New Growth Accounting

Binlei Gong

This article opens the black box of total factor productivity by decomposing this "all-in-one" index into various input-embedded and input-free productivities in a new growth accounting framework. The new method identifies different channels through which growth drivers affect economic growth and finds the most effective way to boost the economy, which is unidentified in standard method. This new approach uses a varying coefficient stochastic frontier model, which integrates the standpoints of the endogenous growth theory and the induced innovation theory into a reduced-form productivity analysis. The new growth accounting is then applied to study the impacts and contributions of R&D investments, international trade, and structural transformation to world agricultural growth during the period of 1962 to 2014. The empirical results provide new evidence to support the endogenous growth theory and the induced innovation theory, indicating the necessity of using the new growth accounting method.

Key words: Economic drivers, economic growth, growth accounting, stochastic frontier analysis, total factor productivity, world agricultural growth.

JEL codes: D24, O40, Q10.

Since the seminal work of Solow (1956), growth accounting has provided a framework to decompose the growth of a country's observed output into two sources: the contributions due to changes in its factor inputs and the residual that cannot be accounted for by changes in input utilization. This unexplained part of growth is usually measured by an increase in total factor productivity (TFP), which is an indicator of technological progress. Therefore, growth accounting is very useful to study whether an economy experiences extensive growth, which relies more on the expansion of inputs, or intensive growth, which is mainly driven by technical change. Moreover, growth accounting is a popular tool to measure the contribution of different economic drivers to economic growth through their impacts on TFP growth.

Productivity analysis plays an important role in growth accounting studies. In standard growth accounting, the production function is used to estimate coefficients of inputs and derive total factor productivity, which can decompose economic growth into growth due to expansion of inputs and growth due to technological progress. Furthermore, some scholars use the TFP determination function to predict the effect of different TFP determinants and then calculate their contributions to economic growth in growth accounting.

However, this standard method has two problems. First, the fixed coefficients assumption in the standard production function, along with the exogenous growth theory, fails to capture the changing input–output relation across countries and over time,[1] and it contradicts the endogenous growth theory in Romer (1986) and Lucas (1988), as well as the induced innovation theory in Hicks (1932) and Hayami and Ruttan (1971). Some studies (e.g., Kumbhakar, Denny and Fuss, 2000; Young 2003) use the time-varying shares of input costs as the time-varying coefficients of inputs, which rely on the

Binlei Gong, Tenured Associate Professor, School of Public Affairs, China Academy for Rural Development (CARD), and Academy of Social Governance, Zhejiang University, China. Binlei Gong thanks Dr. Zuhui Huang, Dr. Wenrong Qian, Dr. Jikun Huang, Dr. Biliang Luo, Dr. Huanguang Qiu, Dr. Jianxing Yu, Dr. Wei Xu, and acknowledges support by the National Natural Science Foundation of China (71903172), the Research Program for Humanities and Social Science Granted by Chinese Ministry of Education (18YJC790034), the Soft Science Research Program of Zhejiang Province (2020C25020), and the Qianjiang Talent Plan.

[1] Take fertilizer in agricultural production as an example; the contribution of 1 kg of fertilizer to output must be greater today than it was five decades ago, as new technologies make fertilizer more efficient and effective.

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assumption of constant returns to scale that may not be valid at macrolevel in endogenous growth theory as shown in Barro (1999).[2]

Second, standard growth accounting can only estimate the overall effect of a growth driver on economic growth but is unable to identify the pathways or channels through which the growth drivers affect economic growth, because all the possible routes are mixed in the "all-in-one" TFP measured by a Solow residual. The lack of identification and partition of the overall effects is sometimes problematic. For example, suppose a country has a constraint in its public R&D budget: Where should we invest and how much should we invest in each field to maximize economic growth? This is an important decision in the real world and requires comparing the effects of R&D on economic growth through different channels, which are unable to be fulfilled by the standard growth accounting approach.

This article introduces the ideas of the endogenous growth theory and the induced innovation theory into a reduced-form framework, which allows a varying coefficient production function to reflect the quality change of inputs without the restriction of constant returns to scale. This article then opens the black box of the "all-in-one" TFP by decomposing its growth into changes in different input-embedded productivities and input-free productivity. As a result, the second source of economic growth in standard growth accounting, the growth in TFP, can be further separated into growth in various input-embedded productivities and input-free productivity in our new growth accounting framework. Finally, new growth accounting can evaluate various channels through which the growth drivers affect economic growth, including their effects on input quantity, input quality, and input-free productivity, which is unidentified in standard growth accounting.

This study makes three central contributions. First, this study uses the endogenous growth theory and the induced innovation theory to justify the utilization of varying coefficient production functions. Second, this study decomposes "all-in-one" total factor productivity into various input-embedded productivities and input-free productivity. Third, this is a generalization of the traditional neoclassical growth accounting methodology to investigate various channels through which growth drivers affect economic growth.

This article applies the new model to investigate agricultural growth in 107 countries during the period of 1962 to 2014. Agricultural sector is selected as an application because there are more input types in this sector besides labor and capital, such as land and feed, which makes it a good example to show how economic drivers can affect growth through different channels. The empirical results show that: (a) labor is being replaced by capital and land is being replaced by fertilizer, which is consistent with the opinion in the induced innovation theory; (b) there is an increasing trend of returns to scale, indicating that the same amount of inputs can generate more output over time, which is consistent with the standpoint of the endogenous growth theory; (c) R&D investment and international trade made great contributions to world agricultural growth, because 15% of all growth is due to these two driving forces; (d) the most effective ways for R&D to boost agricultural growth are through fertilizer and machinery improvement, whereas the most effective ways for trade to boost agricultural growth are through land and livestock capital; and (*e*) input expansion contributed more to agricultural growth in earlier years and in lagging countries, whereas productivity growth (mainly driven by R&D and trade) played a more important role in recent years and in leading countries, which provides evidence of the appropriate technology hypothesis in Basu and Weil (1998).

The remainder of the article is structured as follows. The next section reviews standard growth accounting, the endogenous growth theory, and the induced innovation theory. The following section establishes the new growth accounting model. In the subsequent section, data description is provided. Next, we present empirical results, and in the final section we conclude.

Literature Review

This section begins with a brief review of the literature on growth accounting, which is a popular procedure used in economics to measure the contribution of different factors to economic growth. This methodology, along with the exogenous growth theory, was originally introduced in Solow (1956,

[2] More detailed discussion is provided in the next section.

1957) and Swan (1956); they were later applied by many scholars (e.g., Lin 1992; Jorgenson and Stiroh 2000; Jones 2002; Bai and Zhang 2010). Growth accounting provides a framework for allocating changes in a country's observed outputs into two sources: the contributions due to changes in its factor inputs and the residual that cannot be accounted for by changes in input quantities. The latter is usually called total factor productivity growth, which is measured by the Solow residual in a production function. Therefore, the productivity analysis that estimates the production function plays an important role in growth accounting studies, as it can predict the parameters required to decompose output growth.

Standard Growth Accounting in the Exogenous Growth Theory

A classic production function with Cobb–Douglas formation is frequently used by many scholars (e.g., Gallup and Sachs 2000; Miller 2002; Deininger and Jin 2005; Hammond and Thompson 2008; Pope and LaFrance 2013; Shee and Stefanou 2014; Sheng, Ding, and Huang 2019). For illustration purposes, consider a deterministic Cobb–Douglas production function with constant returns to scale in the form:

$$(1) \qquad y_{it} = \alpha_{it} + \beta k_{it} + (1-\beta) l_{it}$$

where y_{it} is the quantity of output, α_{it} is total factor productivity (TFP) or level of technology, k_{it} is the capital stock, and l_{it} is the quantity of labor, all for country i at time t and all in logarithms. Then, the output growth is $\Delta y_{it} = \Delta\alpha_{it} + \beta\Delta k_{it} + (1-\beta)\Delta l_{it}$, which implies that the output growth ($\Delta y_{it} = y_{it} - y_{it-1}$) only comes from changes in input quantities ($\Delta k_{it} = k_{it} - k_{it-1}$ and $\Delta l_{it} = l_{it} - l_{it-1}$) and changes in TFP ($\Delta\alpha_{it} = \alpha_{it} - \alpha_{it-1}$).[3] The contributions due to quantity changes in capital and labor are $\beta\Delta k_{it}/\Delta y_{it}$ and $(1-\beta)\Delta l_{it}/\Delta y_{it}$, respectively, whereas the contribution due to productivity is $\Delta\alpha_{it}/\Delta y_{it}$.

TFP is often regarded as the major driving force of economic growth with input constraints (Sickles and Streitwieser 1998; Jin et al. 2002; Deininger and Jin 2006). However, it is a Solow residual that measures the portion of output not explained by the amount of inputs used in production (Sickles 2005). Therefore, a growing volume of empirical work aims to investigate the determinants or sources of TFP or its growth by further decomposing the unexplained part α_{it} or $\Delta\alpha_{it}$ with the help of a typical TFP determination regression:

$$(2) \qquad \alpha_{it} = \alpha + \boldsymbol{\lambda Z_{it}}$$

where $\boldsymbol{Z}$ vectors a series of potential TFP determinants that may be the real drivers of economic growth. R&D investment and international trade are usually treated as the growth drivers and can therefore be included in $\boldsymbol{Z}$. λ vectors the corresponding parameters that indicate the sign and magnitude of the effects on productivity. Because the only channel designed for growth drivers to affect economic growth is through their effect on the "all-in-one" TFP, the contribution due to the growth drivers can be calculated by $\hat{\lambda}\Delta Z_{it}/\Delta y_{it}$. Many scholars pay attention to the parameters $\hat{\lambda}$, which reflect the effects of the variables of interest on productivity.

Some Ideas of the Endogenous Growth Theory

The exogenous growth theory treats technological progress, measured by TFP, as the source of economic growth, whereas the endogenous growth theory, building on the studies of Romer (1986) and Lucas (1988), emphasizes the importance of physical and human capital accumulation and spillovers in economic growth. Inspired by the learning-by-doing model in Arrow (1962), Romer (1986) believes the output y_{jt} for company j depends not only on its own inputs k_{jt} and l_{jt} but also on the capital stock of other companies due to spillover effects. Mathematically, the production function is

$$(3) \qquad y_{jt} = \alpha_{jt} + \beta k_{jt} + \gamma k_t + (1-\beta) l_{jt}$$

where y_{jt} is the quantity of output, α_{jt} is the TFP, k_{jt} is the capital stock, and l_{jt} is the quantity of labor, all for firm j at time t and all in logarithms. k_t accounts for the economy-wide capital stock at time t. For company j, positive spillover effects exist if $\gamma > 0$. In Romer (1986), k refers to capital stock and therefore represents a learning-by-investing model. A similar idea can be found in Griliches (1979), where k is a knowledge capital measure based on

[3] $\Delta y_{it} \approx \Delta Y_{it}/Y_{it}$ when ΔY_{it} is relatively small with respect to Y_{it}.

knowledge-creating activities, such as R&D, so that the spillovers represent the spread of knowledge across companies. In Lucas (1988), however, k represents human capital measured by education level to capture spillover effects due to cooperation and learning in groups. Given the firm-level production function in equation (3), Barro (1999) shows that the economy-wide production function in equilibrium for country i is

$$(4) \qquad y_{it} = \alpha_{it} + (\beta + \gamma)k_{it} + (1 - \beta)l_{it}.$$

Increasing returns to scale is observed at the country level if $\gamma > 0$. Decreasing returns to scale ($\gamma < 0$) is also possible for reasons such as traffic congestion and environmental damage, which implies negative spillover effects and diseconomies of scale (Barro 1999).

To summarize, the endogenous growth theory illustrates that the country-level production function does not have to follow constant returns to scale due to spillovers. This article therefore relaxes the assumption of constant returns to scale that is heavily relied on by some scholars (e.g., Kumbhakar, Denny and Fuss, 2000; Young 2003) who use time-varying shares of input costs as input elasticities.[4] Moreover, the spillover effects, measured by γ, depend on R&D in Griliches (1979), which can be positive or negative. Based on these findings concerning the endogenous growth theory, γ may vary across countries and over time, as the condition of R&D changes across countries and over time. As a result, the input elasticity ($\beta + \gamma_{it}$) may be country specific and time variant.

Some Ideas of the Induced Innovation Theory

In his book, Hicks (1932) wrote: "A change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind—directed to economizing the use of a factor which has become relatively expensive." The Hicksian model of induced innovation (also known as induced technical change) believes that changes in relative input prices would not only lead to changes in input proportions but would also affect the direction of innovation. In the Cobb–Douglas production function in equation (1), companies will substitute capital for labor if the relative price (wage–rental ratio) increases. That is, if labor becomes more expensive, companies will try to invent machines to replace labor. As a result of technology changes, β in equation (1) may change.

A group of development economists (e.g., Hayami and Ruttan 1971; Binswanger et al. 1978) uses the model of induced innovation and finds that the direction of technical change in agriculture was induced by changes (or differences) in relative resource endowments and factor prices. In general, mechanical technology is developed to substitute power and machinery for workforce, whereas biological and chemical technology is innovated to substitute fertilizer and other chemicals for land over time. Moreover, the pace of these two trends also depends on the resource endowments of a country. Ruttan (2002) illustrates the process of induced technical change in Japan and the United States, where both of the aforementioned trends are witnessed over time. However, Japanese farmers use more fertilizer and U.S. farmers use more power due to the difference in labor and land endowments in these two countries.

In summary, the difference in resource endowment across countries and the variation of relative input prices over time can change the direction of innovation, which can lead to a change in technology and therefore the shape of the production function. Mathematically, β in equation (1) may be country-specific and time-variant. Moreover, the change in β may depend on the R&D investment in capital and labor.

Some More Extensions

Although having different setups, both the endogenous growth theory and induced innovation theory support that the country-specific and time-variant input elasticities are affected by some variables, such as R&D investment. Mathematically, the production function is

$$(5) \qquad y_{it} = \alpha_{it} + \beta_{it}k_{it} + \delta_{it}l_{it}$$

where $\beta_{it} = f_1(\boldsymbol{Z_{it}})$ and $\delta_{it} = f_2(\boldsymbol{Z_{it}})$. At this point, we assume linear effects of $\boldsymbol{Z_{it}}$ on input elasiticies, which determine the linear relations between growth drivers (e.g., R&D) and the input elasticities. It is worth noting that δ_{it} does not need to equal $1 - \beta_{it}$ due to the potential

[4] These parameters represent output elasticity with respect to different inputs. For simplicity, this article calls them input elasticities.

spillovers introduced in the endogenous growth theory. Therefore, the production function that assumes linear effects of $\boldsymbol{Z_{it}}$ on input elasticities and productivity is

$$(6) \quad y_{it} = \alpha_0 + \boldsymbol{\lambda Z_{it}} + (\beta_0 + \boldsymbol{\rho Z_{it}})k_{it} + (\delta_0 + \boldsymbol{\tau Z_{it}})l_{it}$$

where α_0, β_0, and δ_0 are the level of TFP, capital elasticity, and labor elasticity when $\boldsymbol{Z} = 0$, respectively. $\boldsymbol{\lambda}$, $\boldsymbol{\rho}$, and $\boldsymbol{\tau}$ measure the effects of $\boldsymbol{Z}$ on TFP, capital elasticity, and labor elasticity, respectively.

Besides the illustration of the aforementioned two strands of literature, this article provides more reasons to allow for varying input elasticities. In the production function, k_{it} and l_{it} measure the quantity of the inputs, whereas the input elasticities to some extent can be regarded as the "quality" of the inputs. For a given amount of input, a greater input elasticity can increase output. Considering fertilizer in agricultural production again, other things being equal, the contribution of the same amount of fertilizer to output must be greater today than five decades ago, as new technologies make fertilizer more efficient and effective. Under this condition, fertilizer elasticity (β_{it}) increases, which may be the result of more R&D investment in fertilizer, hence the relation $\beta_{it} = f_1(\boldsymbol{Z_{it}})$. The endogenous growth theory introduces spillovers on inputs, whereas induced innovation theory introduces invention on inputs, but both can result in better quality of the inputs and hence more output given fixed inputs.

International trade is another growth driver in $\boldsymbol{Z_{it}}$ that can affect input elasticities and productivity in addition to R&D. The theory of induced innovation emphasizes that the differences in resource endowment and input prices across countries and over time can change the shape of the production function. International trade, however, can change resource allocation and input prices, and therefore affect input elasticities and productivity. The third growth driver is structural transformation, which refers to the reallocation of economic activity across the broad sectors of agriculture, manufacturing, and services (Herrendorf, Rogerson, and Valentinyi 2014). In most cases, manufacturing and services are more productive than agriculture. Therefore, countries can improve their aggregated TFP by increasing the share of their non-agricultural sector. More importantly, structural transformation can also affect input elasticities, as each sector has its own production technologies and therefore sector-specific input elasticities. Improving the share of a specific sector can make the overall input elasticities of the economy closer to the input elasticities of that sector. Because the ratio of the three sectors varies across countries and structural transformation happens all the time, country-level input elasticities are not constant.

What if equation (6) is the true data-generating process, but we assume constant input elasticities? Equation (6) can be rewritten as

$$(7) \quad y_{it} = \alpha_0 + \boldsymbol{\lambda Z_{it}} + \left[\left(\beta_0 - \hat{\beta}\right) + \boldsymbol{\rho Z_{it}}\right]k_{it} + \left[\left(\delta_0 - \hat{\delta}\right) + \boldsymbol{\tau Z_{it}}\right]l_{it} + \hat{\beta}k_{it} + \hat{\delta}l_{it}$$

where $\hat{\beta}$ and $\hat{\delta}$ are estimates of capital and labor elasticities derived by the conventional production function that assumes constant input elasticities. Then, the estimated TFP is

$$(8) \quad T\hat{F}P_{it} = \alpha_0 + \boldsymbol{\lambda Z_{it}} + \left[\left(\beta_0 - \hat{\beta}\right) + \boldsymbol{\rho Z_{it}}\right]k_{it} + \left[\left(\delta_0 - \hat{\delta}\right) + \boldsymbol{\tau Z_{it}}\right]l_{it}.$$

Rearranging equation (8), we get

$$(9) \quad T\hat{F}P_{it} = [\boldsymbol{\lambda} + \boldsymbol{\rho} k_{it} + \boldsymbol{\tau} l_{it}]\boldsymbol{Z_{it}} + \alpha_0 + \left(\beta_0 - \hat{\beta}\right)k_{it} + \left(\delta_0 - \hat{\delta}\right)l_{it}.$$

Finally, when the TFP determination function in equation (2) is utilized to decompose the estimated TFP given in equation (9), the estimated effect of $\boldsymbol{Z}$ on productivity equals $\boldsymbol{\lambda} + \boldsymbol{\rho} k_{it} + \boldsymbol{\tau} l_{it}$, which not only includes the true impact, $\boldsymbol{\lambda}$, but also mistakenly covers the impacts of $\boldsymbol{Z}$ on capital elasticity ($\boldsymbol{\rho}$) and labor elasticity ($\boldsymbol{\tau}$).

When the main purpose is to estimate the overall effects of $\boldsymbol{Z}$ on output, standard growth accounting is fine, as the impacts of $\boldsymbol{Z}$ on productivity and input elasticities (i.e., $\boldsymbol{\lambda}$, $\boldsymbol{\rho}$, and $\boldsymbol{\tau}$), at the end, all contribute to output. Moreover, because the definition of TFP is the portion of output not explained by the amount of input used in production, it is reasonable to contribute all the residuals besides input quantities, even input qualities, into TFP. Therefore, this article does not negate the credibility of the large volume of empirical studies based on standard growth accounting, if their goal is only to evaluate the sources and the overall contribution of each source to economic growth.

However, standard growth accounting fails to identify the pathways or channels through which the growth sources ($\boldsymbol{Z}$) affect economic growth because all the possible routes are mixed in the "all-in-one" TFP in equation (9), not to mention quantifying the contribution of a specific source, such as R&D, to economic growth across various pathways. The lack of identification and partition can be problematic when we are looking for the most effective channels to boost economic growth. This is an important issue in the real world and requires a comparison of the magnitude of $\boldsymbol{\lambda}$, $\boldsymbol{\rho}$, and $\boldsymbol{\tau}$, which is unable to be fulfilled by standard growth accounting approach.

To summarize, both the endogenous growth theory and induced innovation theory, as well as the idea of input quality heterogeneity, suggest the use of varying input elasticities in the production function. This article establishes a new growth accounting approach with varying coefficient concern. Moreover, this new method allows the impacts of growth drivers on input elasticities in addition to their effects on productivity. Finally, new growth accounting aims not only to partition the economic growth to changes in input quantities and total factor productivity but also to further decompose the growth of "all-in-one" TFP into growth in different input-embedded productivities and input-free productivity. It is worth noting that growth in input-embedded productivity refers to the productivity gain on input quality improvement. Therefore, new growth accounting can identify and quantify the pathways or channels through which the growth drivers affect economic growth. Figure 1 illustrates the difference between standard growth accounting and new growth accounting.

Figure 1 shows how standard growth accounting and new growth accounting evaluate the effect of R&D on economic growth. In the left-hand graph in figure 1, standard growth accounting can only estimate the overall effect of R&D on TFP growth, which is the only channel through which R&D affects economic growth. In the right-hand graph of figure 1, however, new growth accounting can decompose TFP growth into three parts, including capital-embedded, labor-embedded, and the remaining (input-free) productivity growth. As a result, new growth accounting can investigate and calculate how R&D affects economic growth through these three channels. Moreover, as will be shown in the next section, R&D can also affect the contribution of input quantity growth on economic growth, which provides another channel by which R&D affects economic growth. Consequently, it is possible to evaluate and compare the effectiveness of R&D investments through different channels, which is unavailable in standard growth accounting.

Methodology

This section establishes a new growth accounting method. Although the model is built in general, agricultural production is used as an example to illustrate this model and is later used as an application of this model for the following reason. In the production function of the whole economy, as analyzed in the previous section, labor and capital are the only two factor inputs in many datasets and previous studies. For agricultural production, however, capital is further decomposed into land, livestock capital, machinery, fertilizer, and animal feed in datasets such as the Food and Agriculture Organization of the United Nations

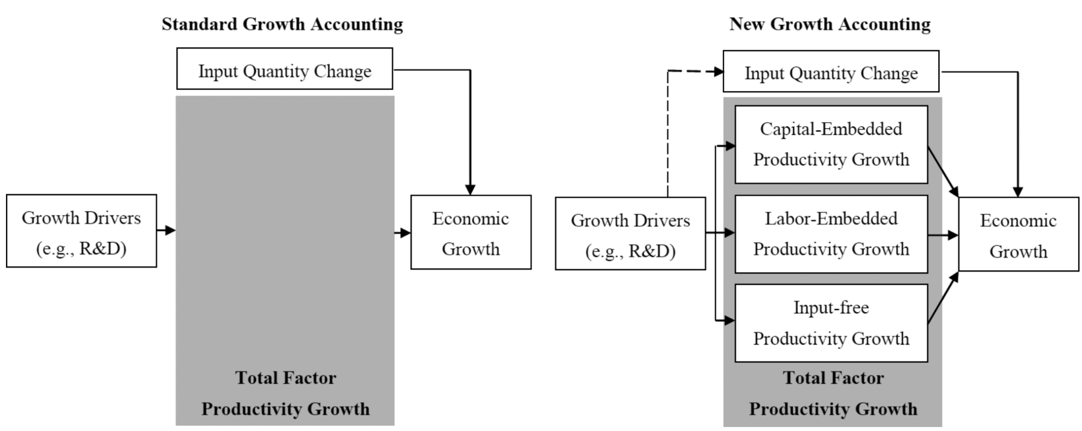

Figure 1. Standard growth accounting and new growth accounting

(FAO) and the Economic Research Service of the United States Department of Agriculture (USDA-ERS). As a result, the central contribution of the new model, identifying the best channel for the growth driver to boost economic development, is greatly expanded. For example, this model can instruct if the fertilizer industry or machinery industry should get more R&D funding to maximize their output level, which leads to more pertinent and effective policy implications.

It is worth noting that this present model can easily be applied to analyses of other sectors, or even the whole economy. However, the value added of the new growth accounting depends on the input variables in hand. If we only have data on labor and capital inputs, TFP can only break down to labor-embedded, capital-embedded, and input-free productivity as shown in figure 1. Suppose we find that the marginal effect of R&D on economic growth is the most efficient through investment in capital-embedded productivity. This finding is more informative than the one in standard growth accounting because it indicates that R&D investment on capital is more efficient than on labor and input-free productivity. But it is still too vague in terms of where to invest, as there are so many fields within capital investment. In contrast, if we have data of different types of capital, such as the aforementioned agricultural datasets, we will have a better idea of where to invest. To summarize, the more detailed information of the input portfolio we have, the more value added from the new growth accounting we can get.

As discussed, the major disadvantage of standard growth accounting based on the conventional production model is the rigid assumption of constant input elasticities. Therefore, it fails to measure the variation of input elasticities and leaves it in the total factor productivity. Under this setup, the pathways through which the growth drivers affect output are unidentified nor do they quantify the contributions across various channels to find the most effective pathway to boost economic growth. Take the effect of R&D investment on agricultural growth as an example: Egli (2008) lists some sources of agricultural productivity, including mechanization, fertilizers, more digestible animal feed, and so on. All these factors can be improved through agricultural R&D spending. Hence, there are multiple pathways by which R&D investment can affect productivity and output growth, which cannot be identified by standard growth accounting, as it combines all these sources to the "all-in-one" TFP.

Let us now focus on the sources of agricultural productivity in Egli (2008), most of which are input related or input embedded. Moreover, R&D investments are improving the quality of these inputs. For example, R&D in the fertilizer industry makes it more effective, R&D on animal feed factories makes them more endurable and efficient, and R&D on machinery results in more powerful and productive tractors today than five decades ago. Therefore, a production function that captures the quality changes of the inputs is needed in order to identify the channels through which a growth driver, such as R&D, affects economic growth.

This article introduces a varying coefficient production frontier model to control the impacts of growth drivers, not only on productivity as in the literature but also on input elasticities that were overlooked by standard growth accounting studies. The estimated varying input elasticities and productivity are then regressed on the growth drivers to identify their effects, which sheds light on the pathways of various sources to growth. Moreover, new growth accounting is established to further quantify the channels and contributions of each growth driver on economic development, which is shown in figure 1.

A varying coefficient production frontier model can be established by introducing the varying coefficient model and stochastic frontier model into the conventional production function. On the one hand, the varying coefficient model is proposed by Hastie and Tibshirani (1993) in the form:

$$y = x_1 h_1(\boldsymbol{\theta_1}) + \ldots + x_k h_k(\boldsymbol{\theta_k}) + \varepsilon$$

where the coefficients of independent variables (x_k) are nonparametric functions ($h_k(\cdot)$) of "threshold" variables $\boldsymbol{\theta_k}$. In other words, the magnitudes of the coefficients (assumed to be fixed β in the conventional model) are affected by these "threshold" variables. Because the coefficients are not fixed, this method is called the "varying coefficient model."

On the other hand, the stochastic frontier model is proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and Van den Broeck (1977), and has been widely used by many scholars (e.g., Jin et al. 2010; Wang, Yamauchi, and Huang 2016; Yang et al. 2016). A classic stochastic frontier model has the form:

$$y_{it} = f(\boldsymbol{X_{it}};\beta) + \boldsymbol{\tau T} + \nu_{it} - u_{it}$$

where $f(\boldsymbol{X_{it}}; \beta)$ measures the production frontier, $\boldsymbol{T}$ vectors a group of year dummy variables, and $TE_{it} = \exp(-u_{it})$ accounts for technical efficiency. It is worth noting that the conventional production function can be written as $y_{it} = f(\boldsymbol{X_{it}}; \beta) + \boldsymbol{\tau T} + \nu_{it}$, where $f(\boldsymbol{X_{it}}; \beta) + \boldsymbol{\tau T}$ measures the average input–output relation over time and any deviation from this function is explained by the disturbance ν_{it} rather than inefficiency. In the stochastic frontier model, however, $f(\boldsymbol{X_{it}}; \beta) + \boldsymbol{\tau T}$ generates the highest attainable output given inputs in each period and therefore measures the optimal input–output relation over time. Meanwhile, any deviation of the actual output from the highest attainable output is explained not only by disturbance ν_{it} but also by inefficiency u_{it}. Finally, total factor productivity is the sum of $\boldsymbol{\tau T}$ and $-u_{it}$, where $\boldsymbol{\tau T}$ accounts for technical level and $-u_{it}$ accounts for efficiency level. As a result, productivity growth can be broken down into technical progress and efficiency change in the stochastic frontier model, which cannot be achieved in the conventional production function.

Considering the varying coefficient model and stochastic frontier model, this article generates a varying coefficient stochastic frontier model to estimate the production process in the form:

$$(10) \qquad y_{it} = h_0(\boldsymbol{\theta_{it}}) + \sum_{k=1}^{p} h_k(\boldsymbol{\theta_{it}}) x_{it}^k + \boldsymbol{\tau T} + \nu_{it} - u_{it}$$

where $\beta_{it}^k = h_k(\boldsymbol{\theta_{it}})$ is a nonparametric function to estimate the varying elasticity of the k-th input so that even nonlinear relations can be captured. The portfolio of the "threshold" variables, including the growth drivers and other controlled variables, will be further discussed. The intercept, $h_0(\boldsymbol{\theta_{it}})$, is also assumed to be a nonparametric function of the "threshold" variables to allow the effects of growth drivers on output through input-free productivity. $\boldsymbol{T}$ vectors a group of year dummy variables, and ν_{it} is a normally distributed disturbance. u_{it} measures the distance between the country's actual production and the world's frontier, and therefore indicates the loss in efficiency.

A few productivity analyses have employed the varying coefficient production model. Ahmad, Leelahanon, and Li (2005) use a firm's R&D spending as the "threshold" variable in a varying coefficient model to estimate the production function of China's manufacturing industry. Zhang et al. (2012) use a varying coefficient production function to analyze the Chinese high-tech industry, where R&D and time trend are selected as the "threshold" variables. Moreover, some scholars introduce the idea of the varying coefficient model in stochastic frontier analysis. Sun and Kumbhakar (2013) investigate the technical efficiency of 3,294 active forest owners in the Norwegian forest industry using R&D and time as the "threshold" variables in a varying coefficient stochastic frontier model. Gong (2018a) establishes a varying coefficient stochastic frontier model to evaluate and compare the efficiency of global oilfield service firms, where revenue shares of the five segments within the oilfield market are treated as the "threshold" variables. Gong (2020) uses ownership and business portfolio as the "threshold" variables in a varying coefficient stochastic frontier model to estimate their impacts on petroleum production.

Some studies use a varying coefficient stochastic frontier model to estimate the productivity of the agricultural sector. Huang and Kalirajan (1997) use a varying coefficient stochastic frontier approach to estimate the potential of grain production in China using household survey data from the period of 1993 to 1995. Gong (2018b) investigates provincial agriculture production in China from 1978 to 2015, where the input elasticities are affected by time and the agricultural structure of farming, forestry, animal husbandry, and fishery. However, most of these studies only consider the impact of one or two growth sources on the production function/frontier. Moreover, no research has linked the varying coefficient production function/frontier to the growth accounting analysis.

In terms of the "threshold" variables used in this article, the first and foremost growth driver is R&D investment, which determines the technology progress. We have illustrated how R&D can affect output through its effect on various inputs in the agricultural sector. Moreover, the growth in input-free productivity estimated by equation (10) is the residual after changes in input qualities are ruled out. R&D spending may also affect TFP though input-unrelated channels, such as the investment in e-commerce to better link producers and consumers.

The degree of openness can be the second growth driver that acts as a "threshold" variable. The openness of a country, measured by its trade-to-GDP ratio, indicates the difficulty of resource and commodities exchange across countries. The free exchange of inputs may avoid resource misallocation, which achieves higher marginal products and therefore improves input elasticities. The free exchange of outputs, on the other hand, can help boost input-free productivity growth, as comparative advantages of the country can play a positive role in economic growth even with constraints in input endowment. In summary, the degree of openness may affect economic growth through its effect on both the input-embedded productivity (input elasticities) and input-free productivity.

The third economic driver is the structural transformation. Even without technological progress, a country's output can still benefit from moving more resources from less productive to more productive segments. In the agricultural sector, structural transformation refers to the reallocation of economic activity between the crops segment and the livestock segment. This article uses the share of the livestock segment to account for the structural transformation, which can be employed as another "threshold" variable.

Besides these three growth drivers, this article also includes time trend in the portfolio of "threshold" variables. The varying coefficient model is first utilized to model time-variant coefficient functions for censored data in survival analysis where time trend is the only "threshold" variable. Time trend can help control time-fixed effects or the changes in the macro environment, such as business cycles, technological revolutions, reforms, and wars. In the agricultural sector, the trend that substitutes power and machinery for workforce and substitutes fertilizer and other chemicals for land may still occur over time, even if the growth drivers are maintained at the same level. Adding the time trend in the portfolio of "threshold" variables can capture this trend. To summarize, the "threshold" variables include R&D, openness (trade), structural transformation, and time trend. Mathematically, $\boldsymbol{\theta_{it}} = (r\,\&\,d_{it}, trade_{it}, structure_{it}, t)$ where $r\,\&\,d_{it}$ is the R&D-to-output ratio, $trade_{it}$ is the trade-to-GDP ratio, $structure_{it}$ is the output share of livestock in total agricultural products, and t is the year trend.

The varying coefficient production function can control the potential effects of the "threshold" variables if these effects indeed exist. This article uses the penalized B-spline approach to estimate the varying coefficient stochastic frontier production function in equation (10) for two reasons. First, spline-based methods are preferred over kernel-based methods, as the five "threshold" variables lead to the "curse of dimensionality" issue if the kernel-based methods are adopted. Second, Lu, Yang, and Li (2008) prove that penalized B-spline estimators of a varying coefficient model can achieve strong consistency and asymptotic normality, which makes it a plausible method to be utilized. This article adopts the estimation strategy in Gong (2018b) to solve the varying coefficient stochastic frontier function in equation (10). More specifically, a two-step approach proposed by Fan, Li, and Weersink (1996) that solves semiparametric and nonparametric stochastic frontier models is employed: in the first step, the inefficiency term $-u_{it}$ is ignored and the penalized B-spline method is used to derive residual in equation (10); in the second step, the inefficiency term $-u_{it}$ is isolated from the residual using the popular "Error Components Frontier" method (Battese and Coelli 1992).

In the new growth accounting model, the varying coefficient method reports the contribution of input quantities change, input-embedded productivity growth, input-free productivity growth, and the change in residuals. It is worth noting that the last part, the change in residuals, is introduced because the production function in equation (10) is a stochastic model with disturbance ν_{it}, rather than a deterministic model, as in equation (1). It is important to include this disturbance to capture noise, as agricultural production is significantly affected by some unobserved and unmeasurable variables, such as weather and pests. Moreover, it is necessary to include the disturbance term because FAO agricultural data, the main data sources for world agricultural studies, may be flawed, especially for small and poor countries without enough capacity for statistical collection (Headey, Alauddin, and Rao 2010). Hence, the output growth can be decomposed to

$$\text{(11)} \qquad \Delta\, y_{it} = \sum_{k=1}^{p}\left(\beta_{it}^{k}x_{it}^{k} - \beta_{it-1}^{k}x_{it-1}^{k}\right) + \Delta IFP_{it} + \Delta\nu_{it}$$

where $IFP_{it} = h_0(\boldsymbol{\theta_{it}}) + \boldsymbol{\tau T} - u_{it}$ measures the input-free productivity for country i at time t and can be derived from equation (10) using the estimation strategy in Gong (2018b). Further decomposing the input-related part,

$\beta_{it}^{k}x_{it}^{k} - \beta_{it-1}^{k}x_{it-1}^{k}$, and dividing both sides by Δy_{it}, we get the new growth accounting:

$$(12)\quad 1 = \underbrace{\sum_{k=1}^{p}\left[\frac{\Delta x_{it}^{k}\left(\beta_{it}^{k}+\beta_{it-1}^{k}\right)}{2\Delta\, y_{it}}\right]}_{\text{input quantity}} + \underbrace{\underbrace{\sum_{k=1}^{p}\left[\frac{\Delta \beta_{it}^{k}\left(x_{it}^{k}+x_{it-1}^{k}\right)}{2\Delta\, y_{it}}\right]}_{\text{input-embedded productivity}} + \underbrace{\frac{\Delta IFP_{it}}{\Delta\, y_{it}}}_{\text{input-free productivity}}}_{\text{Total Factor Productivity}} + \underbrace{\frac{\Delta \nu_{it}}{\Delta\, y_{it}}}_{\text{residual}}$$

where the four parts on the right-hand side of equation (12) are the contributions of changes in input quantities, input-embedded productivity, input-free productivity, and residuals, respectively. For comparison, the standard growth accounting model has the form:

$$(13)\quad 1 = \underbrace{\sum_{k=1}^{p}\left[\frac{\beta^{k}\Delta x_{it}^{k}}{\Delta\, y_{it}}\right]}_{\text{input quantity}} + \underbrace{\frac{\Delta TFP_{it}}{\Delta\, y_{it}}}_{\text{Total Factor Productivity}} + \underbrace{\frac{\Delta \nu_{it}}{\Delta\, y_{it}}}_{\text{residual}}$$

where β^{k} is the conventional coefficient of the k-th input that is fixed across countries over time.

The growth drivers may affect the level of output through the first three parts on the right-hand side of equation (12), because they may affect β_{it}^{k} and IFP_{it}, as shown in equation (10). That is, these sources affect input elasticity and input-free productivity and then contribute to economic growth. It is worth noting that the first and second part each include p channels through which each source can affect the economic outcome, one for each input. This article further identifies the signs and magnitudes of these effects, which identifies each and every possible pathway for each growth driver to boost economic development. Determination regressions in equations (14) and (15) are established to fulfill this goal, where the impacts of the growth drivers on input-free productivity growth and input elasticities are estimated, respectively.

$$(14)\quad \Delta IFP_{it} = \alpha + \lambda_1 r\&d_{it} + \lambda_2 trade_{it} + \lambda_3 structure_{it} + \boldsymbol{\tau T} + \boldsymbol{\delta I} + \varepsilon$$

$$(15)\quad \beta_{it}^{k} = \alpha^{k} + \lambda_1^{k} r\&d_{it} + \lambda_2^{k} trade_{it} + \lambda_3^{k} structure_{it} + \boldsymbol{\tau T} + \boldsymbol{\delta I} + \varepsilon^{k}, \forall k = 1,\ldots,p$$

where ΔIFP_{it} accounts for the growth rate of input-free productivity, and β_{it}^{k} is the coefficient for the k-th input to measure its elasticity. Both are for country i at time t and are derived from equation (10). $\boldsymbol{T}$ and $\boldsymbol{I}$ vectors a group of year dummy variables and country dummy variables, respectively. The estimation results of the parameters λ can identify the effects of the growth drivers. Plugging the estimated parameters in equations (14) and (15) into equation (12), this article can quantify the marginal effects on economic growth through various channels for each source, which helps us find the most efficient pathways to boost the economy using various economic drivers.

Data

This article uses a balanced panel of 107 countries from 1962 to 2014 as an application of new growth accounting in the world agricultural sector. Country-level agricultural input and output data are available from the Economic Research Service of the United States Department of Agriculture (USDA-ERS). This article adopts six kinds of agricultural inputs, including agricultural land ($land_{it}$, in million hectares of rain-fed cropland equivalents), agricultural labor ($labor_{it}$, in million economically active adults), total stock of farm machinery ($machinery_{it}$, in million 40-CV tractor equivalents), fertilizer consumption ($fertilizer_{it}$, in million metric tons of N, P_2O_5, K_2O), livestock capital on farms ($livestock_{it}$, in thousand cattle equivalents), and total animal feed ($feed_{it}$, in million metric tons of crops and crop processing residues in dry-matter equivalents). In terms of output, gross agricultural output (Y_{it}, in billion international dollars at 2005's constant price) measures the sum of the value of production of 189 crop and livestock commodities.

Data on three economic drivers are also collected. This article collects annual R&D investment data from several sources,[5] including the Agricultural Science and Technology Indicator (ASTI)[6]; the Gross Domestic Expenditure on Research and Development (GERD) by the OECD[7]; Pardey and Roseboom (1989); Alston, Pardey, and Smith (1999); and Pardey et al. (2016). However, it is the R&D investment stocks, rather than the flows, that promote economic growth. This is because current R&D investments, for example in fertilizer, not only increase the current output but also benefit future production as well. Analogously, current agricultural growth depends not only on current investments but also on previous investments. Therefore, this article adopts the unified perpetual inventory method (PIM) to convert investment flows to stocks, which is widely used in productivity analysis (e.g., Berlemann and Wesselhöft 2014; Gong 2017; Gong 2018c). In terms of the depreciation rate, Esposti and Pierani (2003) review the depreciation rates for agricultural R&D used in the literature and then adopt 10%, 20%, and 25% in three scenario analyses. This article uses a 20% depreciation rate in PIM to estimate R&D stocks. Finally, this article calculates R&D-to-output ratio (r & d_{it}) to measure the degree of R&D when the country-level agricultural scale is considered. In terms of the degree of openness, the total volume of international trade of agricultural products can be collected from the NBER-UN database for the period of 1962 to 1994 and from the CEPII-BACI database for the period of 1995 to 2014.[8] The degree of openness, measured by the trade-to-output ratio, can be calculated accordingly. Third, the output share of livestock in total agricultural products ($structure_{it}$) is collected and calculated from the FAO database, which accounts for the structural transformation of the agricultural sector between the crops segment and the livestock segment.

Table 1 reports summary statistics of these aforementioned variables. These 107 countries, on average, use 8 million agricultural laborers, 15 million hectares of agricultural land, 0.2 million tractor equivalents of farm machinery, 0.9 million metric tons of fertilizer, 17.3 thousand cattle equivalents of livestock capital, and 7.7 million metric tons of feed to produce agricultural outputs that are worth 11.9 billion international dollars at 2005's constant price. In terms of the growth drivers, the average R&D-to-output ratio is 11% and the average trade-to-output ratio is 104% in the agricultural sector. Finally, 39% of the agricultural outputs are livestock-related products, and 61% are crop-related products.

Estimation Results

This article applies the new growth accounting method on the world agricultural sector to identify and quantify the channels through which the economic drivers promote agricultural growth. The control function test indicates that all six inputs are endogenous and therefore corrected by the IV method suggested in Amsler, Prokhorov and Schmidt (2016), where lagged values of inputs are treated as instruments. This article then models the varying coefficient production frontiers, estimates the effects of economic drivers on input elasticities and productivity growth, and predicts the contributions of various sources to world agricultural growth using the new growth accounting method.

World Agricultural Production Frontier

The varying frontier model in equation (10) allows time- and country-variant elasticities for each of the six inputs. Figure 2 illustrates the average elasticities for the six inputs over time. The dotted lines provide the 95% confidence intervals of elasticity estimates using Efron's nonparametric bias-corrected and accelerated (BCa) bootstrap method with 10,000 replications (Briggs, Mooney, and Wonderling 1999).

The upper left graph demonstrates that labor elasticity was diminishing, showing less

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[5] The heterogeneity in R&D can be better captured and its impact on productivity through various channels can be more precisely estimated if sector-specific R&D data (e.g., R&D spending on fertilizer, machinery, etc.) are available.

[6] ASTI is an open-access data and analysis on agricultural research investment and capacity in low- and middle-income countries. https://www.asti.cgiar.org/data.

[7] http://stats.oecd.org/Index.aspx?DataSetCode=GERD_OBJECTIVE_NABS2007#.

[8] The NBER-UN database is available on the NBER website (Feenstra et al. 2005), and CEPII-BACI is the world trade database (BACI) developed by the French research center in international economics (CEPII; Gaulier and Zignago 2010). This article generates the international trade data of agricultural products according to the definition of agricultural products in the Agreement on Agriculture of the World Trade Organization (WTO). Both NBER-UN and CEPII-BACI are the main sources of international trade for different periods and have been used together in recent studies (e.g., Boschma and Capone 2015; Johnson and Noguera 2017).

Table 1. Summary Statistics

Variable	Notation	Unit	Mean	St. dev.	Min	Max
Output						
Agricultural output	*Y*	Billion international $	11.9	37.7	0.0	591
Input						
Agricultural land	*land*	Million hectares	15.0	43.2	0.0	316
Agricultural labor	*labor*	Million active adults	8.0	35.7	0.0	391
Farm machinery	*machine*	Million tractor equivalents	0.2	0.7	0.0	11.7
Fertilizer consumption	*fertilizer*	Million metric tons	0.9	3.6	0.0	51.4
Livestock capital	*livestock*	Thousand cattle equivalents	17.3	46.7	0.0	415
Animal feed	*feed*	Million metric tons	7.7	25.2	0.0	371
Growth drivers						
R&D-to-output ratio	*r & d*	%	11	9	0	36
Degree of openness	*trade*	%	104	123	0	477
Structural transformation	*structure*	%	39	23	0	99

Notes: The statistics in this table is based on a balanced panel of 107 countries from 1962–2014 (sample size = 5,671). R&D-to-output ratio (%) is defined as the ratio of R&D stock to agricultural output, which measures agricultural R&D intensity of a country. Degree of openness (%) is defined as the total trade volume of agricultural products to agricultural output. Structural transformation (%) is defined as the output share of livestock in total agricultural products.

of a contribution of labor to agricultural output. The upper right graph describes that land elasticity was also falling, but the degree of decrease is less than that in labor elasticity and is slower in recent years. The middle left graph shows flat machinery elasticity, whereas the middle right graph demonstrates increasing fertilizer elasticity during the sample period. The lower left and right graphs show that livestock capital elasticity and feed

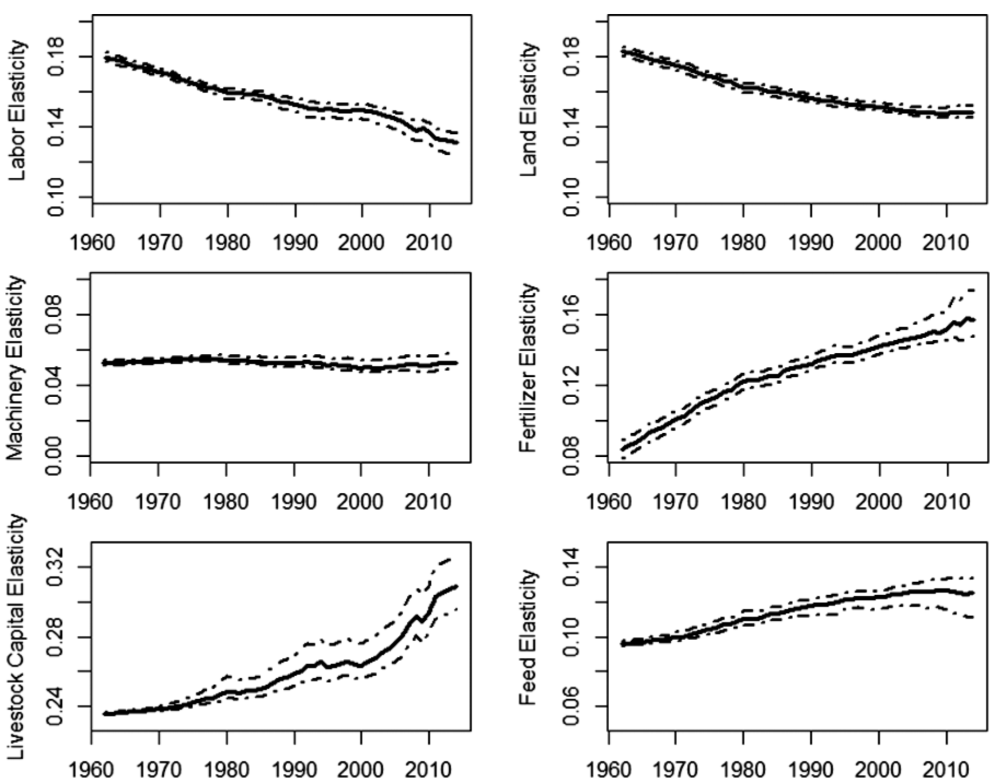

Figure 2. Change in the elasticities of the six inputs over time

Notes: This figure reports the change in output elasticity with respect to six inputs over time. The solid lines are the average level of the 107 countries, whereas the dotted lines give the 95% confidence intervals estimated by Efron's BCa bootstrap method with 10,000 replications.

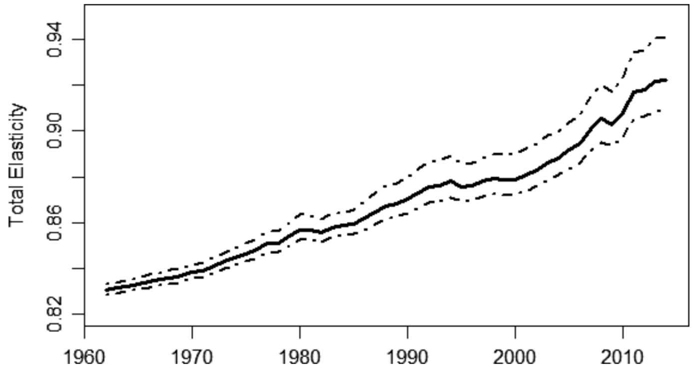

Figure 3. Change in scale economics of world agriculture over time

Notes: This figure reports the change of the sum of output elasticity with respect to six inputs over time, which reflects the change in scale economics of world agricultural sector. The solid lines are the average level of the 107 countries, whereas the dotted lines give the 95% confidence intervals estimated by Efron's BCa bootstrap method with 10,000 replications.

elasticity are both increasing, indicating that livestock-related inputs are more crucial in agricultural production over time. To summarize, it is clear that labor is being replaced by capital (machinery and livestock capital) and that land is being replaced by fertilizer, which is consistent with the induced innovation theory. Moreover, livestock-related production has become more productive, because the two major inputs, livestock capital and feed, witnessed increasing elasticity over time.

Figure 3 describes the changes in the sum of the six input elasticities over time. Similar to figure 1, this graph provides the 95% confidence intervals of the estimates. The total elasticity witnessed a significant increase, improving from 0.83 in 1962 to 0.92 in 2014. Although the results show that agricultural production follows decreasing returns to scale, the increasing trends are consistent with the endogenous growth theory in Romer (1986) and Lucas (1988). Moreover, the increasing returns imply that the same amount of inputs can generate more outputs over time, which is consistent with the fact that input qualities are improving.

World Agricultural Input-Free Productivity Growth

The varying coefficient production frontier captures the change in input–output relation over time and decomposes the classic TFP growth into input-embedded productivity growths and input-free productivity growth. The input-embedded productivity growths can be reflected by changes in input elasticities, whereas the input-free productivity growth can be reflected by changes in the remaining part of TFP. As a result, this article can identify and quantify how growth drivers promote economic growth through different channels (various input-embedded productivity growths and input-free productivity

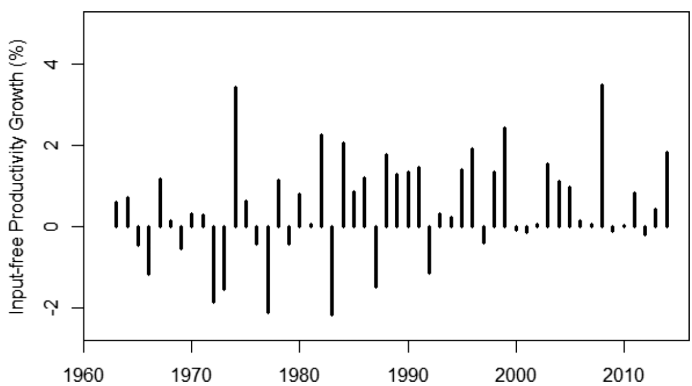

Figure 4. Annual growth rate of input-free productivity over time

growth) rather than the effect of economic drivers on the "all-in-one" TFP. Figure 4 presents the changes in input-free productivity over time, which shows that input-free productivity had a growth rate between −2% and 2% in most years and experienced less of a negative growth rate in recent years.

The Effects of Growth Drivers

The most important question this article seeks to answer regards how growth drivers promote economic growth through different channels. Table 2 reports the effects of the three growth drivers (R&D, trade and structural transformation) on various input-embedded productivity growths and on input-free productivity growth in the world agricultural sector. In columns (1) to (6) of table 2, each of the six input elasticities is the dependent variable to estimate the effect of growth drivers on the corresponding input-embedded productivity, respectively. Column (7) predicts the effect of growth drivers on the input-free productivity growth rate.

All three growth drivers speed up the process that replaces labor by capital, as they all have significantly negative effects on labor elasticity but positive effects on machinery elasticity and livestock capital elasticity. Moreover, R&D and structural transformation also accelerated the process that replaces land with fertilizer, as they both have significant negative impacts on land elasticity but a positive impact on fertilizer elasticity. International trade, on the other hand, decelerated this process, because it has a positive impact on land elasticity but a negative impact on fertilizer elasticity. However, the effect of trade on this replacement is much smaller than those of the other two growth drivers. As a result, the significant replacement of land with fertilizer was witnessed during the sample period. In terms of feed-embedded productivity, the impacts of R&D and structural transformation are both positive, whereas the impact of international trade is negative. Finally, all three growth drivers have significantly positive influences on input-free productivity.

New Growth Accounting for World Agriculture

Table 2 identifies the channels through which growth drivers promoted world agricultural growth. Moreover, the impacts of per unit change in these growth drivers are estimated. Table 3 further uses the new growth accounting method to estimate the contribution of growth drivers on agricultural growth through different channels. As a comparison, this article also reports the results using the standard growth accounting method.

Table 2. Estimated Effects of Growth Drivers on Different Parts of Agricultural TFP

	Labor β_{it}^1 (1)	Land β_{it}^2 (2)	Machinery β_{it}^3 (3)	Fertilizer β_{it}^4 (4)	Livestock β_{it}^5 (5)	Feed β_{it}^6 (6)	IFP growth ΔIFP_{it} (7)
R&D	−0.936***	−0.147***	0.323***	0.607***	0.681***	0.254***	0.0022***
	(0.026)	(0.019)	(0.057)	(0.048)	(0.016)	(0.068)	(0.0004)
Trade	−0.096***	0.018***	0.065***	−0.043***	0.085***	−0.031***	0.0004***
	(0.002)	(0.002)	(0.005)	(0.004)	(0.001)	(0.006)	(0.0000)
Structure	−0.265***	−0.141***	0.035	0.611***	0.123***	0.180***	0.0008***
	(0.018)	(0.013)	(0.040)	(0.034)	(0.011)	(0.047)	(0.0003)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	−1.483***	−1.668***	−3.041***	−2.797***	−1.586***	−2.406***	0.526***
	(0.017)	(0.012)	(0.037)	(0.032)	(0.010)	(0.044)	(0.0003)
Sample size	5,671	5,671	5,671	5,671	5,671	5,671	5,671
R^2	0.82	0.66	0.55	0.67	0.87	0.74	0.82

Note: Asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are in parentheses. In columns (1) to (6), each of the six input elasticities is treated as the dependent variable to predict the effect of growth drivers on the corresponding input-embedded productivity, respectively. Column (7) estimates the impact of growth drivers on the input-free productivity growth rate.

The first column in table 3 presents the results of standard growth accounting. The annual agricultural growth, on average, was 2.13% for 1962 to 2014, where the growth in inputs, total factor productivity, and residual contributed 1.28%, 0.86%, and –0.01%, respectively. Among the six inputs, fertilizer, feed, and livestock capital have the greatest contribution (0.40%, 0.32%, and 0.28%), followed by land and machinery (0.15% and 0.10%), whereas the contribution of labor is negligible (0.02%). The second column in table 3 reports the results of new growth accounting, which contributes 1.53% output growth to input growth, 0.76% output growth to productivity growth, and the remaining –0.16% output growth to disturbance. The results of the standard and new growth accounting approaches are fairly robust, and both show that input growth contributed more than productivity growth to world agricultural growth in the past five decades.

The new growth accounting method, however, can further decompose productivity growth to various input-embedded productivity growths and the input-free productivity growth, which is unavailable in standard growth accounting. The growth in productivity embedded in fertilizer, livestock capital, and feed is positive for all (0.85%, 0.44% and 0.34%), which can fully compensate the decrease in labor-embedded and land-embedded productivities. The growth in machinery-embedded productivity is negligible, because the machinery elasticity is flat, as shown in figure 1. Finally, the remaining input-free productivity contributes to a 0.49% annual increase in world agricultural output.

Because the conventional production function has fixed input elasticities and an "all-in-one" TFP, standard growth accounting can only estimate the overall effect of growth drivers on TFP growth, which is the only channel through which growth drivers affect output growth. In new growth accounting, however, we can investigate different channels by which growth drivers affect agricultural growth. Columns (3) to (5) of table 3 report the contribution of R&D, trade, and structural transformation to agricultural growth through various channels, respectively. It is clear that

Table 3. Standard and New Accounting for World Agricultural Output Growth

	Standard method	New method			
	Total	Total	R&D	Trade	Structure
Sources of annual growth	(1)	(2)	(3)	(4)	(5)
A. Input quantity	1.28%	1.53%	~0%	~0%	~0%
1. Labor	0.02%	0.04%	~0%	~0%	~0%
2. Land	0.15%	0.11%	~0%	~0%	~0%
3. Machinery	0.10%	0.19%	~0%	~0%	~0%
4. Fertilizer	0.40%	0.48%	~0%	~0%	~0%
5. Livestock capital	0.28%	0.33%	~0%	~0%	~0%
6. Feed	0.32%	0.38%	~0%	~0%	~0%
B. Total factor productivity	0.86%	0.76%	0.31%	0.32%	0.05%
1) Input-embed productivity	–	0.27%	0.31%	0.32%	0.05%
1. Labor	–	–0.60%	–0.24%	–2.29%	–0.16%
2. Land	–	–0.74%	–0.07%	0.67%	–0.11%
3. Machinery	–	–0.02%	0.20%	2.50%	0.02%
4. Fertilizer	–	0.85%	0.23%	–1.13%	0.22%
5. Livestock capital	–	0.44%	0.12%	1.15%	0.03%
6. Feed	–	0.34%	0.07%	–0.57%	0.05%
2) Input-free productivity	–	0.49%	~0%	~0%	~0%
C. Residual	–0.01%	–0.16%	–	–	–
Output growth	2.13%	2.13%	0.32%	0.33%	0.06%

Notes: The first and second column provide the results of standard and new accounting for world agricultural output growth based on equations (13) and (12), respectively. The annual average growth rate (2.13% during 1962–2014) can be decomposed into three parts including contribution from input quantity, total factor productivity, and residual. The contribution from input quantity can be further decomposed into six parts, one for each input. Moreover, as the advantage of the new growth accounting, total factor productivity can be further decomposed into input-embed productivity and input-free productivity (see equation (13)). Columns (3) to (5) report the contribution of R&D, trade, and structural transformation to agricultural growth through various channels, which is derived by plugging the estimations of equations (14) and (15) as shown in table 2 into equation (12). It is worth noting that the aggregates of columns (3) to (5) do not equal to the total value in column (2) because there are other factors that affect agricultural growth.

the majority of the contributions are through the six input-embedded productivities.

R&D stocks increased world agricultural output by 0.23%, 0.20%, 0.12%, and 0.07% per year through improvements in fertilizer, machinery, livestock capital, and feed, respectively. The advanced technology brought about by R&D investment also reduced our dependence on traditional agricultural inputs, such as labor and land, which further benefited industrialization and urbanization. R&D mainly improved through fertilizer and machinery to replace land and labor. On the one hand, for developed and leading countries, traditional inputs such as land and labor are expensive and scarce, which attracts research and innovation in fertilizer and machinery, as illustrated in the induced innovation theory. On the other hand, for less developed and lagging countries, the appropriate technology hypothesis in Basu and Weil (1998) argues that there is a limit to what countries can produce with a certain mix of inputs ("The ox-cart can be improved this much."). In order to enjoy spillovers and achieve convergence, these countries must change their input portfolio and accumulate more capital and intermediate inputs, which will motivate them to spend more R&D funding in fertilizer and machinery industries. Overall, agricultural R&D caused 0.32% of annual growth in agricultural output.

The effects of structural transformation are analogous to those of R&D. The transformation of a more livestock-related agriculture relied less on labor and land. Overall, structural transformation increased the world's agricultural output by 0.06% per year, which was mainly through productivity growth embedded in machinery, fertilizer, livestock capital, and feed. In terms of international trade, a 0.33% annual growth in world agricultural sector was due to a higher degree of openness of countries. Different from the other two growth drivers, international trade impeded the process that replaces land with fertilizer. Without international trade, self-sufficient urbanized countries must rely more on fertilizer, given the fixity of agricultural land. With international trade, urbanized countries can import agricultural products from agricultural-based countries, where agriculture relies more on land than fertilizer. Moreover, technology diffusion occurs more freely in the context of trade liberalization, which, for example, helps to spread better breeds of livestock (e.g., Aberdeen-Angus cattle and Holstein-Frisian dairy cow) and thus increases the quality of livestock capital. To summarize, R&D and trade made significant contributions, whereas structural transformation made a smaller contribution to agricultural growth.

Table 4 presents the results of new growth accounting for each of the last five decades. In the 1960s and 1970s, almost all the growth came from input growth, which provides evidence of extensive growth during that period. In the 1980s and 1990s, however, productivity growth accounted for about 40% of output growth, indicating the significant technological progress and the transformation of growth patterns in the world agricultural sector. In the 2000s, productivity growth contributed more to agricultural growth than input growth, which implies that modern agriculture has achieved intensive growth. To summarize, world agricultural growth relied more on productivity growth than on input growth over time.

Table 5 presents the results of new growth accounting for different country groups to show the difference between leading and lagging countries. This article uses three classifications

Table 4. New Accounting for Annual Growth Rates by Period

Period	Output growth (1)	Input growth (2)	Productivity growth (3)	R&D (4)	Trade (5)	Structure (6)
Full sample	2.13%	1.53%	0.76%	0.32%	0.33%	0.06%
1960s	2.68%	2.71%	−0.19%	0.69%	0.08%	0.03%
1970s	1.91%	1.92%	−0.02%	0.31%	0.52%	0.23%
1980s	2.06%	1.24%	0.77%	0.36%	0.32%	0.06%
1990s	1.98%	1.01%	0.89%	−0.09%	−0.05%	0.04%
2000s	2.14%	1.17%	1.38%	0.29%	0.68%	0.44%

Notes: The first column reports the annual growth rate of agricultural outputs, which can be decomposed into three parts, including contribution from input quantity (reported in the second column), total factor productivity (reported in the third column), and residual. Columns (4) to (6) report the contribution of R&D, trade, and structural transformation to agricultural growth rate, which is derived by plugging the estimations of equations (14) and (15) as shown in table 2 into equation (12). The first row reports the accounting for the full period from 1962 to 2014, and therefore all the numbers can also be found in table 3. The second row to the sixth row report the accounting for 1962–1969, 1970–1979, 1980–1989, 1990–1999, and 2000–2009, respectively.

to define leading and lagging groups. First, the new growth accounting method is utilized for developed countries and less developed countries. Second, this article analyzes agricultural growth for low-income, lower middle-income, upper middle-income, and high-income countries. Third, another classification of countries that considers the agricultural development level is provided in the *World Development Report 2008: Agriculture for Development* by the World Bank (Mondiale 2008), which points out that agriculture operates in three different types of countries: agriculture-based, transforming and urbanized countries. Comparing the results of developed countries and less developed countries, leading countries relied more on productivity growth whereas lagging countries relied more on input growth. The same conclusion can be made under the other two classifications, as high-income countries and urbanized countries achieved intensive growth, whereas low-income countries and agriculture-based countries experienced excessive growth.

In terms of overall agricultural growth, leading countries, on average, had a lower growth rate than lagging countries, and their growth relied more on R&D and international trade over the sample period. Basu and Weil (1998) point out that the input mix reflects different technologies (different production functions), so there is a limit to what countries can produce with a certain mix of inputs. Taking agricultural production as an example, lagging countries using mostly labor and land, but little capital and intermediate inputs, must go through a period of increasing inputs (e.g., fertilizer and machinery), simply because there is a limit to TFP growth without changes in a given input mix. The results of this article provide evidence of the appropriate technology hypothesis in Basu and Weil (1998), by showing that earlier growth relies heavily on input accumulation in lagging countries, which can be interpreted as lagging countries "moving" to the production function of the leading countries to benefit from accelerated TFP growth under more productive inputs.

Robustness of the Estimations

First, this article introduces two more models to check the robustness of the current varying coefficient stochastic frontier model in equation (10). On the one hand, this article assumes the Transcendental Logarithmic (T-L) specification, rather than the Cobb–Douglas (C-D) specification, to check the robustness under various specifications. On the other hand, the current varying coefficient stochastic frontier approach is a static model, where inputs affect output in the same period. This article introduces a dynamic stochastic frontier model proposed by Zhang et al. (2015) as the second robustness check, where one-year lagged outputs and inputs are included as independent variables in the dynamic model. Appendix A in the online supplementary Appendix S1

Table 5. New Accounting for Annual Growth Rates by Country Group

Country group	Output growth (1)	Input growth (2)	Productivity growth (3)	R&D (4)	Trade (5)	Structure (6)
Full sample	2.13%	1.53%	0.76%	0.32%	0.33%	0.06%
development groups						
A.1 Less developed	2.46%	1.96%	0.50%	0.14%	0.02%	0.08%
A.2 Developed	0.92%	−0.10%	1.72%	0.99%	1.44%	−0.03%
income groups						
B.1 Low-income	2.37%	2.43%	0.03%	0.16%	−0.25%	0.02%
B.2 Lower middle-income	2.85%	2.19%	0.36%	0.11%	−0.13%	−0.03%
B.3 Upper middle-income	2.46%	1.71%	0.71%	0.20%	0.13%	0.06%
B.4 High-income	1.16%	0.26%	1.63%	0.67%	1.23%	−0.03%
agricultural groups						
C.1 Agriculture-based	2.68%	2.60%	0.20%	0.17%	−0.22%	0.06%
C.2 Transforming	2.41%	1.76%	0.75%	0.16%	0.24%	−0.04%
C.3 Urbanized	1.56%	0.56%	1.23%	0.51%	0.82%	0.11%

Notes: The first column reports the annual growth rate of agricultural outputs, which can be decomposed into three parts, including contribution from input quantity (reported in the second column), total factor productivity (reported in the third column), and residual. Columns (4) to (6) report the contribution of R&D, trade, and structural transformation to agricultural growth rate, which is derived by plugging the estimations of equations (14) and (15) as shown in table 2 into equation (12). The first row reports the accounting for all the countries from 1962 to 2014 and therefore all the numbers can also be found in table 3. The remaining rows report the accounting for different country groups based on development levels, income levels, and agricultural development levels, respectively.

provides the results and confirms the robustness of the baseline estimators.

Second, it is worth noting that the stochastic frontier model, rather than the conventional production model, is adopted as the main model, because the former approach can break down productivity growth into technical progress and efficiency change, which is an attempt to decompose productivity. Using the stochastic frontier model as the benchmark can better highlight the contribution of the varying coefficient techniques adopted in this article, which provides another attempt to decompose productivity. This article also uses a varying coefficient production function model (removing $-u_{it}$ from equation (10)) as a robustness check to see if the new decomposition approach is generalized in regular production function models. As mentioned, this article uses a two-step approach proposed by Fan, Li, and Weersink (1996) to solve the varying coefficient frontier model in equation (10), where the inefficiency term $-u_{it}$ is ignored in the first step. Therefore, this first step is indeed a varying coefficient production function. As a result, all the input elasticities β_{it}^{k} are consistent using the frontier model and the conventional production function model. The only difference between the frontier model and the conventional production function is the estimation of the input-free productivity, because the second step in Fan, Li, and Weersink (1996) separates the inefficiency from the residual and adds it back to productivity in the main model. Appendix A in the online supplementary Appendix S1 also compares the input-free productivity derived from the main model with the input-free productivity derived from the varying coefficient production function model, which again confirms the robustness of the estimators.

Third, there are other variables that may affect agricultural productivity and bring about biased estimators. On the one hand, the government's other expenditures on agricultural support (such as irrigation infrastructure and subsidies) may have an impact on agricultural production and may be correlated with R&D. On the other hand, the development of non-agricultural sectors may also affect agricultural growth. Appendices B and C in the online supplementary Appendix S1 add the share of irrigated land and the share of Agricultural GDP over total GDP into equations (14) and (15), respectively. The estimated effects of the three economic drivers on different parts of agricultural productivity (input-embedded productivity and input-free productivity) in the main model are quite robust.

Finally, this article also considers the potential endogeneity problem of the growth drivers in equations (14) and (15). On the one hand, lagged values of the three growth drivers are used to replace their current values in the regressions to deal with the possible causality problem. On the other hand, this article also derives GMM estimators in which the data from previous years are used to instrument those in the current period as a second robustness check with endogeneity concern. Appendix D in the online supplementary Appendix S1 compares the estimated impacts of the three growth drivers (R&D, trade, and structural transformation) in the main model, the regression with lagged regressors, and the GMM model. The results show that the baseline estimators are robust, which can be used to further decompose agricultural growth using the growth accounting analysis.

Conclusion

This article integrates the ideas of the endogenous growth theory and the induced innovation theory into a varying coefficient stochastic frontier model, which allows for a quality change of inputs that are ignored in existing studies. The "all-in-one" TFP growth in standard growth accounting is then decomposed into growth in various input-embedded productivities and input-free productivity in our new growth accounting framework. This newly introduced growth accounting method outperforms standard growth accounting because it is able to identify different channels through which the growth drivers affect economic growth, where possible channels include input quantity, input quality, and input-free productivity.

New growth accounting is adopted to study world agricultural growth using a balanced panel of 107 countries from 1962 to 2014. Results show that, on the one hand, labor is being replaced by capital and land is being replaced by fertilizer, which is consistent with the induced innovation theory. On the other hand, there is an increasing trend of returns to scale, which is consistent with the endogenous growth theory. R&D investment and international trade are the major driving forces of economic growth, because each of them contributed to over 0.3% of annual growth in the 2.13% total growth rate. Moreover, the most effective ways for R&D to boost agricultural growth are through fertilizer and machinery improvement, whereas the most effective ways for international trade to boost agricultural growth are through land and livestock capital. Finally, productivity growth, mainly driven by R&D and trade, plays a more important role in agricultural growth in recent years and in leading countries, whereas input expansion contributes more in earlier years and in lagging countries.

Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

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