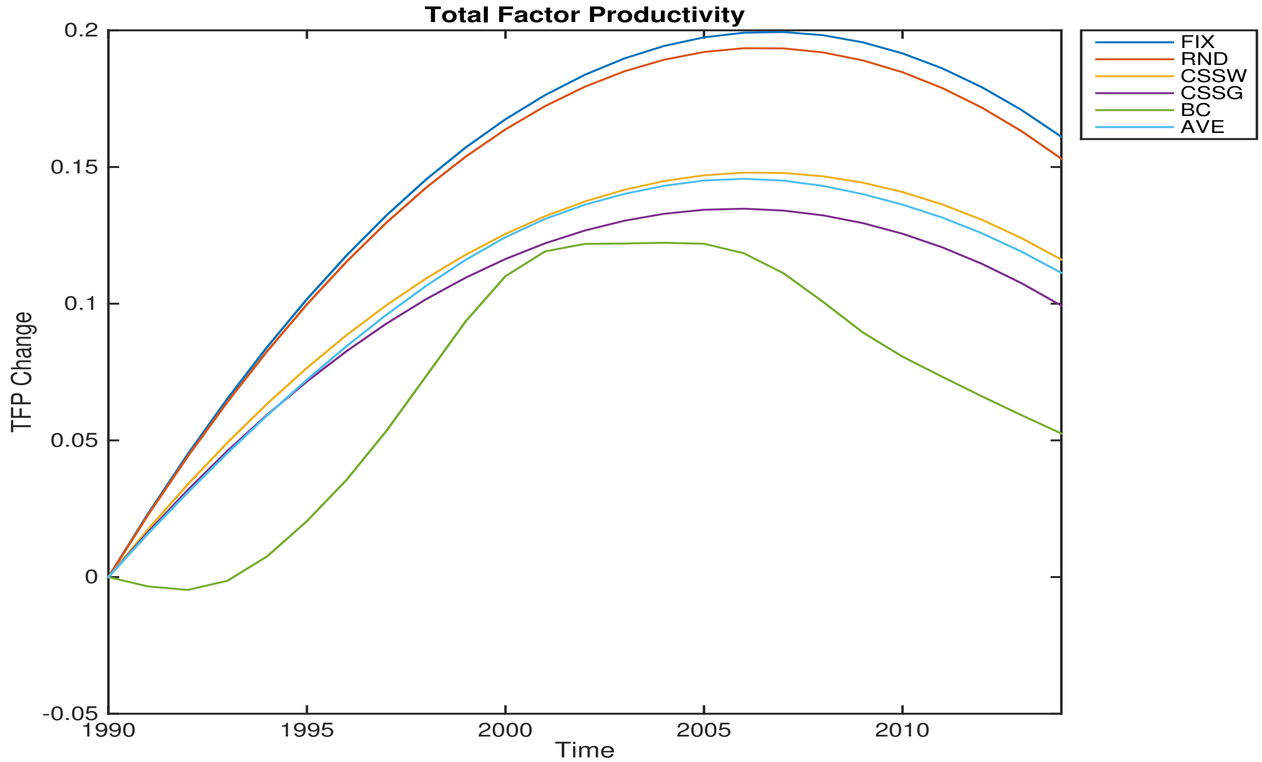
Figure 4: Total Factor Productivity-GDP Weighted I

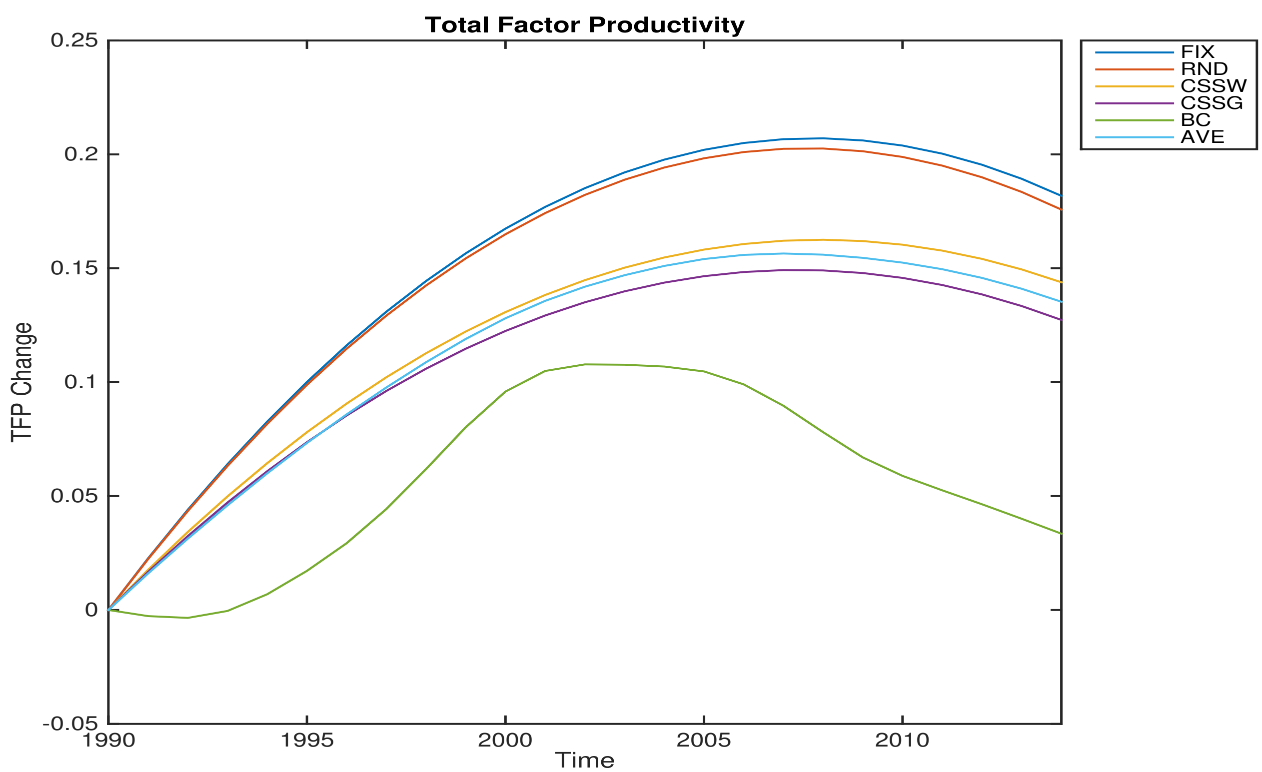




(b) K06, ES

Figure 5: Total Factor Productivity- GDP Weighted II





(b) K13, ES

Figure 6: Total Factor Productivity- GDP Weighted III