Essays on Agricultural Production, Risk, and Productivity

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Abstract

This dissertation takes two different research perspectives to address the central theme of agricultural production and productivity.

The first two essays focus on household production, which, as the primary form of agriculture to date, not only affects the welfare of individual rural families but also food supplies on a global scale. Agricultural productivity hinges largely upon farmers' choice of technology, inputs, and management strategies. Specifically, the first two essays investigate land fragmentation, a common farming practice worldwide, and evaluate its impacts on agricultural production. Chapter 2 argues that land fragmentation enables farmers to reduce risk by diversifying production among discrete plots of land which may be subject to heterogeneous growing conditions. Using Tanzanian household survey data, this essay finds robust evidence to support a risk-reduction hypothesis and indicates that land fragmentation is positively associated with production efficiency. Chapter 3 develops a production model that incorporates risk, production efficiency, and risk preferences and shows that land fragmentation may encourage risk-averse farmers to increase labor intensity, thereby leading to higher efficiency. It is also shown that exclusion of risk preferences from efficiency analysis may lead to biased or even misleading estimates.

The second focus of this dissertation is an assessment of the published evidence on the payoffs to investments in agricultural research and development (R&D). The related two essays focus on methodological as well as policy issues underlying the agricultural R&D

evaluation literature. Specifically, Chapter 4 scrutinizes the prevailing internal rate of return (IRR) measure and argues that it is based on implausible assumptions that often lead to inflated estimates of the returns to research. This essay develops a novel method for recalibrating the reported rates of return using a more plausible modified internal rate of return (MIRR) measure and derives more modest estimates. Using the detailed information collected for each R&D evaluation, Chapter 5 examines how the wide variation in the reported IRR estimates can be explained by factors such as research type, research focus, commodity type, institutional aspects of the research, target region, and methodological specifications. The findings have important implications for future agricultural R&D policy as well as R&D evaluation methodologies.

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Chapter 1. Introduction

Access to sufficient, safe, and nutritious food to maintain a healthy and active life is among the basic rights of humankind. According to the 2014 statistics from the Food and Agricultural Organization (FAO), however, there are more than 800 million people in the world still struggling toward this goal and 98 percent of them live in the developing world. Even in developed countries like the United States of America, there are millions of people suffering from hunger and food insecurity. Food security has become one of the most urgent issues faced by national governments and human society as a whole.

There are different ways to meet food security challenges worldwide. One solution is to increase food supplies with more efficient agricultural production and improved productivity. Efforts to fight poverty and hunger in past decades, such as the Green Revolution, have demonstrated that increasing agricultural production, particularly through enhanced technologies, can save hundreds of millions of people from starvation. How to pursue that goal, while addressing the growing pressure from issues such as population growth, environment protection and climate change, is at the forefront of academic research. In this context, this dissertation aims to contribute to the discussion surrounding global food security by addressing issues related to agricultural efficiency and productivity.

One approach to scrutinizing agricultural production and searching for improved productivity is to look from the perspective of agricultural households, since household production, especially by smallholder farms, remains the dominant mode of agriculture production worldwide. According to the International Fund for Agricultural Development (IFAD 2013), there are an estimated 500 million smallholder farms in the world, supporting about two billion people. How efficiently agricultural production is being carried out at the household level not only matters for the welfare of individual rural families but also influences whether we can effectively address food security concerns on a global scale.

A key challenge facing farm households is pervasive production risk arising from climatic, biotic, technical, and economic factors. The presence of risk and farmers' aversion towards risk may prevent them from producing efficiently through their choice of technology, optimal input use, and other farm management strategies. Policy instruments such as agricultural insurance and government subsidy programs have been introduced to shield farmers in developed countries from risk; however, these instruments are hardly available to farmers in the vast developing world, most of whom are still living on the verge of hunger and poverty. How do those farmers manage their production under risk and uncertainty? Is there room for improvement? A better understanding of questions like these is an essential step towards mitigating the negative impacts of risk on agricultural productivity.

The first two chapters of this dissertation investigate land fragmentation, a production strategy employed by farmers worldwide, and examine how cultivating on multiple, discrete plots affects agricultural production. Many researchers and policy-makers see land fragmentation as an impediment to efficient farming for various reasons; however, the practice remains common in many parts of the world. Voluntary plot exchanges among farmers have been rare even in the presence of land markets, while land consolidation programs promoted by governments have not always been successful and even been resisted by farmers in some cases (e.g., Heston and Kumar 1983). What has made this phenomenon so prevalent and persistent?

Chapter 2, "**Land Fragmentation with Double Dividends – The Case of Tanzanian Agriculture,**" argues that by spreading production among separate land plots with heterogeneous growing conditions, land fragmentation may help farmers mitigate production risk, and thus practiced by farmers in spite of its potential shortcomings. Applying a stochastic frontier model to household level data taken from the 2008-2009 Tanzania Living Standard Measurement Study (LSMS) survey, Chapter 2 finds robust evidence to support a risk-reduction hypothesis along with indications that land fragmentation is positively correlated with production efficiency, thereby suggesting that land fragmentation may be advantageous in two respects (and thus a "double dividend"). The findings in this chapter highlight the potential role of land fragmentation as a partial substitute for missing insurance markets in countries like Tanzania and warn against a general recommendation of land consolidation as a guarantee of enhanced efficiency.

Starting from the curious positive relationship between land fragmentation and efficiency reported in Chapter 2 and several other studies, **Chapter 3**, "**Land Fragmentation, Risk Preferences, and Production Efficiency**", looks into more channels through which land fragmentation may affect production and further examines the applicability of the stochastic frontier framework, which has been the predominant approach in efficiency analysis and measures technical efficiency. It argues that although land fragmentation is disadvantageous to technical efficiency, it may still encourage farmers to use inputs (e.g., labor in this case) more intensively and lead to a higher payoff.

Chapter 3 first develops a model that incorporates production efficiency and production risk as well as risk preferences, which will relate land fragmentation's efficiency effects with its risk effects but are absent from stochastic frontier models. Using numerical examples, it is shown that the labor-intensity hypothesis holds true under certain circumstances and more importantly, that excluding risk preferences will lead to biased or even misleading estimates of efficiency effects. These findings should not only help clarify the confusion surrounding the immediate topic of land fragmentation but also have implications for the general literature of production efficiency estimation.

In addition to improving production efficiency at the household level, investing in agricultural research and development (R&D) has been a demonstratively effective way of promoting agricultural productivity growth, and thereby generating exceptionally high reported rates of return (see Alston et al. 2000 for a comprehensive review) and fighting hunger and poverty (FAO 2009). Investment areas of this type include the development of improved (staple) crops varieties, prevention and control strategies for crop and livestock diseases, environmental conservation programs in fishery and forestry, and sectors strongly linked to agricultural productivity growth, such as agricultural institutions, extension services, storage, and irrigation systems.

Given the appropriability problems often associated with agricultural research, a substantial proportion of past investments in this area have been made by the public sector, including governments and various international institutions (Pardey et al. 2014). However, private investments can also be leveraged toward a better functioning agricultural system and improved food security (Hebebrand 2011). This poses an especially difficult challenge for developing countries where the overall amount of agricultural R&D investments is still low and there is a lack of funding opportunities and incentives for investments by both sectors.

Despite the overwhelming evidence of exceptionally high rates of return to food and agriculture R&D investments, growth in public spending has slowed worldwide, especially in rich countries. One possible explanation for the slowdown is a determination that the evidence for high rates of return is not credible. "**Re-examining the Reported Rates of Return to Food and Agricultural Research and Development**", **Chapter 4** of this dissertation, looks into the methodological conventions that pervade the R&D evaluation literature and shows that the internal rate of return (IRR) measure has often resulted in inflated rate of return estimates.

Chapter 4 develops a novel method for recalibrating previously published IRR estimates using the modified internal rate of return (MIRR) measure, which is based upon more plausible assumptions. Applying this recalibration methodology lowers the average rate of return estimate from around 43 to about 11 percent per year, a level that is more modest but typically still larger than the opportunity cost of funds used to finance the research. This suggests that society has persistently underinvested in public agricultural

R&D, notwithstanding the distorted view of the evidence accumulated in the literature over the past half century.

Chapter 5, "**Accounting for Variation in the Reported Rates of Return to Agricultural R&D**", focuses on the wide dispersion in the reported rates of return. Applying a carefully-designed meta-analysis to a sample of 1,303 internal rate of return estimates, this chapter identifies factors, both those associated with the R&D investment portfolio itself and those associated with the evaluation methodologies used to assess the returns to R&D, that help account for the large dispersion in the reported internal rates of returns to research. The findings in this chapter not only help researchers identify critical methodological issues in the evaluation literature but also provide clues to policymakers regarding future public agricultural R&D policy options.

Overall, this dissertation contributes to the current debate about how best to solve global food security problems through more efficient and stabilized agricultural production. The arguments, methodologies, and findings here will be of interest not only to economists who specialize in fields such as agricultural production, poverty, and economic development but also to governments and various institutions that have a direct stake in improving agricultural development outcomes, such as the Bill & Melinda Gates Foundation and the CGIAR centers.

Chapter 2. Land Fragmentation with Double Dividends – The Case of Tanzanian Agriculture

2.1 Introduction

Land fragmentation—that is, a single farm consisting of numerous discrete plots scattered over a wide area (Binns 1950)—, has long been deemed an impediment to agricultural production and rural development. Policymakers describe it as "the blackest of evils" (Farmer 1960), and researchers claim that it undermines efficiency and lowers profitability (e.g. Jabarin and Epplin 1994; Nguyen et al. 1996; Wan and Cheng 2001; Fan and Chan-Kang 2005; and Tan et al. 2008). Until recently, however, land fragmentation has remained a common phenomenon in both developed and developing countries. For example, Japanese rice growers operated more than four plots on average during the period 1985-2005 (Kawasaki 2010); Albanian farmers owned an average of four plots per farmer in 2005 (Deininger et al. 2012); and Tanzanian farms in the Mount Kilimanjaro regions cultivated an average of 2.5 plots per family in 2000 (Soini 2005). This raises the question—why has land fragmentation been so prevalent and persistent?

Scholars have provided various explanations to account for the prevalence and persistence of land fragmentation, including demographic, cultural and institutional reasons (see, for example, Heston and Kumar 1983; Bentley 1987; Blarel et al. 1992; Niroula and Thapa 2005). Meanwhile, some economists have attempted to re-interpret the role of land fragmentation in agricultural production from the perspective of risk management. McCloskey (1976) was among the first to formally hypothesize that cultivation on scattered plots with different soil and location can reduce risk, even though it incurs additional travel costs and other inconveniences. This risk-reducing function of land fragmentation has been corroborated by several other empirical studies such as Blarel et al. (1992), Goland (1993), and Di Falco et al. (2010).

In practice, voluntary land exchanges among farmers have been extremely rare (Bentley 1987). Governments in many places have thus been advised to launch consolidation programs in the expectation that farmers will benefit from more concentrated land holdings. Some of those programs have been deemed successful with more consolidated farms as the result, while others have failed due to resistance from farmers (See Heston and Kumar 1983 for the failure cases in India; see Niroula and Thapa 2005 for the failure cases in India, Pakistan and Thailand). Therefore, whether the existence of land fragmentation is economically justifiable is still largely inconclusive.

The variation in agricultural incomes as a consequence of risk in agricultural production has profound implications for the well-being of many farmers in developing countries. Unlike their counterparts in the developed world, many of who can avail themselves of crop insurance programs or deploy production strategies (such as the use of irrigation or pest control chemicals) to protect themselves from adversity, developing-country farmers have viable access to far fewer risk management options, such as crop diversification and land fragmentation. Further, as observed in many studies (for example, Liu 2013), farmers’ aversion to risk may prohibit them from adopting new technologies and improved crop varieties even though they will be rewarded with higher expected returns.

To investigate the role of land fragmentation in agricultural production, this study will discuss the economic implications of land fragmentation and evaluate its effects on both efficiency and risk. Applying a stochastic frontier model to the analysis of land fragmentation, we expect to derive an improved characterization of this phenomenon through a careful discussion of determinants of production efficiency and production risk. The results from our model will be compared with those from similar studies to shed light on future land tenure reforms that aim to secure agricultural production and improve farmers' well-being.

2.2 Land Fragmentation and Plot Heterogeneity

There is no single measurement of land fragmentation given its economic implications in more than one aspects. King and Burton (1982) propose a six-parameter characterization: farm size, plot number, plot size, plot shape, plot spatial distribution, and the size distribution of the fields, while Bentley (1987) argues that efforts to quantify the notion of land fragmentation that fail to account for measures of distance are flawed. Among economists, the predominant measure has been the Simpson Index (SI), which may be used along with other dimension(s) of land fragmentation (e.g. Blarel et al. 1992; Hung et al. 2007; Tan et al. 2007; and Kawasaki 2010). For a farm household cultivating a total of J plots, denote the area for plot j (j=1,2...J) by A_j, the Simpson Index is then defined as:

$$(2\text{-}1) \qquad SI = 1 - \sum_j^J \left(\frac{A_j}{\sum_j^J A_j}\right)^2 = 1 - \frac{1}{\left(\sum_j^J A_j\right)^2}\sum_j^J {A_j}^2 = 1 - \frac{1}{A^2}\sum_j^J {A_j}^2$$

where $A = \sum_j^J A_j$ is the total farm area. This index returns a value lying within the unit interval and increasing in fragmentation. SI=1 refers to an infinite fragmentation scenario while SI=0 refers farms consisting of a single plot of land. The estimated SI value is jointly determined by the number of plots, the farm size, plot size and the plot size distribution.

One common phenomenon that usually confounds considerations of land fragmentation per se is the occurrence of heterogeneous soil quality and growing conditions across plots, or plot heterogeneity for short. It is sometimes believed to be a cause of land fragmentation or a restricting condition for land consolidation to be implemented (Mearns 1999; Niroula and Thapa 2005). What is significant about plot heterogeneity is its risk-management role discussed in the literature. By cultivating plots with varying micro-environments, farmers are able to reduce the variation in output or income because the risk caused by drought, flood and diseases is spread out for the same crop (Hung et al. 2007). Bentley (1987) reviewed several studies from this perspective, covering both grain crops and cash crops and concluded that the risk management advantage of fragmented farms is applicable in many contexts.

Another value of plot heterogeneity is that it may encourage crop diversification (Bellon and Taylor 1993; Hung 2006), a popular strategy for risk reduction. By matching the proper crop portfolio with the agro-ecological conditions across the whole farm, farmers are induced to increase crop diversity and stabilize the total farm output. Di Falco et al. (2010) present an empirical analysis which finds that land fragmentation fosters crop diversification.

To summarize, the literature has spent a great deal of attention on land fragmentation's impacts on either productivity or profitability, and land fragmentation has been found to be detrimental in general. Meanwhile, the risk-management hypothesis of land fragmentation has not received much empirical scrutiny, even though it was first proposed in the economics literature some time ago. The few existing studies that examine the risk effect of land fragmentation have focused solely on the dispersion of fields without considering plot heterogeneity. Considering the observation that land consolidation programs have succeeded mostly in places with uniform soils but failed in places with heterogeneous soils (Heston and Kumar 1983; Mearns 1999; Niroula and Thapa 2005), it is reasonable to conjecture that the risk-reducing benefit of land fragmentation may be jointly determined by both plot dispersion and plot heterogeneity.

2.3 Conceptual Framework

In this section, we will provide a formal framework to characterize how land fragmentation affects both production efficiency and production risk, which is often measured by the variation in crop yield. The dominant approach to production efficiency analysis has been the stochastic frontier model, which was simultaneously developed by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977). To begin, write the yield y_i (in its original unit) of farmer i (i=1, 2...N) as:

(2-2) $$y_i = F(\boldsymbol{X}_i;\ \boldsymbol{\beta}) * exp(-u_i) * exp(v_i).$$

In (2-2), $F(\boldsymbol{X}_i;\ \boldsymbol{\beta})$ is the deterministic production function where $\boldsymbol{X}_i$ is the input vector, including a constant term, and $\boldsymbol{\beta}$ is the corresponding parameter vector. The inefficiency term, u_i, is assumed to be greater than or equal to zero (hence it is also known as the one-sided error term) such that $exp(-u_i)$ lies within the unit interval, representing the proportion of $F(\boldsymbol{X}_i;\ \boldsymbol{\beta})$ that is actually produced. When $exp(-u_i) = 1$, the production is completely efficient and lies right on the production frontier; otherwise, inefficiency exists and production lies below the frontier. Lastly, the term $exp(v_i)$ contains the regular error term v_i (also known as the two-sided error term), which captures all random factors such as noise and model misspecification. By having two separate error terms, the stochastic frontier model, which is also called the compound error model, allows the estimation of a stochastic production frontier with individual-specific inefficiency.

Empirical studies often focus on inputs and output in the logarithmic form and assume the deterministic production function after the logarithmic transformation, $f(\cdot)$, to take either the Cobb-Douglas form or the transcendental logarithmic (translog) form. This study will take the translog assumption as the more general case. This transformation allows us to see the three components of y more clearly:

(2-3) $$lny_i = f(ln\boldsymbol{X}_i;\ \boldsymbol{\beta}) + v_i - u_i.$$

The primary interest of stochastic production frontier analysis falls on the inefficiency term u_i, and more specific assumptions have been made about its distribution. With a truncated normal distribution for u_i, Kumbhakar et al. (1991) and Huang and Liu (1994) propose a model to parameterize the mean of the pre-truncated inefficiency distribution, μ_i, such that inefficiency could be explained by a group of exogenous variables $\boldsymbol{Z_i}$, including a constant term, through a linear function. That is:

(2-4) $$u_i \sim N^+(\mu_i, \sigma_u^2)$$

Where

(2-5) $$\mu_i = \boldsymbol{Z_i\gamma}$$

The parameter vector $\boldsymbol{\gamma}$ in (2-5), or the so-called inefficiency effects, is left to be estimated. We will adopt the truncated normal assumption on u_i for the purpose of this study. Further, the two-sided error v_i is always assumed to follow the normal distribution $N(0, \sigma_v^2)$. Both v_i and u_i are often assumed to be independent of each other and $i.i.d.$ across observations.

In the traditional single-error model, heteroscedasticity usually does not cause too much empirical trouble. In case of its presence, the coefficient estimates are still consistent although not efficient, and the problem can be easily fixed by using more robust estimation procedures. However, heteroscedasticity is a much more serious problem in stochastic frontier models and may lead to inconsistent estimates of the inefficiency effects, the parameters of primary interest. This is because estimation of the inefficiency term is based upon residuals derived from the estimation of a frontier (Caudill et al. 1995; Hadri 1999). Even worse, heteroscedasticity could be present in either or both of the one-sided error term u_i and the two-sided error term v_i, and mis-specification of either variance term, σ_v^2 or σ_u^2, will result in inconsistent estimates (Hadri 1999). Therefore, a reliable stochastic frontier model demands a careful analysis of its two variance terms.

As reviewed in the previous section, land fragmentation has long been suspected of being related to production risk. In this study, we make the formal hypothesis that land fragmentation can diversify production risk onto separate land plots such that it reduces the risk on the entire farm. To see this, we follow a similar decomposition to the one used by Blarel et al. (1992) and rewrite the actual yield (in its original unit) on the jth plot of the ith farm by y_{ij} such that

(2-6) $$y_{ij} \equiv \bar{y}_i + d_{ij} + \theta_{ij} + e_{ij}$$

In (2-6), $\bar{y}_i$ is the expected farm-level yield. The term d_{ij} captures the plot-specific fixed effects that cause y_{ij} to deviate from $\bar{y}_i$, such as soil attributes. For example, if certain plot is more fertile than the other plots on the same farm, the yield on this plot will tend to be higher than the average yield on the whole farm. As opposed to d_{ij}, θ_{ij} is also plot-specific but stochastic, and it may be associated with precipitation, insolation, wind, and other random factors that define the microclimatic environment on each plot (Bentley 1987). In general the distribution of θ_{ij} should vary from plot to plot and hence we assume $E(\theta_{ij}) = 0$ and $Var(\theta_{ij}) = \sigma_{\theta ij}^2$ for any j. Finally, e_{ij} captures all stochastic effects that are uniquely distributed for any plot on any farm, such as measurement errors, and it is assumed that $E(e_{ij}) = 0$ and $Var(e_{ij}) = \sigma_e^2$, for any i and j.

With such a decomposition, we are taking the production on the farm level as a portfolio of production on all individual plots, each of which has its own distribution of returns. To aggregate into the farm-level yield y_i, we have

$$y_i = \frac{1}{A_i}\sum_j^J y_{ij}\, A_{ij} = \frac{1}{A_i}\sum_j^J\left[\left(\bar{y}_i + d_{ij}\right) * A_{ij} + \left(\theta_{ij} + e_{ij}\right) * A_{ij}\right] \tag{2-7}$$

Since we are concerned with the farm-level risk, take variance of y_i to get

$$Var(y_i) = Var\left[\frac{1}{A_i}\sum_j^J\left[\left(\theta_{ij} + e_{ij}\right) * A_{ij}\right]\right] \tag{2-8}$$

$$= \frac{1}{A_i^2} Var\left[\sum_j^J\left(\theta_{ij} * A_{ij}\right)\right] + \frac{1}{A_i^2}\sum_j^J \sigma_e^2 A_{ij}^2$$

$$\equiv \sigma_{\theta i}^2 + (I - SI) * \sigma_e^2$$

Firstly, the second term on the right-hand side of (2-8), $(I - SI) * \sigma_e^2$, shows clearly that land fragmentation, measured by the Simpson Index, is negatively related to the yield variability on the whole farm by spreading out the common stochastic effects σ_e^2 across the plots. What is less obvious is the first term, $\sigma_{\theta i}^2$, which is the aggregation of stochastic effects that are specific to each plot and whose effect on yield variability is generally unknown unless the distribution (or at least the variance) of each θ_{ij} is given. In general, we should expect $\sigma_{\theta i}^2$ to be related to soil heterogeneity for reasons argued in Hung et al. (2007). Moreover, if we believe that farmers can match the growing conditions on all plots with the proper crop portfolio as suggested by the high correlation between the two (Bellon and Taylor 1993; Hung 2006), we should expect $\sigma_{\theta i}^2$ to be negatively associated with crop diversification given the latter's evident role for risk reduction.

In this way, we see that yield variability is not identical among all farms but is determined by several farm-specific factors, echoing our concern of heteroscedasticity. To be more specific, the variance of the common error term v_i should have its own explanatory variables; that is

(2-9) $$\sigma_{vi}^2 = \exp(\boldsymbol{h}_i \boldsymbol{\alpha})$$

where $\boldsymbol{h}_i$ will include a constant term, the Simpson Index and variables for plot heterogeneity and crop diversification. Further, some factors of production have been found to affect either or both variance terms, such as labor (Hadri et al. 2003). To avoid potential bias in the coefficient estimates, we retain the most general specification of σ_{ui}^2 at this step by allowing its own vector of determinants, $\boldsymbol{k}_i$, with the coefficient vector $\boldsymbol{\varphi}$:

(2-10) $$\sigma_{ui}^2 = \exp(\boldsymbol{k}_i \boldsymbol{\varphi})$$

If heteroscedasticity is found to be absent from σ_{ui}^2 by the empirical estimation, $\boldsymbol{k}_i$ will contain only a constant term as in the homoscedastic case.

2.4 Data and Context

The data used for the empirical analysis come from the Tanzania National Panel Survey 2008-2009 as part of the Living Standards Measurement Study (LSMS)—Integrated Surveys on Agriculture project led by the World Bank. This survey adopted a stratified, multi-stage cluster design to obtain a nationally-representative sample. Rural family members were interviewed by team enumerators regarding their family socioeconomics and agricultural activities. Information such as location, ownership, soil conditions, crop varieties, input use and harvest was collected for each cultivated plot.

For the purpose of this study, we will focus on plots that were grown either partially or fully with annual crops in the long rainy season (March, April and May) by realizing that the production of annual crops differs tremendously from that of perennial crops and trees. In this way, our sample contains 1,503 households with 2,756 plots; nearly half of the households cultivated only one plot and around 95 percent of households cultivated less than 4 plots (Table 2-1). Maize is the predominant crop in terms of either frequency or planting area, and other popular annual crops include beans, groundnuts, paddy rice, and sorghum. More background information and descriptive statistics for key variables will be presented below.

In Tanzania, smallholder farming has been the predominant form of agriculture, which accommodated about 75 percent of the national population and accounted for about 45 percent of the GDP in 2008. Although Tanzania has vast areas of cropland that are suitable for intensive cultivation, the use of inputs is limited and productivity is generally low. In 2008, 37 percent of the rural population, i.e. more than one fourth of the total population, lived below the poverty line. Therefore, efficient and secure food production has significance for Tanzania's millions of impoverished rural citizens as well as its national economy.

There is one particular issue of Tanzania's agriculture that is highly pertinent to the topic of this study -- land fragmentation. At the beginning of its independence, Tanzania adopted a communist approach and promoted collective land cultivation and shared labor for its agricultural production. An estimated 75% of the population were relocated from scattered homesteads and smallholdings to live in communal villages of 2,000-4,000 residents (Dondeyne et al. 2003; Maoulidi 2004), even though there was a strong preference of farmers for individually allocated and individually cultivated farmland (USAID 2011).

This approach was quickly abandoned by the following administration in the 1980s and a new legal framework was gradually installed to support private property rights and individualized control of farming. The law recognizes the rights to land and encourages productive and sustainable use of land. In principle, farmers have the rights to buy, sell, lease and mortgage their plots and decide on matters such as their crop choices and land use. More interestingly, farmers could have chosen to have a single-plot farm although most of them still keep multiple plots on their farms. By 2008, each rural household owned or cultivated an average of 2.5 plots. The shifts in Tanzania’s land tenure system in the past several decades may better address the underlying economic motivations of land fragmentation as investigated in this research.

2.5 Empirical Model

Dependent Variable

Among the households in our sample, nearly 70 percent grew more than one crop and the crop portfolio varied from farm to farm, rendering it difficult to compare production efficiency across farms using a yield frontier. Moreover, the lack of price data on hired labor makes it impossible to estimate the profits of crop production. Therefore, we use a revenue frontier for this study by implicitly assuming revenue-maximizing farmers. Specifically, the dependent variable of our empirical model is the logarithmic form of revenue per acre, which equals the aggregated value (in Tanzania shillings) of all crops grown on each farm divided by the farm area. In this survey, farmers were asked to estimate the value of their crops and the proportion of harvest finished by the time of the survey. Crop prices reported by village leaders are not adopted because of apparent anomalies and missing observations.

Given that we are estimating a revenue frontier, the one-sided error term u_i now measures the revenue efficiency, which is defined as the ratio of actual revenue to maximum revenue. As opposed to the generic stochastic production frontier, where the dependent variable is output and u_i measures the technical efficiency, revenue efficiency to be measured in this study is one type of economic efficiency and hence consists of both technical efficiency and allocative efficiency. Allocative efficiency refers to the ability to combine inputs and/or outputs in optimal proportions stipulated by the first-order optimality conditions in light of prevailing prices.

To illustrate the measurement and decomposition of revenue efficiency, we plot a revenue frontier[1] for two outputs in Figure 2-1 and use Point A to represent an actual output combination. Point E on the revenue frontier maximizes the revenue at the relative output price W, which equals the slope of the price line. Now revenue inefficiency is represented by the vector difference between Point A and Point E. To decompose revenue efficiency into the two components of interest, we push Point A up to Point B on the revenue frontier by keeping the corresponding price lines parallel. The vector difference between Point A and Point B represents technical inefficiency since the radial movement from A to B fully employs output slackness given the output prices. The allocative inefficiency is then determined residually as the vector difference between Point B and Point E, which illustrates the deviation from the optimal output combination. Quantitatively speaking, the magnitudes of technical, allocative and revenue efficiency in this example are all measured by ratios of price-weighted output vectors. Hereby, we use the term (in)efficiency to denote revenue (in)efficiency unless otherwise noted.

Explanatory Variables of the Revenue Frontier

As stated earlier, farm area is calculated as the aggregated area for all annual crops and is included in the revenue function as an input. Besides land, labor is of utmost importance in Tanzanian agriculture. The LSMS survey documents labor days spent by family members and, if any, hired workers on each plot at three stages of production,

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[1] Here we implicitly assume that the output sets are closed and convex and that outputs are freely disposable.

i.e., land preparation and planting, weeding, and harvesting, making it possible to differentiate labor spent on these activities as different inputs. For this study we add hired labor onto family labor for each activity and include in the inefficiency term (to be discussed below) the ratio of total hired labor to total family labor in order to control for the impact of labor heterogeneity on efficiency.

Inputs other than labor and land, such as fertilizers, irrigation, herbicides and pesticides, have been rare in Tanzania (Panel 1, Table 2-2). Even fewer farmers have access, through either rental or possession, to draft animals (e.g., oxen) or farm machinery (e.g., tractor and thresher) although they may increase revenue significantly (Panel 2, Table 2-2). Instead, the most common farm implement in Tanzania are hand hoes with all the households in our sample having at least one. In the empirical model, we will include the number of hand hoes per acre and a dummy variable for the use of any draft animal or machinery to control for their probable contribution to revenue.

Variables for average temperature and precipitation of the wettest quarter rather than those of the whole year are included as inputs to account for weather's impact on the agricultural production undertaken in the long rainy season[2]. Finally, our revenue

[2] As a matter of fact, the average number for all year around is highly correlated with the average number for the wettest season. This is the case for both temperature and precipitation with the correlation coefficients equal to 0.98 and 0.92 respectively. Switching to the yearly statistics will not lead to any essential changes in our major findings as confirmed by our sensitivity test on this.

frontier model contains a price index which equals the average price of all annual crops harvested on the farm weighted by their quantities (all in kilograms)[3].

Explanatory Variables of Inefficiency

Land Fragmentation. Variables from this category are of primary interest in this study regarding the determination of efficiency. Table 2-3 lists the descriptive statistics of the various dimensions of land fragmentation. It shows that the majority of the farms in our sample have a relatively small size with a mean of 4.96 acres and 95 percent of them less than 15 acres. The average plot size of 2.70 acres is even smaller owing to the fragmentation of land on over half of the farms. Land fragmentation measured by the Simpson Index presents a clear bimodal distribution as a result of the large percentage of single-plot farms, while there exists only weak correlation between farm size and the Simpson Index. In terms of distance, about three fourths of the plots are located within 3 kilometers (approximately 2 miles) from either home or road. Meanwhile, less than 40 percent of the plots are within that distance from a nearby market.

To estimate the inefficiency term in the model, we will include farm size, the Simpson Index, an interaction term between the two as well as the three distance variables (from plot to home, road and market, respectively). To account for the varying effects of land fragmentation on plots with different sizes, we calculate the average plot area and average distance variables weighted by plot size. It turns out that the weighted average

[3] We also tried generating an average crop price weighted by their contribution to total value and included it in the empirical model. All major findings remain the same except for the changes in the magnitude of coefficient estimates and therefore the inefficiency estimates and marginal effects.

plot area, a somewhat obscure concept, equals farm area minus its interaction term with the Simpson Index; hence there is no need to add it to the model. To see this connection, recall that the area for the jth plot is denoted as A_j then the weighted average plot area is by our definition derived as

(2-11) $$\frac{1}{A} * \sum_j^J A_j\, A_j = A * \sum_j^J \left(\frac{A_j}{A}\right)^2 = A * (1 - SI)$$

Finally, the number of plots on each farm will be excluded from the model since it is already captured by the Simpson Index[4].

Household Characteristics. In a cross-section analysis like this one, household characteristics, especially those related to labor, usually help to explain the variation in efficiency across households. Here we adopt the average age and average education[5] (measured in school years) of family workers who actually worked in the fields instead of those of all family workers, some of whom may work in non-agricultural sectors. Labor days by male workers and labor days by hired workers as the respective proportion of the total labor days will also be included.

[4] Also, it will be difficult to interpret the marginal effects if we include both the Simpson Index and number of plots.

[5] Many studies choose to use the age and education of household head as a proxy for experience. However, as argued in Fuwa (2000) and others, there have been various definitions of household headship (e.g., demographics-based or economics-based) and the household head elicited in the common household-level surveys may not necessarily be the one that is most relevant to the economic analysis under many circumstances. Therefore, we believe the average age and education of family laborers who actually worked in the fields to be a better proxy variable of farming experience in this study.

Further, households will allocate their resources to activities other than the growing of annual crops, such as housework and perennial crops or fruit trees. With the information available, we will include the ratio of the number of children under the age of five to the number of family field workers and the ratio of farm area used for perennial crops/fruit trees to farm area used for annual crops to control for their potential negative impacts on efficiency. Table 2-4 in the appendix lists the descriptive statistics of these household characteristics variables.

Soil Conditions. Using the geo-referenced homestead location data, the LSMS survey has imported soil and terrain data from the Harmonized World Soil Database at a resolution of 0.083degree (about 10 kilometer grids). The measures we choose to explain production efficiency are: nutrient availability, oxygen availability to roots, and workability for field management (Table 2-5). To include each of the measures in the estimation, we use "severe constraints" as the reference and create respective dummy variables for the other two categories, “Moderate constraints” and “No or slight constraint”, both of which expect a negative coefficient.

Explanatory Variables for Heteroscedasticity

Plot heterogeneity and Crop Diversification. As argued in the conceptual framework, the variance of yield is related to plot heterogeneity, crop diversification, and land fragmentation measured by the Simpson Index. In the LSMS survey, Tanzanian farmers are asked to report the soil type (sandy, loam, clay and others), erosion type (existent or not) and steepness of slope (flat bottom, flat top, slightly sloped and very steep) for each plot. Assuming that soil conditions can be jointly characterized by these three dimensions, we use the number of different soil profiles normalized by the number of plots to compare plot heterogeneity across farms (Table 2-6).

Nearly 70 percent of farms in our sample have diversified their crop portfolio by either growing more than one crop on single plot and/or growing different crops on different plots (Table 2-7). In this study, we simply use the number of different crops on the whole farm to account for its influence on revenue variance.

Labor Inputs. Researchers have long emphasized the effects of various inputs on risk, and a convenient specification has been the Just-Pope production function, which incorporates inputs into both the mean and variance functions of output. Evidence regarding the role of certain inputs, especially labor, has been mixed. For example, Antle and Crissman (1990) find labor to be risk reducing while Villano and Fleming (2006) argue that labor increases output variability. Further, the variance of either or both the one-sided error and two-sided error in a stochastic frontier model may be associated with producers' input use (Schmidt 1986; Hadri 1999; Hadri et al. 2003). Hadri et al. (2003) report that expenditure on labor and machinery by farms will increase variability in efficiency, whereas land area and fertilizer cost have the opposite effect. In this paper, we will divide the aggregated labor days for all three activities by farm area and put the ratio in the variance function.

2.6 Estimation and Results

We are estimating a stochastic production frontier with a group of exogenous explanatory variables for the inefficiency term. Moreover, heteroscedasticity may be present in either or both variance terms. Instead of using the common two-step estimation approach which will generate biased estimates Wang and Schmit (2002)[6], this study uses the simultaneous estimation package in Stata 12.0 developed by Belotti et al. (2012).

Variance Structure

The main challenge to the empirical estimation stems from the indeterminate effects of labor on the two variance terms. Kumbhakar and Lovell (2003) propose a procedure that starts with a model that incorporates heteroscedasticity in both error components and then test the homoscedasticity restriction that respective coefficient(s) equals to zero. For this study, we start with a model, named HUV, where labor inputs appear in both variance terms with the Simpson Index, and the measures of plot heterogeneity and crop diversification in the variance of the two-sided error term. Then we move on to the two single-heteroscedasticity specifications, denoted as HU and HV respectively, where either the one-sided-error variance (U) or the two-sided-error variance (V) has its own determinant(s). Since labor input may affect the two variance terms differently from the other three variables, estimates from two alternative specifications (HU_1 and HUV_1) are also derived for model comparisons. Finally, the homoscedasticity model is estimated with only a constant term for each variance, and it is denoted as HO hereafter.

[6] This estimation procedure has been operationalized in Stata 12 by Belotti et al. (2012).

Table 2-8 lists the variance coefficient estimates for the six models above. Since model HUV could be seen as the unrestricted model for the other five, the likelihood ratio test can be applied to make pairwise comparisons between HUV and each of the other five. It shows that HUV is preferred to HU, HV_1 and HO but not HV and HUV_1, the likelihood of which are close enough to that of HUV to reject the specification of HUV. Further, both the significance test of coefficient estimates and the likelihood dominance criterion (Pollak and Wales 1991), an approach to non-nested model selection, suggest that HV is preferable to HUV_1.

To conclude this section, as far as heteroscedasticity is concerned, HV is the statistically preferred model where heteroscedasticity appears only in the two-sided error term with four explanatory variables: Simpson Index, labor input, plot heterogeneity, and crop diversification. Discussions in the next section will be based on the HV model unless otherwise noted.

Hypothesis Tests

Following from the previous section, we can see that the Simpson Index is negatively correlated with the two-sided error variance as predicted by the conceptual framework, and its coefficient estimate is significant at the 10% level according to a two-tailed test. A similar result also holds for crop diversification, measured by the number of different crop types on the whole farm. In contrast, plot heterogeneity is found to have a positive impact on the variance although the estimated coefficient is statistically insignificant. This finding is not completely surprising given the close connection between plot heterogeneity and crop diversification. With a better characterization of plot heterogeneity and its relationship with crop diversification, we may be able to derive its "net effect" on the variance in future work. Lastly, revenue variance increases with the labor input, a result in accordance with the risk-increasing role of labor found by many studies.

Regarding the determinants of efficiency (Column 2, Table 2-9), we find that average education of family workers and proportion of male labor have the expected positive effects on efficiency, and the ratio of farm land devoted to perennial crops and fruit trees and average age of workers have the expected negative effects, and all these effects are statistically significant at the 5% level. Meanwhile, the ratio of children under the age of five to the number of family workers does not seem to affect efficiency. Leaving out this variable will not impact the overall performance of the model as shown by the comparison between Column 3 and 2 in Table 2-9. This may be because over three fourths of families in our sample have only one young child or no child at all such that they place no big burden on family workers.

What turns out to be puzzling is the effect of hired labor, and the results suggest that the higher the ratio of hired labor to the overall labor is, the more efficient the production will be. This contradicts the common belief that hired labor is less efficient than family labor since hired workers may lack enough farm-specific experience and is difficult to supervise (Feder 1985; Binswanger and Rosenzweig 1986). A potential explanation is that we are unable to include more variables related with hired labor such as their age and education, which are not reported in this survey. These variables will affect production efficiency as their counterparts for family labors and may be correlated with hired labor ratio; hence excluding them from the regression will lead to omitted variable bias.

Among the variables that are associated with soil conditions, the two for nutrient availability report positive coefficient estimates while neither of the estimates is statistically significant. An exclusion test (Column 4, Table 2-9) on the two variables shows that leaving them out from the model will not significantly change the estimates of other variables or the overall model fit. As for oxygen availability, the dummy representing the category of "Moderate constraint" is found to be negative at the 10% significance level, whereas the one for "No or slight constraint" is not significant, implying that soil of this type has the same effects on production efficiency as that of "Severe constraint". This unusual estimate may be caused by the lack of variation in our sample, as 90% observations report no or slight constraint (Table 2-5). Finally, both the two dummies for "Workability" report significantly negative coefficient estimates, and the difference in magnitude between the two estimates suggests that the less constraining the workability is, the more efficient the production would be, a conclusion that is consistent with our expectation.

Our primary interest falls on the variables related to land fragmentation. The Simpson Index, the most popular measure in the literature, is found to have a significantly negative impact on inefficiency (Part 2, Table 2-9); in other words, the more fragmented the farm is, the more efficient the production. This relationship seems counterintuitive and contradicts the results in many other studies, although it is robust to various model specifications in this research. As for other dimensions of land fragmentation, neither of them reports a statistically significant coefficient estimate on its own; however, they are jointly significant as can be seen from the results in Part 5 of Table 2-9. This finding echoes previous call for a complete characterization of land fragmentation to measure its economic effects.

Finally for the production frontier, the coefficient estimates of various inputs are less relevant to our topic and are thus waived from discussion. The only thing worth noting here is that the use of ox or machinery in the production shows a significantly positive effect on revenue as expected.

Efficiency Estimates and Marginal Effects

Given the results from the significance tests, we estimate a parsimonious and also statistically preferable model of HV, HV_P, to derive estimates for mean inefficiency term or its opposite, the mean efficiency, for each farm. Since our production frontier is defined for the logarithms of revenue and inputs, those mean efficiency estimates are subject to a proper transformation before comprehensible economic interpretations could be reached. The estimator proposed by Jondrow et al. (1982) is used to facilitate the calculation of marginal effects in the next step, although the results turn out to be very close to those using the alternative Battese and Coelli (1988)'s estimator (Table 2-10 and Figure 2-1). It can be seen that the average revenue efficiency across the 1,503 farms is 0.42, implying that these farms realize, on average, 42 percent of the revenue of a fully efficient farm, i.e. one that has zero inefficiency. Table 2-10 also shows the wide gap between the most efficient farms and those least efficient ones. This is consistent with our knowledge of agricultural production in Tanzania, where the productivity is low and varies tremendously across its many agro-ecological zones (USAID 2011).

Using the convenient estimates of efficiency from the last step, we are able to derive the farm-specific marginal effects as presented in Table 2-11. For example, if the average education of labor is increased by one year, it can add 0.75 percentage points on average to the existing efficiency; if farmers can update the workability of his land from "Severe Constraints", the reference category for the regression, to "No or Slight Constraints", they can expect the efficiency to grow by 10.13 percentage points.

As for the Simpson Index, the estimated mean marginal effect suggests that if all the plots are consolidated into one, i.e. the Index goes from one to zero, the efficiency will be reduced by 12.20 percentage points. Since a Simpson Index equal to one refers to the infinite fragmentation case, which is practically impossible, a more meaningful interpretation of its marginal effect would be a proposed consolidation from its current state. Recall that our sample contains 2,756 plots from 1,503 farms. The average value of the Simpson Index equals about 0.25 and the estimated average efficiency score of 42 percent. If all the multi-plot farms are consolidated into single-plot farms, then the mean Simpson Index would be zero and the new average efficiency score will drop by three percentage points to 39 percent, i.e., a 7.2 percent decrease from its current level.

Finally for a robustness check, we try more specifications of the empirical model, such as using aggregated labor instead of three separate labor inputs or using alternative measure of crop diversification, and find no substantial changes to our major findings[7].

2.7 Discussion and Conclusions

To investigate the role of land fragmentation in agricultural production, this study applies a stochastic frontier model with heteroscedasticity to the Tanzania LSMS data and finds robust evidence to support the hypothesis that land fragmentation may reduce production risk as measured by revenue variability. This finding is consistent with the few empirical studies that have addressed the risk-reduction effect of land fragmentation, such as McCloskey (1976), Blarel et al. (1992), and Goland (1993). Moreover, we emphasize the necessity of including plot heterogeneity in characterizing land fragmentation and more importantly, quantitatively measuring its effects on revenue by showing how revenue variability is jointly determined by the two factors and the closely associated crop diversification. This may explain the curious observations made by Heston and Kumar (1983) and Niroula and Thapa (2005) that land consolidation programs have succeeded mostly in places with uniform soils but failed in places with heterogeneous soils.

[7] Since the primary model includes the Simpson Index in both the mean inefficiency function and the risk function, there may be concerns over the identification of this variable. To address this issue, we conduct sensitivity tests by excluding the Simpson Index from either of the two functions at a time. In either case, the model is identifiable and reports coefficients estimates similar to the primary findings in terms of sign of direction, magnitude, and statistical significance.

Meanwhile, our analysis suggests that land fragmentation may be efficiency enhancing by increasing the revenue per unit of land, leaving it instrumental to farmers in terms of both efficiency and risk management (we dub this result "double dividends"), a finding that contradicts those of many studies in the literature but not all. For example, a few studies have found either a statistically insignificant (e.g. Blarel et al. 1992; Di Falco et al. 2010) or economically insignificant (e.g., Wan and Cheng 2001) effect of land fragmentation. On the other hand, our result is not without companions in the literature. Deininger et al. (2012) apply the stochastic frontier model to the LSMS survey data of Albania and find land fragmentation measured by number of plots has a statistically significant positive effect on technical efficiency although the authors suggest that this positive economic impact is small (Page 13)[8]. An even more interesting observation has been made by Niroula and Thapa (2007), who report that in Nepal parcels with smaller size resulted from land fragmentation see more labor inputs and a higher yield. They further argued that "land fragmentation has a rather positive impact on production… However … the higher crop yield from small parcels is attributed to the application of considerably higher amount of labor, fertilizers and compost." Yet they did not give any clue on whether or how input intensity is connected with land fragmentation.

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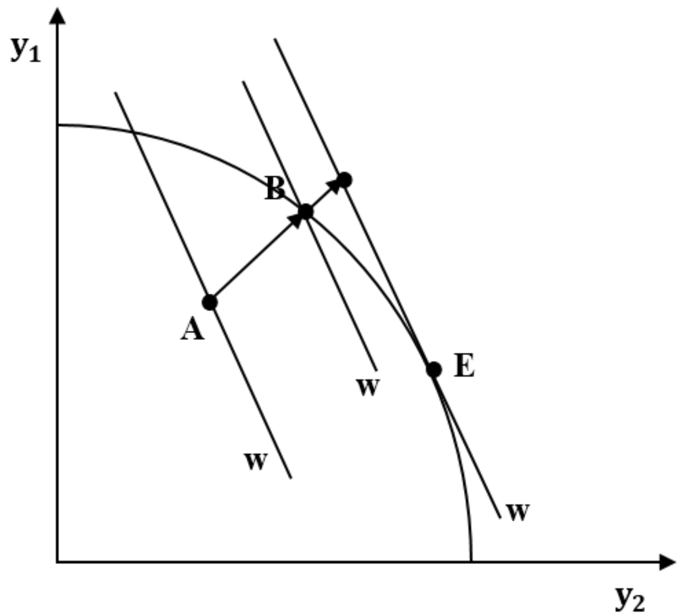
[8] Their study also investigates land fragmentation's impact on farmers' cropland abandonment decisions. They found that about 10 percent of Albania's productive land has been left idle mostly because of land market imperfections. In contrast, there are only a few cases of land abandonment where land fragmentation leads to plots too small for economically viable cultivation. Among those currently cultivated plots, land fragmentation is found to have a statistically significant positive effect on efficiency. Although their study does not give an overall appraisal of land fragmentation when both cultivation-related and abandonment-related productivity are considered, they conclude that their analysis does not support the argument of land fragmentation undermining productivity.

To provide one possible explanation to Niroula and Thapa's unanswered question and the puzzling positive relationship between land fragmentation and production efficiency found in this paper and Deininger et al. (2012), we argue that an important component has been absent from this study and similar studies – risk preference, which could play a pivotal role in interpreting land fragmentation and its effects. As observed by most studies, farmers generally show aversion toward risk in agricultural production, a preference which can preclude them from using as many inputs as they would under risk neutrality and thus lead to a reduced yield or revenue. It can be anticipated that a shift in production risk, such as the one caused by land fragmentation as corroborated by this study, would result in changes in input use decisions, which will ultimately affect economic performance. An improved analytical framework that accommodates risk, efficiency and risk preference should improve our understanding of land fragmentation's role in agricultural production.

Despite the counterintuitive impact of land fragmentation on efficiency, this study still generates sufficient implications for future land reforms. First and foremost, land fragmentation as a tool for farmers to manage risk should be recognized. By utilizing the heterogeneous growing conditions, land fragmentation can spread out risk onto separate plots and reduce the revenue variability on the whole farm. This aspect is of special significance to farmers with no or limited access to crop insurance to secure their agricultural income. Second, the vast differences in farm structure, agricultural productivity and farming traditions warn against any hasty generalization on fragmentation and once-and-for-all consolidation propositions. In a smallholding and traditional agriculture like the Tanzanian case, the small plot size and rare use of machinery can minimize the potential negative effects of land fragmentation, while it may become a more serious issue for places with a more mechanized agriculture such as Japan[9].

[9] According to Kawasaki (2010) who finds that land fragmentation reduces the cost efficiency of Japanese rice growing, the average farm size in his sample is about 6.8 acres, roughly comparable to the 6.1 acres among the Tanzanian farmers in our sample when area used for perennial crops and trees is also counted. In contrast to the Tanzanian case, in Japan the planting and harvesting is done mostly with small machines. Large machines are hardly used because they cannot maneuver around in small plots and need long tracts of uniform land to do the job efficiently (Hays 2009).



Source: Developed by author.

Figure 2-1 An Illustration of Revenue Efficiency

Table 2-1 Households by Number of Plots

No. of Plots per Household	Frequency	Percent	Cumulative Percent
1	687	45.71	45.71
2	514	34.20	79.91
3	215	14.30	94.21
4	55	3.66	97.87
5	25	1.66	99.53
6	4	0.27	99.80
8	1	0.07	99.87
9	1	0.07	99.93
10	1	0.07	100.00
Total	1,503	100.00	

Source: Developed by author.

Table 2-2 Use of Advanced Inputs

Panel 1: Other inputs (N=2,756)

Inputs	No. of Plots	Percent
Irrigation	83	3.01
Organic Fertilizer	332	12.05
Inorganic Fertilizer	416	15.09
Herbicide/Pesticide	308	11.18

Panel 2: Draft animals and machinery (N=1,503)

Inputs	No. of Households	Percent
Hand Hoe	1,503	100.00
Ox Plough	128	8.52
Ox Seeder	143	9.51
Ox Cart	1	0.07
Tractor	42	2.79
Mechanical Plough	3	0.20
Mechanical Harrow	6	0.40
Thresher	1	0.07

Source: Developed by author.

Table 2-3 Descriptive Statistics of Dimensions of Land Fragmentation

	Unit	No. of Obs.	Mean	Median	Standard Deviation
Farm Area	Acre	1,503	4.96	2.5	11.88
Number of Plots	1	2,756	1.83	2	1.01
Plot Area	Acre	2,756	2.70	1	12.78
Simpson Index	1	1,503	0.25	0.20	0.26
Distance, plot to home	Kilometer	2,755	3.12	1.5	6.44
Distance, plot to road	Kilometer	2,755	1.91	1	3.02
Distance, plot to market	Kilometer	2,773	7.78	5	9.03

Source: Developed by author.

Note: One acre ≈ 0.405 hectares or 0.0015625 square miles; one kilometer ≈ 0.621 miles.

Table 2-4 Descriptive Statistics of Household Characteristics

(N=1,503)

	Mean	Median	S.D.
Area ratio	0.050	0	0.245
Average age	36.499	32.667	13.577
Average education	4.740	5	2.665
Male labor proportion	0.470	0.50	0.255
Child ratio	0.368	0.25	0.456
Hired labor proportion	0.092	0	0.174

Source: Developed by author.

Notes:
1. Average age and average education are measured in years; the other four variables are measured on a scale of zero to one.
2. Average age and average education are for family workers only. If certain family use only hired labor, the average age and average education are reported with a value of zero.

Table 2-5 Soil Variables

	Nutrient Availability		Oxygen Availability to Roots		Workability	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
No or Slight Constraint	498	33.13	1,344	89.42	850	56.55
Moderate Constraint	838	55.76	124	8.25	421	28.01
Severe Constraint	167	11.11	35	2.33	232	15.44
Total	1,503	100.00	1,503	100.00	1,503	100.00

Source: Developed by author.

Notes: The following definitions of variables are adapted from the Harmonized World Soil Database accessible at: http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/SoilQuality.html?sb=10

1. Nutrient availability is decisive for successful low level input farming and to some extent also for intermediate input levels.
2. Oxygen availability in soils is largely defined by drainage characteristics of soils.
3. Workability or ease of tillage depends on interrelated soil characteristics such as texture, structure, organic matter content, soil consistence/bulk density, the occurrence of gravel or stones in the profile or at the soil surface, and the presence of continuous hard rock at shallow depth as well as rock outcrops. For the variable of workability, we combine “Severe Constraint”, “Very Severe Constraint” and “Mainly Non-Soil” into one category called “Severe Constraint”.

Table 2-6 Plot heterogeneity

No. of plots	No. of different soil profiles					Total
	1	2	3	4	5	
1	687	0	0	0	0	687
2	166	348	0	0	0	514
3	51	98	66	0	0	215
4	11	22	17	5	0	55
5	3	4	10	7	1	25
6	0	2	2	0	0	4
8	0	1	0	0	0	1
9	0	0	1	0	0	1
10	0	0	0	1	0	1
Total	918	475	96	13	1	1,503

Source: Developed by author.

Table 2-7 Crop Diversification by Number of Plots

Panel a: Number of commodities

No. of plots	No. of Crop Varieties							Total
	1	2	3	4	5	6	7	
1	359	215	76	25	9	3	0	687
2	90	234	120	52	13	5	0	514
3	21	65	79	36	8	3	3	215
4	2	20	15	12	5	1	0	55
5	1	7	9	4	4	0	0	25
6	0	2	1	1	0	0	0	4
8	0	0	0	1	0	0	0	1
9	0	1	0	0	0	0	0	1
10	0	1	0	0	0	0	0	1
Total	473	545	300	131	39	12	3	1,503

Panel b: Major commodities

	One-plot farms		Two-plot farms		Three-plot farms		Other farms		All farms	
	Area	Percent	Area	Percent	Area	Percent	Area	Percent	Area	Percent
Maize	564.41	24.88	972	31.39	926.95	38.15	770.81	36.18	3234.17	32.58
Groundnut	19.5	0.86	81.1	2.62	335.71	13.82	245.63	11.53	681.94	6.87
Beans	31.43	1.39	255.02	8.24	202.05	8.32	167.18	7.85	655.68	6.61
Paddy rice	100.46	4.43	176.69	5.71	132.48	5.45	101.39	4.76	511.02	5.15
Sorghum	17.88	0.79	82.43	2.66	173.69	7.15	146.63	6.88	420.63	4.24
Cotton	28.75	1.27	119.25	3.85	136.05	5.60	79.25	3.72	363.3	3.66
Cassava	34.85	1.54	49.63	1.60	16.32	0.67	16.25	0.76	117.05	1.18
Others	1471.68	64.86	1360.57	43.94	506.52	20.85	603.43	28.32	3942.2	39.72
Sum	2268.96	100.00	3096.69	100.00	2429.77	100.00	2130.57	100.00	9925.99	100.00

Source: Developed by author.

Table 2-8 Comparison of Various Variance Structures

	HUV	HV	HU	HO	HUV_1	HV_1
One-sided error (*U*) variance						
Labor intensity	-0.000429		-8.90E-05		-0.000338	
	(0.001)		(0.000)		(0.000)	
Constant	-0.882***	-0.904***	-0.1	-0.104	-0.934***	-0.0293
	(0.277)	(0.302)	(0.283)	(0.286)	(0.304)	(0.306)
Two-sided error (*V*) variance						
Simpson index	-0.512*	-0.497*			-0.535*	
	(0.295)	(0.295)			(0.295)	
Labor intensity	0.000178*	0.000187*				0.000222**
	(0.000)	(0.000)				(0.000)
Plot heterogeneity	0.16	0.161			0.18	
	(0.323)	(0.323)			(0.322)	
Crop diversification	-0.231*	-0.223*			-0.227*	
	(0.125)	(0.132)			(0.129)	
Constant	-0.305	-0.325	-0.852***	-0.852***	-0.28	-0.891***
	(0.356)	(0.352)	(0.101)	(0.101)	(0.354)	(0.101)
No. of observations	1,503	1,503	1,503	1,503	1,503	1,503
Log likelihood	-1,877.20	-1,877.75	-1,891.83	-1,892.06	-1,878.57	-1,889.50
Degree of freedom	N.A.	1	4	5	1	4
2*(LR1-LR2)	N.A.	1.096	29.258	29.712	2.745	24.598
Critical value (10%)	N.A.	2.71	7.78	9.24	2.71	7.78
Critical value (5%)	N.A.	3.84	9.49	11.07	3.84	9.49

Source: Developed by author.

Notes:
1. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
2. Estimates of the revenue frontier and the mean inefficiency function are omitted from here for presentation clarity.
3. All the statistics for the Likelihood Ratio tests are calculated from the pairwise comparisons between the corresponding models with model HUV.

Table 2-9 Hypothesis Tests

Part 1: Revenue Frontier Function

Variables	HV	HV_1	HV_2	HV_P
Labor1*Labor1	-0.00951	-0.00985	-0.00958	-0.00515
	(0.025)	(0.025)	(0.025)	(0.026)
Labor1*Labor2	-0.0686	-0.0662	-0.0672	-0.0818*
	(0.045)	(0.045)	(0.045)	(0.045)
Labor1*Labor3	0.0731**	0.0702*	0.0702*	0.0713*
	(0.037)	(0.037)	(0.037)	(0.037)
Labor1*Area	-0.085	-0.0845	-0.0833	-0.0741
	(0.065)	(0.065)	(0.065)	(0.065)
Labor1*Price	-0.0275	-0.0284	-0.0298	-0.0233
	(0.046)	(0.046)	(0.046)	(0.046)
Labor1*Precipitation	0.0114	0.0122	0.0118	0.0036
	(0.105)	(0.105)	(0.105)	(0.105)
Labor1*Temperature	0.0454	0.0453	0.047	0.0518
	(0.130)	(0.129)	(0.129)	(0.130)
Labor1*Hoes	-0.104	-0.102	-0.102	-0.106
	(0.068)	(0.068)	(0.068)	(0.068)
Labor2*Labor2	0.00537	0.00303	0.00292	0.00808
	(0.033)	(0.033)	(0.033)	(0.034)
Labor2*Labor3	0.0441	0.0454	0.0461	0.0464
	(0.036)	(0.036)	(0.036)	(0.036)
Labor2*Area	-0.033	-0.0378	-0.0348	-0.0234
	(0.071)	(0.071)	(0.071)	(0.071)
Labor2*Price	-0.0696	-0.0681	-0.0664	-0.0692
	(0.049)	(0.049)	(0.049)	(0.049)
Labor2*Precipitation	0.00577	0.00373	0.00607	0.0148
	(0.106)	(0.106)	(0.106)	(0.107)
Labor2*Temperature	0.076	0.0776	0.0731	0.0658
	(0.131)	(0.131)	(0.131)	(0.131)
Labor2*Hoes	0.0241	0.0218	0.0252	0.0352
	(0.074)	(0.074)	(0.074)	(0.074)
Labor3*Labor3	-0.0893***	-0.0875***	-0.0879***	-0.0900***
	(0.020)	(0.020)	(0.020)	(0.020)
Labor3*Area	0.0205	0.0219	0.0216	0.0218
	(0.051)	(0.051)	(0.051)	(0.051)
Labor3*Price	-0.112***	-0.112***	-0.113***	-0.113***
	(0.035)	(0.035)	(0.035)	(0.035)

Labor3*Precipitation	-0.0138	-0.0132	-0.0128	-0.0151
	(0.082)	(0.082)	(0.082)	(0.083)
Labor3*Temperature	0.187*	0.186*	0.186*	0.190*
	(0.101)	(0.102)	(0.102)	(0.102)
Labor3*Hoes	0.0679	0.0658	0.0653	0.0725
	(0.056)	(0.056)	(0.056)	(0.056)
Area*Area	0.113*	0.110*	0.109*	0.0653
	(0.063)	(0.063)	(0.063)	(0.060)
Area*Price	-0.0863	-0.0855	-0.0848	-0.0821
	(0.060)	(0.060)	(0.060)	(0.060)
Area*Precipitation	0.317**	0.321**	0.314**	0.314**
	(0.130)	(0.129)	(0.129)	(0.129)
Area*Temperature	-0.285*	-0.289*	-0.284*	-0.283*
	(0.167)	(0.167)	(0.167)	(0.167)
Area*Hoes	0.281**	0.280**	0.275**	0.227*
	(0.121)	(0.121)	(0.121)	(0.120)
Price*Price	0.0326**	0.0331**	0.0331**	0.0347**
	(0.015)	(0.015)	(0.015)	(0.015)
Price*Precipitation	-0.284***	-0.285***	-0.286***	-0.288***
	(0.106)	(0.106)	(0.106)	(0.107)
Price*Temperature	0.479***	0.479***	0.480***	0.477***
	(0.123)	(0.123)	(0.123)	(0.125)
Price*Hoes	0.0029	0.00375	0.00384	0.0139
	(0.070)	(0.070)	(0.070)	(0.069)
Precipitation*Precipitation	0.118	0.107	0.122	0.107
	(0.168)	(0.167)	(0.163)	(0.163)
Precipitation*Temperature	-0.0499	-0.0233	-0.0576	-0.019
	(0.402)	(0.400)	(0.390)	(0.391)
Precipitation*Hoes	0.306**	0.309**	0.305**	0.302**
	(0.141)	(0.141)	(0.141)	(0.141)
Temperature*Temperature	-0.322	-0.337	-0.318	-0.343
	(0.267)	(0.265)	(0.261)	(0.262)
Temperature*Hoes	-0.363**	-0.367**	-0.364**	-0.368**
	(0.180)	(0.179)	(0.179)	(0.180)
Hoes*Hoes	0.142*	0.143**	0.140*	0.117
	(0.073)	(0.073)	(0.073)	(0.072)
Dummy	0.339***	0.340***	0.345***	0.351***
	(0.077)	(0.076)	(0.076)	(0.076)
Constant	12.02***	11.94***	11.97***	12.10***
	(0.741)	(0.721)	(0.715)	(0.712)

Part 2: Mean Inefficiency Function

Variables	HV	HV_1	HV_P	HV_2
Area Ratio	0.359***	0.379***	0.379***	0.387**
	(0.135)	(0.141)	(0.144)	(0.150)
Average Age	0.00528**	0.00616**	0.00607**	0.00626**
	(0.003)	(0.003)	(0.003)	(0.003)
Average Education	-0.0265**	-0.0278*	-0.0283*	-0.0323**
	(0.013)	(0.014)	(0.015)	(0.016)
Male Labor Ratio	-0.401***	-0.420***	-0.425***	-0.395**
	(0.142)	(0.153)	(0.156)	(0.160)
Child Ratio	-0.0821			
	(0.071)			
Hired Labor Ratio	-1.500***	-1.625***	-1.673***	-1.779***
	(0.527)	(0.565)	(0.586)	(0.688)
Nutrient Availability	0.00338	-0.00461		
-- No Constraint	(0.114)	(0.122)		
Nutrient Availability	0.0679	0.0643		
-- Moderate Constraint	(0.101)	(0.108)		
O2 Availability to Roots	-0.316	-0.342	-0.357	-0.370
--No Constraint	(0.205)	(0.217)	(0.220)	(0.238)
O2 Availability to Roots	-0.415*	-0.445*	-0.475*	-0.459*
--Moderate Constraint	(0.235)	(0.252)	(0.256)	(0.269)
Field Workability	-0.367***	-0.395***	-0.380***	-0.377***
--No Constraint	(0.126)	(0.135)	(0.131)	(0.141)
Field Workability	-0.252**	-0.277**	-0.261**	-0.252**
--Moderate Constraint	(0.116)	(0.126)	(0.124)	(0.128)
Farm Area	0.0047	0.00522	0.006	
	(0.007)	(0.007)	(0.007)	
Farm Area* SI	0.00409	0.00382	0.003	
	(0.009)	(0.009)	(0.009)	
SI	-0.425**	-0.454**	-0.457**	-0.350**
	(0.166)	(0.182)	(0.183)	(0.174)
Distance to Home	-0.0189	-0.0218	-0.023	
	(0.014)	(0.015)	(0.016)	
Distance to Road	0.00507	0.00699	0.008	
	(0.017)	(0.018)	(0.018)	
Distance to Market	-0.00901	-0.0103	-0.011	
	(0.006)	(0.007)	(0.007)	
Constant	2.026***	1.953***	1.978***	1.847***
	(0.295)	(0.288)	(0.272)	(0.266)

Part 3: One-sided Error Variance Function

Variables	HV	HV_1	HV_P	HV_2
Constant	-0.904***	-0.848***	-0.844***	-0.825**
	(0.302)	(0.317)	(0.324)	(0.372)

Part 4: Two-sided Error Variance Function

Variables	HV	HV_1	HV_P	HV_2
SI	-0.497*	-0.481*	-0.476*	-0.468
	(0.295)	(0.292)	(0.289)	(0.292)
Labor Intensity	0.000187*	0.000190**	0.000189**	0.000244***
	(0.000)	(0.000)	(0.000)	(0.000)
Plot Heterogeneity	0.161	0.138	0.126	0.148
	(0.323)	(0.309)	(0.304)	(0.305)
Crop Diversification	-0.223*	-0.208*	-0.206*	-0.203*
	(0.132)	(0.117)	(0.114)	(0.110)
Constant	-0.325	-0.324	-0.306	-0.331
	(0.352)	(0.344)	(0.339)	(0.342)

Part 5: Statistics and Tests

Variables	HV	HV_1	HV_P	HV_2
Observations	1,503	1,503	1,503	1,503
Log Likelihood	-1,877.750	-1,878.399	-1,878.886	-1,885.590
Degree of freedom	0	1	2	5
2*(LR1-LR2)	0	1.298	0.9734	13.4088
Critical value (10%)	2.71	2.71	4.61	6.25
Critical value (5%)	3.84	3.84	5.99	7.81

Source: Developed by author.

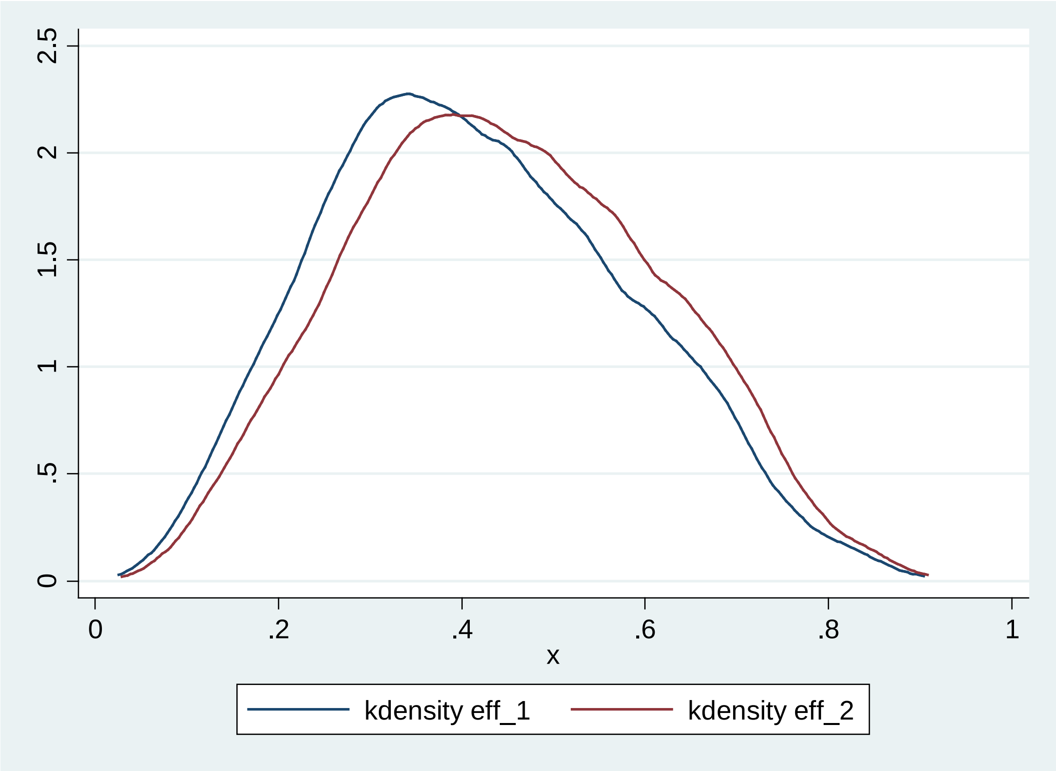
Notes:
1. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
2. Labor1: Labor days used for land preparation and planting per acre, in the log form;
Labor2: Labor days used for weeding per acre, in the log form;
Labor3: Labor days used for harvest per acre, in the log form;
Area: Total area planted with annual crops, in the log form;
Price: Crop price index weighted by quantity (in kilograms), in the log form;
Precipitation: Precipitation of the wettest quarter, in the log form;

Temperature: Average temperature of the wettest quarter, in the log form;
Hoes: Average number of hand hoes used per acre, in the log form;
Dummy=1 if any ox or machinery ever used, =0 otherwise;
Area Ratio: Ratio of farm area planted with perennial crops/trees to area planted with annual crops;
Age: Average age of family workers in the fields;
Education: Average number of years in school of family workers in the fields;
Male Labor Ratio: Ratio of labor days by male workers to labor days by both genders;
Hoes Ratio: Ratio of number of hoes to number of family workers in the fields;
Child Ratio: Ratio of number of children under age of 5 to the number of family workers in the fields;
Hired Labor Ratio: Ratio of labor days by hired workers to days by both family and hired workers;
SI: the Simpson Index for land fragmentation;
Distance to Home/Road/Market: weighted by plot area;
Labor Intensity: Total labor days for all three activities per acre, i.e. Labor1+Labor2+Labor3;
Plot heterogeneity: Number of different soil profiles across the farm, normalized by number of plots;
Crop Diversification: Number of different annual crop varieties grown on the entire farm.
3. All the statistics for the Likelihood Ratio tests are calculated from the pairwise comparison of the corresponding model with the preceding model.

Table 2-10 Descriptive Statistics of Efficiency Score Estimates

	No. of Obs.	Mean	S.D.	Minimum	1st Quartile	Median	3rd Quartile	Maximum
Jondrow et al. (1982) estimator	1,503	0.42	0.16	0.03	0.29	0.40	0.53	0.90
Battese & Coelli (1988) estimator	1,503	0.45	0.16	0.03	0.32	0.44	0.57	0.91

Source: Developed by author.



Source: Developed by author.

Note: Kernel density *eff_1* is derived using the Jondrow et al. (1982) estimator, and kernel density *eff_2* is derived using the Battese & Coelli (1988) estimator.

Figure 2-2 Distributions of Inefficiency Estimates

Table 2-11 Marginal Effects on Efficiency

(N=1,503, in percentage points)

	Direction of Effect	Minimum	Maximum	Mean	Median
Area Ratio	Negative	0.96	22.23	10.11	9.97
Average Age	Negative	0.02	0.36	0.16	0.16
Average Education	Positive	0.07	1.66	0.75	0.74
Male Labor Proportion	Positive	1.08	24.94	11.34	11.18
Hired Labor Proportion	Positive	4.26	98.22	44.64	44.04
O2 Availability to Roots --No Constraint	Positive	0.91	20.97	9.53	9.40
O2 Availability to Roots --Moderate Constraint	Positive	1.21	27.88	12.67	12.50
Field Workability --No Constraint	Positive	0.97	22.29	10.13	9.99
Field Workability --Moderate Constraint	Positive	0.66	15.32	6.96	6.87
Farm Area	Negative	0.01	0.32	0.15	0.15
Farm Area * SI	Negative	0.01	0.20	0.09	0.09
SI	Positive	1.16	26.84	12.20	12.03
Distance to Home	Positive	0.06	1.33	0.61	0.60
Distance to Road	Negative	0.02	0.46	0.21	0.21
Distance to Market	Positive	0.03	0.64	0.29	0.29

Source: Developed by author.

Note: Variable definitions are the same as those in Table 2-8.

Chapter 3. Land Fragmentation, Risk Preferences, and Production Efficiency

3.1 Introduction

Over time, land fragmentation in agriculture has been observed in many places around the world, whereas there is still an ongoing debate over its advantages, disadvantages, and implications for agricultural production and land policies. This paper looks into the contradictory evidence on how land fragmentation would affect production efficiency and aims to improve our understanding of farmers' production decisions under risk and uncertainty.

In principle, land fragmentation is believed to be a hurdle to agricultural productivity or profitability for a multitude of reasons. For example, multi-plot farms may suffer from extra losses of arable land or harvest on the corners and boundaries compared to single-plot farms (Binns 1950; Blarel et al. 1992; Hung and MacAulay 2002). Also, the spatial dispersion of plots requires extra labor time for commuting between plots and the homestead and travel between different plots, making farm production less efficient or more costly (Richardson 1974; Blarel et al. 1992; Tan et al. 2008). Last but not least, land fragmentation has been often accused of prohibiting the use of large-scale investment such as machinery and irrigation as a result of the reduced size and irregular plot shape (Johnston 1972; Bentley 1987; Hung et al. 2007).

Despite the obvious disadvantages in many aspects, there has been mixed evidence regarding land fragmentation's impact on agricultural productivity or efficiency. While the majority of the related studies find that it undermines efficiency and lowers profitability (e.g., Jabarin and Epplin 1994; Nguyen et al. 1996; Fan and Chan-Kang 2005; Tan et al. 2008), a few studies have found either statistically insignificant (e.g., Blarel et al. 1992; Di Falco et al. 2010) or economically insignificant (e.g. Wan and Cheng 2001) effects of land fragmentation. More curiously, several recent studies have shown that in some cases more fragmented farms are associated with a higher yield once other factors, e.g., soil attributes and household characteristics, are accounted for. For example, Deininger et al. (2012) apply a stochastic frontier model to the Albanian household survey data and find land fragmentation measured by number of plots has a positive effect on efficiency. Using a similar framework but with Tanzanian household data and accounting for the risk effects, Rao (2014) reaches a similar conclusion and finds the results to be robust to various model specifications.

The positive relationship between land fragmentation and production efficiency may seem rather odd on the surface given its obvious shortcomings. However, Niroula and Thapa (2007) made an interesting observation that in Nepal plots with smaller size resulting from land fragmentation see more labor inputs and a higher yield. They argued that land fragmentation has a positive impact on production although the higher crop yield is directly attributed to the application of considerably higher amount of labor. If their argument is justified, land fragmentation will affect production efficiency in opposite directions, leaving the sign of the net effect indeterminate.

One potential explanation for how land fragmentation can lead to more intense labor input (and other inputs) is the heterogeneous soil quality and growing conditions, or plot heterogeneity, as a result of the spatial farm dispersion. Farmers can take advantage of plot heterogeneity to diversify the crop portfolio and smooth out their labor use over time, thus increasing their labor inputs per unit of land especially when the labor available is abundant relative to the arable land. However, the positive relationship between land fragmentation and production efficiency is often reported when soil quality and/or crop diversification are accounted for (e.g., Deininger et al. 2012; Rao 2014). An alternative explanation may come from the related discussion on the inverse relationship between farm size and productivity. A key argument[10] in that literature is that the market failure of multiple factors such as labor and credit (Barrett et al. 2010; Ali and Deininger 2014; etc.) will encourage smallholding farmers to use more inputs, especially labor, per unit of land. However, market failure is unlikely to explain the differences in efficiency between farms of the same size but with different levels of fragmentation, i.e., having different numbers of plots.

In this study, we aim to provide an alternative explanation to the curious positive relationship between land fragmentation and production efficiency. The key argument is that, in addition to its probable negative impacts on technical efficiency, land

[10] Some studies take this inverse relationship as a spurious one for either statistical reason (i.e., measurement errors) or methodological reason (i.e., exclusion of soil quality variables). Most recent studies, however, have shown more robust evidence to support the inverse relationship (Barret et al. 2010, Ali and Deninger 2014, etc.). Here in this study we tend to believe that this relationship exists as most studies have argued.

fragmentation may also affect how farmers would choose their optimal input use, i.e., the allocative efficiency, through its impacts on production risk. The chance is that allocative efficiency could either be increased or decreased, depending on how farmers adjust their input use, a decision which further depends on farmers' risk preferences. Therefore, the direction of overall efficiency, which is comprised of both technical efficiency and allocative efficiency, is indeterminate.

The most common methodologies used in the related literature include the stochastic production function approach and the stochastic frontier approach. The former does not directly embrace the measure of efficiency while the latter measures only technical efficiency. Moreover, both approaches fail to account for risk preferences, an essential element in analyzing farmers' production decisions. The following sections of this paper will introduce a framework that incorporates risk preferences into efficiency analysis and shows how failing to do so can result in misleading conclusions. The findings in this study are expected to contribute to the discussion on the immediate topic of land fragmentation, as well as efficiency analysis.

3.2 Theoretical Framework

We start with a Just-Pope production function which incorporates a stochastic technical inefficiency term u in the multiplicative form:

(3-1) $$y = f(\boldsymbol{X}) \exp(-u) + g(\boldsymbol{X}, \boldsymbol{Z})\varepsilon$$

The stochastic error term ε is often assumed to follow a standard normal distribution, while the inefficiency term u is assumed to be non-negative such that $\exp(-u)$ is less than or equal to one. At the efficiency frontier ($u = 0$), the mean output function and output variance function are derived respectively as follows:

(3-2) $$E(y|_{u=0}) = f(\boldsymbol{X})$$

(3-3) $$\text{Var}(y|_{u=0}) = g^2(\boldsymbol{X}, \boldsymbol{Z})$$

For simplicity, we call $g(\boldsymbol{X}, \boldsymbol{Z})$ the risk function given that its square equals output variance. Note that $g(\cdot)$ may be a function of some or all the elements in the input vector $\boldsymbol{X}$ as well as some variables $\boldsymbol{Z}$ that are exogenous to production.

As opposed to the additive form where the inefficiency u is first added to the stochastic error term ϵ and then multiplied by the risk function, the multiplicative form used in this study allows both technical efficiency (TE) and technical inefficiency (TI) to be defined independently of input quantities, a standard feature of the stochastic frontier model proposed by Aigner, Lovell and Schmidt (1977) and Battese and Coelli (1977). To see this, TE and TI can be derived from their definitions:

(3-4) $$TE = \frac{E(y|_{\boldsymbol{x},\boldsymbol{z},u})}{E(y|_{\boldsymbol{x},\boldsymbol{z},u=0})} = \exp(-u)$$

and

(3-5) $$TI = \frac{E(y|_{\boldsymbol{x},\boldsymbol{z},u=0}) - E(y|_{\boldsymbol{x},\boldsymbol{z},u})}{E(y|_{\boldsymbol{x},\boldsymbol{z},u=0})} = 1 - \exp(-u)$$

Further, if we assume that $\exp(-u)$ approximates $1-u$ quite well as the literature usually does, $TE \approx 1-u$ and $TI \approx u$. In this way, the term u can be conveniently interpreted as the proportion of potential output that is actually being produced and we can focus on the distribution of u instead of its exponential form. Finally, given the output price P and input price vector $\boldsymbol{W}$, we can write the profit Π as

(3-6) $$\Pi = Py - \boldsymbol{WX} = Pf(\boldsymbol{X})\exp(-u) + Pg(\boldsymbol{X},\boldsymbol{Z})\varepsilon - \boldsymbol{WX}$$

Now we assume that the objective is to maximize the expected utility of profit generated from the given production function, i.e., $max\ EU(\Pi)$, where $U(\cdot)$ is assumed to be a continuous and differentiable utility function. Since the expected utility function is unique up to an affine transformation, we normalize the profit by the output price P and denote the normalized input price vector by w. Hence, the first-order condition for each variable input x_j $(j = 1,2 \ldots J)$ is derived as

(3-7) $$f_j(\boldsymbol{X}) \cdot (1-\lambda) = w_j - \theta \cdot g_j(\boldsymbol{X},\boldsymbol{Z}) + \eta_j$$

where $f_j(\boldsymbol{X}) = \partial f(\boldsymbol{X})/\partial x_j$, $g_j(\boldsymbol{X},\boldsymbol{Z}) = \partial g(\boldsymbol{X},\boldsymbol{Z})/\partial x_j$, $\theta = E[U'(\Pi)\varepsilon]/E[U'(\Pi)]$, $\lambda = E[U'(\Pi)u]/E[U'(\Pi)]$, and η_j is the departure from the first-order optimality condition, representing allocative inefficiency associated with input x_j. Using a second-order Taylor-series approximation of $U'(\Pi)$ at $\varepsilon = u = 0$, Kumbhakar (2002) derives the following expressions for θ and λ:

(3-8) $$\theta = \frac{-AR \cdot g(\boldsymbol{X}, \boldsymbol{Z}) - DR \cdot g(\boldsymbol{X}, \boldsymbol{Z}) \cdot f(\boldsymbol{X}) \cdot a}{1 + AR \cdot f(\boldsymbol{X}) \cdot a + \frac{1}{2} DR \cdot [g^2(\boldsymbol{X}, \boldsymbol{Z}) + f^2(\boldsymbol{X}) \cdot (a^2 + b^2)]}$$

and

(3-9) $$\lambda = \frac{a + AR \cdot f(\boldsymbol{X}) \cdot (a^2 + b^2) + \frac{1}{2} DR \cdot [g^2(\boldsymbol{X}, \boldsymbol{Z}) \cdot a + f^2(\boldsymbol{X}) \cdot (c + 3ab^2 + a^3)]}{1 + AR \cdot f(\boldsymbol{X}) \cdot a + \frac{1}{2} DR \cdot [g^2(\boldsymbol{X}, \boldsymbol{Z}) + f^2(\boldsymbol{X}) \cdot (a^2 + b^2)]}$$

In the two expressions above, a, b and c are the first three central moments associated with the distribution of the inefficiency term u. That is, $a = E(u)$, $b^2 = Var(u)$, and $c = E(u - a)^3$. Moreover, $AR = -U''(E[\Pi|_{\varepsilon=u=0}])/U'(E[\Pi|_{\varepsilon=u=0}])$ is the Arrow-Pratt measure of absolute risk aversion, $DR = U'''(E[\Pi|_{\varepsilon=u=0}])/U'(E[\Pi|_{\varepsilon=u=0}])$ is the measure of downside risk aversion, and AR and DR have the following relationship:

(3-10) $$DR = \frac{-\partial AR}{\partial \Pi} + AR^2$$

In this way, Kumbhakar's approach allows the characterization of risk preferences alongside production risk without assuming an explicit functional form for utility as is commonly done in the literature. Now it is easy to see that the optimal use of inputs dictated by the conditions in (3-6) is jointly determined by input prices ($\boldsymbol{w}$), production technology $f(\boldsymbol{X})$, production risk ($g(\boldsymbol{X}, \boldsymbol{Z})$, a, b, and c), and risk preferences (AR and DR). In other words, given the observed use of inputs, it is possible to infer a farmer's risk preferences.

In the context of land fragmentation, it is found to directly influence both production efficiency and production risk. One motivation of this study is to investigate how a shift in an exogenous factor to agricultural production, such as land fragmentation, can affect the optimal use of inputs and further affect yield and production risk. In mathematical terms, we are interested in the sign and magnitude of the following terms:

$$\frac{dE(y)}{dZ_i} = \frac{\partial E(y)}{\partial Z_i} + \frac{\partial E(y)}{\partial \boldsymbol{X}^*}\frac{d\boldsymbol{X}^*}{dZ_i} \tag{3-11}$$

and

$$\frac{dVar(y)}{dZ_i} = \frac{\partial Var(y)}{\partial Z_i} + \frac{\partial Var(y)}{\partial \boldsymbol{X}^*}\frac{d\boldsymbol{X}^*}{dZ_i} \tag{3-12}$$

The two expressions above show that the net effect of an exogenous factor Z_i on the expected yield (or yield variability) is jointly determined by its direct effect on $E(y)$ (or $Var(y)$) and the indirect effect through the optimal use of input $\boldsymbol{X}^*$. It is clear that the sign of the net effect may not be necessarily the same as that of the direct effect.

3.3 Numerical Examples

To numerically examine the relationship among variables of interest, it is necessary to make assumptions on the functional form and the distribution of the inefficiency term u. First for the deterministic production function $f(\boldsymbol{X})$, labor X_l is assumed to be the only variable input so that we can waive the substitution effects among inputs as in a multiinput setting. Further, we assume $f(X_l) = \beta_0 X_l^{\beta_1}$ where $0 < \beta_1 < 1$, $\beta_1 = 1$, or $\beta_1 > 1$ represent the possible cases of decreasing, constant or increasing returns to scale, respectively. Second, it is assumed that the risk function $g(\boldsymbol{X}, \boldsymbol{Z}) = \exp(\alpha_0 + \alpha_1 X_l + \alpha_2 Z_l)$ where Z_l is the exogenous variable of interest, such as land fragmentation. The coefficients α_1 and α_2 capture the risk effects of explanatory variables in the risk function, e.g., labor X_l will be risk-increasing if $\alpha_1 > 0$. The inefficiency term u is assumed to follow a truncated normal distribution. That is, $u \sim N^+(\mu, \sigma^2)$, where μ and σ^2 are the mean and variance of the pre-truncated normal distribution, respectively, and μ is further assumed to be a linear function of Z_l: $\mu = H(Z_l) = \delta_0 + \delta_1 Z_l$. In this way, we are able to encapsulate determinants of production inefficiency into the so called mean inefficiency function $H(\cdot)$. Given the truncated normal distribution of u, the distribution parameters a, b^2, and c can be derived as follows[11]:

(3-13) $$a = \mu + \sigma\rho(h)$$

(3-14) $$b^2 = \sigma^2[1 + \rho(h)(h - \rho(h))]$$

(3-15) $$c = -\sigma^3\rho(h)[1 + 3h\rho(h) + 2\rho(h)^2 - h^2]$$

where $h = \frac{-\mu}{\sigma}$, $\rho(h) = \frac{\phi(h)}{1-\Phi(h)}$, $\phi(h)$ and $\Phi(h)$ are the density and distribution functions of the standard normal distribution, respectively. The inefficiency term u may be further

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[11] The moments are calculated based on the recursive formula derived by Dhrymes (2005).

assumed to be heteroskedastic such that σ^2 may have its own explanatory variables. In this section we assume for simplicity that u is homoskedastic and, without loss of generality, normalize σ^2 to a constant through the parameters in the mean inefficiency function.

Numerous studies have found risk aversion to be the plausible behavioral pattern under most circumstances, suggesting $AR > 0$. Further, researchers have been interested in comparing risk attitudes at different levels of wealth or income and absolute risk aversion is often used as a viable measure. Many empirical studies find evidence of decreasing or constant absolute risk aversion, i.e., DARA or CARA. For the purpose of this study, we assume an exponential functional form for AR: $AR = \exp(\gamma \Pi)$ without ruling out the possibility of increasing absolute risk aversion (IARA). Given the relationship between AR and DR, the downside risk aversion DR is given as $DR = -\gamma * AR + AR^2$. A positive value of DR corresponds to aversion to downside risk, implying that the decision-maker would avoid situations which may offer the potential for substantial gains but may also leave him even slightly vulnerable losses below critical level (Menezes et al. 1980).

Given the goal of this study and the complexity of the model, we are forced to focus on the relationship among only a few parameters in the system, namely land fragmentation, the risk preferences parameter, the optimal labor use, and the optimal output, while assuming a constant value for other parameters. In the comparative statics section, we will change the values of other parameters and examine the ensuing effects on our key conclusions.

A Baseline Case

First, we use the Simpson Index to measure land fragmentation. This measure is the predominant measure in the related economic literature and returns a value within the interval of [0,1], making it easy for the following simulation practice. Moreover, we focus on the more reasonable case of decreasing returns to scale by assuming $\beta_1 = 0.70$[12]. The values of β_0 and the normalized wage rate, w, are jointly selected from many trials to make sure the expected maximal profit, $\pi = \beta_0 L^{0.7} - wL$, is positive; hence we choose $w = 1$ and $\beta_0 = 3$. In the risk function $g(\boldsymbol{X}, \boldsymbol{Z}) = \exp(\alpha_0 + \alpha_1 X_l + \alpha_2 Z)$, we assume $\alpha_0 = 1, \alpha_1 = 5.0,$ and $\alpha_{2=} - 5.0$. It signifies that land fragmentation (Z) is risk decreasing while labor X_l is risk increasing. As for the coefficient in the absolute risk aversion function $AR = \exp(\gamma \Pi)$, we assume γ=-5 such that the calculated relative risk aversion coefficients are comparable to those surveyed by Cohen and Einav (2007). Finally for the distribution of inefficiency, we assume the pre-truncated normal distribution has a variance of one, i.e., $\sigma^2 = 1$, and the mean inefficiency function is specified as follows: $\mu = 0.1Z$ (i.e., $\delta_1 = 0.1$). The coefficient in front of Z is selected to guarantee that the calculated inefficiency change resulting from shifts in land fragmentation will fall into a reasonable range. For example, if the Simpson Index goes from zero to one, the efficiency term $\exp(-\mu)$ will go from

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[12] To derive a reasonable value for this parameter, we estimated a translog production function with labor as the only input using the LSMS sample from Chapter 2. The coefficient estimate of labor is close to 0.7.

one to 0.90, meaning that land fragmentation will cause the efficiency score to drop by 10 percentage points at most.

Given the selected functional forms and initial values, we change the value of the Simpson Index from zero to one with a step of 0.01, representing an increasing level of land fragmentation, and calculate the optimal use of labor, L^*, the corresponding maximal output, $f(L^*) * \exp(-\mu)$, and the expected maximal profit $\pi^* = f(L^*) * \exp(-\mu) - L^* w$. Our goal is to see whether a more fragmented case will lead to a more intense use of labor and potentially a higher output and profit.

Figure 3-1 shows clearly that as land becomes more fragmented, that is, the Simpson Index increases from zero to one, the optimal use of labor first increases up to a certain point and then starts to decrease. To understand this relationship, let's start from an optimal state where a risk-averse farmer has reached a "desired tradeoff" between his expected payoff and risk, a tradeoff characterized by his risk preferences. Now propose a slightly higher level of land fragmentation. The immediate effects include a reduced risk and a reduced output given the parameter values we specified before, and this change tips the previous balance between expected payoff and risk and will deviate from the previous optimal state. How this farmer would adjust his labor use to reach a new optimal state will depend on labor's marginal effects on expected payoff and risk. More specifically, if additional labor inputs will produce sufficient output/payoff to compensate the increased risk incurred at the same time, this farmer will increase his optimal labor input. Otherwise, he will decrease the optimal labor input. Given that the marginal effect of labor on expected output/profit is negatively related with land fragmentation, we should expect that it is more likely for this farmer to use more labor to reach a new optimal state at a lower level of land fragmentation while using less labor at a higher level of land fragmentation, a speculation that is consistent with the pattern in Figure 3-1.

Since the entire model comprises nonlinear relationships and the solution depends on the values of multiple parameters, the optimal use of labor is not necessarily a linear or monotonic function of the Simpson Index on the interval of [0,1]. As a matter of fact, we should expect a different shape of the relationship if we change the values of the parameters in the model. Figure 3-2 represents the case where we change the risk effect of labor, α_1, from 5 to 0, i.e., labor does not have any impact on production risk.

Regarding the relationship between land fragmentation and optimal output and profit, we use the parameter setting underlying Figure 3-1 to exemplify one possible case. In Figure 3-3, we calculate both the expected optimal output, Y^*, based on the formula $Y^* = f(L^*) * \exp(-\mu)$, and the expected optimal profit, π^*, based on the formula $\pi^* = f(L^*) * \exp(-\mu) - w * L^*$, where L^* is the optimal labor use calculated from the first step[13]. It clearly shows that land fragmentation may be positively correlated with either output or profit in a certain range (in this case, SI <= 0.67). This finding may well explain the observation made by Niroula and Thapa (2007), who reports that in Nepal

[13] We can also calculate the expected optimal output and profit at the efficiency frontier (i.e., $\mu = 0$). It turns out that the graphical patterns are very similar to the two patterns shown in Figure 3-3. Therefore, we omit these two curves from Figure 3-3 to keep the presentation concise.

plots with smaller size resulting from land fragmentation see more labor inputs and a higher yield.

Risk Preferences

One motivation of this study is to look into how risk preferences may affect the adjustments in the optimal use of inputs and the corresponding optimal expected output and profit as a result of a shift in land fragmentation. In the previous section, we assumed the risk preference coefficient $\gamma = -5$ in the absolute risk aversion function $AR = \exp(\gamma \Pi)$, representing the most-reported case of decreasing absolute risk aversion (DARA). Firstly, we assume that DARA still holds but allow the coefficient γ to vary from -0.1 to -6 with an increment of -0.1, thereby representing different degrees of DARA. The surface graph in Figure 3-4 shows that at different levels of DARA, the optimal labor use will roughly increase as the Simpson Index goes up to a certain point and then start to decrease, an intuitive pattern as we explained in the baseline case.

Finally we focus on the cases with constant absolute risk aversion (CARA) and increasing absolute risk aversion (IARA) by assume $\gamma = 0$ and $\gamma = 1$, respectively. Figure 3-5 and Figure 3-6 show a similar pattern –an increasing and then decreasing trend -- of optimal labor use as that in the DARA case. The trend illustrates the underlying tradeoff decision to be made by farmers between the marginal effects of labor on expected output/profit and its marginal effects on risk, a decision which is intrinsically determined by, among others factors such as the level of land fragmentation, their attitude towards risk, i.e., risk preferences.

A More General Case

Up to this point we may be ready to conclude that risk preferences are essential to efficiency analysis because the exogenous determinants of efficiency (land fragmentation in the current example) and/or certain input (labor in the current example) have effects on risk. However, if we assume away all these risk effects, that is, $\alpha_1 = \alpha_2 = 0$ and the risk function $G(L, z)$ is now a constant, our model still returns a non-constant optimal labor use when the Simpson Index varies between zero and one (Figure 3-7). The explanation is that, even without risk effects, a shift in land fragmentation still changes the previous tradeoff between expected payoff and risk through its efficiency effects. To reach a new optimal state, farmers now can only adjust the expected payoff through the use of labor since labor is now assumed to have no marginal effect on risk. Since the marginal contribution of additional unit of labor to the expected payoff is decreasing as the Simpson Index goes up, farmers now tend to use less labor to reach the new optimal state, as demonstrated by the negatively-sloped curve in Figure 3-7.

3.4 Implications for Model Estimation

From the numerical example above, we see clearly how the relationship between land fragmentation, an exogenous factor that affects both production efficiency and production risk, and the optimal use of inputs (e.g., labor) as well as the optimal output and profit is determined by farmers' risk preferences. However, the current analytical framework of land fragmentation's efficiency effects, the stochastic frontier model, fails to account for risk preferences. Given that most empirical studies use observational data such as those from household surveys to estimate efficiency effects and the near consensus of farmers' risk aversion, we are curious of the probable bias arising from applying the stochastic frontier model to the analysis.

To show the bias, we retain the functional forms and parameter values in the numerical example above to represent the underlying data generating process[14]. Meanwhile, we estimate a stochastic profit frontier model with a mean inefficiency function and heteroskedasticity in the variance term, using outputs from the numerical model that are usually observable in practice, namely, land fragmentation measured by the Simpson Index, labor input, and profit. The goal of this exercise is to compare the estimated efficiency effect coefficient of the Simpson Index in the stochastic frontier model with the one in the "real" data generating process. We change the values of some of the key parameters in the numerical example, e.g., the risk preference coefficient γ and the risk effect coefficient α_1, and repeat the comparison many times. It turns out that in general the estimated inefficiency effect of land fragmentation is not close to the true effect: $\delta_1 = 0.1$. In some cases, the estimated efficiency effect could be negative even though the true effect is positive. For example, if we change the risk effect of labor, α_1 from five to zero while keeping all the other initial values in the numeric example unchanged, the estimated inefficiency effect of land fragmentation will be -2.85 with a 95%

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[14] Now we change the increment in the Simpson Index from 0.1 to 0.002 to generate enough observations (N=500) for the estimation of the stochastic frontier model.

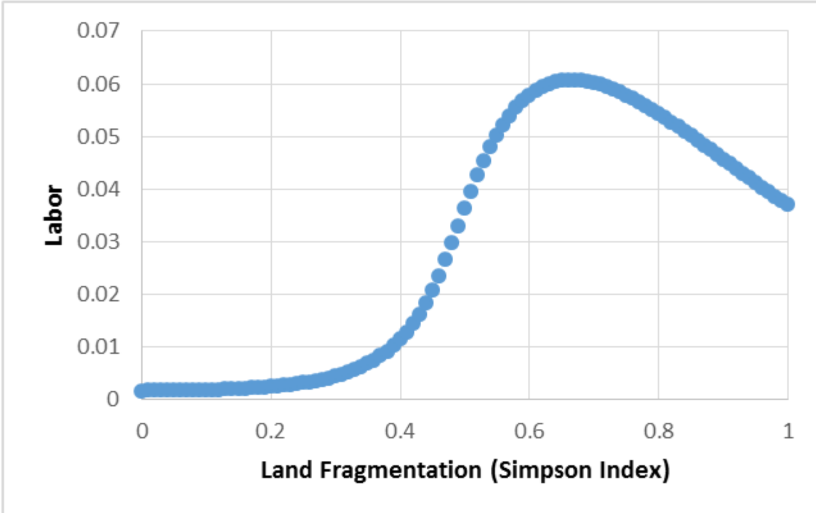
confidence interval of (-3.66, -2.05). This exercise highlights the importance of including risk preferences in the analysis of efficiency effects.

3.5 Discussion and Conclusions

In this study, we started from the curious empirical estimates of land fragmentation's efficiency effects and questioned the applicability of the current framework often applied to this topic. We argued that even though land fragmentation is obviously disadvantageous to technical efficiency, it may still encourage farmers to use labor more intensively and probably results in a higher payoff. Based on Kumbhakar (2002)'s model, we extended it to one that can analyze efficiency effects of exogenous factors such as land fragmentation. Using a numerical example, we showed that our hypothesis about labor intensity may hold true under certain circumstances. More importantly, we found that excluding risk preferences from the estimation will lead to biased or even counter-intuitive estimates of efficiency effects regardless of whether the related exogenous variable has a risk effect. These findings should not only help clarify the confusion surrounding land fragmentation's impacts on agricultural production but also have implications for the general literature of production efficiency estimation.

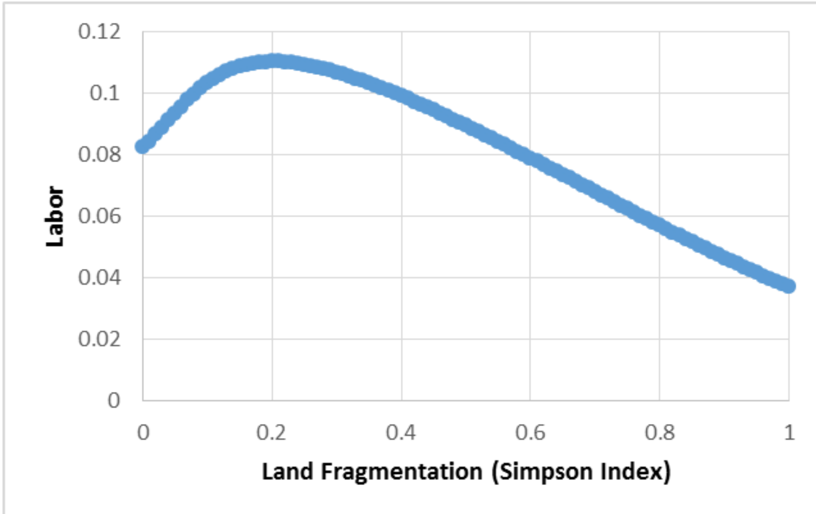
For future research, it will be meaningful to apply the framework in this study to empirical estimations using observational data. There have been a few applications of Kumbhakar (2002)'s model, such as Di Falco and Chavas (2006) and Serra et al. (2008). However, they are either simply estimating a random inefficiency term instead of a mean inefficiency function with a group of exogenous variables or based on some oversimplified assumptions about risk preferences[15]. The empirical estimation is anticipated to be challenging given the complexity of the model. Nevertheless, further research on this topic shall add to our understanding of economic agents' behaviors under risk and their economic performance.

[15] For example, Serra et al (2008) use a second order Taylor series expansion of the utility function instead of the marginal utility function to derive the risk preference-related coefficients, i.e., γ and λ, to simplify the expressions. By doing that, however, they implicitly assume away the downside risk aversion and will have inaccurate approximation of the optimal input uses which are based upon the marginal utility function through the first-order conditions instead of the utility function.



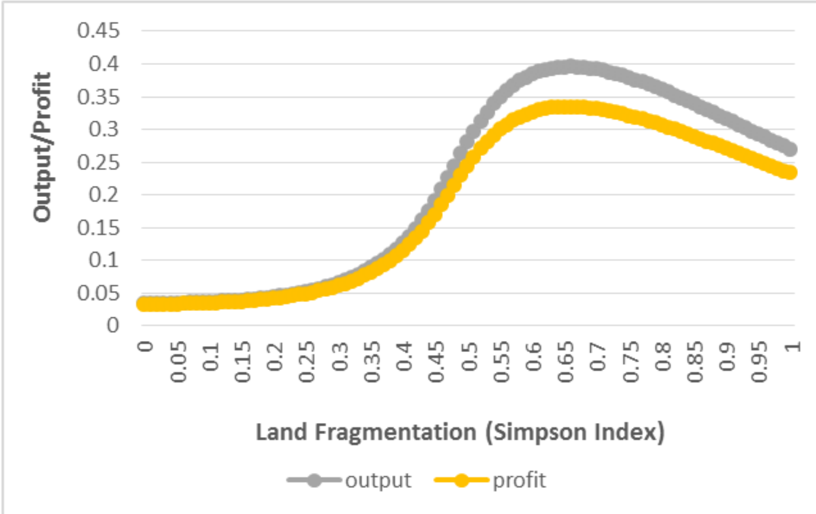
Source: Developed by author.

Figure 3-1 Optimal Labor Use with DARA



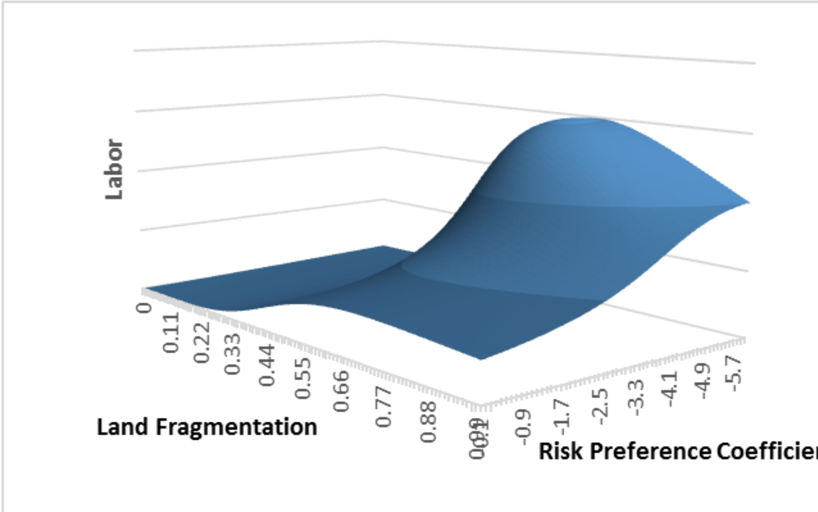
Source: Developed by author.

Figure 3-2 Optimal Labor Use when Labor is Risk Neutral and DARA



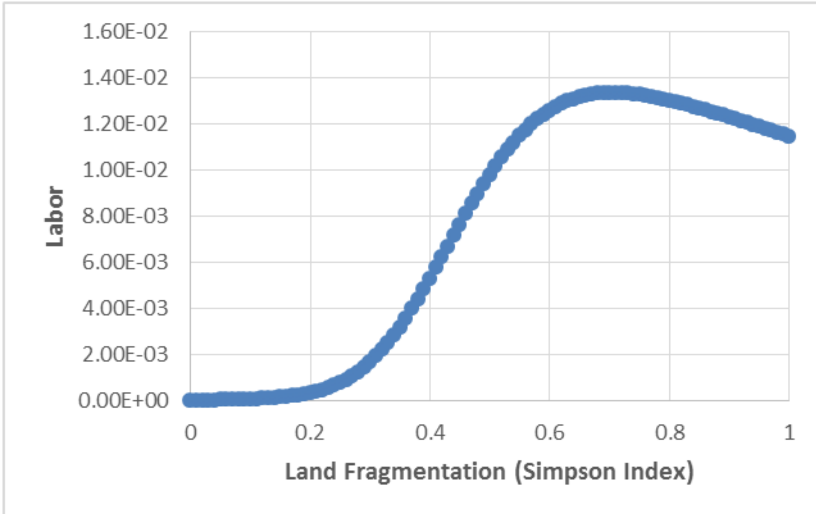
Source: Developed by author.

Figure 3-3 Optimal Output and Profit with DARA



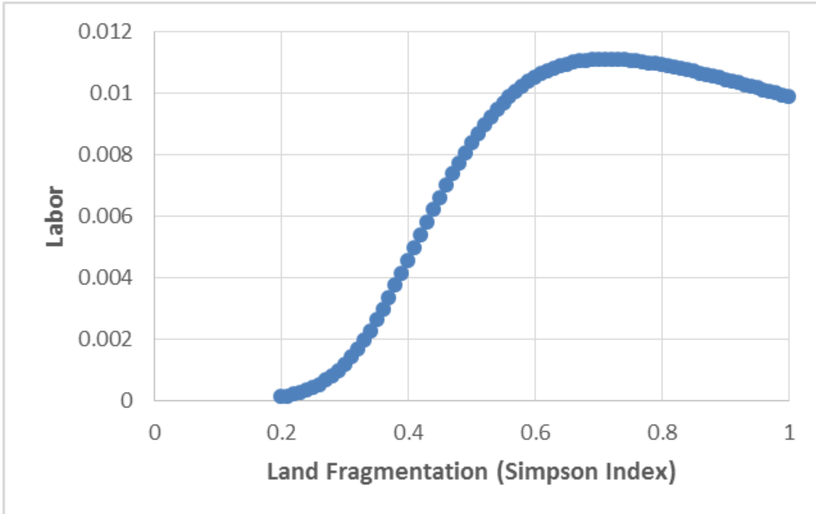
Source: Developed by author.

Figure 3-4 Optimal Labor Use with Various Degrees of DARA



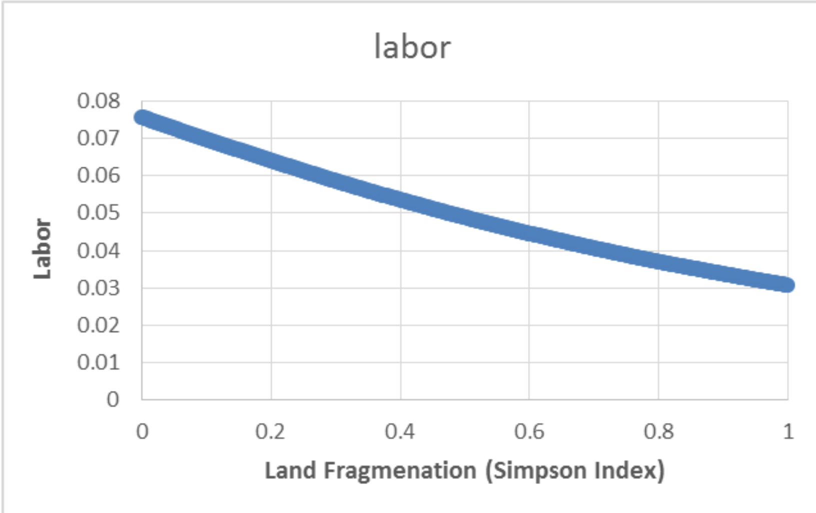
Source: Developed by author.

Figure 3-5 Optimal Labor Use with CARA (γ=0)



Source: Developed by author.

Figure 3-6 Optimal Labor Use with CARA (γ=1)



Source: Developed by author.

Figure 3-7 Optimal Labor Use with DARA but without Risk Effects

Chapter 4. Re-Examining the Reported Rates of Return to Food and Agricultural Research and Development[16]

4.1 Introduction

More than half a century has passed since Zvi Griliches published the first formal economic estimate of the rate of return to food and agricultural R&D in 1958[17]. Since then many economists have published a large number of similar estimates. Alston et al. (2000) reported on 292 such studies with 1,886 evaluations of the payoffs to investments in agricultural R&D either in the form of internal rates of return or benefit-cost ratios[18]. Averaging across all studies, the internal rate of return was 81 percent per year, indicative of a widespread and persistent underinvestment[19]. But rather than ramping up spending to more economically justifiable amounts, growth in agricultural R&D spending has slowed over the past several decades in many countries, particularly rich countries who collectively accounted for 48 percent of the world's public expenditures in 2009 (Pardey, Alston and Chan-Kang 2013).

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[16] This chapter is coauthored with Terrance M. Hurley and Philip G. Pardey. A revised submission of this draft has been published in the American Journal of Agricultural Economics 96(5): 1492-1504, 2014.
[17] Heckman (2006) wrote that "[Griliches 1958] early empirical work on the social rate of return to research activity, and on the role of economic incentives in determining the distribution of benefits from new technologies [Griliches 1957], laid the foundations for scientific study of these topics." Schultz (1953) gives the earliest known economic estimate of the overall benefits attributable to public agricultural research in the United States, but did not report a formal benefit-cost ratio or internal rate of return.
[18] See also the summaries of this evidence by Evenson (2001) and Fuglie and Heisey (2007).
[19] Ruttan (1980 and 1982) presents arguments regarding the underinvestment hypothesis.

One plausible explanation for this investment behavior is that economists got it wrong—systematically overstating the rates of return to R&D. Alternatively, but with equal effect, those making R&D investment decisions may have simply dismissed the reported rates of return as unbelievably high. There is certainly precedent for that perspective. McMillen's 1929 account of then U.S. Secretary of Agriculture "Tama Jim" Wilson's attempt to compile a report on what, if any, profit could be shown from the Department of Agriculture's research spending reads:

> Numerous interests and industries were asked to estimate conservatively the value of such of the department's findings as affected their operations. Finally the expenditures were totaled in one column, the estimates of the returns in another, and the sheets placed before the venerable secretary.
>
> "This will never do!" he protested. "No one will swallow these figures!" The report revealed that for every single dollar that had been spent for scientific research in the Department of Agriculture, the nation was reaping an annual increase of nearly a thousand dollars in new wealth.
>
> "Cut it down to $500," insisted Wilson. "That's as much as we can expect the public, or Congress, to believe."
>
> (McMillen 1929, p. 141)

In this paper we address the question, is the reported rate of return evidence credible, and if not what can or should be done to recalibrate that evidence? To do so we develop and deploy a comprehensive compilation of rate-of-return estimates published since 1958. We argue that the weight of evidence supports the conclusion that the vast majority of rate of return estimates are implausibly high. To understand why, we analytically explore key methodological conventions that have pervaded the literature despite criticisms dating back to Griliches' seminal contribution. Where data permit, we recalibrate the prior estimates in light of these criticisms. While our analysis serves to downsize the overall average of the returns to food and agricultural R&D, the recalibrated estimates are still substantial enough to question the current scaling back of public agricultural R&D spending in many countries.

4.2 Evidence at Face Value

Among the 2,242 published evaluations we compiled from 372 separate studies published between 1958 and 2011, the internal rate of return (*IRR*)—the discount rate that equates the present value of an investment's stream of benefits with the present value of its stream of costs—was predominant, reported for 91.4 percent of the published evaluations[20]. Alternatively, 28.2 percent of the evaluations reported benefit-cost ratios (*BCR*)—the present value of an investment's stream of benefits divided by the present value of its stream of costs. Both *IRR*s and *BCR*s were reported for 19.6 percent of the evaluations.

The database we compiled includes studies of the impact of agricultural R&D for 79 countries. Nearly half of the evaluation studies (and 42 percent of the estimates) were published in the 1990s with 38 percent of these studies appearing in peer reviewed journals. The rest come from books, graduate dissertations, conference papers, and the grey literature, including reports published by various international and national agencies. Nine out of ten evaluations constitute ex post appraisals of past R&D investments; the remainder assessed the prospective returns to R&D investments yet to

[20] See the supplementary online appendix for details regarding how we compiled our database of rate-of-return estimates to agricultural R&D. The supplementary online appendix also includes an overview of the number of studies and evaluations, and descriptive statistics for the reported *IRR* estimates based on the type (e.g., basic, applied, or extension), commodity orientation, and geographic location of the research and research performer.

be made. Most of the studies (88 percent) focused on investments with both cost and benefit streams that spanned multiple years.

Figure 4-1, panel a shows the kernel density estimate for the reported *IRR*s in addition to other descriptive statistics. The average *IRR* across all 2,049 observations is 67.6 percent per year, ranging from a low of -100 to a high of 5,645 percent per year. The distribution is skewed with a median of 42.6 percent per year, well less than the average[21]. Three quarters of the *IRR*s exceed 24.6 percent per year. To gain some perspective on the implications of such high rates of return, we evaluated just how much the $4.1 billion (2005 prices) invested in 2000 in agricultural R&D by the United States Department of Agriculture (USDA) and state agricultural experiment stations (SAES) (Alston et al. 2010) would be worth in 2050 assuming benefits accrued over 50 years, which is not atypical for these types of investment (Alston et al. 2000). At the average rate of return reported in the literature, this investment would yield $670 quintillion ($\times 10^{18}$) in net benefits. At the median rate of return, a more robust measure of central tendency given some extreme *IRR* estimates, it would still be worth $208 quadrillion ($\times 10^{15}$). Even the first quartile estimate would be worth $244 trillion. Comparing these results with U.S. and global gross domestic product (GDP) makes it hard not to question their plausibility. The U.S. GDP in 2000 was about $11 trillion (2005 U.S. dollars), while the world GDP was $40 trillion (World Bank 2012). By 2050, the forecasted GDP

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[21] Notably, the reported returns to the 737 *IRR* estimates culled from peer reviewed studies (mean of 74.7 percent per year, median of 43.7 percent per year) are larger on average than the 1,312 estimates taken from studies published in non-peer reviewed journals (mean of 63.6 percent per year, median 42 percent per year).

for the United States and world are $28 and $148 trillion (2005 U.S. dollars) respectively (Foure, Benassy-Quere and Fontagne 2010). Therefore, the median *IRR* estimate suggests the benefits attributable to just public agricultural R&D investments by the United States in 2000 would be more than 1,400 times the projected world GDP in 2050!

Figure 4-1, panel b shows the kernel density for the reported *BCR*s in addition to other descriptive statistics. The mean *BCR* was 22.9 implying a more plausible return of $93.9 billion on a $4.1 billion investment. The median *BCR* of 10.5 implies a return of $43.0 billion, while the first quartile estimate of 3.2 implies a return of $13.1 billion. Compared with the returns implied by the *IRR* estimates, the *BCR*s' implications are much more plausible, yet just over one out of four studies in our agricultural R&D returns database reported *BCR*s.

4.3 Modified Internal Rate of Return

The *IRR* for an investment is implicitly defined by

$$\sum_{t=0}^{T} b_t(1+IRR)^{-t} = \sum_{t=0}^{T} c_t(1+IRR)^{-t} \tag{4-1}$$

where $T > 0$ is the term of the investment, and $b_t \geq 0$ and $c_t \geq 0$ for $t = 0,\ldots, T$ are the investment's stream of benefits and costs such that in aggregate there are some benefits and some costs: $B = \sum_{t=0}^{T} b_t > 0$ and $C = \sum_{t=0}^{T} c_t > 0$. While the *IRR* has served as the predominant measure of investment performance in the agricultural R&D evaluation literature, it has been viewed critically by economists for more than half a century.

Lorie and Savage (1955) and Solomon (1956) noted it need not be unique[22]. Hirshleifer (1958) and Baldwin (1959) argued that with more than two periods the *IRR* assumes intermediate cash flows can be reinvested (or borrowed) at the same rate of return as the initial investment, which is generally not correct or reasonable. Griliches shared these concerns, but still reported *IRR* bounds, implicating Martin J. Bailey for suggesting such a calculation (Griliches 1958, p. 425, footnote 16).

Criticisms of the *IRR* have included suggestions for improvement such as the modified internal rate of return (*MIRR*). The *MIRR* is defined as

(4-2) $$MIRR = \sqrt[T]{\frac{FVB(\delta^r)}{PVC(\delta^c)}} - 1$$

where $FVB(\delta^r) = \sum_{t=0}^{T} b_t(1+\delta^r)^{T-t}$ is the future value of benefits assuming a reinvestment discount rate δ^r and $PVC(\delta^c) = \sum_{t=0}^{T} c_t(1+\delta^c)^{-t}$ is the present value of costs assuming a borrowing discount rate of δ^c. A more intuitive interpretation is apparent from the formulation $PVC(\delta^c)(1 + MIRR)^T = FVB(\delta^r)$, which shows that the *MIRR* is the annual compounding interest rate for a deposit $PVC(\delta^c)$ at time 0 that pays back $FVB(\delta^r)$ at time T. While Lin (1976) appears to be the first to have coined the term "Modified Internal Rate of Return," Biondi (2006) traces its origins back to Duvillard (1787). Alston et al. (2011) appears to be the first to apply the *MIRR* to agricultural R&D (see also Andersen and Song 2013). For investments from 1949 to 2002

[22] Norstrøm (1972) shows a sufficient condition for a unique *IRR* is that the sign of the sequence of cumulative sums of the net value of benefits and costs over time can change only once.

undertaken by the USDA and each of the contiguous 48 SAESs, they found an average *IRR* of 22.7 percent per year with a range of 15.3 to 23.1 percent. Assuming reinvestment and borrowing discount rates of 0.03, the average *MIRR* was a more modest 9.9 percent per year, with a range of 7.7 to 11.7 percent. These results raise an interesting and pertinent policy question. How attractive would prior estimates of the returns to agricultural R&D be if they were based on the *MIRR* instead of the *IRR*? To answer this question, we first analytically explore how the *IRR* and *MIRR* differ.

IRR versus MIRR: Analytics and Intuition

The differences between the *IRR* and *MIRR* are more transparent when Equation (4-1) is written as $IRR = \sqrt[T]{\frac{FVB(IRR)}{PVC(IRR)}} - 1$, which shows the *IRR* assumes the simultaneous equality of the reinvestment and borrowing discount rates, and the *MIRR*: $\delta^r = \delta^c = MIRR$. Figure 4-2 shows the implications of these assumptions using a contour map of the reinvestment and borrowing discount rates that yield the same *MIRR*. Qualitatively, individual contours slope downward with contours for higher δ^rs and higher δ^cs representing higher *MIRR*s[23]. By assuming $\delta^r = \delta^c$, the definition of the *IRR* confines attention to points along the 45^o line. By further assuming $MIRR = \delta^r = \delta^c$, the definition only picks points where the value corresponding to the *MIRR* contour equals the value on the 45^o line where the two intersect. In figure 4-2, this occurs at point *a* where $MIRR = \delta^r = \delta^c = 0.31$. This example was designed with a unique *IRR*, though this need not be

[23] See corollary S1 in the supplementary online appendix.

the case. The *MIRR* is unambiguously greater (less) than the *IRR* when both δ^r and δ^c are greater (less) than the *IRR*[24]. The *MIRR* requires specifying values for δ^r and δ^c. The chosen values yield a unique *MIRR*: $\delta^r = 0.05$ and $\delta^c = 0.15$ correspond to the contour with *MIRR* = 0.2 in Figure 4-2.

Recall that the average of reported *IRRs* in our database is 67.6 percent per year with three-quarters of these estimates exceeding 24.6 percent. Alternatively, for the 599 *BCR* estimates in our database that reported the common discount rate ($\delta = \delta^r = \delta^c$) used in the calculation, the average, minimum and maximum discount rates are 7.2, 2.0 and 15.0 percent per year respectively. This suggests the discount rates deemed reasonable by agricultural R&D evaluation researchers have tended to be lower than the reported *IRR*s. Combining Figure 4-2 insights with our analytic findings leads us to hypothesize:

Hypothesis 1: The rates of return to agricultural R&D reported in the literature would have typically been lower if the *MIRR* was used instead of the *IRR*.

The high *IRR*s and *BCRs* found in the literature suggest quite profitable investments. With Figure 4-2 showing the *IRR* and *MIRR* are likely to differ except by coincidence, the question of whether this difference is smaller or larger for more profitable investments is of interest. The profitability of an investment can be measured by its net present value—the present value of benefits minus the present value of costs. A parsimonious parameterization of profitability can be constructed by defining the present

[24] Based on equation S11 in the supplementary online appendix.

value of benefits as $PVB(\delta^r) = B\sum_{t=0}^{T} w_{b_t}(1+\delta^r)^{-t}$ and present value of costs as $PVC(\delta^c) = C\sum_{t=0}^{T} w_{c_t}(1+\delta^c)^{-t}$ where w_{b_t} and w_{c_t} for $t = 0,\ldots, T$ are the distributions of benefits and costs over time such that $\sum_{t=0}^{T} w_{b_t} = \sum_{t=0}^{T} w_{c_t} = 1$. Profitability is then increasing in the undiscounted benefit-cost ratio $BCR_0 = B/C$ for profitable investments—i.e., have a positive net present value[25]. This reformulation also allows Equation (4-2) to be written as

(4-3) $$MIRR = \sqrt[T]{BCR_0\Phi(\delta^r,\delta^c)} - 1$$

where $\Phi(\delta^r,\delta^c) = \frac{\sum_{t=0}^{T} w_{b_t}(1+\delta^r)^{T-t}}{\sum_{t=0}^{T} w_{c_t}(1+\delta^c)^{-t}} > 0$ for proper discount rates — i.e., where $\delta^r > -1$ and $\delta^c > -1$.

Equation (4-3) implies the *MIRR* is increasing in the BCR_0[26]:

(4-4) $$\frac{dMIRR}{dBCR_0} = \frac{1}{T}\frac{MIRR+1}{BCR_0} > 0$$

which intuitively suggests more profitable investments, in terms of a higher undiscounted benefit-cost ratio, have higher rates of return, in terms of the *MIRR*. Substituting the *IRR* for δ^r, δ^c and the *MIRR*, Equation (4-3) also implies

(4-5) $$\frac{dIRR}{dBCR_0} = \frac{\sum_{t=0}^{T} b_t T(1+IRR)^{-t}}{\sum_{t=0}^{T}(b_t - c_t)t(1+IRR)^{-t}}\frac{1}{T}\frac{IRR+1}{BCR_0}$$

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[25] See proposition S1 in the supplementary online appendix.
[26] See proposition S1 in the supplementary online appendix.

assuming the *IRR* is unique[27]. Unlike Equation (4-4), Equation (4-5) is not unambiguously positive. It is positive (negative) as $\sum_{t=0}^{T}(b_t - c_t)t(1 + IRR)^{-t} > (<) 0$[28]. The implication is that more profitable investments, in terms of a higher undiscounted benefit-cost ratio, need not have higher rates of return, as measured by the *IRR*.

Comparing equations (4-4) and (4-5), the results would essentially be identical if the first quotient on the right-hand side of Equation (4-5) equaled one, which cannot be the case for proper *IRR*s, that is *IRR* > -1. The reason for this confounding term is illustrated in Figure 4-3 for unique and positive *IRR*s (98.5 percent of the evaluations in our database). Each panel shows the relationship between the *MIRR* and $\delta = \delta^r = \delta^c$ for two investments that differ only in terms of the BCR_0. All examples were constructed with unique *IRR*s. The assumption $\delta^r = \delta^c$ serves only to facilitate graphical exposition. Four qualitative characteristics in Figure 4-3 hold generally: 1) the *MIRR* is increasing in the BCR_0 (i.e., the *MIRR* curve with the higher BCR_0 is above the one with the lower BCR_0), 2) the *MIRR* is increasing in δ (i.e., *MIRR* curves are positively sloped), 3) the difference in the *MIRR*s for alternative BCR_0s is increasing in δ (i.e., *MIRR* curves diverge as δ increases), and 4) for unique and positive *IRR*s, the *IRR* is increasing (decreasing) in the BCR_0 when BCR_0 >(<) 1[29].

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[27] Equation (4-5) follows from the substitution of equation (S18) into equation (S16) in the supplementary online appendix.
[28] See proposition S3 in the supplementary online appendix.
[29] See propositions S2 and S4, and corollaries S2 and S4 in the supplementary online appendix.

In panel a, BCR_0 is greater than one for both investments, so the *MIRR* curves must intersect the 45^o line (where the *MIRR* and δ are equal) from above. When δ = 0.1 and BCR_0 = 3, the *MIRR* is 0.2. The *IRR* is 0.31 where the *MIRR* crosses the 45^o line at point a^1. Increasing the BCR_0 to 9, the *MIRR* increases to 0.38, while the *IRR* increases to 0.69 where the *MIRR* curve now crosses the 45^o line at point c^1. Increasing the BCR_0 from 3 to 9 changes the *MIRR* from point a^0 to b^0 reflecting a shift in the *MIRR* curve holding δ constant at 0.1. The change in the *IRR* reflects a more complicated shift in the *MIRR* curve, from point a^1 to b^1 holding δ = *IRR* constant at 0.31, as well as a movement along the curve from point b^1 to c^1 in order to bring the *MIRR* back into equality with δ. Note that the divergence of *MIRR* curves implies the difference in the *MIRR* between points b^1 and a^1 is larger than the difference between points b^0 and a^0 because δ is less than the *IRR* for BCR_0 = 3. If δ was greater than the *IRR* for BCR_0 = 3, then the difference between points b^0 and a^0 would be larger. The difference in the *MIRR* between points c^1 and b^1 is positive because increasing the BCR_0 shifts the *MIRR* curve up and the *MIRR* curve is positively sloped. For this example, the net effect is that the difference between the *IRR* and *MIRR* is increasing in the BCR_0. More generally, for a unique and positive *IRR*, the difference in the *IRR* and *MIRR* is increasing in profitability, in terms of the undiscounted benefit-cost ratio, if δ^r and δ^c are less than the *IRR*, the undiscounted benefit-cost ratio is greater than one, and the investment is profitable[30].

[30] Follows from propositions S1, S4 and S5(a) in the supplementary online appendix.

In panel b, BCR_0 is less than one for both investments, so the *MIRR* curves must intersect the 45^o line from below. When $\delta = 0.1$ and $BCR_0 = 0.4$, the *MIRR* is 0.03, while the *IRR* is 0.26. Increasing the BCR_0 to 0.6, the *MIRR* increases to 0.08, while the *IRR* decreases to 0.14. Increasing BCR_0 from 0.4 to 0.6 changes the *MIRR* from point a^0 to b^0 again reflecting a shift in the *MIRR* curve holding δ constant at 0.1, while the change in the *IRR* reflects a shift in the *MIRR* curve from point a^1 to b^1 holding $\delta = IRR$ constant at 0.26 and movement along the curve from point b^1 to c^1 in order to bring the *MIRR* back into equality with δ. Note that once again the divergence of the *MIRR* curves implies the difference in the *MIRR* between point b^1 and a^1 is larger than the difference between point b^0 and a^0. The difference in the *MIRR* between point c^1 and b^1 is negative because increasing the BCR_0 shifts the *MIRR* curve up and the *MIRR* curve is positively sloped. For this example, the net effect is that the difference between the *IRR* and *MIRR* is decreasing in the BCR_0. More generally, for a unique and positive *IRR*, the difference between the *IRR* and *MIRR* is decreasing in profitability, in terms of the undiscounted benefit-cost ratio, if the undiscounted benefit-cost ratio is less than one and the investment is profitable[31].

Whether panel a or b in Figure 4-3 is more typical of the 98.5 percent of evaluations in our database with positive *IRR*s depends on whether BCR_0 is typically greater or less than one for these evaluations. If the large *IRR*s found in the literature are indeed indicative of profitable investments, it seems most likely that aggregate benefits

[31] Follows from propositions S1, S4 and S5(b) in the supplementary online appendix.

typically exceed aggregate costs such that $BCR_0 > 1$, which Figure 4-3 and our analytic results then lead us to hypothesize:

Hypothesis 2: The difference between the reported rates of return to agricultural R&D based on the *IRR* and the rates of return estimated using the *MIRR* is typically larger for more profitable investments.

To further explore Hypotheses 1 and 2 empirically, we compare previously published rates of return based on the *IRR* with recalibrated rates of return based on the *MIRR* where feasible.

4.4 Reconstructing Rates of Return Using the MIRR

Athanasopoulos (1978) and Negrete (1978) identify the relationship

$$MIRR = (1+\delta)\sqrt[T]{BCR} - 1 \tag{4-6}$$

This relationship is convenient for recalibrating previous *IRR*s using the *MIRR* for evaluations that reported a *BCR*, discount rate, and investment term as well as an *IRR*. However, such a recalibration still neglects concerns that the appropriate reinvestment discount rate need not equal the borrowing discount rate, which is especially true for publicly funded agricultural research investments where many benefits accrue privately (to producers, consumers, or both) from R&D financed from general government revenues.

The relationship in Equation (4-6) can be generalized for differing discount rates:

(4-7) $$MIRR = (1+\delta^r)\sqrt[T]{BCR\frac{\sum_{t=0}^{T} w_{c_t}(1+\delta)^{-t}}{\sum_{t=0}^{T} w_{c_t}(1+\delta^c)^{-t}}\frac{\sum_{t=0}^{T} w_{b_t}(1+\delta^r)^{-t}}{\sum_{t=0}^{T} w_{b_t}(1+\delta)^{-t}}} - 1$$ [32]

Note that Equation (4-7) reduces to (4-6) when $\delta = \delta^r = \delta^c$. More importantly, Equation (4-7) indicates that the *MIRR* implicit in previous studies can be calculated given the term of the investment, the *BCR* and its associated discount rate, the distribution of costs and benefits, and the reinvestment and borrowing discount rates. Unfortunately, while *T*, *BCR*, and δ are reported in many previous studies, seldom are the detailed distributions of costs and benefits. Therefore, calculation of the *MIRR* for previous studies requires some method for reconstructing the distributions of costs and benefits given commonly reported information.

There is a relationship between the *IRR* and *BCR* that can be exploited in an effort to reconstruct the distributions of costs and benefits over time:

(4-8) $$BCR = \frac{\sum_{t=0}^{T} w_{c_t}(1+IRR)^{-t}}{\sum_{t=0}^{T} w_{b_t}(1+IRR)^{-t}}\frac{\sum_{t=0}^{T} w_{b_t}(1+\delta)^{-t}}{\sum_{t=0}^{T} w_{c_t}(1+\delta)^{-t}}$$ [33]

Equation (4-8) provides a direct relationship between the *BCR* and *IRR* that also depends on δ and the distributions of benefits and costs. This relationship is useful because it indicates which distributions of cost and benefits (i.e., profiles of w_{b_t}s and w_{c_t}s for t =0,…, *T*) are consistent with the *T*, *BCR*, *IRR*, and δ reported in a study. Therefore, if we can identify distributions that reasonably satisfy Equation (4-8), we can use these

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[32] Our derivation of Equation (4-7) is reported in the supplementary online appendix. See equation (S29).
[33] Our derivation of Equation (4-8) is reported in the supplementary online appendix. See equation (S28).

distributions with Equation (4-7) to calculate the *MIRR* for any desired reinvestment and borrowing discount rates.

We reconstructed the distributions of costs and benefits assuming each can be reasonably approximated with a beta distribution[34]. The beta distribution is appealing for modeling phenomena that undergo growth and decline, which is characteristic of the different stages of technological diffusion in agricultural production and the profile of benefits attributed to the uptake of these research-induced technologies. The distribution is flexible enough to capture investment streams characterized by rapid growth followed by a slow decline, slow growth followed by rapid decline, and more balanced growth and decline. In addition to being quite flexible, the unit beta with only two-parameters each for the characterization of costs and benefits provides a parsimonious parameter space that can be searched to find the distributions that come closest to satisfying Equation (4-8) (e.g., that minimizes the squared difference between the right- and left-hand sides of the equation).

The distributions of costs and benefits were approximated separately for each of the 270 evaluations that reported both the *IRR* and *BCR* as well as other necessary information. The best fitting beta parameters were found by minimizing the squared difference in the

[34] See **Reconstruction of the Rates of Return Using the *MIRR*** section of the supplementary online appendix.

observed and approximate *BCR*s using Matlab and its fminunc function. All observed *BCR*s were within 0.01 percent of the approximated *BCR*[35].

4.5 The Returns to Research Recalibrated

There were 446 R&D evaluations from 75 studies that reported a *BCR* along with the other necessary information for recalibration based on Equation (4-6). Assuming the reinvestment and borrowing discount rates equal the discount rate used to compute these *BCR*s, Equation (4-6) yields an average *MIRR* of 17.9 percent per year, with a minimum and maximum of -100 and 321.5 percent per year respectively. The median *MIRR* is 14.2 percent per year, with an interquartile range of 14.3 percent per year (9.0 to 23.3 percent per year).

Sensitivity Analysis

Relaxing the assumption of equal discount rates for the 270 *BCR* evaluations that also reported an *IRR* and using the unit beta distribution to approximate the costs and benefits distributions, Equation (4-7) can be used to explore the sensitivity of the *MIRR*s implied by these evaluations to alternative reinvestment and borrowing discount rates. Figure 4-4, panel a shows the results as the reinvestment and borrowing rates vary from 0 to 10

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[35] We were conscious that a beta distribution may not yield a global solution and that functional form may influence the *MIRR*s we derived with this method. Thus we also considered a trapezoidal distribution (which makes it possible to identify global solutions, though admittedly imprecisely due to the numerical inefficiency of the algorithm) to test the influence of functional form. Comparisons of the results using the two alternative distributions are provided in the supplementary online appendix. The beta distribution provided a better fit for all of the observations, though both distributions still provided similar *MIRR* estimates.

percent per year. The median *MIRR* is at a minimum of 9.8 percent per year when the reinvestment and borrowing discount rates are both 0 percent per year. It is at a maximum of 16.6 percent per year when both discount rates are 10 percent per year. Figure 4-4, panel b shows that the interquartile range varies relatively little between about 9.5 and 12.8 percent per year as the reinvestment and borrowing discount rates vary from 0 to 10 percent per year.

We further explore the implications of recalibrating the *IRR* using the *MIRR* assuming a borrowing discount rate $\delta^c = 0.03$ reflecting the average real rate of return for long-term U.S. treasuries, and a reinvestment discount rate $\delta^r = 0.035$ falling between the average rate of return to long-term U.S. treasuries and Standard & Poor's 500 equity index from 1969 to 2010[36]. Two additional issues we address that have been largely neglected in the literature, but are particularly relevant for publicly funded R&D that generates privately accruing benefits, are the deadweight loss of taxation (e.g., Harberger 1964; Fox 1985) and the proportion of benefits that are consumed versus saved. With a marginal excess burden (*MEB*) from taxation equal to $\delta^{MEB} \geq 0$ and a savings rate equal to $1 \geq \delta^s \geq 0$, the *MIRR* can be rewritten as

(4-7')
$$MIRR = \sqrt[T]{BCR \frac{\sum_{t=0}^{T} w_{c_t}(1+\delta)^{-t}}{\sum_{t=0}^{T} w_{b_t}(1+\delta)^{-t}} \frac{\sum_{t=T}^{T} w_{b_t}\left((1-\delta^s)+\delta^s(1+\delta^r)^{T-t}\right)}{\sum_{t=0}^{T} w_{c_t}(1+\delta^{MEB})(1+\delta^c)^{-t}}} - 1$$

[36] Data for the nominal rates of return of long-term U.S treasuries were obtained from James and Sylla (2006) and BGFRS (2012). These data were inflation adjusted using the consumer price index obtained from BLS (2012).

for real benefits and costs. Jones (2010) reviews estimates of the *MEB* from around the world finding values ranging from 0.0 to 0.56 due to variation in methodologies, the types of taxes evaluated, and the tax rates. For our purpose, we initially consider $\delta^{MEB} = 0.25$. To approximate the proportion of benefits that are consumed and saved, we use the U.S. private savings rate taken as a proportion of personal income from 1969 to 2010 (BEA 2012): $\delta^{s} = 0.045$.

Figure 4-5 provides a detailed look at the reported *IRR*s and *MIRR*s estimated with Equation (4-7') for the subsample of 270 evaluations ranked by our estimates of BCR_0[37]. Table 4-1 compares the *IRR*s to the *MIRR*s estimated using both equations (4-6) and (4-7') for this same subsample. As Figures 4-2 and 4-3 and our analytic results suggest, the *IRR* typically exceeds the *MIRR*. Indeed, the *IRR* exceeds the *MIRR* estimates for all 270 observations in this subsample. On average, the *IRR* is 3.8 times larger than the *MIRR* when Equation (4-6) is used and 5.0 times larger when Equation (4-7') is used, which is even more dramatic than the 2.3 proportional difference found by Alston et al. (2011).

Comparing the subsample of 270 *IRR*s to the remaining 1,779 *IRR*s in the full sample using the two-sample Kolmogorov-Smirnov test, we can reject the equality of the distributions (D = 0.11, p-value < 0.01). To get some sense of how our results might change if we had more information on the full sample, we regressed (using a simple linear equation with an intercept) the *MIRR* on the *IRR* for our subsample and then used

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[37] Analogous results were obtained using Equation (4-6).

these results to project *MIRR*s for the rest of the full sample. For *MIRR*s based on Equation (4-6) with a regression R^2 of 0.25, the average *MIRR* was nearly identical, while the median was somewhat larger for the full sample (16.6 versus 14.3 percent per year). For *MIRR*s based on Equation (4-7’) with a regression R^2 of 0.29, the average *MIRR* was again nearly identical, with a somewhat larger median for the full sample (12.5 versus 9.8 percent per year).

Comparing the *MIRR*s calculated with Equation (4-6), which did not rely on an approximation of the distributions of costs and benefits, to those calculated with Equation (4-7’) for the subsample of 270 evaluations reveals that the means, medians, and 1st and 3rd quartiles are all lower when using Equation (4-7’). This result is attributable to the fact that the average discount rate used to evaluate the *BCR* was 6.3 percent per year, which is higher than both the reinvestment and borrowing discount rates used in the calculations with Equation (4-7’). It is also attributable to our adjustment of costs to account for the marginal excess burden of taxation, and our adjustments of benefits to account for the proportion of benefits that are saved versus consumed. As the *MEB* in Equation (4-7’) is varied from 0 to 0.56 the median *MIRR* varies from 10.4 to 9.1 percent per year. Alternatively, varying the proportion of benefits reinvested in Equation (4-7’) from 0 to 0.5 results in variation in the median *MIRR* from 9.7 to 10.4 percent per year. Together these results show the robustness of the *MIRR* to alternative assumptions regarding the approximation methodology, the reinvestment and borrowing discount rates, the *MEB* of taxation, and the proportion of reinvested benefits.

4.6 Conclusion

The plethora of estimates of returns to agricultural R&D investments that have emerged since Griliches' seminal evaluation of hybrid corn suggests these investments have paid off handsomely, and continue to do so. Yet, contrary to what one might expect from this evidence, growth in agricultural R&D spending over the past several decades has ratcheted down in many countries—economists have failed to make their case to policy makers for the value of these investments. However, when considering the implications of the rates of return to agricultural R&D reported by economists over the past half a century and more, it is easy to understand why policy makers might be skeptical and choose to reject them.

The predominant measure of the rate of return to agricultural R&D investments used by economists during this time has been the internal rate of return (*IRR*). The *IRR* has prevailed even though it has been widely criticized, including by Griliches, for as long as it has been the preferred summary measure of investment performance in the agricultural R&D evaluation literature. We explore how the body of agricultural R&D rate of return evidence might have taken shape if economists had heeded Griliches' (and others') warnings and used some other summary measure for the returns to R&D. In particular, we explore the conceptually more appealing modified internal rate of return (*MIRR*), which as equations (4-6) and (4-7) reveal is just a direct transformation of the benefit-cost ratio.

Analytically, we show how the *IRR* must exceed the *MIRR* when the appropriate reinvestment and borrowing discount rates are below the *IRR*. Furthermore, we show

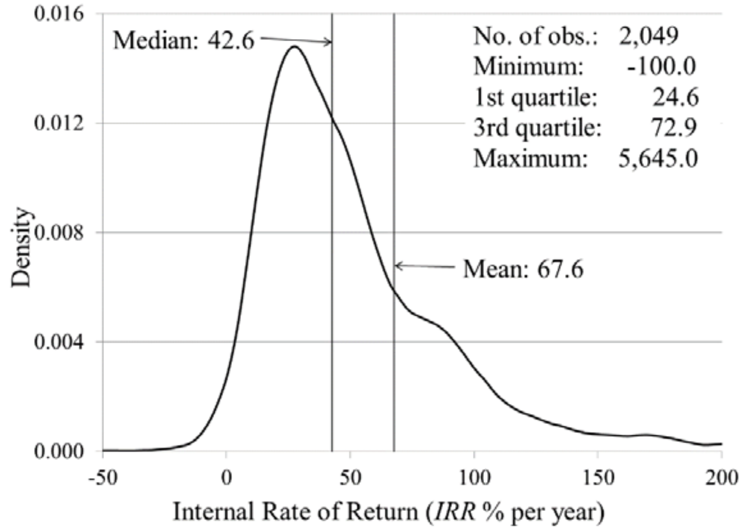
how the difference in the *IRR* and *MIRR* tends to be larger for more profitable investments when aggregate benefits exceed aggregate costs—which is typically the case explored in the agricultural R&D evaluation literature. These results are driven by the restrictive assumptions employed in the *IRR* calculation—the simultaneous equality of the reinvestment and borrowing discount rates and the *MIRR*. The magnitude of the difference, however, is an empirical question.

Using the *MIRR* to recast previous estimates of the *IRR*, we find much more muted returns to agricultural R&D: a median of 9.8 versus 39.0 percent per year (Table 4-1) or means of 13.6 versus 67.9 percent per year for the 270 *IRR* estimates we recalibrated. With a return of 39.0 percent per year, the U.S.'s $4.1 billion investment in agricultural R&D in 2000 would generate $58 quadrillion ($\times 10^{15}$) in net benefits by 2050—more than 390 times the projected world GDP in 2050. With a 9.8 percent per year rate of return, this investment would produce $439 billion—just 1.6 percent of the projected U.S. GDP in 2050. Overall, we find that the *MIRR* not only provides more muted, but also more plausible estimates for the rate of return to agricultural R&D for a wide range of assumptions regarding important aspects of the calculation.

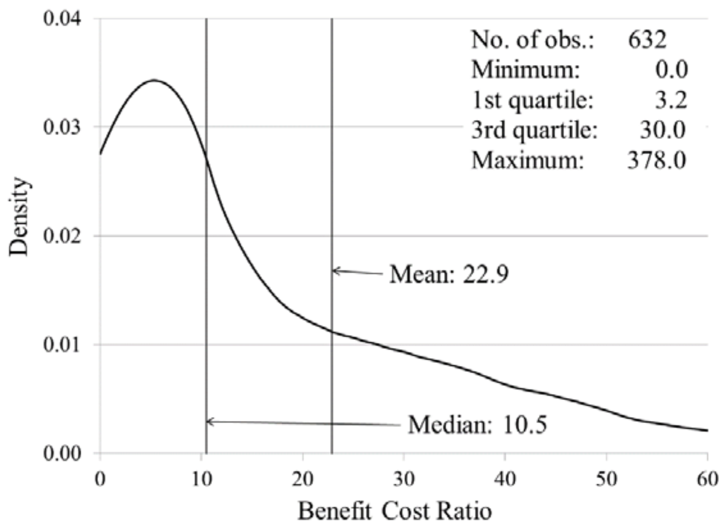
Our recalibrated estimates of the rates of return to public agricultural R&D are more modest but still substantial enough to question the current scaling back of public agricultural R&D spending in many countries. If this slowdown in the rate of growth of public spending continues, the growth in supply of important agricultural staples will fail to keep pace with the growth in demand, putting upward pressure on food prices and further stressing the world's most vulnerable populations.

It is fair to question whether our estimates of rates of return based on the *MIRR* are still too high. This may indeed be the case, which is why additional work remains to further refine the methodologies used to quantify research benefits and costs over time (Alston and Pardey 2001), and identify more appropriate discount rates whether they vary by benefits and costs (or over time as Hirshleifer (1958) suggests). Still, we do not think this in any way diminishes the importance of discarding the *IRR* as a summary measure of the performance of agricultural R&D or any other investments—a purpose for which it was never intended in the first place.

Panel a: *Internal Rates of Return*



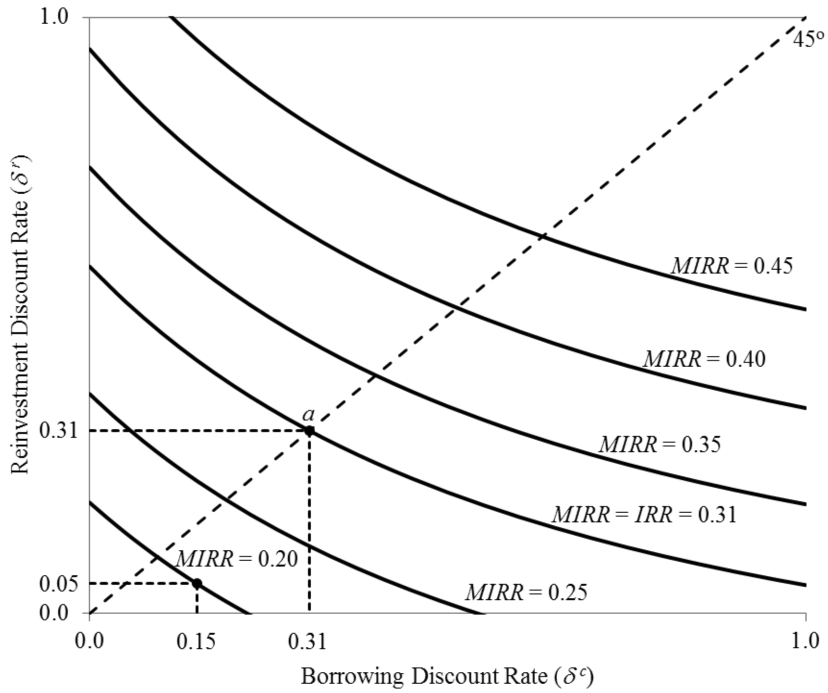
Panel b: *Benefit-Cost Ratios*



Source: Authors' compilation.

Note: Panel a represents a kernel density estimate (kernel = epanechnikov, bandwidth = 7.0) fitted across 2,049 *IRR* estimates. For presentation purposes, the plotted observations were truncated. Panel b represents a kernel density estimate (kernel = epanechnikov, bandwidth = 4.9) fitted across 632 *BCR* estimates. For presentation purposes, the plotted observations were truncated.

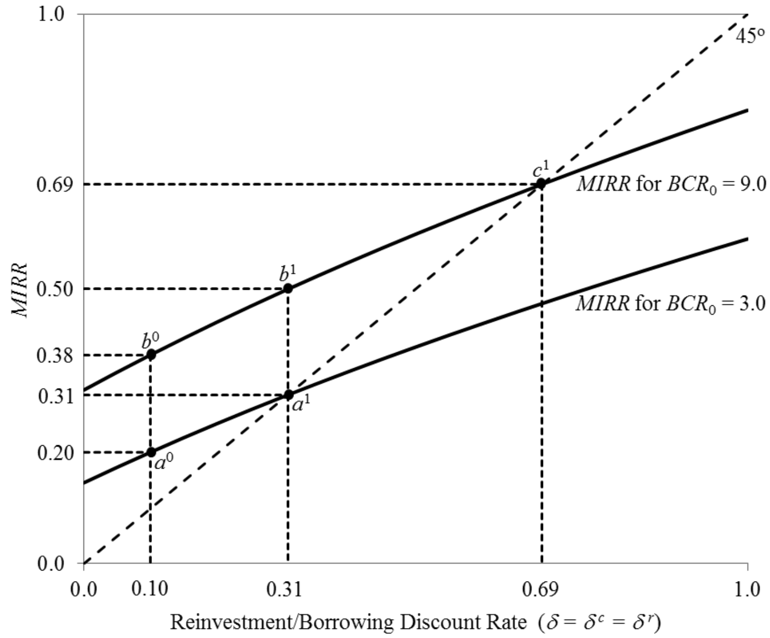
Figure 4-1 Distribution of reported internal rates of return and benefit-cost ratio estimates



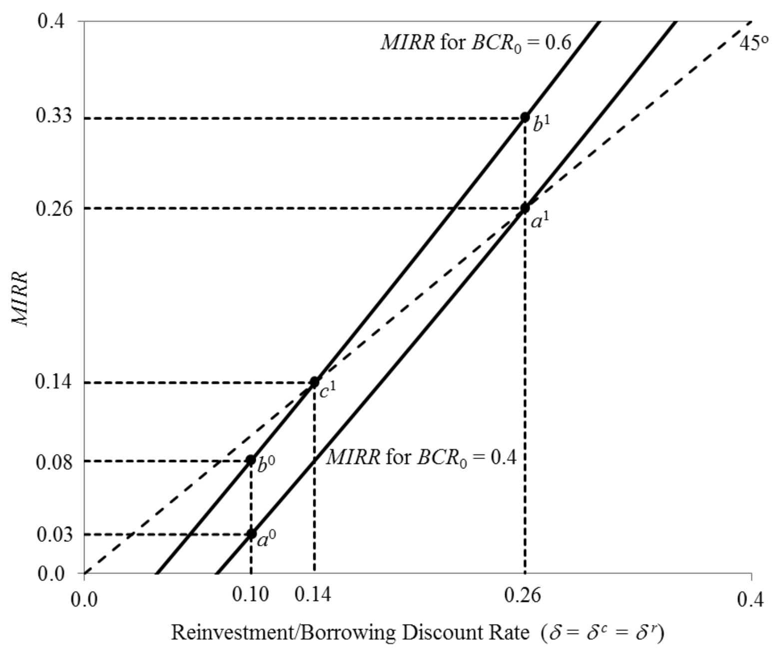
Source: Developed by authors. See supplementary online appendix section **Examples Used to Construct Figures 4-2 and 4-3**.

Figure 4-2 Example MIRR contour map given the reinvestment and borrowing discount rates

Panel a



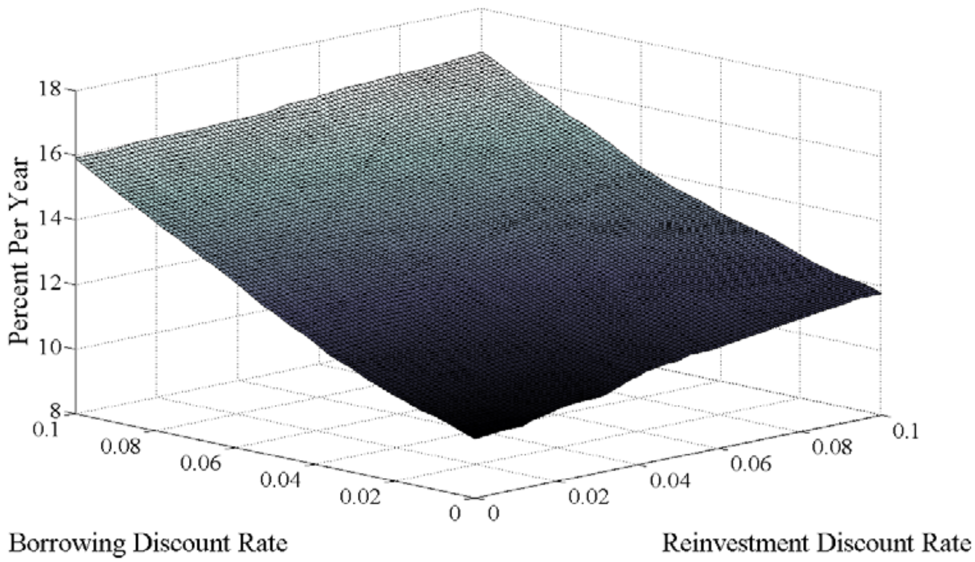
Panel b



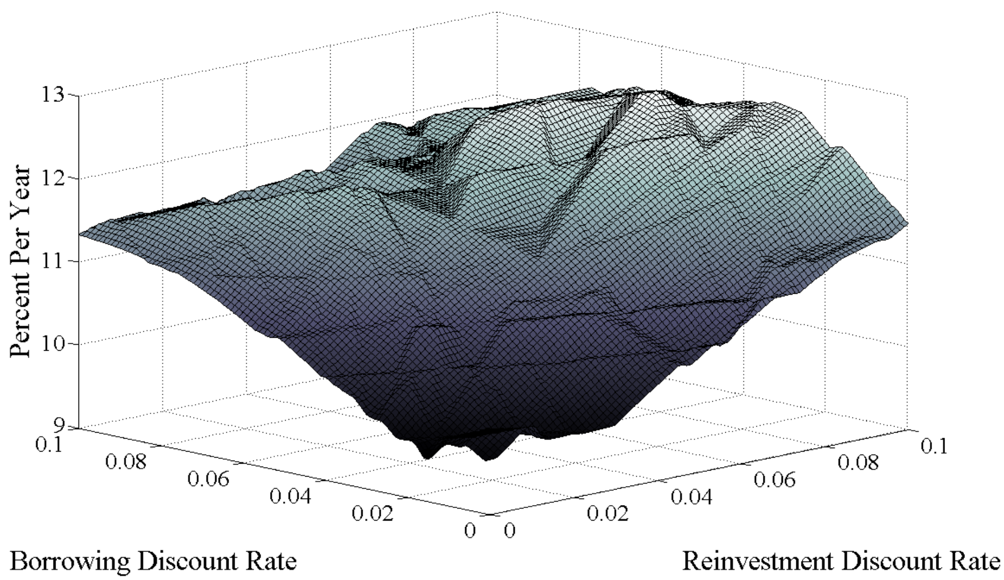
Source: Developed by authors. See supplementary online appendix section **Examples Used to Construct Figures 4-2 and 4-3**.

Figure 4-3 Example IRR and MIRR comparisons with increasing profitability

Panel a: Median of the modified internal rates of return

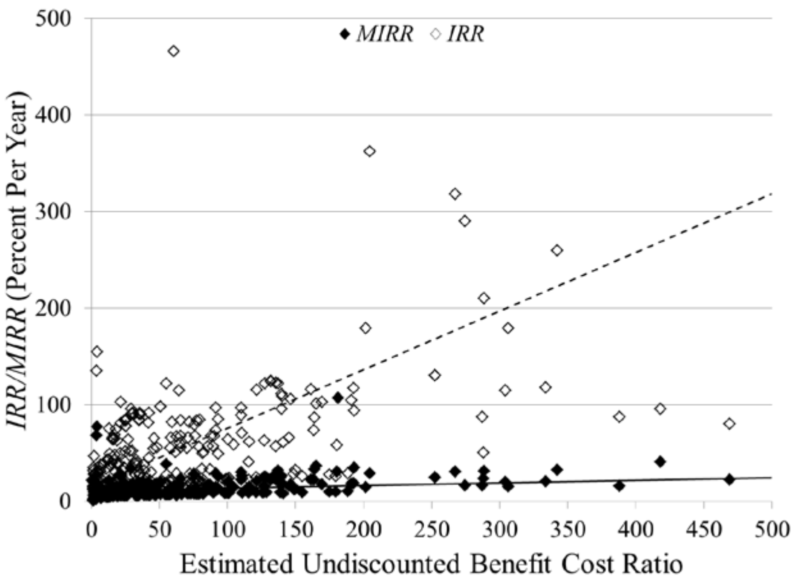


Panel b: Interquartile range of the modified internal rates of return



Source: Developed by authors.

Figure 4-4 Sensitivity of the modified internal rates of return to alternative reinvestment and borrowing discount rates



Source: Authors' estimates.

Note: We assume the reinvestment discount, borrowing discount, and saving rates are 3.5, 3, and 4.5 percent per year respectively, plus marginal excess burden (*MEB*) of taxation of 25 percent. For presentation purposes the plots have been truncated. The lines representing the best-fitting linear trends (solid for the *MIRR*s and dashed for the *IRR*s) are calculated based on the full range of data.

Figure 4-5 Comparison of the internal rates of return (IRR) to the modified internal rates of return (MIRR) estimated using Equation (4-7')

Table 4-1 Comparison of the Reported Internal Rates of Return (IRR) and Recalibrated Modified Internal Rates of Return (MIRR)

	IRR	***MIRR***	
		Equation (4-6) with $\boldsymbol{\delta^r = \delta^c = \delta}$	**Equation (4-7') with $\boldsymbol{\delta^r}$ = 3.5%, $\boldsymbol{\delta^c}$=3%, $\boldsymbol{\delta^s}$=4.5%, $\boldsymbol{\delta^{MEB}}$=25%**
		Percent Per Year	
Mean	67.9	17.8	13.6
Minimum	7.4	4.7	-2.0
1^{st} Quartile	21.6	10.0	7.8
Median	39.0	14.3	9.8
3^{rd} Quartile	81.8	22.0	16.9
Maximum	1,736.0	127.8	107.0
Observation with *IRR* < *MIRR*		0	0

Source: Authors' estimates.

Note: Comparison for the subsample of 270 evaluations that reported the *IRR*, benefit-cost ratio (*BCR*), discount rate used to calculate the *BCR*, and time when the investment's costs and benefits started and ended.

Chapter 5. Accounting for Variation in the Returns to Agricultural R&D[38]

5.1 Introduction

Research is a risky business. While the reported economic returns to investments in food and agricultural R&D (research and development) are high, on average—with a mean internal rate of return (IRR) of 67.6 percent per year for research conducted from 1958 to 2011 (Chapter 4)—, as one might expect there is a large dispersion in the returns to R&D around this average (Figure 5-1). The minimum is a dismal -100 percent per year, while the maximum is an incredible 5,645 percent per year. A closer look at the IRR estimates grouped into various categories (see Hurley, Rao and Pardey 2014, Supplementary Table S1) reinforces the notion that the returns to research are highly variable. For example, the mean reported IRRs for agricultural commodities range from 44.6 percent per year for research on natural resources to 256.0 percent per year for poultry research.

Figure 5-2 plots a moving average of the median of the reported IRRs indexed by two notions of time: one the publication date of the study that reported the estimated IRR, and the other the date of the initial investment in the R&D that gave rise to the reported IRR. A line of best fit through both these plots indicates little change in the moving-average-median of the reported rate of return over time when indexed by date of initial

[38] This chapter is coauthored with Terrance M. Hurley and Philip G. Pardey.

investment versus a decline in the moving-average-median return when indexed by the publication date of the study.

These stylized facts prompt two immediate and substantive questions. First, to what extent does the wide dispersion in the reported rates of return to returns reflect intrinsic differences in those returns versus differences in the methodologies used to estimate them? Second, and relatedly, does the decline in the median reported return to research stratified by publication date suggest a change in the methodologies used to estimate those returns is giving rise to this decline? To the extent the actual rate of return varies among areas of research or has declined over time, this would indicate that a reallocation of research resources is required. However, to the extent that methodological differences account for (at least some of) the variation in the reported rates of return to research, then the research investment implications of this evidence are less clear cut.

The research described in this chapter sets out to answer these two questions, and uses meta-evaluation methods applied to version 3 of the InSTePP rate-of-return database compiled by Hurley, Rao and Pardey (2014) to do so.[39] More specifically, we will examine the factors that account for the variation in the internal rate of return (IRR), or the effect size in the jargon of meta-analysis studies, thereby identifying crucial methodological details that induce variation in the reported returns to agricultural R&D

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[39] See their online appendix for a detailed procedure used to assemble the original rates of return database.

evaluations as well as provide clues to meaningfully addressing the policy questions listed above.

5.2 Conceptual Model

Meta-evaluation studies commonly involving pooling estimates of a variable of interest, in this case a measure of the rate of return to research, and then assessing the source of variation among these estimates. In this section, we briefly review the factors that arise in meta-evaluation studies in general and assessments of the rate-of-return estimates arising from the agricultural research evaluation literature in particular.

Sample Heterogeneity

The wide variation in the reported IRRs are attributable to two basic causes, factual and methodological. In the agricultural R&D evaluation literature, factual causes refer to variables associated with different aspects of the R&D investment, such as the research orientation (e.g., basic versus applied research), commodity orientation (e.g., crop research versus livestock research), geographical orientation (e.g., developing countries versus developed countries), and timing of the investment (as indicated, for example, by the initial year of the stream of R&D investments being evaluated).

For most of the variables falling within the “factual” category, there is no *a priori* knowledge or consensus regarding how changes in any one of these variable may affect the rate of return estimate. For example, many have speculated as to whether or not the rate of return of agricultural R&D conducted in developed countries is intrinsically higher than that conducted in developing countries, the answer to which has substantive implications for economic development policy. Similarly, it is not readily apparent whether or not the returns to agricultural R&D are likely to increase or decrease over time (Alston et al. 2000). On the one hand it maybe that all the easier (or less costly) research problems were tackled first, such that, other things being constant, one might expect there to be diminishing returns to R&D over time. On the other hand, more recent research stands on the ever-broader shoulders of the research that went before it, so to the extent that we accumulate new scientific insights, basic knowhow, and methods of research that open up entirely new scientific possibilities, then the returns to research might be expected to increase over time. Accounting for the effects of the myriad likely sources of variation in the reported returns to R&D can help reveal answers to important policy questions such as the time path of the (actual distinct from estimated) returns to R&D in ways that have important policy implications.

Setting aside the fundamental (or so-called factual) sources of variation in the reported returns to R&D, two other general sources of variation are differences among research evaluation studies in the methodological details they deployed, and differences arising by way of the widely dispersed nature of the publications—and by implication the review processes associated with these publications—from which the estimated returns to research were gleaned. Moreover, the nature of the agricultural R&D being evaluated, the institutional affiliations of authors, and their relationship with the research being evaluated (i.e., self-evaluation or not) are also other potential sources of variation in the reported returns to R&D. For example, authors of self-evaluation studies may have a tendency to overstate the returns to research (relative to the returns that would be estimated if the evaluation was undertaken by an evaluator external to the organization whose research is being assessed), although, as Alston et al. (2000) described, even this seemingly secondary issue is complicated and plausible, a priori, arguments can be made for a reversal in these postulated relative returns to research.

Finally, the wide array of methods and model specifications used in the R&D evaluation literature constitute another source of variation in the rates of return estimates. The most common variables of this kind include the choice of the rate of return measure (e.g., real versus nominal), assumptions about the time profile of the benefits from R&D (e.g., trapezoidal, polynomial, or free form), assumptions on various lags (i.e., research lag, gestation lag, and adoption lag), assumptions on spillover effects and the presence (or not) of various distortions in the economy (e.g., exchange rate, environmental impacts, and deadweight loss from taxation), and so forth. Some but not all of these variables may have an expected influence on the estimate indicated by the methodology. For instance, holding other things constant, a lower internal rate of return estimate should be expected from a longer gestation lag, since a longer gestation lag imposes an even bigger discount on the benefits. The same effect also applies to research lag, the truncation of which is likely to lead to upwardly biased econometric estimates of the returns to R&D as discussed by Alston, Craig and Pardey (1998). These theoretically established relationships will be useful in validating our empirical model.

When implementing any meta-analysis study, there are variables, either factual or methodological, that will influence the reported effect size but are either unobservable or lack the proper measurement. This is especially pertinent for a meta-analysis of the agricultural R&D evaluation literature, where the attributes among studies can vary in so many different ways that it is infeasible to completely characterize each and every study. Perhaps the most relevant aspect is the time path of the costs and benefits associated with an investment in research, which is missing or incomplete in many of the published studies. By construction, IRR estimates are especially sensitive to variation in the patterns of benefits and costs over time. Another source of variation concerns the method by which the IRR is estimated. We use a categorical score to differentiate between estimates arising from self-evaluations versus “external” evaluations, which surely fail to fully capture the differences in the extent, quality, and treatment of the data developed by an evaluator from within an institution versus one form outside the institution whose research is being assessed. Likewise, using dummy variables are also likely to capture all the relevant sources of differences among estimates generated by econometric versus market model approaches.

Correlation Within and Between Published Studies

There is the potential for correlation among IRR estimates drawn from the same publications, only some of which is captured by the variables designed to account for the variation in IRRs. IRR estimates from the same study are likely to be correlated to the extent they share the same underlying data and entail similar model specifications and other (undocumented) features by dint of their shared pedigrees. This interdependence among estimates can affect the statistical properties of a meta-analysis. The InSTePP rate-of-return database used for this study includes 2,049 IRRs drawn from 346 published studies averaging 5.9 IRR estimates per study (and ranging from 1 to 72 IRRs in a given study, with a median of three.

Moreover, IRR estimates sourced from different published studies may also be correlated to the extent they share common attributes, including, among other things, common or overlapping authorship. The InSTePP rate-of-return database has studies ranging from one to six author, with 578 unique author names across the 346 studies in version 3.0 of the database.[40] Table 5-1 gives a rank order listing of the top 20 authors differentiated according to number of time an author was associated with a published study (Panel a) and the number of times an author was associated with a published IRR estimate. The top 20 authors (or just 3.5 percent of the all authors in the database) account for 15 percent of the studies and 31.7 percent of the IRR estimates, leaving open the real possibility of author-induced correlation among a substantial share of the estimates.

Heteroskedasticity

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[40] The structure of the database limited the number of recorded authors per publication to a maximum of six. Thus there is potential for undercounting authors, but only four (one percent) of the publications reported more than six authors.

In many meta-evaluation studies, the impact variable (or effect size) of interest, be it the effect of certain medical treatment, is itself a stochastic variable estimated with error. To the extent this error is heteroskedastic, such that estimates with lower variance are deemed more reliable than estimates with higher variance it is common in meta-analyses to weight impact variables, with more relievable variables receiving higher weight (Hedges and Olkin 1985). This issue is particularly salient for meta-analysis whose effect size is estimated by way of clinical trials with varying numbers of patients. In these instances it is common practice for meta analyses to use the sample sizes, estimated variances, or related *t*-statistics reported in the published study as weights when conducting the meta study.

The nature of the data generation process is quite different for most if not all the research evaluation studies in the InSTePP database. IRR estimates in these evaluation studies reflect point estimates of the rate of return for a project, possibly under varying assumptions. Thus, they are not typically conceived as a stochastic variable.

5.3 Empirical Model and Data

Regression-based approaches using meta-evaluation methods have often been used to examine the likely source of variation in published effect-size estimates. Most economic studies use ordinary least squares (OLS) methods owing to their ease of implementation and interpretation (for example, Alston et al. 2000). In this context, this particular regression approach has several potential drawbacks. First, it fails to account for systematic unobservable factual and methodological variation across studies, and thus may lead to biased coefficient estimates. Second, by failing to specify a proper covariance structure, OLS models will generate non-robust standard errors. A potential remedy is to use weighted least squares or even generalized least squares models, which require strong assumptions on the nature of the correlation.

An alternative to using OLS methods is the panel data approach, particularly the fixed-effect (FE) panel data model[41], which can estimate a separate intercept for each panel but to do so requires multiple observations for each panel. The approach will not only consume degrees of freedom but by construction also reduces the sample size by excluding panels with a single observation, raising further concerns about sample selection. Moreover, the different number of observations across published studies will entail an unbalanced panel data model, which can further add to the heteroskedasticity problem (Baltagi 2005).

Given the purpose of this meta-analysis, potential issues in the reported rate of return estimates, and the nature of the available data, we opted to use a random-effect-size multi-level approach. To illustrate, we use subscript j to denote individual rate of return estimate and subscript i to denote groups of individual estimates. Rosenberger and Loomis (2000) point out that there are several possible ways to stratify individual estimates into levels or groups, which may be stratified by publication or authorship. Clustering the IRR estimates into different groups according to authorship results in too

[41] The random-effect panel data model will produce virtually identical estimates to those using multilevel/hierarchical model to be introduced right below.

many groups to generate efficient estimates for this analysis. We therefore proceeded by grouping individual IRR estimates according to their source publication, which in some instances were further grouped by their refereed versus non-refereed status as a robustness check.

Let R_{ij} represent the *j*-th rate-of-return estimate obtained from the *i*-th published study with $J = \sum_i J_i$ as the total number of estimates across studies. The multilevel model is written as

(5-1) $$R_{ij} = \alpha + \boldsymbol{\beta X}_{ij} + u_i + e_{ij}$$

In equation 5-1, α is a constant term, $\boldsymbol{X}$ is a vector of explanatory variables, and $\boldsymbol{\beta}$ is the corresponding vector of marginal effects. Moreover, e_{ij} is a level-one error term, which shows how an individual rate-of-return estimate deviates from the mean rate of return of the published study from which it comes, while u_i is a level-two error term, which shows how the mean of the rate of return from one particular published study deviates from the overall mean rate of return averaged across all studies. We assume e_{ij} and u_i to be independent and normally distributed with zero mean and a variance of σ_e^2 and σ_u^2, respectively. In this way, each individual rate-of-return estimate R_{ij} is modeled as a random draw from a distribution with a random mean $\alpha + \boldsymbol{\beta X}_{ij} + u_i$ instead of one with a deterministic mean $\alpha + \boldsymbol{\beta X}_{ij}$ as indicated in the GLS model, thereby controlling for the systematic unobserved variation. With this setup, the intercept $\alpha + u_i$ is now random across each of the published studies while the slope parameters $\boldsymbol{\beta}$ are constant. Thus we are estimating a random intercept rather than a random slope multilevel model, where $\boldsymbol{\beta}$ varies across published studies[42]. Finally, in order to derive consistent estimates for $\boldsymbol{\beta}$, the random intercept $\alpha + u_i$ is assumed to be independent of the explanatory variables $\boldsymbol{X_{ij}}$, and the error term e_{ij} is also assumed to be independent of $\boldsymbol{X_{ij}}$.

To mitigate the influence of outliers, we use the natural log of the IRRs which introduces two additional estimation consequences for this meta-analysis. First, observations reporting a non-positive IRR estimate must be excluded from the regression analysis, raising concerns over potential sample selection bias. In practice this is likely to be of little consequence in this study. There are just 31 non-positive IRR estimates out of a total of 2,049 estimates; barely 1.5 percent of the total. Second, the logarithmic transformation ameliorates the effects of outliers. Figure 5-1 shows that the distribution of IRR estimates in our sample are right-skewed distribution. The mean is 67.6 percent per year and 50 percent of the observations lie in the range of 24.6 to 72.9 percent per year. There are 512 observations in the upper tail of the distribution above the 3rd quartile, the maximum being 5,645 percent per year. By contrast, the distribution of the logarithmic transformation of the IRRs is close to normal[43], and the range is much reduced, thus diminishing concerns about unrepresentative or overly influential observations, especially in the upper tail of the distribution.

[42] An alternative is to estimate a random slope multilevel model, which significantly increases the number of parameters to be estimated. In fact, the underlying maximum likelihood estimation fails to converge for such a model using our data.

[43] Applying a skewness and kurtosis test for normality to the sample of 2,018 logarithmic IRR estimates, we reject the null hypothesis of normal distribution based on the calculated p-value of 0.0000.

Following the common practice of meta-analysis using stratified survey data, we opted to use the number of IRR estimates in each published study as weights to normalize the contribution of each published study in accounting for variation in the reported returns to research. For example, if study A contains three estimates and study B contains only one, then the IRR estimates from study A are each assigned a weight of one third (given these estimates are likely to be highly correlated), while the sole IRR estimate from study B enters the analysis unweighted (i.e., implicitly has a weight of one).

As did Alston et al. (2000), the variables we used to account for variation in the reported rates of return were notionally grouped into four basic categories: characteristics of the rate of return measure, characteristics of the analyst (in this instance, the first author of each published study), characteristics of the research project, and characteristics of the research evaluation. Our regression sample contains 1,303 IRR estimates from 241 published studies[44]. Comparing this regression sample to the remaining 746 IRRs in the full sample of the InSTePP database using the two-sample Kolmogorov-Smirnov test, we reject the equality of the distributions (D=0.10, p<0.00). Table 5-2 presents the summary statistics of the reported IRRs in the regression sample conditional on (most of the) explanatory variables. Most of the variables are dummies generated from the corresponding categorical factors used in the survey book, such as the geographical location of the research performer and commodity focus of the research. Continuous

[44] By comparison, Alston et al.'s (2000) study included 1,128 IRR observations in their regression analysis out of a total of 1,884 observations. The 756 excluded observations lacked information on one or more of the required explanatory variables.

variables used in this analysis include the publication date (by year) of each published study, the first year when the research investment was made, as well as the total research lag and the gestation lag, which were both measured in years. In addition, we add an interaction term between nominal IRR and developing countries and one between nominal IRR and developing countries for reasons argued in Alston et al. (2000).

5.4 Results and Interpretation

Stata's *xtmixed* command was used to estimate Equation (5-1) with relevant syntax specifications. Appendix Table 5-3 shows the estimation outputs, which are divided into three sections. On top right of the table is descriptive information about the multilevel regression analysis, such as the number of groups (i.e., published studies) included in the regression. Then upper section of the table provides estimates of the constant term and the associated explanatory variables, $\boldsymbol{\beta}$. The lower part of the table reports the estimates for the variance components, σ_e^2 and σ_u^2. Based on information in this table, we can compute the intra-class correlation (ICC), which measures how strongly individual observations in the same group resemble each other. The ICC estimator used in this study is defined as

(5-2)
$$ICC = \frac{\hat{\sigma}_u^2}{\hat{\sigma}_u^2 + \hat{\sigma}_e^2}$$

Substituting 0.35 for $\hat{\sigma}_u^2$ and 0.24 for $\hat{\sigma}_e^2$, the ICC is estimated to be 0.59, meaning that after controlling for the explanatory variables, 59 percent of the overall variance in the reported IRR estimates is attributable to differences in the IRRs among published studies with the remaining 41 percent attributable to differences in the IRRs within the same published studies.

Calculation of Marginal Effects on IRR

The dependent variable is expressed in logarithmic form in this regression model, whereas we are ultimately interested in the marginal effects of each of the explanatory variables (or a group of explanatory variables) on IRR (in level or natural form). To translate the estimates for $\boldsymbol{\beta}$, which are merely semi-elasticity estimates, into the marginal effects of each explanatory variable on IRR, requires calculating the corresponding percentage effects; that is, the percentage change in the dependent variable given a marginal change in each of the explanatory variables. The nature of the transformation is different for continuous versus discrete (or dummy) variables, both of which appear in our model. For each of the continuous variables, we multiply their respective $\boldsymbol{\beta}$ estimates by 100; for each of the discrete or dummy variables we use the almost-unbiased estimator suggested by Kennedy (1981)[45]. Table 5-4 displays the estimated percentage effects of all explanatory variables with their corresponding statistics.

[45] There is a well-established literature on interpreting a dummy variable's coefficient when the dependent variable has been log-transformed (in other words, when it is a log-linear model). David Giles (1982) derived the exact minimum variance unbiased estimator for the percentage effects. However, the calculation is rather convoluted and in practice it adds very little improvement to Kennedy (1981)'s estimator (Steward, 2004). Therefore, here we choose Kennedy's estimator for convenience without too much loss of accuracy.

The second step in estimating marginal effects is to fix the IRR at a reference level to which the marginal changes are applied. Given that most of our explanatory variables are dummy variables generated from categorical factors, a sensible approach is to take the minimum value, i.e., zero, of those variables as the reference level. By doing that, we are setting the reference IRR at a level where the default categories prevail, i.e., the real-term, average IRR for privately-funded research and so on and so forth (See Table 5-2 for the default categories). For the continuous variables we benchmark the analysis at the mean values for the gestation lag (4.4 years) and the research lag, (21.6 years) and set both the publication date and beginning year of investment at 2000. Doing this means that our assessment of the marginal effects of each explanatory variable on the IRR to investments in R&D are somewhat comparable to those reported in Alston et al. (2000).

With this calibration, the benchmark IRR for assessing the marginal effects derived from the multilevel regression model is 53.38 percent per year, which is the point of reference for the marginal effects reported in Table 5-5, Column 1. For comparison, Table 5-5, Column 2 presents the same marginal effects, again using the multilevel model but this time benchmarked off the mean value of the IRRs in the regression sample which is 65.87 percent per year.[46] Further, we estimate two alternative OLS models, one with IRR as the dependent variable and the other with the log-form IRR, and calculated the respective marginal effects. These are presented in Columns 3 and 4 respectively of

[46] The median value of the IRRs used in the regression is 44 percent per year.

Table 5-5. It is evident that different model specifications return different, in some cases quite different, marginal effect estimates.

Interpretation of Marginal Effects

The explanatory variables that have statistically significant and positive marginal effects on the IRR estimate include *University researcher*, *Private research performer*, C*rops*, *Livestock*, and S*pill-outs*. Those variables that have significant negative marginal effects include *Marginal IRR*, *Extension Only*, *Research & extension*, *International funder*, *Private sector researcher*, *Public and private R&D*, *Program evaluated*, *Institution-wide*, *Multi-institutions*, *Pivotal demand shift*, *Lag gestation*, and *Spill-ins*.

(1) Characteristics of the rate of return measure

Firstly, marginal IRR estimates are found to be more than 9 percentage points lower than average IRR estimates. Compared with *Research only* (the default group), the IRRs to *Extension only* and *Research and extension* are found to be 25 and 6 percentage points lower respectively, a relationship that is statistically significant and consistent with our expectation. This is because the cost of extension effort is not accounted for in the research-only measures, whereas extension effects are difficult to exclude from the benefit stream (Alston et al. 2000). Social rates of return to research should be greater than private returns provided that there are positive spillovers. However, our finding suggests no difference between social and private rates of return. Some think *ex post* studies are likely to report higher than normal IRRs to the extent the studies are cherry picked and thus more likely to evaluate “successful” research. Alternatively, *ex post* studies may report smaller than normal IRRs to the extent they are based on observed past outcomes rather than the hypothetical, and perhaps overly optimistic, future outcomes that are incorporated into *ex ante* studies. We reveal no significant difference between ex post versus ex ante IRRs, holding other things constant.

Some caution is warranted when assessing the marginal effect of the nominal-term IRR measure, as this effect is jointly determined by the coefficient estimates for *Nominal ROR*, its interaction term with *Developing countries*, and its interaction term with the period of the 1970s. None of the three coefficient estimates are statistically significant though the joint effects may be deemed influential in an economic sense. Our results suggest that, other things held equal, the nominal IRR for agricultural research carried out in a developing country is more than 6 percentage points (7.99 minus 1.67) higher than its counterparts in real terms. It also suggests that the nominal IRR for a research investment made in the inflationary 1970s is as much as 12.3 percentage points (13.94 minus 1.67) higher than those in other periods.

(2) Characteristics of the analyst

There are appreciable differences in the estimated IRRs among authors with different institutional affiliations. For example, researchers associated with universities tend to report IRRs that are 11 percentage points higher than those associated with governments (the default group). Meanwhile, the IRRs reported in self-evaluation studies are more than 10 percentage points higher than otherwise, although this difference is not statistically significant.

(3) Characteristics of the research

Among all the types of institutional affiliations we tagged in our study, research performed by private institutions (134 cases in the regression sample) yields IRRs that are 26 percentage points higher than the IRRs for other types of institutions. With research classified as *All agriculture* being the default group, IRRs are about 21 percentage points higher for crop research and 18 percentage points higher for livestock research. Compared with research that is either publicly or privately funded research, research that is jointly funded by both sources report significantly lower IRRs (nearly 14 percentage points). Notably, our results suggest there is no significant difference between IRRs for research done in developed versus developing countries, or between basic research and non-basic research (i.e., applied research, extension, and research jointly with extension). Finally, and of significant policy interest, after accounting for a host of methodological and other attributes that affect the returns to research we find no evidence that these returns have been trending either up or down over time. Across all model specification, the coefficient on the *Beginning year of costs* variable is trivially small and lacks statistical significance.

(4) Characteristics of research evaluation

The sign and relative size of the estimated coefficients for variables proxying differences among studies in their evaluation methodologies are more predictable, and thus useful in assessing the suitability of our model. For example, more aggregative studies (that encompass successful and unsuccessful research) are more likely to report lower rates of return, a prior that is consistent with our estimated effects for *Program evaluated,* *Institution-wide* and *Multi-institutions* where *Single Project* is the default group. We estimate that increasing the gestation lag by a year reduces the IRR by about 3.8 percentage points, again consistent with our priors. Likewise, the sign on the research lag coefficient is negative, meaning longer lags are associated with lower IRRs. This is also consistent with our priors, and although the magnitude of the estimated effect is sizable, the coefficient is statistically insignificant

Both *Spillins* and *Spillouts* report statistically significant coefficient estimates with opposite signs that is also conforms to our priors. When the spill-in of benefits from other research projects is excluded from the target region, our model suggests that the rate of return estimate will be 12 percentages lower than otherwise. In contrast, when spillout benefits are included, the estimated IRR is more than 25 percentages higher than if these benefits were ignored, as one would expect. Finally, when both spill-in and spill-out benefits are accounted for the net effect is intrinsically ambiguous. In our study, this net effect is statistically insignificant.

One might expect refereed studies to report more conservative estimates (that may be more likely to make it past the scrutiny of reviewers and editors alike) and we find that to be the case (although the difference is not statistically significant). In fact, some of the more implausible IRR estimates in our regression sample (e.g., the highest estimate of 5,645 percent per year) were sourced to refereed studies.

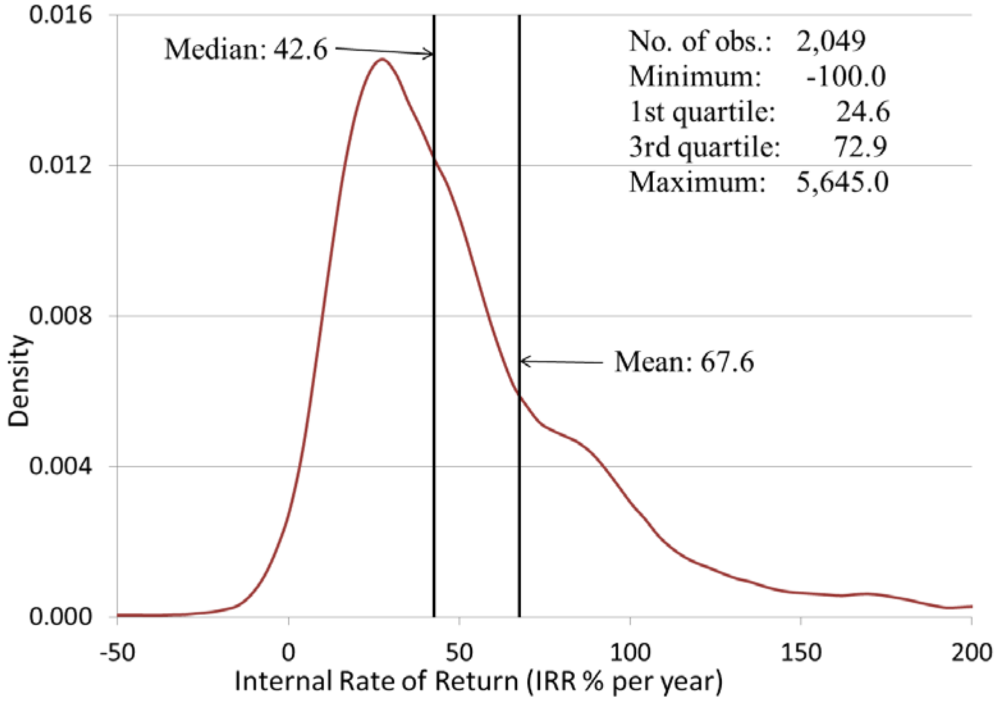
As a robustness check of our model, we estimated a random-intercept three-level model with publication type added as the third level in order to test more formally whether refereed versus non refereed publications account for systematic differences in the reported IRRs. Our results indicate that the variation between the two groups explains a minimal amount of the overall variation, thereby fail to reject the null hypothesis that there is no systematic difference between refereed and non-referenced publications in the agricultural R&D literature.

Finally , a number of remaining methodological attributes—such as publication date, distorting policy effects, and supply/demand system assumptions—were of little if any statistically significant consequence in accounting for measured variation in the reported IRR to research.

5.5 Conclusion

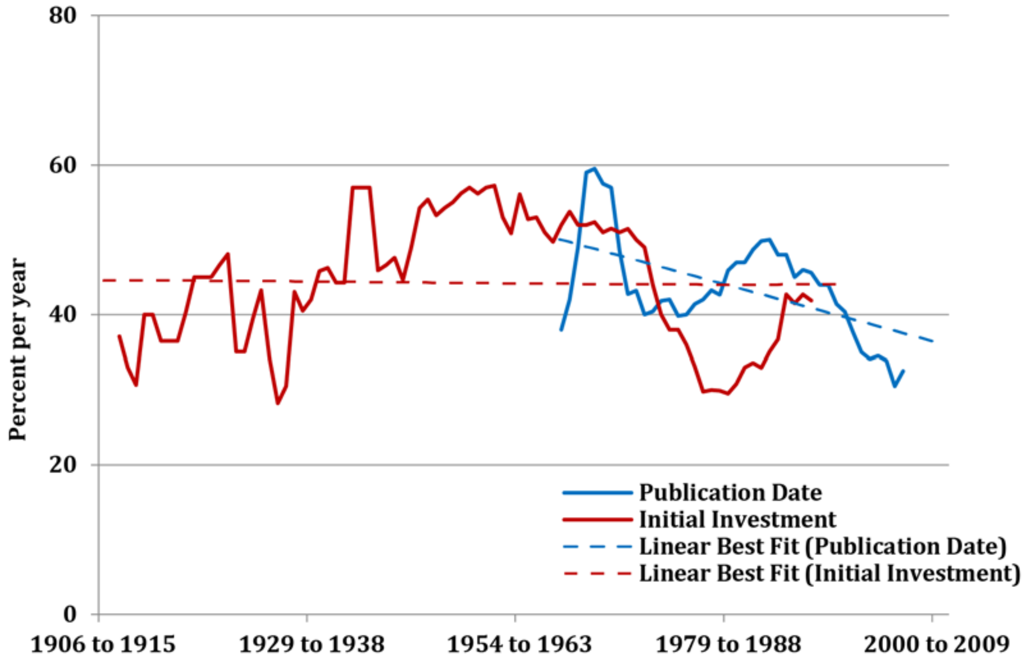
This chapter reports the results of a meta-analysis of the sources of variation in 1,303 IRR estimates gleaned from 241 published studies over the past half century on the returns to agricultural research around the world. After controlling for unexplainable heterogeneity, correlation, and other methodological issues, we identified factual and methodological variables that account for the variation in the reported IRRs. Among the factual variables, i.e., those associated with different aspects of an R&D investment, the public versus private nature of R&D, its commodity orientation, the institutional affiliation of the analyst and the research performer all have significant influences on the IRR estimates. Methodological variables that were statistically significant in accounting for variation in the reported IRRs included the scope of R&D, the type of IRR measure (i.e., marginal versus average), the institutional orientation of the R&D, assumptions about the supply/demand shift, the presence or absence of spillover effects, and the length of gestation lag.

These findings have several important implications. First they reveal that differences in the methodological approaches employed by different studies have measurable and significant consequences for the measured IRR to research. A failure to fully document these methodological differences compromises the value of these evaluation efforts, especially if the estimated rates of return are being compared with ostensibly similar measures from other studies. Secondly, our findings help clarify long-standing speculations concerning several important policy-related issues. After accounting for multiple sources of variation in the reported returns to R&D, we find in favor of higher-than-average rates of return crops and livestock research vis-à-vis other types of research (such as research on natural resource issues). Our results also indicate there is no appreciable difference in returns to agricultural R&D performed in developed versus developing countries, and, critically, that the returns to investments in agricultural R&D have not waned over time. The payoffs to recent spending on food and agricultural R&D appear as high as they were in yesteryears. This calls into serious question the widespread decline in the rate of growth of investment in (public) food and agricultural R&D, especially if the purpose of those investments is to sustain and spur productivity growth ion agriculture that eventually reveals itself in the returns to R&D estimates studied here.



Data source: Hurley, Rao, and Pardey (2014).

Figure 5-1 Kernel Distribution of the Reported Rate of Return Estimates



Data source: Hurley, Rao, and Pardey (2014).

Figure 5-2 Moving Median of Reported Internal Rates of Return Over Time

Table 5-1 Contributions by Top Authors to Rate of Return Primary Studies and Estimates

Panel a Contributions to Primary Studies

Rank	Author	No. of studies	Percent
1	Evenson R	30	2.53
2	Thirtle C	17	1.43
3	Norton G	11	0.93
4	Davis J	9	0.76
5	Scobie G	9	0.76
6	Araji A	8	0.67
7	Avila A	8	0.67
8	Brinkman G	8	0.67
9	Fox G	8	0.67
10	Huffman W	8	0.67
11	Mullen J	8	0.67
12	Alston J	7	0.59
13	Byerlee D	7	0.59
14	Lubulwa G	7	0.59
15	Bottomley P	6	0.51
16	Pardey G	6	0.51
17	Traxler G	6	0.51
18	White F	6	0.51
19	Fan S	5	0.42
20	Khatri Y	5	0.42
	Sum	179	15.08
	Total	1,187	100.00

Panel b Contributions to Estimates

Rank	Author	No. of estimates	Percent
1	Evenson R	227	4.34
2	Araji A	141	2.70
3	Norton G	136	2.60
4	Alston J	117	2.24
5	Thirtle C	111	2.12
6	Pardey G	103	1.97
7	Brinkman G	84	1.61
8	Dey M	73	1.40
9	Fox G	68	1.30
10	Prein M	65	1.24
11	Briones R	64	1.22
12	Stobutzki I	64	1.22
13	Anderson M	55	1.05
14	James J	55	1.05
15	Byerlee D	53	1.01
16	Scobie G	53	1.01
17	Sim R	52	0.99
18	Nagy J	47	0.90
19	Mullen J	46	0.88
20	Lu Y-C	43	0.82
	Sum	1,657	31.69
	Total	5,229	100.00

Source: Developed by authors.

Table 5-2 Conditional Mean Internal Rate of Return (IRR) for Explanatory Variables in Regression Data Set

	Summary Statistics				Summary Statistics		
Default category	Count	Mean	S.D.	Explanatory variables	Count	Mean	S.D.
	(percentage)				(percentage)		
Characteristics of the rate of return measure							
Real	1,076	65.26	103.10	Nominal	227	68.77	56.20
Ex ante evaluation	170	70.27	170.13	Ex post	1,133	65.21	80.02
Average	724	56.23	91.01	Marginal	579	77.93	101.91
Private	96	40.79	102.32	Social	1,207	67.87	95.87
Research only	751	77.25	118.72	Extension only	42	88.63	103.06
				Research & extension	510	47.25	40.63
Characteristics of the analyst (first author)							
First author affiliation – government	223	74.30	148.37	University researcher	876	68.09	88.76
				International researcher	82	47.27	26.57
				International funder	17	35.95	26.53
				Private sector researcher	48	47.51	41.31
				Unknown affiliation	57	49.90	46.17
Independent assessment	831	61.77	74.39	Self-evaluation	215	67.19	144.30
				Unclear evaluation type	257	78.04	109.00
Characteristics of the R&D							
Government research performer	977	60.13	82.46	University research performer	337	80.89	104.42
				International organization research performer	63	44.23	24.10
				Private researcher performer	134	57.22	45.10
				Unknown research performer	200	74.78	130.67
Commodity focus -- All agriculture	698	59.77	84.55	Crops	147	66.99	61.71
				Livestock	305	72.13	117.15
				Natural resource & forestry	25	46.49	33.04
				Aquaculture & fishery	8	25.25	6.23
				Other commodity	120	90.81	138.14

Table 5-2 continued

Default category	Summary Statistics Count	Mean	S.D.	Explanatory variables	Summary Statistics Count	Mean	S.D.
Scope of R&D specified as non-basic	1,298	65.98	96.72	Basic research	5	38.82	39.82
Public R&D	1,120	64.29	94.35	Private R&D	13	79.77	68.11
				Public and private R&D	170	75.26	111.62
Developing country performers	536	56.68	60.28	Developed country performer	697	74.24	116.76
Characteristics of the R&D evaluation							
Single project evaluated	829	74.66	115.91	Program evaluated	249	52.02	48.18
				Institution-wide	209	48.60	35.33
				Multi-institution	16	51.63	19.20
Non-refereed publication	885	68.52	107.27	Refereed publication	418	60.27	68.43
Non-econometrically estimated supply shift	701	53.82	93.81	Econometric supply shift	602	79.91	97.92
Benefits calculated using an implicit surplus model	829	74.66	115.91	Pivotal supply shift	249	52.01	48.18
				Parallel supply shift	209	48.60	35.33
				Pivotal demand shift	0	N.A.	N.A.
				Parallel demand shift	16	51.63	19.20
Industry data for supply shift	906	67.71	84.71	Experimental data	397	61.68	119.33
Spillovers not considered	1,014	60.00	95.99	Spill-ins	173	108.64	106.24
				Spill-outs	19	128.02	123.84
				Both spill-ins and spill-outs	97	38.80	31.66
Distortions not considered	1,084	69.27	104.52	Farm program distortion	93	53.79	30.94
				Exchange rate distortion	70	52.66	36.78
				Deadweight losses from taxation	8	53.85	36.98
				Environmental impacts	0	N.A.	N.A.
				Other distortion	0	N.A.	N.A.
Overall IRR	1,303	65.87	96.57				

Source: Developed by authors.

Table 5-3 Stata *xtmixed* Output for a Random Intercept Two-Level Model

Mixed-effects regression — Number of observations = 1303
Group variable: Publication ID — Number of groups = 241
Observations per group: minimum = 1
Average = 5.4
Maximum = 55
Wald chi2(47) = 564.54
Log pseudolikelihood = -12446.451 — Prob > chi2 = 0.0000
(Std. Errors adjusted for 241 clusters in Publication ID)

ln_ROR	Coef.	Robust Std. Err.	z	P>z	[95% Conf.	Interval]
Nominal IRR	-0.0168	0.1731	-0.1000	0.9230	-0.3560	0.3224
Publication date	-0.0081	0.0077	-1.0500	0.2940	-0.0232	0.0070
Nominal IRR × developing countries	0.1566	0.1859	0.8400	0.4000	-0.2078	0.5211
Nominal IRR × 1970s	0.2453	0.1631	1.5000	0.1330	-0.0744	0.5649
Ex post study	0.0723	0.2053	0.3500	0.7250	-0.3301	0.4748
Marginal IRR	-0.1728	0.1140	-1.5200	0.1300	-0.3962	0.0506
Social IRR	-0.2374	0.6459	-0.3700	0.7130	-1.5034	1.0285
Extension only	-0.5562	0.4073	-1.3700	0.1720	-1.3546	0.2421
Research & Extension	-0.1196	0.0498	-2.4000	0.0160	-0.2173	-0.0219
University researcher	0.1999	0.1233	1.6200	0.1050	-0.0418	0.4416
International researcher	-0.1461	0.2117	-0.6900	0.4900	-0.5611	0.2689
International funder	-0.5636	0.3643	-1.5500	0.1220	-1.2775	0.1504
Private sector researcher	-0.5876	0.3078	-1.9100	0.0560	-1.1909	0.0157
Unknown affiliation	0.0177	0.2370	0.0700	0.9400	-0.4469	0.4823

Self evaluation	0.1846	0.1317	1.4000	0.1610	-0.0735	0.4428
Unclear evaluation type	0.2001	0.1458	1.3700	0.1700	-0.0856	0.4858
University research performer	0.3705	0.2312	1.6000	0.1090	-0.0827	0.8236
Intl institute research performer	-0.0356	0.1387	-0.2600	0.7970	-0.3075	0.2362
Private research performer	0.4270	0.2436	1.7500	0.0800	-0.0504	0.9044
Unknown research performer	-0.0892	0.1694	-0.5300	0.5980	-0.4212	0.2428
Crops	0.3352	0.0984	3.4100	0.0010	0.1424	0.5280
Livestock	0.2964	0.0803	3.6900	0.0000	0.1389	0.4538
Natural resource & forestry	0.1294	0.2544	0.5100	0.6110	-0.3692	0.6280
Aquaculture & fishery	-0.0759	0.7485	-0.1000	0.9190	-1.5429	1.3911
Other commodity	0.2747	0.1882	1.4600	0.1440	-0.0940	0.6435
Basic research	0.2464	0.3568	0.6900	0.4900	-0.4530	0.9457
Private R&D	-0.1889	0.4750	-0.4000	0.6910	-1.1200	0.7421
Public and Private R&D	-0.2971	0.0912	-3.2600	0.0010	-0.4759	-0.1184
Developed country performer	-0.1147	0.1421	-0.8100	0.4200	-0.3932	0.1638
Program evaluated	-0.4084	0.0720	-5.6700	0.0000	-0.5494	-0.2673
Institution-wide	-0.2123	0.1787	-1.1900	0.2350	-0.5626	0.1379
Multi-institutions	-0.2424	0.1370	-1.7700	0.0770	-0.5109	0.0261
Refereed publication	-0.0275	0.1003	-0.2700	0.7840	-0.2241	0.1691
Econometric supply shift	0.0139	0.1532	0.0900	0.9280	-0.2863	0.3140
Pivotal supply shift	0.0258	0.1415	0.1800	0.8550	-0.2516	0.3032
Parallel supply shift	-0.0063	0.1891	-0.0300	0.9730	-0.3769	0.3643
Pivotal demand shift	-0.6806	0.1450	-4.6900	0.0000	-	-

					0.9649	0.3963
Experimental data for supply shift	-0.1128	0.2600	-0.4300	0.6640	-0.6224	0.3968
Research lag	-0.0028	0.0100	-0.2800	0.7780	-0.0225	0.0168
Gestation lag	-0.0709	0.0401	-1.7700	0.0770	-0.1496	0.0077
Spill-ins	-0.2573	0.0723	-3.5600	0.0000	-0.3989	-0.1156
Spill-outs	0.4008	0.1180	3.4000	0.0010	0.1695	0.6320
Both spill-ins and spill-outs	0.2694	0.2697	1.0000	0.3180	-0.2591	0.7980
Farm program distortion	-0.0427	0.1570	-0.2700	0.7860	-0.3505	0.2651
Exchange rate distortion	0.0529	0.1056	0.5000	0.6160	-0.1541	0.2599
Environmental impact distortion	-0.2317	0.3155	-0.7300	0.4630	-0.8502	0.3867
Deadweight loss distortion	0.0000	(omitted)				
Other distortion	0.0000	(omitted)				
Beginning year of costs	0.0004	0.0005	0.8800	0.3790	-0.0005	0.0013
Constant	19.6505	15.8216	1.2400	0.2140	-11.3593	50.6602

Random-effects Parameters	Estimate	Robust Std. Err.	[95% Conf. Interval]	
Publication ID: Identity				
Variance (Constant)	0.3502	0.0475	0.2684	0.4568
Variance (Residual)	0.2380	0.0401	0.1711	0.3311

Source: Developed by authors.

Notes:

1. The coded variable names have been replaced with the corresponding economic names.
2. The estimates for *Deadweight loss distortion* and *Other distortion* are omitted because of collinearity in the data.

Table 5-4 Estimates of Percentage Effect on the Internal Rate of Return (IRR) Measure

Number of observations = 1,303

Variables	Percentage Effect Coefficient	Robust Standard Error	z	P>|z|	[95% Conf.	Interval]
Nominal IRR	-3.13	16.64	-0.19	0.43	-35.78	29.52
Publication date	-0.81	0.77	-1.05	0.15	-2.32	0.70
Nominal IRR × developing countries	14.95	21.19	0.71	0.24	-26.62	56.53
Nominal IRR × 1970s	26.11	20.43	1.28	0.10	-13.97	66.19
Ex post study	5.26	21.39	0.25	0.40	-36.70	47.22
Marginal IRR	-16.42**	9.50	-1.73	0.04	-35.05	2.22
Social IRR	-35.98	37.39	-0.96	0.17	-109.33	37.37
Extension only	-47.23**	20.63	-2.29	0.01	-87.71	-6.75
Research & Extension	-11.38***	4.41	-2.58	0.01	-20.04	-2.72
University researcher	21.20*	14.89	1.42	0.08	-8.01	50.41
International researcher	-15.51	17.69	-0.88	0.19	-50.21	19.20
International funder	-46.74***	18.78	-2.49	0.01	-83.57	-9.90
Private sector researcher	-47.00***	15.93	-2.95	0.00	-78.26	-15.75
Unknown affiliation	-1.03	23.13	-0.04	0.48	-46.42	44.35
Self evaluation	19.24	15.64	1.23	0.11	-11.44	49.92
Unclear evaluation type	20.86	17.52	1.19	0.12	-13.52	55.24
University research performer	41.02	32.17	1.28	0.10	-22.10	104.14
Intl institute research performer	-4.42	13.19	-0.34	0.37	-30.31	21.46
Private research performer	48.79**	35.71	1.37	0.09	-21.27	118.85
Unknown research performer	-9.84	15.17	-0.65	0.26	-39.59	19.91
Crops	39.15***	13.66	2.87	0.00	12.35	65.94
Livestock	34.06***	10.75	3.17	0.00	12.97	55.16
Natural resource & forestry	10.19	27.58	0.37	0.36	-43.92	64.30
Aquaculture & fishery	-29.95	45.87	-0.65	0.26	-119.95	60.04
Other commodity	29.31	24.12	1.22	0.11	-18.00	76.62
Basic research	20.05	41.50	0.48	0.31	-61.38	101.47
Private R&D	-26.05	33.24	-0.78	0.22	-91.26	39.16

Public and Private R&D	-26.01***	6.73	-3.86	0.00	-39.22	-12.80
Developed country performer	-11.73	12.48	-0.94	0.17	-36.21	12.75
Program evaluated	-33.70***	4.76	-7.07	0.00	-43.05	-24.35
Institution-wide	-20.41*	14.11	-1.45	0.07	-48.09	7.27
Multi-institutions	-22.26**	10.60	-2.10	0.02	-43.05	-1.46
Refereed publication	-3.20	9.69	-0.33	0.37	-22.20	15.80
Econometric supply shift	0.21	15.26	0.01	0.49	-29.72	30.15
Pivotal supply shift	1.59	14.31	0.11	0.46	-26.48	29.66
Parallel supply shift	-2.39	18.29	-0.13	0.45	-38.28	33.50
Pivotal demand shift	-49.90***	7.23	-6.90	0.00	-64.08	-35.72
Experimental data for supply shift	-13.64	22.08	-0.62	0.27	-56.96	29.68
Research lag	-0.28	1.00	-0.28	0.39	-2.25	1.69
Gestation lag	-7.09**	4.01	-1.77	0.04	-14.97	0.78
Spill-ins	-22.88***	5.57	-4.11	0.00	-33.81	-11.96
Spill-outs	48.26***	17.43	2.77	0.00	14.06	82.46
Both spill-ins and spill-outs	26.25	33.43	0.79	0.22	-39.34	91.84
Farm program distortion	-5.35	14.77	-0.36	0.36	-34.33	23.63
Exchange rate distortion	4.85	11.04	0.44	0.33	-16.81	26.51
Environmental impact distortion	-24.54	23.23	-1.06	0.15	-70.11	21.04
Deadweight loss distortion	0.00	0.00			0.00	0.00
Other distortion	0.00	0.00			0.00	0.00
Beginning year of costs	0.04	0.05	0.88	0.19	-0.05	0.13

Source: Developed by authors.

Note:
1. *** p<0.01, ** p<0.05, * p<0.1
2. The percentage effect coefficient and its standard error are calculated from the estimates in Figure 3 using Kennedy (1981)’s estimators.
3. All the numbers in this table should be interpreted as percentage change. Take the coefficient estimate for Marginal *IRR*, -8.77, for example. It means, other variables held constant, marginal IRR estimate will be 8.77 percentage lower than average IRR estimate.

Table 5-5 Estimates of Marginal Effects on the Internal Rate of Return (IRR) Measure

	Number of observations = 1,303			
Variables	(1)	(2)	(3)	(4)
Nominal IRR	-1.67	-2.06	-50.49***	-32.23***
Publication date	-0.43	-0.53	0.8	-0.76***
Nominal IRR × developing countries	7.99	9.85	47.25***	39.01***
Nominal IRR × 1970s	13.94	17.20	26.6	22.47**
Ex post study	2.81	3.47	17.83	16.28**
Marginal IRR	-8.77**	-10.82**	29.06***	13.51*
Social IRR	-19.21	-23.71	25.51	18.19*
Extension only	-25.22**	-31.12**	-29.1*	-26.69**
Research & Extension	-6.08***	-7.50***	-48.56***	-21.22***
University researcher	11.32*	13.97*	-12.72	4.67
International researcher	-8.28	-10.22	15.27	31.10***
International funder	-24.96***	-30.80***	13.18	20.89
Private sector researcher	-25.10***	-30.98***	-60.67***	-40.86***
Unknown affiliation	-0.55	-0.68	-34.98*	-8.57
Self evaluation	10.27	12.68	4.74	0.87
Unclear evaluation type	11.14	13.75	12.58	12.32**
University research performer	21.91	27.03	-11.41	-15.22***
Intl institute research performer	-2.36	-2.92	13.19	-1.61
Private research performer	26.05**	32.15**	23.66*	7.31
Unknown research performer	-5.25	-6.48	7.59	6.19
Crops	20.90***	25.80***	-23.79	13.97*
Livestock	18.19***	22.45***	-40.85***	6.32
Natural resource & forestry	5.44	6.71	-61.72**	-4.32
Aquaculture & fishery	-16.00	-19.74	-54.76***	-16.67
Other commodity	15.65	19.31	8.27	37.63***
Basic research	10.70	13.21	5.68	-7.97
Private R&D	-13.91	-17.17	15.27	25.04
Public and Private R&D	-13.89***	-17.14***	-5.22	8.96
Developed country performer	-6.26	-7.73	36.54***	15.82***
Program evaluated	-17.99***	-22.21***	-23.29**	-16.87**
Institution-wide	-10.90*	-13.45*	-10.62	-0.82
Multi-institutions	-11.89**	-14.67**	-59.54***	-28.27***
Refereed publication	-1.71	-2.11	-25.73**	-14.43***
Econometric supply shift	0.11	0.14	-32.94***	1.48

Pivotal supply shift	0.85	1.05	-9.29	-4.76
Parallel supply shift	-1.27	-1.57	-10.02	-4.10
Pivotal demand shift	-26.65***	-32.88***	-52.34	-30.78**
Experimental data for supply shift	-7.28	-8.99	15.77**	14.56**
Research lag	-0.15	-0.19	-1.44**	-0.93***
Gestation lag	-3.79**	-4.67**	-3.49***	-3.57***
Spill-ins	-12.22***	-15.08***	54.98***	38.88***
Spill-outs	25.77***	31.80***	63.65**	45.80***
Both spill-ins and spill-outs	14.02	17.30	-37.48**	5.98
Farm program distortion	-2.86	-3.53	5.21	7.91*
Exchange rate distortion	2.59	3.20	-21.99*	-3.51
Environmental impact distortion	-13.10	-16.17	-46.98	-5.88
Deadweight loss distortion	0.00	0.00	0	0.00
Other distortion	0.00	0.00	0	0.00
Beginning year of costs	0.02	0.03	0	-0.02***

Source: Developed by authors.

Note:
1. Column (1) and (2) display the marginal effects of the percentage effects on IRR (see Table 5-3) at different IRR levels, i.e., Column (1) at IRR=53.40 percent (the reference level preferred by this study) and Column (2) at IRR=65.90 percent (the mean value of IRR estimates in the regression sample). Column (3) and (4) displays the marginal effects calculated using the OLS approach. More specifically, Column (3) simply estimates an OLS model with IRR as the dependent variable; Column (4) first estimates an OLS model with the log-form IRR as the dependent variable and then calculate the marginal effects using Kennedy (1981)'s estimators.
2. *** p<0.01, ** p<0.05, * p<0.1
3. All the numbers in this table should be interpreted as changes in percentage points. Take the coefficient estimate for *Marginal IRR*, -8.77, for example. It means, other variables held constant, marginal IRR estimate in will be 8.77 percentage points lower than average IRR estimate.

Chapter 6. Conclusion

The objective of this dissertation is to examine both empirical and methodological issues related to agricultural production efficiency and productivity. Four chapters are organized under two different research lines.

Chapter 2 looks into land fragmentation, also known as scattered land holdings, a common phenomenon in agriculture around the world. It evaluates the effect of land fragmentation on agricultural production and hypothesizes that it may be beneficial to farmers by diversifying risk onto separate land plots that usually have heterogeneous growing conditions. Applying a stochastic frontier model to the Tanzania Living Standards Measurement Study (LSMS) data, this chapter finds evidence to support the risk-reduction hypothesis and indications that land fragmentation is positively associated with efficiency. It is further argued that accounting for risk preferences that are absent from the current framework in future research may help explain the double dividends of land fragmentation.

Chapter 3 hypothesizes that by reducing production risk, land fragmentation may encourage risk-averse farmers to increase their optimal labor use, thus leading to a higher payoff in spite of its negative effects on technical efficiency. Further it is argued that land fragmentation's impacts on production efficiency and risk are interrelated through farmer's risk preferences, an element which is absent from the current analytical framework. A production model is developed to incorporate production efficiency, production risk, and risk preferences. Numeric examples are used to support the aforementioned hypothesis and it is found that ignoring risk preferences from efficiency analysis will generally generate biased or even misleading estimates.

Chapter 4 examines the agricultural R&D evaluation literature by scrutinizing 2,242 investment evaluations reported in 372 separate studies from 1958 to 2011. It is found that the internal rate of return (*IRR*) is the predominant summary measure of investment performance used in the literature despite methodological criticisms dating back more than a half century. The reported *IRR*s imply rates of return that are implausibly high. This chapter investigates the reasons for these implausibly high estimates by analytically comparing the *IRR* to the modified internal rate of return (*MIRR*). The *MIRR* addresses several methodological concerns with using the *IRR*, has the intuitive interpretation as the annual compounding interest rate paid by an investment, and is directly related to the benefit-cost ratio. To obtain more credible rate of return estimates, Chapter 4 then develops a novel method for recalibrating previously reported *IRR* estimates using the *MIRR* when there is limited information on an investment's stream of benefits and costs. The recalibrated estimates of the rate of return are more modest (median of 9.8 versus 39 percent per year) but are still substantial enough to question the current scaling back of public agricultural R&D spending in many countries.

Chapter 5 applies a carefully-designed meta-analysis to explain the wide dispersion in the reported rates of return. It identifies factors, both those associated with R&D investment portfolio and those associated with evaluation methodologies, that help account for the variation in IRR estimates while controlling for unobserved heterogeneity and potential correlations between individual rate of return estimates. Findings in this chapter will not only help researchers to detect critical methodological issues in the evaluation literature but also provide clues to policymakers regarding future public agricultural R&D policy.

In conclusion, this dissertation makes substantial contributions to the understanding of agricultural production efficiency and productivity from a few aspects. Firstly, it provides an explanation for the prevalence and persistence of land fragmentation by pointing out its role in risk management. By evaluating its efficiency effects along with the risk effects, this dissertation further suggests improvements on current methodology of efficiency analysis. The empirical findings of this dissertation will help inform future land policies that have development goals, while the mathematical model developed in this dissertation will be instrumental for future efforts to better measure production efficiency in the context of risk. Secondly, this dissertation contributes to the methodologies underlying the agricultural R&D evaluation literature by proposing the more accurate rate of return measure MIRR as opposed to the prevalent IRR measure. It also identifies factors that account for the variation in the reported rate of return estimates using a rigorous meta-regression model. This dissertation not only pinpoints critical methodological issues in evaluating agricultural R&D investments but also informs future public policies on agricultural R&D and productivity.

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