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Essays on Agricultural Productivity, Poverty, and Farm Size

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Economics

by

Matthew Paul Hrobsky Taylor

September 2020

Dissertation Committee:
Dr. Steven M. Helfand, Chairperson
Dr. Joseph R. Cummins
Dr. Anil B. Deolalikar

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The Dissertation of Matthew Paul Hrobsky Taylor is approved:

Committee Chairperson

University of California, Riverside

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To my wife, Veronica Ann Taylor, and our children, Jackson, Dakota, Emily, and Johnathan.

I am forever blessed by your presence in my life. You are my motivation.

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ABSTRACT OF THE DISSERTATION

Essays on Agricultural Productivity, Poverty, and Farm Size

by

Matthew Paul Hrobsky Taylor

Doctor of Philosophy, Graduate Program in Economics
University of California, Riverside, September 2020
Dr. Steven M. Helfand, Chairperson

This dissertation presents three essays on agricultural productivity and its relationship with farm size and poverty. Chapter 1 addresses the relationship between farm size and productivity, a recurrent topic in development economics. We clarify the common productivity measures used in this literature, their relationships, and their advantages and limitations. Second, we argue that total factor productivity, not land productivity, is the appropriate indicator for most policy questions. Lastly, using a pseudo-panel of Brazilian farms spanning the period 1985-2006, we provide new evidence on the inverse relationship between farm size and productivity. The inverse relationship between size and land productivity is alive and well. The relationship between total factor productivity and size, in contrast, has evolved with modernization during this period. An inverse relationship between farm size and land productivity is

neither necessary nor sufficient for an inverse relationship between farm size and total factor productivity.

The hypothesis of a dynamic farm size – productivity relationship is extended to the context of Mexico in Chapter 2, identifying the relationship in a panel of family farms drawn from the Mexican Family Life Survey (MxFLS). We find a time invariant inverse relationship between farm size and both land productivity and total factor productivity. Stochastic frontier analysis reveals that, while technical change is expanding the frontier and technical inefficiency is growing for the entire sample, these changes are more pronounced for larger farms. An inverse relationship along the productivity frontier is disappearing in the wake of Mexico's NAFTA-era reforms to agricultural policy, yet this change has not affected the farm size – total factor productivity relationship due to growing technical inefficiency.

Chapter 3 conducts a counterfactual analysis of the contribution of changing land productivity to poverty alleviation on the farm. Stochastic frontier analysis enables a parametric decomposition of changes to the land productivity distribution in a panel of Mexican family farms. Using the decompositions, the contribution of productivity channels to poverty alleviation are estimated. The counterfactual analysis suggests that raising land productivity through intensification and technical change would be a more pro-poor approach than through increases in technical efficiency.

Contents

List of Tables

List of Figures

CHAPTER 1

The Inverse Relationship between Farm Size and Productivity: Refocusing the Debate[1]

1.1 Introduction

The relationship between farm size and productivity is a recurrent topic in development economics, almost as old as the discipline itself. John Stuart Mill observed an inverse relationship as early as 1848, later positing that this had changed due to increasing capital intensity of farming (Lipton, 2009). The issue appeared in the works of Marx, resurfaced with Lenin and Chayanov in the early 20th century, and has captivated modern agricultural and development economists for over fifty years. Debate around the nature and causes of this relationship continues despite a mountain of empirical analysis, posing a puzzling question for 21st century researchers (Binswanger et al., 1995; Eastwood

[1] We thank the USDA for a grant that assisted with the construction of the database used in the empirical portion of the paper (project number 58-6000-5-0059), and the Brazilian Institute of Geography and Statistics (IBGE) for access to the Agricultural Census microdata in a secure data processing site in Rio de Janeiro.

et al., 2010). Conventional economic wisdom expects resources to be allocated such that returns to land are equalized across farms; however, the empirical research on developing countries contradicts this and frequently identifies an inverse relationship. Policy-makers in developing countries have engaged the debate, as an inverse relationship between farm size and productivity indicates a role for small farms in development strategies and the potential for land reform to simultaneously generate improvements in equity and efficiency.

Harnessing such a relationship to inform policy requires accurate interpretation of the empirical evidence as well as an understanding of its causes, the channels through which it operates, and the factors that condition its strength. Theoretical explanations for2 this phenomenon often result from household heterogeneity and/or (multiple) market failures, for example Sen's (1966) dual labor market hypothesis, Eswaran and Kotwal's (1986) model of household endowments with credit constraints, and Feder's (1985) model of moral hazard and costly monitoring of hired labor. Risk aversion (Barrett, 1996) and plot-level behavioral and agronomic issues (Bevis and Barrett, 2020) provide alternative explanations. Measurement error (Lamb, 2003; Carletto et al., 2013; Carletto et al., 2015; Desiere and Jolliffe, 2018; Dillon et al., 2019; Gourlay et al., 2019; Abay et al., 2019a; Abay et al., 2019b) and omitted variables, such as soil quality (Bhalla and Roy, 1988; Benjamin 1995; Assunção and Braido, 2007; Barrett et al. 2010), are two empirical issues that could lead to a spuriously observed inverse relationship. Attempts to sort out the relative importance of these mechanisms have been mixed.

Adding to the confusion is the variety of productivity measures and empirical approaches that have been used. As with Sen (1962), Deolalikar (1981), Assunção and Braido (2007), Barrett et al. (2010), Deininger et al. (2018), Dillon et al. (2019), and Abay et al. (2019b), much of the early literature used land productivity—output per unit of land—as a measure of performance.[2] Conditioning land productivity on input use by estimating a production function is a second commonly used approach that generates an alternative measure of performance (Bardhan, 1973; Carter, 1984; Barrett et al., 2010; Ali and Deininger, 2015; Muyanga and Jayne, 2016). Controlling for a partial set of inputs (Bhalla and Roy, 1988; Desiere and Jolliffe, 2018) is distinct from estimating a full production function. Still others employ value added per unit of land (Heltberg, 1998; Carletto et al., 2013; Henderson, 2015), profit per unit of land (Heltberg, 1998; Foster and Rosenzweig, 2017), profit (Benjamin, 1995; Lamb, 2003; Ali and Deininger, 2015), or technical efficiency (Helfand and Levine, 2004; Kagin et al., 2016). Despite the recognition that partial measures such as land productivity are problematic (Berry and Cline, 1979; Binswanger et al., 1995; Muyanga and Jayne, 2016), they continue to be used, often alongside alternative productivity measures, and are frequently discussed synonymously with a more general notion of productivity. Where multiple productivity measures are used, the distinctions between the relationships being estimated are seldom addressed directly. As Barrett (1996) notes, this literature "habitually, perhaps cavalierly," uses

[2] The literature often uses the terms yield and land productivity interchangeably. We only use yield when talking about a physical measure of productivity for a single product (tons/hectare). Land productivity is more appropriate in a multiple-output context, requiring a method for aggregation.

physical yields and productivity synonymously. Conceptual clarity is needed on how these measures relate to each other and to farm size, and which is most relevant from a policy perspective.

We do not attempt to explain the IR, as do many of the contributions in this field. Rather, we seek to clarify the relationships between the various productivity measures used in this literature and explore the implications of the choice of measure. We show that an inverse relationship between farm size and a partial productivity measure, such as land productivity, is neither necessary nor sufficient for an inverse relationship between farm size and a comprehensive measure of productivity, such as total factor productivity. As such, these measures are not generally comparable. An inverse relationship may be observed when using land productivity, but not necessarily when using a comprehensive measure of productivity. Where comprehensive measures of productivity are more relevant and of interest, a focus on land productivity effectively introduces omitted variable bias by not controlling for the intensity with which other inputs are used. In fact, Bardhan (1973), Berry and Cline (1979), Carter (1984), and Heltberg (1998) are all examples where, in the presence of an inverse relationship between farm size and land productivity, the use of more comprehensive productivity measures leads to an attenuated, if not direct, farm size – productivity relationship. This highlights the importance of how productivity is measured when assessing its relationship with farm size, and for drawing policy conclusions and recommendations from these relationships.

The lack of an explicit focus on total factor productivity is a curious feature of the inverse relationship literature, especially given the early and widespread acknowledgement of its superiority over partial measures. From a policy perspective, total factor productivity is likely the most relevant measure where poverty alleviation, equity and the productive use of all resources are pressing concerns. Policy discussions of the future of small farms, for example, emphasize the role of small farms in agricultural development in part because of their superior efficiency (Hazell, 2005; Hazell et al. 2010). This argument leans heavily on the inverse farm size – productivity relationship, but requires that small farms be more efficient with their use of all resources and not just land. Whereas a farm size – land productivity relationship does not provide clarity on this issue, a farm size – total factor productivity relationship does.

In this light, we argue that the inverse relationship literature needs to shift its focus from land productivity to total factor productivity. In fact, empirical studies assessing the productivity – farm size relationship in the developed world, such as Garcia et al. (1982), Alvarez and Arias (2004), and Rasmussen (2010), almost exclusively use measures of technical efficiency or total factor productivity.[3] Similarly, the literature estimating national level agricultural productivity is clear in its use of total factor productivity as a preferred measure (Fuglie, 2008; and Headey et al., 2010).

[3] We have chosen not to focus on the literature estimating a stochastic production frontier to explore technical efficiency, as it is still an infrequent, albeit important, approach taken in the existing literature on developing countries.

We illustrate the importance of productivity measures with new empirical evidence on the farm size – productivity relationship across regions of Brazil from 1985 to 2006 . Our evidence is only suggestive because we are unable to correct for potential issues of measurement error in farm size, output, and inputs that have been identified in recent literature. However, this period in Brazil provides an excellent case study because it includes regions with relatively advanced agricultural sectors, those characterized by more traditional agricultural production, and others experiencing rapid agricultural transformation, allowing us to assess the farm size – productivity relationship and its dynamics at different stages of agricultural development. Using a pseudo-panel of farms aggregated at the municipality by farm size level, we show that estimating the farm size – productivity relationship using land productivity is potentially misleading. While we always identify an inverse relationship using land productivity, we find disparate results when using total factor productivity. In the modern agricultural regions of Brazil, we find a direct relationship between farm size and total factor productivity, and in the rapidly transforming region of the Center-West we identify dynamics that suggest the inverse relationship is disappearing over time. The analysis highlights that the relationship between total factor productivity and farm size has evolved with modernization, shedding some light on the issues raised by Mill over 150 years ago.

The remainder of this paper is organized as follows. In Section 2 we seek to clarify the common measures, their relationships, and their advantages and limitations in empirical work. Section 3 presents the empirical exercise, generating new evidence on the relationship between size and productivity in several macro regions of Brazil. In Section 4 we summarize and conclude with policy implications.

1.2 Measures of Agricultural Productivity

Farm size may be related to a broad range of economic outcomes, such as employment, poverty, inequality, food security, efficiency and growth. While these are important issues connected to the role of farm size in development, here, as with most of the literature on the inverse relationship (IR), we focus specifically on the concept of productivity. The following discussion seeks to clarify the relationships between the various productivity measures most commonly used in the literature, allowing us to draw conclusions on the impact that choice of measure may have on finding an IR and the potential implications for policy.

1.2.1 The Unconditional Relationship between Land Productivity and Farm Size

Historically, land productivity is the most commonly used measure in the literature on the inverse relationship. Where alternative productivity measures are used, the relationship between land productivity and farm size is often a starting point, serving as a benchmark for the expansive existing literature. Land productivity, q, is a partial measure of productivity:

$$Land\ Productivity = \frac{Q}{A} = q = \psi_u(A) \tag{1.1}$$

where A is the area of the farm, Q is an index of agricultural output, q is agricultural output per unit of land, and $\psi_u(A)$ connotes that land productivity may be a function of farm size. In a world where farm size and land productivity are unrelated we have $\frac{\partial\psi_u(A)}{\partial A} = 0$. However, the regularity with which empirical work finds $\frac{\partial\psi_u(A)}{\partial A} < 0$ has led to the stylized fact that they are inversely related, generating an abundance of interest in the relationship and its potential explanations. Figure 1.1 displays this relationship using data from Brazil for the years 1985, 1996, and 2006. While the relationship is potentially non-linear and may not be monotonic, for now we focus on the first order approximation.

The relationship captured by $\psi_u(A)$ is unconditional (u) in the sense that it is the simple bivariate relationship between land productivity and farm size. Factors that may be causing or influencing this relationship have not been controlled for. Using land productivity as a measure is inherently limited—as would be any partial measure of productivity—whenever there is more than one factor of production. If use of other factors vary systematically with farm size, the IR between land productivity and farm size may simply reflect more input intensive practices of small farms. Higher land productivity may reflect overuse of fertilizer, for example, which would not necessarily reflect any underlying productivity advantage of small farms. In such situations, estimates of the farm size – land productivity relationship introduces omitted variable bias into estimates of the underlying farm size – productivity relationship. From this perspective, a focus on the relationship between land productivity and the size of farms may be misplaced.

Similarly, analysis using different partial productivity measures may result in conflicting policy recommendations. Indeed, Sen's (1962) seminal contribution revealed precisely this type of systematic relationship between the intensity of labor use and farm size, leading to his formal exposition of the dual labor market hypothesis (Sen 1966). Figure 1.2 illustrates the problem in the case of Brazil. While there is an inverse relationship between land productivity and farm size, there is a direct relationship between labor productivity and size. Analysis of the farm size and productivity relationship using labor productivity suggests that larger farms are more productive than are their smaller counterparts. Policy recommendations from the two partial measures of productivity would differ, underscoring the need for a comprehensive measure of productivity when identifying any relationship with farm size.

1.2.2 The Conditional Relationship between Land Productivity and Farm Size

In spite of its limitations, the unconditional relationship between land productivity and farm size continues to be used, even if in conjunction with comprehensive measures of productivity. A more appropriate approach is to use a conditional relationship, where the relationship is conditioned on a vector of controls, $X(A)$, that are potentially correlated with both land productivity and farm size:

$$q = \psi_u(A) = g\big(X(A), \psi_c(A)\big) \tag{1.2}$$

The conditional (c) relationship, $\psi_c(A)$, should differ from the unconditional relationship to the extent that the controls explain the unconditional IR. For example, the impact of varying input intensities can be controlled for by including those inputs as controls, household heterogeneity can be controlled for with household fixed effects, market failures controlled for with regional fixed effects, and other omitted variables such as soil quality can be introduced. This is a useful approach for exploring the theoretical channels that explain the IR and is a strategy commonly used by researchers in recent empirical studies of the farm size – productivity relationship (Assunção and Braido, 2007; Barrett et al., 2010; Desiere and Jolliffe, 2018; Gourlay et al., 2019).

As discussed above, partial measures such as land productivity are potentially misleading when there are other factors of production. At the very least, understanding any relationship between productivity and farm size requires empirical analysis that controls for the intensity with which other factors of production are used. For exposition, assume that land, labor (L), and capital (K) are the only factors of production and that their intensities, labor per unit of land and capital per unit of land, are given by l and k, respectively. Then (1.2) becomes:

$$q = \psi_u(A) = g\big(k(A), l(A), \psi_c(A)\big) \tag{1.3}$$

showing that the IR as identified by the unconditional relationship between land productivity and farm size, $\frac{\partial \psi_u(A)}{\partial A}$, is composed of the relationship between capital intensity and farm size, labor intensity and farm size, and any conditional relationship between farm size and land productivity, $\frac{\partial \psi_c(A)}{\partial A}$. When differences in the use of other factors of production are controlled for, the conditional relationship between farm size and productivity is revealed, providing a more comprehensive measure of productivity. If the two measures diverge, the unconditional relationship suffers from omitted variable bias.

Exploring (1.3) highlights how omitted variables can lead to ambiguity in how the land productivity and farm size relationship, as captured by $\psi_u(A)$, is related to the more general productivity and farm size relationship captured by $\psi_c(A)$. Differentiating (1.3) with respect to farm size shows:

$$\left(\frac{\partial \psi_u}{\partial A}\right) = \left(\frac{\partial g}{\partial k}\right)\left(\frac{\partial k}{\partial A}\right) + \left(\frac{\partial g}{\partial l}\right)\left(\frac{\partial l}{\partial A}\right) + \left(\frac{\partial g}{\partial \psi_c}\right)\left(\frac{\partial \psi_c}{\partial A}\right) \tag{1.4}$$

Assuming, quite reasonably, that output per unit of land is increasing in both capital and labor per unit of land, it is plausible for the conditional relationship to be positive $\left(\frac{\partial \psi_c}{\partial A} > 0\right)$ even if the unconditional relationship is negative $\left(\frac{\partial \psi_u}{\partial A} < 0\right)$ if, as is often the case, $\frac{\partial k}{\partial A}$, $\frac{\partial l}{\partial A}$, or both are negative.[4] In short, an unconditional IR is neither a necessary nor a sufficient condition for an inverse relationship between the broader measure of productivity and farm size captured by $\psi_c(A)$.

When, as in (1.3), the conditional relationship includes all factors of production as controls, the approach is equivalent to estimating a production function and the conditional relationship can be interpreted as total factor productivity (TFP). Across a host of policy objectives – for example, improving the efficiency of resource use in the rural economy or alleviating poverty among agricultural households – policymakers are best

[4] Abay et al. (2019a) show clear evidence of input intensities declining with farm size in four African countries. The same is true in all regions using our Brazil data.

informed by comprehensive measures such as TFP that take into account the productivity with which all resources are utilized.

1.2.3 Profitability and Farm Size

Empirical studies have often looked to the farm size – profitability relationship as an alternative to measuring the farm size – productivity relationship. While assessing profitability raises its own practical challenges, the use of a profit rate to measure farm performance faces the same conceptual issues as does the use of productivity. Partial measures of profitability – such as profit (or value added) per unit of land – are potentially misleading, and for most policy considerations a comprehensive profit rate is most relevant.

Profit is expressed as:

$$\Pi = Q - p_L L - p_K K - p_A A \tag{1.5}$$

where p_L is the price of labor, p_K the price of capital, and p_A the price of land. In expression (1.5) if the output quantity index, Q, is constructed using prices in the aggregation process, it can be interpreted as the value of output. The level of profit can be expressed as the product of output and profit per unit of output: $Q\frac{\Pi}{Q}$. Regardless of whether the profit per unit of output rises or falls with size, we would expect the level of output to dominate in the determination of the level of profit. A large farm that produces a value of output of 1,000, for example, should generate more profit than a small farm that produces 10. The level of profit, then, is not a particularly good measure for comparing the productivity of farms of different sizes.

It is not profit per se that matters but rather profitability, requiring the transformation of the profit level into a profit rate. Profit per unit of land, as used by Carletto et al. (2013) among others, is one approach:

$$Profit\ per\ unit\ of\ land = \pi_A = \frac{\Pi}{A} = q - p_L l - p_K k - p_A = \phi(A) \tag{1.6}$$

Profit per unit of land is a measure of farm performance that controls for the levels of other inputs additively, providing an improvement over land productivity. Notions of value added are similar, however they fall short of profit measures as they control only for intermediate inputs and not the complete set of factors of production. Despite being an improvement over land productivity and value-added, profit per unit of land is itself problematic because it is fundamentally a partial measure. The finding of a systematic inverse relationship with farm size, $\frac{\partial \phi(A)}{\partial A} < 0$, provides limited information to policy makers because, as with productivity measures, it is the profitability of overall resource use that matters.

To highlight this, note that partial profitability measures potentially provide conflicting perspectives on the relative profitability of farms:

$$\pi_A = \frac{\Pi}{A} = \frac{\Pi}{K}\frac{K}{A} = \pi_K * k \tag{1.7}$$

Here we see that the profit per unit of land is the product of profit per unit of capital, π_K, and capital intensity. An observed inverse relationship between profit per unit of land and farm size could be associated with declining capital intensity as farm size increases, even if profit per unit of capital is increasing. If true, then the use of one partial measure or the other would lead to conflicting policy recommendations. Overcoming these limitations requires the use of a comprehensive measure of profitability. Indeed, Binswanger et al. (1995) advocate normalizing profit by "capital invested" or "assets," an approach that is appropriate as long as the assets included are restricted to those used in agricultural production and do not include all of household wealth. In practice, this approach to measuring profits has rarely been used, in part due to inexistent or imprecise information about the value of assets used in production. Where partial profit rates have been employed, bias can arise from incomplete information on input prices as well as unobservable inter-farm variation in prices that is potentially correlated with farm size.

1.2.4 TFP as a Comprehensive Measure

Comprehensive measures of either productivity or profitability are the appropriate means to measure the efficiency of resource use and, in most cases, will provide the information necessary for effective policy design.[5] Total factor productivity can be defined as the ratio of output to all inputs used, where output and input quantity indices are typically required to aggregate physical quantities. TFP can be written as:

$$TFP = \frac{Q}{Inputs} = \varphi(A) \tag{1.8}$$

[5] Under certain conditions, TFP can be shown to be a monotonic transformation of profitability.

TFP effectively captures the productivity with which all inputs are used in the production process, and in this sense is a comprehensive measure of productivity. If this measure is a function of farm size, i.e. $\frac{\partial \varphi(A)}{\partial A} \neq 0$, then there is an unambiguous difference in how productively farms of different sizes utilize resources in agricultural production. An understanding of the determinants of $\varphi(A)$ would support effective policy design, whether the objective is poverty reduction or economic growth, because these are concerned with the use of all resources available to farms. Although this is widely acknowledged, an explicit focus on TFP is seldom the approach of empirical analyses of the IR in developing economies.

While the difference is rarely noted, empirical analyses of the IR that estimate a production function effectively pivot from estimating the farm size – land productivity relationship towards estimating the farm size – TFP relationship. To illustrate this point, assume a standard Cobb-Douglas production function homogenous of degree t, where T is the unobserved measure of total factor productivity and production is a function of labor, capital, and land:

$$f(L, K, A) = TL^{\alpha}K^{\beta}A^{\gamma} \tag{1.9}$$

If, as has often been confirmed, CRS holds, then farm size disappears from the right hand side of (1.9) after dividing through by farm size.[6] If not, then the natural log of the production function takes the form:

[6] To see this, if we assume the production function is homogenous of degree t then $f(\lambda L, \lambda K, \lambda A) = \lambda^t f(L, K, A)$, with constant returns to scale (CRS) holds if $t = 1$. Setting $\lambda = \frac{1}{A}$ implies that $f(l, k, 1) =$

$$lnq = (t-1)lnA + lnT + \alpha lnl + \beta lnk \qquad (1.10)$$

and if, as in (1.8), there exists a relationship between total factor productivity and size, $\varphi(A)$, we have:

$$lnq = (t-1)lnA + ln\varphi(A) \ + \alpha lnl + \beta lnk \qquad (1.11)$$

From (1.11) it is clear that the conditional relationship identified in (1.3), $\psi_c(A)$, is composed of the relationship between TFP and farm size ($\varphi(A)$) as well as any deviations from CRS in the production function (as captured by $(t-1)lnA$).

Equation (1.11) highlights two useful features of the production function approach. First, if CRS holds then the conditional relationship, $\psi_c(A)$, captures the relationship between TFP and farm size, $\varphi(A)$. Second, if CRS does not hold then it will be difficult to empirically differentiate whether a conditional relationship is driven by non-CRS, a relationship between TFP and farm size, or a combination of the two. One cannot have confidence in tests of returns to scale if there is also a relationship between farm size and TFP. This highlights the importance of interpreting any observed conditional relationship as including both a relationship between farm size and TFP and any potential deviations from CRS.[7]

$A^{-t} f(L,K,A)$, implying that when the production function is expressed in intensities we have $q = \frac{f(L,K,A)}{A} = A^{t-1} f(l,k,1)$.

[7] Future research should seek to develop an approach to disentangle the relationship between farm size and these two sources of productivity. Aragon et al. (2019) have taken a step in this direction, proposing a sequential approach which estimates RTS first and then uses this to correct their estimates of the farm size - TFP relationship. While this recognizes the need to account for deviations from CRS, the first stage estimates of returns to scale likely suffer from omitted variables bias.

Thus, when empirical researchers estimate a production function to explore the relationship between farm size and productivity they are, in effect, estimating the relationship between farm size and TFP and not farm size and land productivity. All too often, empirical work that takes this approach estimates the unconditional relationship first (non-parametrically, and parametrically with some controls), followed by the estimation of a production function and then interpretation of the two approaches as if they were exploring the same relationship. However, the conditional and unconditional relationships are by no means the same, can plausibly take different signs, and will almost certainly have different magnitudes.

1.2.5 TFP and Land Productivity Redux

The relationship between TFP and output per unit of land can be explored further. TFP is a unit-less measure, but multiplying and dividing by $\frac{1}{A}$ allows the measure to be rewritten as:

$$TFP = \frac{q}{\tau} = \varphi(A) \tag{1.12}$$

where TFP is expressed as land productivity normalized by inputs per unit of land, τ.

Taking a derivative with respect to farm size:

$$\frac{\partial TFP}{\partial A} = \left(\frac{\partial q}{\partial A}\right)\left(\frac{1}{\tau}\right) - \frac{\left(\frac{\partial \tau}{\partial A}\right)q}{\tau^2} \tag{1.13}$$

Employing a little bit of algebra (see Appendix A.1):

$$\frac{\partial TFP}{\partial A} = \left(\frac{\partial q}{\partial A}\right)\left(\frac{1}{\tau}\right)\left[\frac{\varepsilon_{q,A} - \varepsilon_{\tau,A}}{\varepsilon_{q,A}}\right] \tag{1.14}$$

where $\varepsilon_{q,A}$ is the elasticity of land productivity with respect to farm size, and $\varepsilon_{\tau,A}$ is the elasticity of input use per unit of area with respect to farm size. If there is an empirically observed inverse relationship between the partial measure and farm size such that $\frac{\partial q}{\partial A} < 0$, then we know $\varepsilon_{q,A}$ is negative. This implies that one of two possibilities must hold:

(i) $\frac{\partial TFP}{\partial A} < 0$ *and* $\varepsilon_{q,A} < \varepsilon_{\tau,A}$

(ii) $\frac{\partial TFP}{\partial A} > 0$ *and* $\varepsilon_{q,A} > \varepsilon_{\tau,A}$

If (i) is true then an IR between a partial measure and farm size reflects an IR between productivity and farm size as measured by TFP. When this is the case either input use per unit of land is increasing in farm size or it is decreasing, but slower than the rate at which output per unit of land is decreasing. If (ii) is true then use of a partial measure is generating an incorrect indication about the productivity and farm size relationship, and TFP is actually directly related to farm size. However, this requires that $0 > \varepsilon_{q,A} > \varepsilon_{\tau,A}$. In such a case, input use per unit of land is negatively related to farm size and is relatively elastic compared to output per unit of land. Use of a partial measure implies policy recommendations inconsistent with those that would result if a comprehensive measure were used. This discussion highlights the conclusion that an IR between a partial measure of productivity and farm size is neither necessary nor sufficient for the existence of an IR between farm size and a comprehensive measure of productivity such as TFP.

The conditions set out in (i) and (ii) provide a framework for considering how a modernizing agricultural sector can lead to a changing farm size – productivity relationship. Depending upon the stage of development and the institutional structure, partial measures of productivity may fail to capture the dynamics of the farm size – productivity relationship. Land productivity may provide an adequate proxy for TFP at an early stage of development, even if the magnitudes of the two relationships differ. At an intermediate stage of development characterized by mechanization and technical improvements, capital and the ability to adopt modern technologies become increasingly important. Substitution away from labor may move large farms towards a more efficient mix of factors of production. In such a context condition (ii) might hold, with a direct relationship between TFP and farm size emerging even as an IR continues to exist for land productivity. Further agricultural development could realign the relationships between TFP, land productivity, and farm size as institutions improve and distortions in land, labor, and capital markets begin to disappear. In such an environment, the inverse relationship between land productivity and farm size could disappear, implying $\varepsilon_{q,A} \geq 0$ and both land productivity and TFP could conceivably exhibit a direct relationship with farm size.[8] We return to this discussion following the empirical exercise on Brazil.

1.3 Empirical Analysis

We now provide an example using data on Brazilian agriculture. The intention here is not to explain the relationship between farm size and productivity by controlling

[8] There is evidence of a direct relationship between land productivity and farm size among grain farmers in the U.S. (Key, 2019), and for specific crops in Brazil (Filho and Vian, 2016).

for its potential determinants. Rather, we seek to use a regional analysis within Brazil to highlight how the choice of measure influences the observed relationship and how these patterns can change across stages of agricultural development. Our evidence is only suggestive because we are unable to correct for the measurement issues in farm size, outputs, and inputs that recent literature has focused on. We discuss this further below. The results provide an important counterpoint to much of the literature that has focused on countries in Africa and Asia where the overwhelming majority of farms have less than 2 hectares (Eastwood et al., 2010). Mean and median farm size in Brazil, in contrast, were around 65 and 10 hectares in 2006.

1.3.1 Data and Variables

The data come from the 1985, 1995/1996, and 2006 rounds of the Brazilian agricultural census. For confidentiality reasons, we constructed a pseudo-panel in which all farms in the census are aggregated into five farm size classes within each municipality of Brazil.[9] Aggregation requires that we assume homogeneity within each observation (for example, farms with 0–5 ha in the municipality of Cachoeira). We call these "representative-farms," as they reflect the average behavior of a given farm size in a given municipality. The pseudo-panel approach has been used recently to study agricultural

[9] The size classes in hectares (ha) are 0-5 ha, 5-20 ha, 20-100 ha, 100-500 ha, and 500+ ha. To protect the confidentiality of the farms, the Brazilian Institute of Geography and Statistics (IBGE) requires that each aggregate observation have at least 3 farms. As the aggregation was conducted on site prior to analysis, we are not able to expand the number of farm size bins. However, previous work using the underlying Brazilian census data found little difference in qualitative results across alternative bin specifications (Helfand et al., 2014; Moreira et al., 2007; Helfand and Levine, 2004).

productivity growth by Key (2019) and Rada et al. (2019). Antmann and McKenzie (2007) demonstrate that, in the context of mobility studies, pseudo-panels can be used to consistently estimate parameters of interest. The averaging within cells (representative farms) in each period reduces the influence of individual-level measurement error, and the fact that it is not a true panel of farms makes it less vulnerable to non-random attrition. They show the approach is also robust to some forms of non-classical measurement error.

We begin with 47,365 representative farms for all of Brazil across the three survey years. Due to concern about the comparability of a small number (84) of extremely large observations, we remove all representative farms in the Northeast and South over 4,000 ha and all of those over 5,000 ha in the North, Southeast, and Center-West. We then identify land productivity outliers taking into account the IR shown in Figure 1.1 and potential non-linearities. Thus, rather than trim the tails of the unconditional land productivity distribution, we use a quadratic specification to regress land productivity on farm size with municipal fixed effects and survey year dummy variables.[10] From this regression we identify and remove outliers, defined as all representative farms with

[10] The changing composition of Brazil's municipalities—rising from around 4,100 to over 5,500 in the period of study—requires the construction of geographic units that are spatially consistent over time. We create 3,861 consistent geographic units—called minimum comparable areas—and continue to refer to them as "municipalities" for simplicity.

residuals greater than four standard deviations from their size specific predicted values. Together, the data cleaning exercises remove 1.8% of the initial sample.[11]

The Census data were gathered by the Brazilian Institute of Geography and Statistics (IBGE) through end of season in-person farmer interviews based on recall. Output is measured as the real value of total agricultural production, deflated to 2006 with a price index developed from the data in Gasques et al. (2010). Farm size is measured in hectares (ha), and unlike in many African and Asian countries the overwhelming majority of farms operate a single plot. Additional factors of production used in the production function are family labor, purchased inputs including hired labor, and an index of capital. The number of male, female, and child family members working on each farm are used to develop a family labor index measured in adult male equivalents. The index assigns weights of 1.0 to men, 0.75 to women and 0.5 to children under 14.[12] In 2006 around two thirds of family labor was provided by men, and over 90% of working family members were 14 years or older. The real value (R$2006) of purchased inputs, including expenditure on fertilizer, seeds, hired labor, fuel, energy, soil amendments, and other items, are deflated with the same price index used for output. A proxy for the total capital

[11] See Appendix Table A.2.1 for the results of data cleaning from each stage of the process. Sensitivity analyses using alternative approaches to trimming the data had no qualitative impact on our results, and only a negligible impact on the magnitude of the estimated coefficients. The alternatives included 1) the same as in the core approach but using a linear rather than a quadratic specification, 2) only trimming the 84 extremely large representative farms, 3) trimming the 84 and the top and bottom 1% of the unconditional land productivity distribution, 4) trimming the 84, the top and bottom 1%, and using the quadratic specification as in the core approach, and 5) the same as the core approach but trimming residuals greater than three rather than four standard deviations.

[12] The weights are drawn from Moreira et al. (2007), and reflect average hours worked on-farm according to data in the national households survey (PNAD).

stock is calculated as a quantity index comprised of machine, animal, and tree capital stock sub-indices following Moreira et al. (2007) and Butzer et al. (2012). The machine capital stock index values tractors of five horsepower classes, trucks, harvesters and other agricultural equipment using a constant set of sale prices drawn from the Instituto de Economia Agrícola in São Paulo. The stock of animal capital is measured in cattle equivalents of the nine most important animal stocks and aggregated with a set of time-invariant relative prices (following the approach in Hayami and Ruttan, 1985). The stock of tree capital is measured as the present discounted value of expected future profits for thirteen different tree crops, using region-specific estimates of expected profits. The sub-indices are aggregated using region-specific weights estimated by regressing output on the three capital stock sub-indices in the base year 1985.[13]

Additionally, we control for unexpected shocks in rainfall and temperature to each municipality in each survey year utilizing data described in Wilmott and Matsuura (2001). These quarterly shocks are measured as standardized deviations from 25-year moving averages ending in the year prior to each Census. The data are transformed into categorical variables capturing extremely low, below average, average, above average, and extremely high values relative to the historical municipal average. Weather shocks

[13] While there are many assumptions that go into the construction of the capital stock index, capturing the capital invested in perennial crops and animals is an improvement over most of the literature on Brazil that often uses tractors as the sole proxy for capital. The Census data used to construct the indices here relies on the number of machines, trees, and animals present on farm at the end of the season. Because these are stocks and the recall period is shorter, bias should be less of a concern for these variables than for inputs that are used irregularly or are more marginal to the production process.

between -1 and 1 standard deviations are treated as normal weather years and are the reference category, with extremely high and extremely low values occurring at more than ± 1.645 standard deviations.[14]

1.3.2 Measurement error

The data used are drawn from a nation-wide decennial census and are potentially subject to multiple sources of measurement error. The literature on measurement error and its implications for the IR has grown rapidly in recent years. Of greatest concern are non-classical types of measurement error that are correlated with farm size. Carletto et al. (2013), Carletto et al. (2015), Abay et al. (2019b) and Dillon et al. (2019) examine measurement error in self-reported farm size relative to more accurate approaches to measuring land (GPS or compass-and-rope). They demonstrate clearly that farmers report area with error, that this error varies systematically with farm size, and that whereas small farms tend to overestimate farm size, large farms tend to underestimate their size. The implications for the IR literature are mixed, as Carletto et al. (2013) and Abay et al. (2019b) find that the IR becomes stronger when measurement error in farm size is the sole correction made, but Carletto et al. (2015) and Dillon et al. (2019) both find that correcting for such measurement error partially mitigates the IR in some of their data but has no statistically significant impact elsewhere.

Similarly, several recent papers have explored the implications of non-classical measurement error in output. Desiere and Jolliffe (2018), Gourlay et al. (2019), and Lobell

[14] Further discussion of the entire dataset can be found in Rada et al. (2019).

et al. (2020) show non-classical measurement error in self-reported output when compared to "crop cuts" as the gold standard measure. Importantly, small farms over-report output more so than larger farms in their data. Conditional on GPS land measurement, the IR disappears in these papers when they utilize the more objective measure of output. Abay et al. (2019b) explore measurement error in both farm size and output, and concur that in their data the IR disappears when land is measured objectively and then crop cuts are used to correct for measurement error in production. However, they caution that the IR strengthens when land is self-reported and measurement error in output alone is corrected.

Lastly, measurement error in the use of inputs such as labor is potentially an issue. Relative to weekly surveys conducted in-person or by phone, end of season surveys of labor usage can contain substantial errors (Arthi et al., 2018; Gaddis et al., 2019). The implications for the IR, however, are ambiguous because the degree and direction of recall bias depends on a number of factors that can offset each other. Overestimation is likely to be greatest when surveys ask about hours worked per person per plot, but can be substantially smaller or even underestimated when focusing on total household hours per farm. At this level, the authors conclude that labor productivity might be underestimated in Tanzania (Arthi et al., 2018) and overestimated in Ghana (Gaddis et al., 2019).

How can this brief review of the recent literature on measurement error guide our empirical analysis of Brazil? First, we recognize that these are serious concerns. Because we do not have more objective measures that could be used to correct the data, our results should only be considered suggestive. Second, the pseudo-panel approach based on cohort averages should reduce the influence of classical measurement error, and may even help diminish some of the non-classical measurement error. In the case of land measurement, for example, the evidence from Africa suggests that the largest errors happen for the smallest of farms (under 0.5 acres), with the sign of the bias flipping from positive to negative somewhere between 0.75 ha (Abay et al., 2019b) and 2.0 ha (Carletto et al., 2015). Since our smallest farm size class is 0-5 ha, over- and under-estimation in this group may partially cancel. Third, while the literature suggests that the largest errors occur on the smallest of farms, it has little to say about measurement error for the larger farms included in our study. In the case of measurement error in output, for example, ninety five percent of parcels in the Ethiopian sample used by Desiere and Jolliffe (2018) were smaller than 1 ha, and mean plot size in the Ugandan sample used by Gourlay et al. (2019) is under 0.18 ha. What happens to measurement error in area and output as we move from farms of 10 to 100 to 1000 ha is an open question, and the IR in land productivity continues out this far in our data. Fourth, any sources of measurement error that are correlated with size, but constant over time, would not explain how the farm size – productivity gradient changes over time. This is an important aspect of our empirical analysis. Finally, Abay et al. (2019b) provide a unifying framework for thinking about data with multiple sources of non-classical measurement error. In this case, they show that the "signs and magnitude of resulting biases in estimates of a key parameter are analytically ambiguous." Thus, any attempt to correct for some, but not all, sources of measurement error could "prove inferior to a `second best' approach that uses multiple variables measured with error" (p. 183). In light of this discussion, we remain agnostic on measurement error and make no attempt to correct for it, reiterating that our results are only suggestive.

1.3.3 Empirical Methodology

We estimate an average production function assuming a Cobb-Douglas technology. Output and inputs for a representative farm in municipality m of size s in year t are normalized by area A_{mst}. Estimating the model using intensities imposes constant returns to scale on the technology coefficients and forces any deviation from CRS into the estimated relationship between farm size and productivity. Because of the difficulties discussed in Section 1.2 of distinguishing deviations from CRS from other causes of an IR, and because our focus here is not on explaining the IR, this approach simplifies the interpretation of the results. Survey year specific dummy variables for five farm size classes, δ_{st}, are used to flexibly capture the relationship between farm size and TFP. The farm size class 0-5 ha in 1985 is excluded and used as a reference. While this structure allows the farm size and productivity relationship to change over time, the technology coefficients are assumed to be time invariant. This assumption forces technical change into our measure of TFP. The estimated equation takes the form:

$$lny_{mst} = \beta_0 + \boldsymbol{\beta x}_{mst} + \boldsymbol{\alpha w}_{mt} + \delta_{st} + \lambda_m + \varepsilon_{mst} \tag{1.15}$$

where y_{mst} is aggregate output per unit of land, $\boldsymbol{x}_{mst}$ is a vector of logged factors of production per unit of land (capital, family labor, and purchased inputs including hired labor), $\boldsymbol{w}_{mt}$ is a vector of municipality-specific rainfall and temperature shocks in each period, and λ_m are municipal fixed effects. The relationship between farm size and TFP in each year is identified from within-municipality variation. The parameters are estimated using ordinary least squares, with standard errors clustered at the municipal level. Because the number of farms represented by each representative farm varies, each observation is weighted by the number of farms that it represents.

With the above approach the systematic portion of TFP is a function of $\beta_0, \delta_{st}, \text{and } \lambda_m$, but it is only the component that varies by farm size and over time for each region that is of interest here. This size-specific component in each period can be calculated as:

$$TFP_{st} = e^{\delta_{st}} \tag{1.16}$$

A TFP index is then calculated for each size class in each period using the size class 0-5 ha in 1985 as a base level set to 100.

While the use of municipality fixed effects controls for time-invariant differences across municipalities, such as soil quality, omitted variables that vary across farm size within municipalities remains a concern. Similarly, endogeneity of inputs could lead to bias in our estimated coefficients. This is a limitation of the production function approach in the IR literature, and remains a concern here.[15]

1.3.4 Empirical Results

By focusing on a regional analysis we are able to examine the relationship between farm size and productivity in light of each region's characteristics and stage of development. The five macro-regions of Brazil differ in both the type of predominant agricultural activities and the degree of modernization. They include the Amazon rainforest in the North, a large semi-arid region in the Northeast, a highly mechanized and commercial agriculture in the Southeast, a predominance of family farms in the South, and the Cerrado (savannahs) of the Center-West where grains have rapidly expanded and agriculture has modernized in recent decades. We restrict attention to the North, Center-West, and Southeast, three macro-regions that capture sufficient regional variation in Brazilian agriculture to illustrate our argument.[16] Descriptive statistics for output and input intensities for these regions in 2006 are shown in Table A.2.2 of the appendix. Differences in input intensities reflect the heterogeneity in agricultural production across regions. The more traditional agricultural region in the North relies more heavily on family labor, whereas the mechanized Southeast and Center-West use capital and purchased inputs more intensively. We also observe that the intensities of capital and labor decline

[15] Estimation of profit or cost functions is a potential solution, but as discussed in Section 1.2 the necessary input price data frequently does not exist in developing countries to make this strategy feasible.
[16] The results for the Northeast are similar to those in the North, and the results in the South are most similar to those in the Southeast.

with farm size, whereas the intensity of purchased inputs declines through the first three or four size classes, and then inverts. This was not the case in 1985. The use of purchased inputs on farms in the 500- ha class has grown more rapidly than in all the other size classes during this period.

Figure 1.3 shows the unconditional relationship between land productivity and farm size class for the three regions under study. Despite considerable regional heterogeneity in their agricultural activities and agrarian structures, each region mirrors the country as a whole in displaying a strong inverse relationship between land productivity and farm size. There is no evidence of it disappearing during this period.

The estimated coefficients from region-specific estimates of equation (1.15) are shown in Table A.3.1 of the appendix, which generate the TFP estimates presented in Figures 1.4 through 1.6. Recall from Section 1.2 that these relationships potentially include the influence of deviations from constant returns to scale.[17] In the North (Figure 1.4), we estimate an inverse relationship between farm size and TFP. It is not, however, a linear relationship, but rather an emerging U-shaped inverse relationship with farms over 500 ha becoming more productive than medium-sized farms. The significance tests in Table 1.1 confirm this, showing that while the productivity of farms between 20 ha and

[17] Note that the variables are measured per unit of land, and thus the sum of the coefficients in Table A.3.1 does not indicate the returns to scale (RTS). We do not investigate RTS because we are unable to identify deviations from CRS separately from other causes of a size – productivity relationship. And because of potential non-linearities in this relationship, RTS do not have to be constant over all farm sizes, as they are with a Cobb-Douglas. Thus, where CRS does not hold this would be captured in our size dummies δ_{st}.

500 ha is statistically less than the smallest farms in all periods, the largest farms are not statistically different from the smallest farms after the first period. Thus, while a strong negative relationship would be found in this region when using land productivity, a U-shaped relationship begins to emerge when TFP is used and linearity is not imposed.

The Center-West (Figure 1.5) demonstrates a more dynamic pattern. Table 1.1 shows that the farm size – TFP relationship in the Center-West in 1985 looked very similar to the inverse relationship in the North. However, by 2006 the inverse relationship had disappeared in the Center-West, with the TFP of all farm sizes being statistically indistinguishable from that of the smallest farms. The point estimates show that the largest farms in the Center-West were 46% less productive than the smallest farms in 1985, yet by 2006 they were 8% more productive, albeit statistically insignificantly so. Once again, a U-shape begins to emerge, driven by rapid growth of the productivity of larger farms. Increased use of purchased inputs played an important role in this transformation, as they grew roughly three to four times as fast on farms over 500 ha than on farms in the middle three size classes. This is the clearest case of a strong inverse relationship becoming reversed over the 21 year period. Using land productivity to measure the farm size – productivity relationship in a rapidly modernizing agricultural region such as the Center-West would completely miss this transformation.

The Southeast, in contrast, shows a positive non-linear relationship between farm size and TFP. The relationship was statistically flat in 1985, although the point estimates show that even in 1985 the largest farms were 25% more productive than the smallest.

Rapidly rising TFP at the upper end of the farm size distribution makes the relationship more positive over time, and by 2006 the largest farms were 48% more productive than the smallest, and statistically so. Once again, the relationship appears non-linear. This contrasts sharply with the persistent IR found in the Southeast when using land productivity as a measure.[18]

1.3.5 Discussion

In comparison to much of the development literature surrounding the IR, the Brazilian data used here represent a very heterogeneous group of farms and span a much greater range of farm sizes. A more accurate comparison group to the international literature might be farms less than 100 ha, which indeed make up approximately 90% of all Brazilian farms. Even when restricting our analysis to this subset of farms, the use of land productivity would still show a marked inverse relationship while the use of TFP would reveal a negative relationship that has disappeared in the more modernizing regions. Perhaps more importantly, inclusion of the largest farm size class reveals that these farms have notably higher productivity in the more modern regions, and it is only when TFP is used that this becomes apparent. These are commercial farms that are unlikely to be included in most household surveys in developing countries, but they are present in the Agricultural Census data used here.

[18] The empirical results obtained here are comparable to those reported at the national level by Rada et al. (2019) using a similar dataset. One difference is that they find somewhat faster TFP growth for the smallest farm size class, resulting in a more pronounced U-shape in 2006. The principal differences in empirical methodology are that they estimate TFP growth separately for each farm size class, and do not explore regional heterogeneity.

The regional analysis of Brazil provides insight into how the farm size – productivity relationship that was discussed in Section 1.2 can evolve with the modernization of agriculture. In the least developed regions of the country, the North and Northeast, the inverse relationship persists through the 100-500 ha size class regardless of the productivity measure used, and it is only with TFP that an emerging U-shape begins to appear. In the Center-West, where farms over 500 ha operated 80% of the land and accounted for around 75% of output in 2006, modernization of agriculture in this period converted an initially strong negative TFP relationship into one that was statistically flat by the end of the period. And in the Southeast, the most modern region of the country, the use of TFP reveals that the largest farms had higher productivity than all other size classes as early as 1985, but that this only became statistically significant in 2006. While it is beyond the scope of this paper to explain the causes of these changes, we note that conditions (i) and (ii) from Section 1.2 provide insight. They suggest that modernization has led output per ha to fall more slowly than inputs per ha as farm size rises. The use of modern inputs and technology appears to have successfully inverted the size – TFP relationship. Future research should seek to address whether these changes are due to increasing returns to scale above a certain size, diminishing importance of market failures, measurement error or other factors.

1.4 Conclusions and Policy Implications

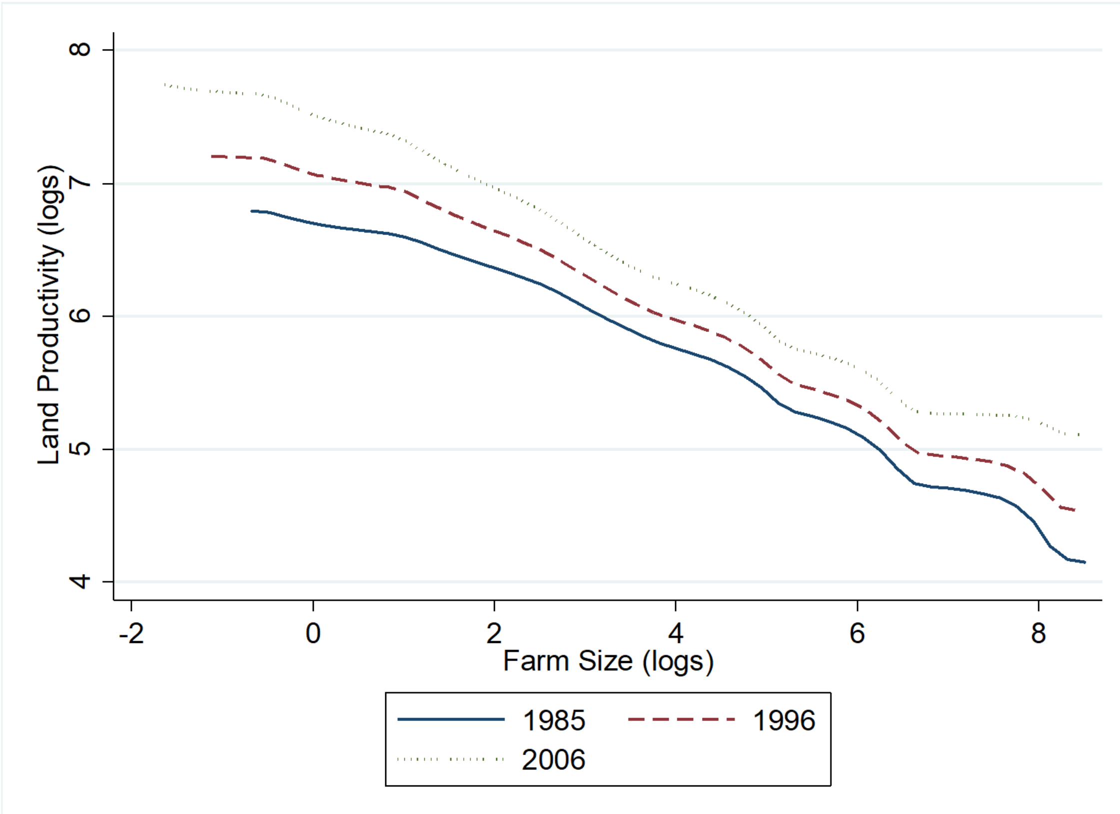
We have sought to address an important weakness of the development economics literature on the inverse relationship between farm size and productivity. We argued that a variety of productivity measures are used when estimating this relationship, that the choice of measure matters for its identification and interpretation, and that total factor productivity is, in most cases, the preferred and most informative measure for policy. Furthermore, we argued that a commonly used measure – land productivity – is problematic and potentially misleading when used in modernizing agricultural contexts or when assessing a full range of farm sizes. Where comprehensive measures of productivity are more relevant and of interest, a focus on land productivity introduces omitted variable bias by not controlling for the intensity with which other inputs are used. Our conceptual discussion provides a framework for assessing the implications of the choice of productivity measure. Theoretically, it is clear that an inverse relationship between land productivity and farm size is neither necessary nor sufficient for an inverse relationship to exist between farm size and TFP.

How much does this critique matter? We conduct an empirical analysis at the regional level in Brazil using a pseudo-panel from 1985 to 2006 to contrast the land productivity – farm size relationship with the TFP – farm size relationship. While the analysis is only suggestive due to potential bias stemming from non-classical measurement error or endogeneity of inputs, the results indicate that the choice of productivity measure matters greatly. As in many developing country contexts, there exists an inverse relationship between land productivity and farm size for Brazil, and within each of its macro-regions in every period. In contrast, the TFP and farm size relationship varies across time and space. The regional analysis of the TFP and farm size relationship shows 1) land productivity is not always an appropriate proxy for TFP; 2) the relationship is dynamic, changing with agricultural modernization; 3) the relationship is non-linear, often characterized by a U-shape; and 4) the very largest farms, such as those with more than 500 ha, are important to consider when assessing any relationship between farm size and productivity.

From a policy perspective, our findings have important implications for the debate about the future of small farms in developing countries. When using TFP, we see that superior productivity of small farms in traditional agricultural contexts is fully consistent with emergent productivity advantages for larger commercial farms in modernizing agricultural sectors. As economies develop, superior productivity may not continue to provide a valid argument for the importance and future of small farms, as we expect larger farms to play a more important role in driving national-level agricultural productivity growth. As such, it is increasingly unlikely that redistributive land reform could positively impact both equity and efficiency. However, this does not imply that small farms will, nor should, disappear. We expect them to remain important for generating livelihoods for rural households, providing food security, and contributing to the development of rural economies. Total factor productivity gains among small farmers will also continue to be essential for poverty alleviation. Importantly, rather than resting on an inverse farm size – productivity relationship, policy that seeks to impact both equity and efficiency should focus on ensuring that smallholders have access to the productivity gains experienced by their larger counterparts. Thus, policies that help build human capital, facilitate adoption of new technologies, and enhance access to markets via a reduction in transactions costs will continue to be indispensable for reducing rural poverty in developing countries.

Chapter 1 Tables and Figures

Figure 1.1: Farm Size and Land Productivity, Brazil (2006 R$/ha)



Note: Smoothed as a local polynomial regression with bandwidth of 1.25 and Epanechnikov kernel.

Figure 1.2: Land and Labor Productivity, Brazil 2006

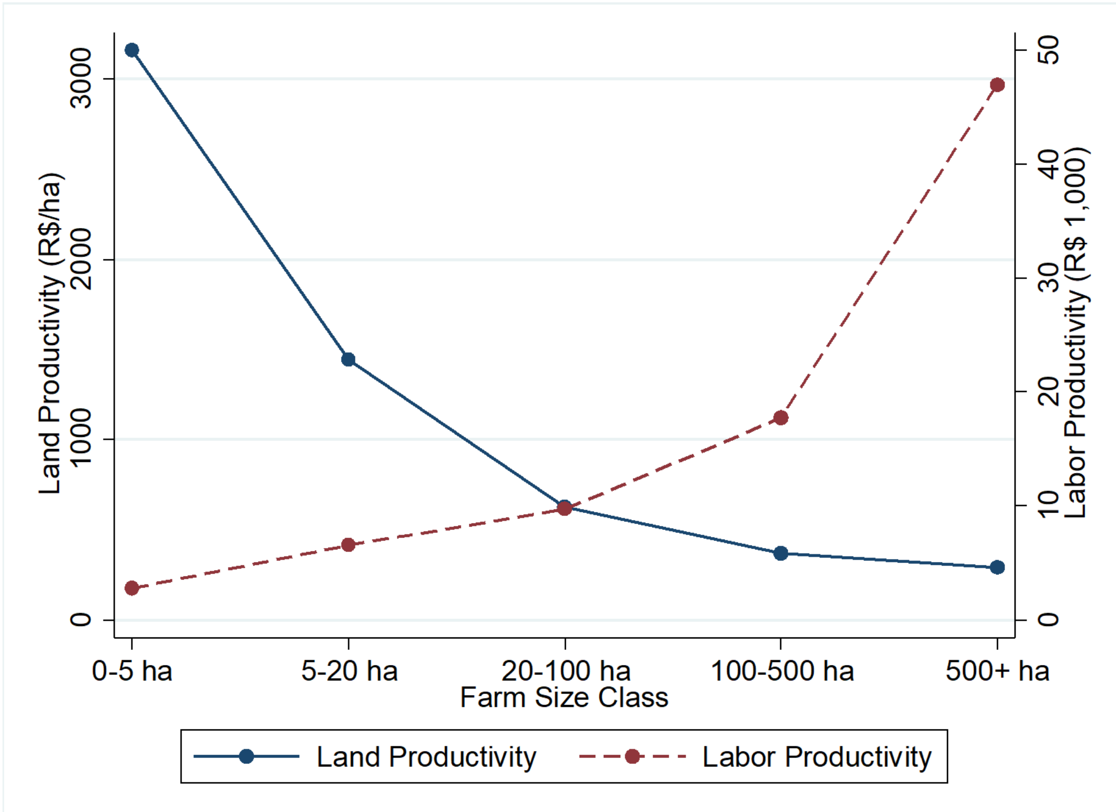


Figure 1.3: Land Productivity in Brazil by Region

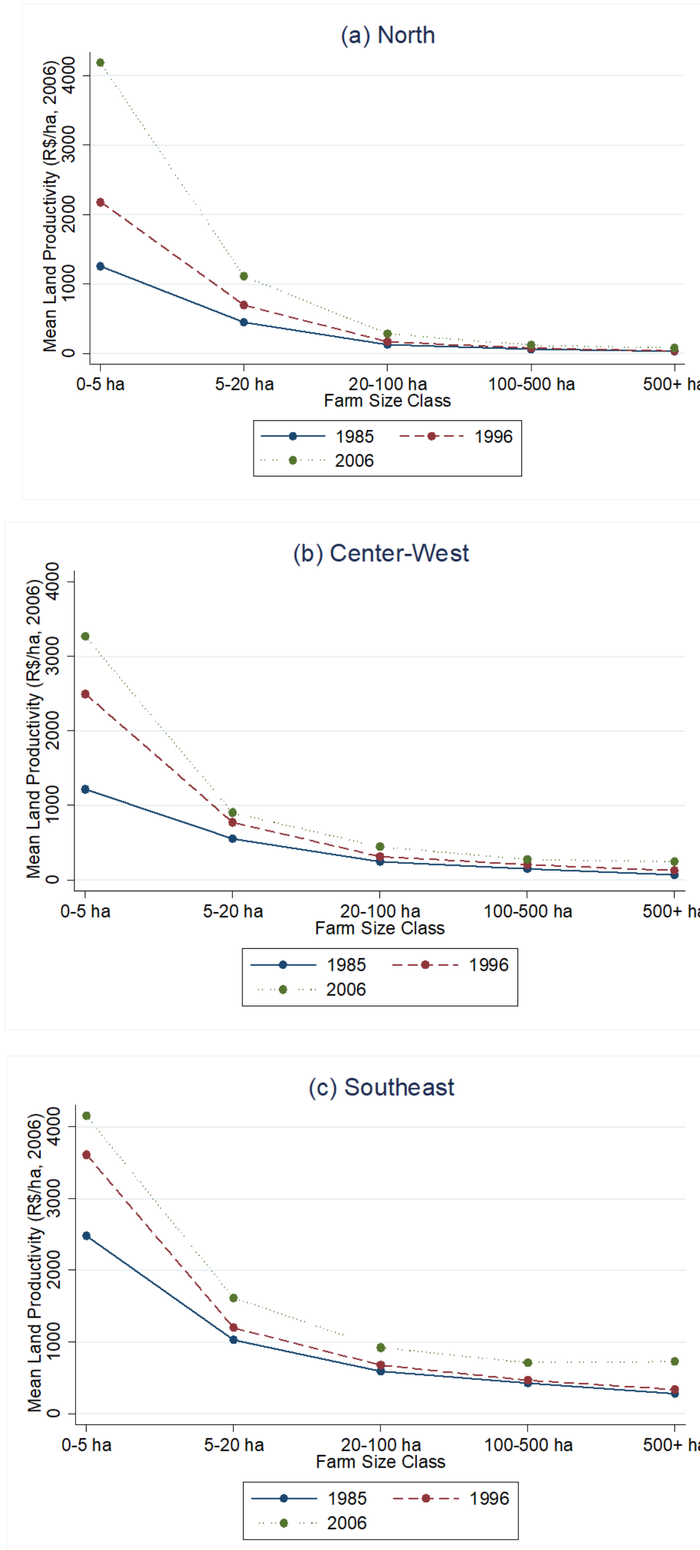


Figure 1.4: Total Factor Productivity in Brazil's North

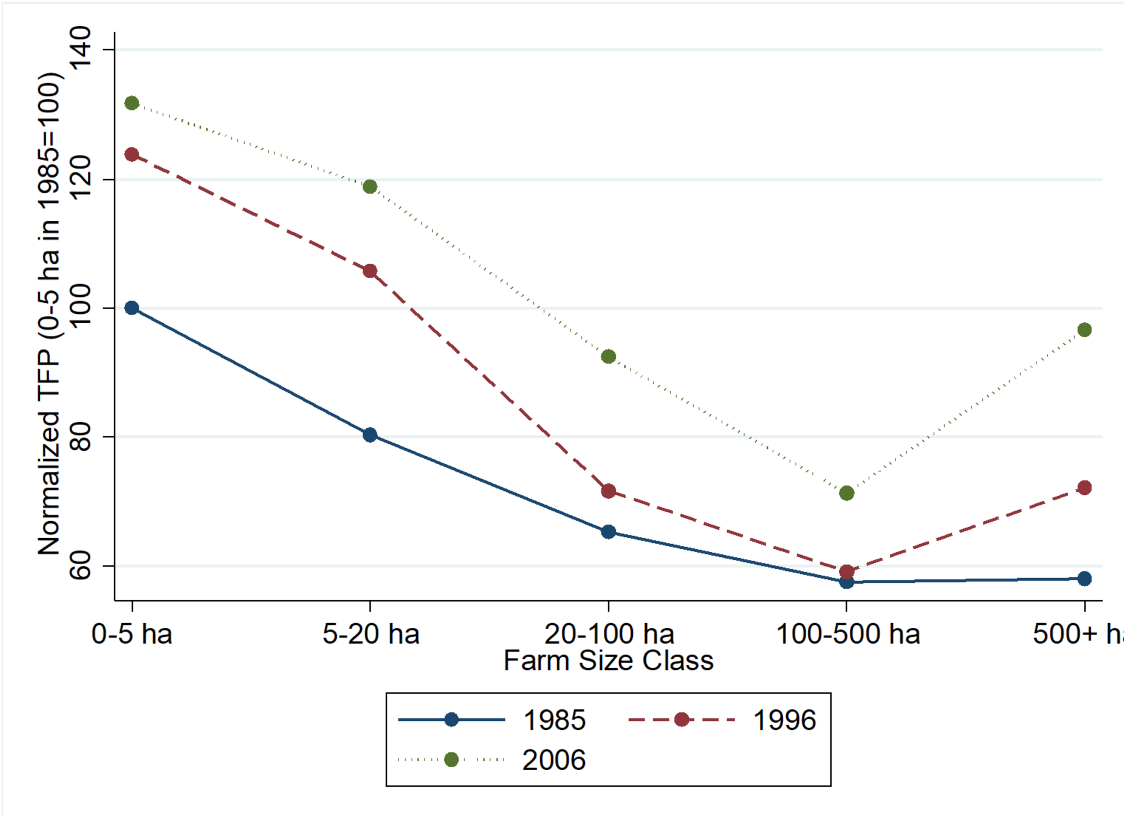


Figure 1.5: Total Factor Productivity in Brazil’s Center-West

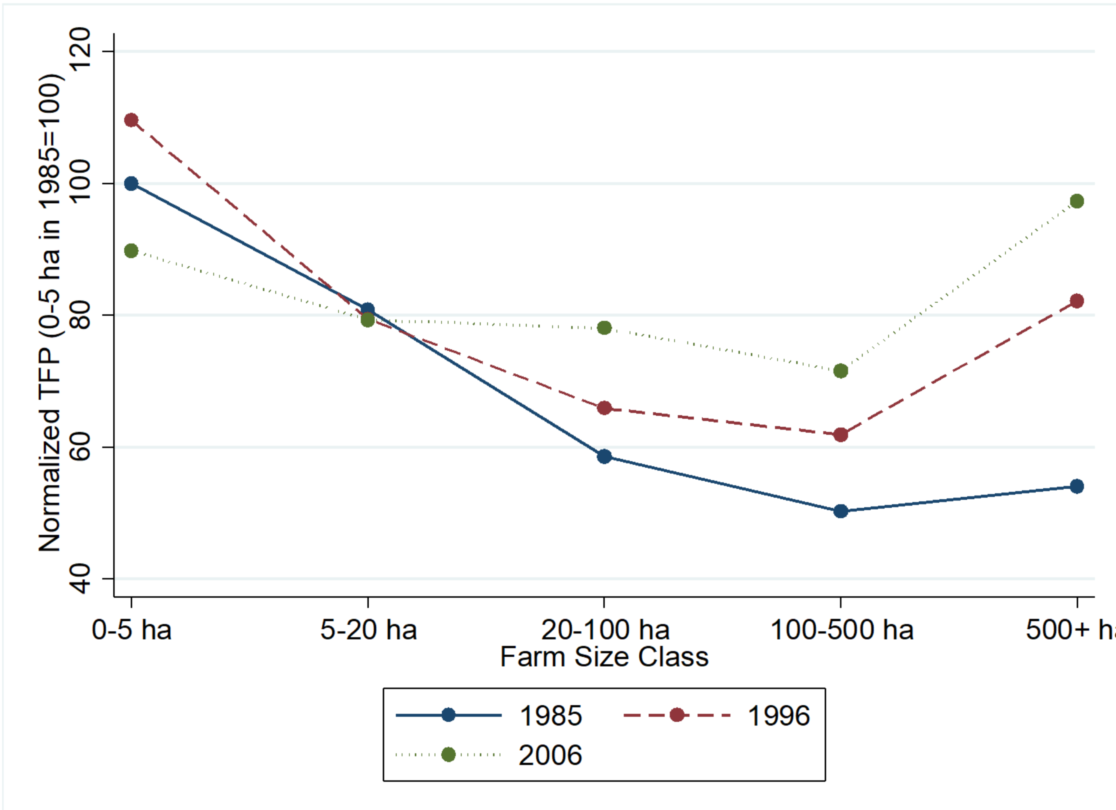


Figure 1.6: Total Factor Productivity in Brazil's Southeast

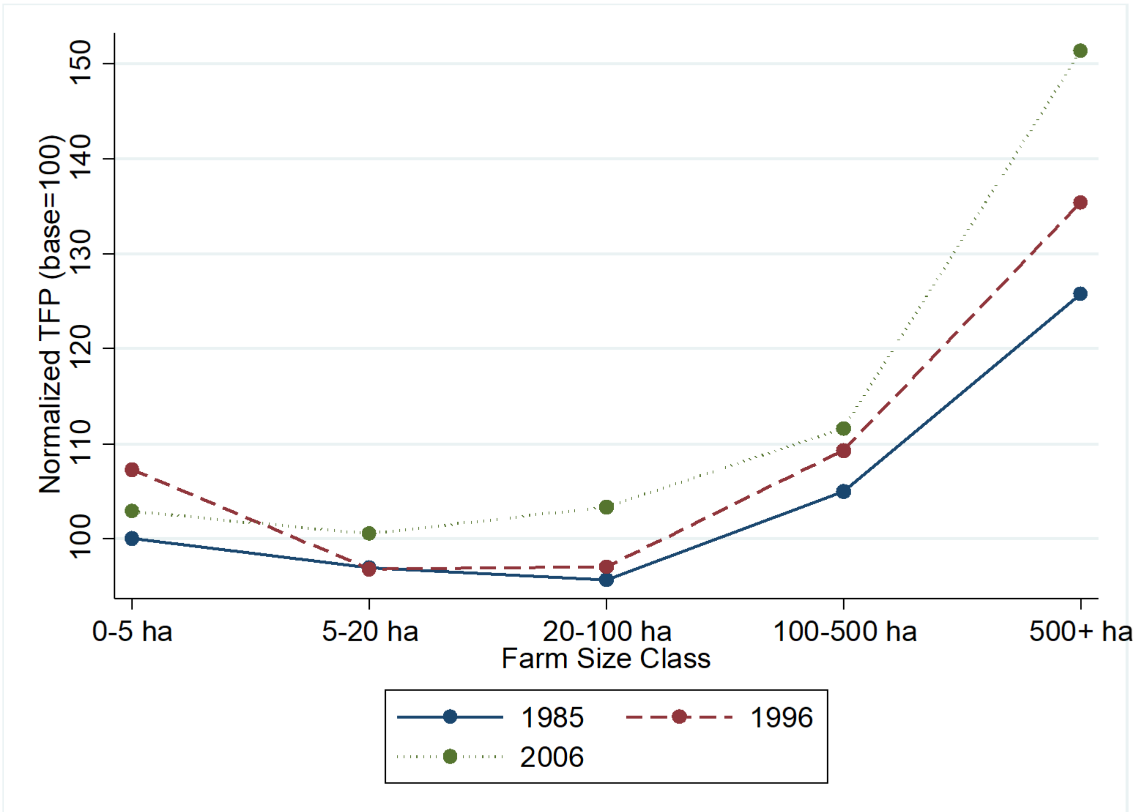


Table 1.1: Percentage Difference in TFP Relative to 0-5 ha Farms

	North			Center-West			Southeast		
	1985	1996	2006	1985	1996	2006	1985	1996	2006
5-20 ha	-19.71**	-14.63*	-9.79	-19.22***	-27.49***	-11.65	-3.07	-9.22**	-2.25
	(0.018)	(0.068)	(0.481)	(0.001)	(0.002)	(0.334)	(0.369)	(0.011)	(0.578)
20-100 ha	-34.69***	-42.11***	-29.85*	-41.43***	-39.88***	-13.10	-4.42	-8.94	1.11
	(0.005)	(0.001)	(0.070)	(0.000)	(0.003)	(0.283)	(0.510)	(0.190)	(0.870)
100-500 ha	-42. 53***	-52.25***	-45.89**	-49.83***	-43.53***	-20.30	5.05	2.59	8.61
	(0.009)	(0.001)	(0.027)	(0.000)	(0.013)	(0.286)	(0.637)	(0.816)	(0.441)
500 + ha	-41.97*	-41.72	-26.68	-46.01**	-24.99	8.37	24.98	27.82	47.66**
	(0.100)	(0.146)	(0.453)	(0.036)	(0.361)	(0.795)	(0.144)	(0.117)	(0.013)
N	1,888	1,888	1,888	3,038	3,038	3,038	17,742	17,742	17,742

Base farm size bin, 0-5 ha. Tests are conducted by region and year. P-values from significance tests are in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

CHAPTER 2

The Farm Size – Productivity Relationship in the Wake of Market Reform: An Analysis of Mexican Family Farms[1]

2.1 Introduction

Beginning with the seminal work of Sen (1962), economists have documented an inverse relationship between farm size and land productivity throughout much of the developing world (Bardhan, 1973; Berry and Cline, 1979; Deolalikar, 1981; and Barrett et al., 2010, among others). This inverse relationship has been found in a broad range of geographies, time periods, and crop mixes, and has been featured in discussions of development policy, including land reform (Lipton, 2009) and the future of small farms (Wiggins et al., 2010).

[1] We thank the World Bank for a grant that supported the early stages of this research, and Graciela Teruel at the Iberoamerican University in Mexico City for her support and expertise in working with the Mexican Family Life Survey.

The regularity with which an inverse relationship between farm size and land productivity is observed led to many theoretical explanations for the phenomenon. Early explanations centered around multiple market failures (Sen, 1966; Eswaran and Kotwal, 1986), asymmetric information (Feder, 1985), and risk aversion among farmers (Barrett, 1996). A second set of explanations emphasized empirical issues such as systematic measurement error in farm size and/or output (Lamb, 2003; Carletto et al., 2013; Gourlay et al., 2019; Desiere and Jolliffe, 2018) and omitted variables (Bhalla and Roy, 1988; Benjamin, 1995; Assunção and Braido, 2007). Empirical studies have typically found that existing theory fails to fully explain the observed inverse relationship, generating a body of mixed and at times contradictory evidence.

Chapter 1 illustrates how the choice of productivity measure can alter the relationship observed and how it can obscure a changing relationship between farm size and total factor productivity, the more relevant productivity measure. A dynamic relationship was found between farm size and total factor productivity in the rapidly modernizing agricultural regions of Brazil, contributing to an emerging literature that documents changing farm size – productivity relationships as agricultural sectors modernize and develop (Foster and Rosenzweig, 2017; Deininger et al., 2018; Rada and Fuglie, 2019). This is consistent with Helfand et al. (2015), whose findings suggest that both the larger commercial farms and smaller family farms in Brazil have advantages in harnessing technical change and achieving rapid gains in productivity.

In this paper the hypothesis of a dynamic farm size – productivity relationship is extended to the context of Mexico, identifying the relationship in a panel of family farms from the Mexican Family Life Survey (MxFLS) and testing for changes over the sample period of 2002-2009. Mexico is an interesting case for assessing changes in the farm size – productivity relationship because of its long history of land reform and the recent agricultural policy reform associated with the North American Free Trade Agreement (NAFTA) in the 1990s. These policies are a prime example of the Washington Consensus, liberalizing markets for land, agricultural inputs, and agricultural output in Mexico with the objective of spurning the modernization, competitiveness, and productivity of the agricultural sector and the broader economy. An environment with such market reforms, if successful, is expected to diminish the multiple market failure explanation of the inverse relationship between farm size and productivity, and any observed inverse relationship might weaken accordingly.

We test for changes in the farm size – productivity relationship and, contrary to expectations, find that an inverse relationship exists and has remained strong in the wake of Mexico's market reforms. We explore the relationship further by estimating a stochastic production frontier, an approach often applied in developed economy agriculture but infrequently applied in developing economy contexts. While frontier productivity growth has increased rapidly for larger farms, eliminating the inverse relationship at the frontier, the average relationship has remained unchanged due to more rapidly increasing technical inefficiency amongst the larger farms in the sample. This finding highlights the need for, and echoes calls for, policies that support family farms' transitions towards modern agriculture and adaptation to market liberalization in Mexico.

The proceeding section discusses agricultural policy in Mexico, providing context for the empirical analysis. This is followed by an introduction of the empirical methodology, a description of the data, and the presentation of empirical results. Policy recommendations for Mexican agriculture and research implications conclude.

2.2 The Mexican Agricultural Experience

The institutional structure of Mexican agriculture continues to reflect agricultural policies implemented after the Mexican Revolution of the early 20th century. Land policy of the 1934 Agrarian Code established the *ejidos* – tracts of communally held land with individual plots farmed by designated households – as a principle tool for redistributing land and property rights to peasants. Agrarian communities, a distinct form of land tenure located predominantly in the South where farmers had pre-existing claims to agricultural land, were similarly formed although to a lesser extent. A dual system of agricultural tenure emerged, with ejido farmers on the one hand and private landowners on the other. Within both the ejido and private farm sectors there exists both the larger, commercially oriented farms and the smaller predominantly subsistence farms.

It is in this context that Berry and Cline (1979) first studied the farm size – productivity relationship in Mexico. Drawing from the Mexican Agricultural Census of 1940 and of 1960, they compared land productivity of small and large private farms. They found land productivity of small farms to be 6.5 times larger than that of larger farms in 1940, but just 3.5 times as large by 1960. More importantly, when output per unit of land *and* capital was measured, a more comprehensive measure of productivity, small farms were 1.7 times more productive than large farms in 1940 but just 0.8 times as productive in 1960. This early evidence illustrates that an inverse relationship between farm size and land productivity is neither necessary nor sufficient for an inverse relationship between farm size and more comprehensive productivity measures, similar to the findings of chapter 1 in the context of Brazil.

Berry and Cline (1979) hypothesized that the changing productivity ratios reflected a shift from livestock to crops on large farms, facilitated by government investment in infrastructure, provision of credit, and other supportive policies. As the birthplace of the Green Revolution, Mexican agriculture experienced productivity growth throughout this period, notably becoming net exporters of important staples such as wheat and maize. A weakening of the IR between farm size and land productivity accompanied this period of agricultural modernization and development, as did a reversal of the IR between farm size and output per unit of capital and labor.

More recent research using farm-level panel data from the Mexico National Rural Household Survey (ENHRUM), a household survey statistically representative of 80% of rural Mexico, showed evidence of an inverse relationship between farm size and productivity in 2003 and 2008 (Kagin et al., 2016). By estimating an average production function and a stochastic production frontier, they find an inverse relationship between farm size and land productivity, farm size and average TFP, and farm size and TFP along the production frontier. They conclude that the observed farm size – TFP relationship was driven, in part, by larger farms being further from the frontier (i.e. smaller farms being more efficient than their larger counterparts).

Mexican agriculture in the early 20th century is an interesting setting for studying the farm size – productivity relationship because of the policy changes and market reforms associated with The North American Free Trade Agreement (NAFTA) going into effect in 1994. As part of an economy-wide reduction in tariffs, agricultural tariffs were gradually eliminated over a 14-year span ending in 2008. The liberalization of agricultural trade exposed the Mexican agricultural sector to increased competition and imports from Northern neighbors. As a result, a flood of cheap imports has led to a decline in the price of staple crops for many Mexican farmers (Pérez et al., 2008).

For Mexican agriculture, NAFTA was part of a broader program of reform and market liberalization. One important change was the Program for the Certification of Ejido Rights and Titling of Urban Plots (Procede), which included reform of the ejido system of land tenure. Following a constitutional amendment, Procede facilitated the new option for ejidos to privatize individual parcels that could then be mortgaged, rented, or sold. Further, agricultural rights to ejido parcels ceased being contingent upon actual agricultural production, strengthening property rights for the ejido sector. Importantly for the private sector, the practice of expropriating large private holding for the formation of ejidos was ended. By securing property rights and integrating ejidos into the market, these changes were expected to increase opportunities throughout the rural farm sector. A World Bank (2001) evaluation of the ejido reforms found that, while Procede had been widely successful in securing property rights, often in the form of certificates of agricultural rights, the program had not led to widespread land transfers and ejido farms remained credit constrained at the turn of the century.

A second set of policy changes affected the manner in which government supported agricultural input and output markets. Policy shifted away from heavily subsidizing inputs and providing price supports for output towards a system of direct transfers for those impacted by increased international competition. In general, producers of staple products have suffered due to increased competition with relatively cheap imports whereas exports of high-valued horticultural products have benefited (Pérez et al., 2008). The Program for Direct Assistance in Agriculture (Procampo), primarily an income support program, offered per hectare payments to any farms with a history of producing any of nine key staples prior to 1993 that were actively farming one of those crops. An important change to the program in 1995 allowed participation of any farm producing any legal crop that had previously qualified for the program. Further changes to the program in 2001 included higher per-hectare payments for farms under 5 hectares and a shift of the timing of payments to the start of the planting season. Upper limits on land size included for payments are larger for corporate-run than for family-run farms. Alongside Procampo is *Alianza para el Campo*, a suite of programs designed to increase agricultural productivity primarily through investment in infrastructure and extension assistance.

As government programs withdrew, farms became increasingly reliant upon markets for access to key agricultural inputs such as fertilizer, pesticides, and seed and for access to credit. Although government credit programs have scaled back, well-functioning credit markets have not appeared in rural Mexico and access to credit markets is not widespread, inhibiting access to key inputs and modern technology. As in other developing country contexts, market concentration in both input markets and post-harvest processing and marketing has hurt the profitability of family farms and generated economies of scale in transacting with the agricultural supply chain.

We hypothesize that the farm size – TFP relationship is likely to be changing over time in the wake of Mexico's NAFTA-era reforms, much as it appears to have done in Mexico during the Green Revolution (Berry and Cline, 1979) and in Brazil's modernizing agricultural regions (see chapter 1). This hypothesis rests upon the assumptions that (i) market imperfections contribute to any pre-existing IR in Mexican agriculture and (ii) Mexico's NAFTA-era market liberalization has improved the efficiency of agricultural input and output markets. Beyond the farm size – productivity relationship, agricultural productivity is important to Mexico for both rural economic development and poverty reduction. According to data from the World Bank,[2] agricultural output made up 3.6% of Mexico's GDP but employed 13-14% of the workforce in 2015. Further, approximately

[2] All data taken from the World Bank: http://data.worldbank.org/.

62% of Mexico's rural population is impoverished when using the national poverty line, suggesting that agricultural productivity has a potentially important role in Mexico's rural economic development and efforts to reduce poverty. There are similar implications for trends in migration, as increasing agricultural productivity on family farms facilitates the ability to generate adequate livelihoods and effectively support families, reducing an important push factor in migration decisions.

2.3 Empirical Methodology

As discussed in chapter 1, land productivity is a partial measure of productivity and does not account for the use of inputs other than land. Where other inputs are used in production, failing to account for the use of those resources potentially introduces bias into estimates of the relationship between farm size and productivity if the intensity of input use (inputs per hectare) varies with farm size. Controlling for all inputs in agricultural production can be accomplished with estimation of a production function, uncovering TFP, the comprehensive and preferable measure of productivity.

We use two complementary approaches to explore the relationship between farm size and TFP with a panel of Mexican farms. First, we use an average production function to estimate average TFP and its relationship with farm size. Second, we use a stochastic production frontier to estimate both TFP along the technological frontier and technical inefficiency, identified as deviations from the frontier. The frontier analysis identifies any relationship between farm size and frontier TFP and any relationship between farm size and technical inefficiency. As is standard in the literature (Coelli et al., 2005; and Kumbhakar et al., 2015), we view TFP change as a combination of changes in the technological frontier and changes in the deviations from the frontier.

We identify TFP by estimating a Cobb-Douglas production function with inputs measured per hectare, implicitly imposing constant returns to scale on the production technology. In such a setting, the inclusion of a measure of farm size as an explanatory variable identifies any relationship between farm size and TFP (see chapter 1 for detail). Any deviation from constant returns to scale is effectively forced into the farm size term so that the estimated farm size – TFP relationship includes any non-constant returns to scale. We estimate the following production function using OLS regression:

$$y_{ict} = \beta_0 + \boldsymbol{\beta x}_{ict} + \boldsymbol{\omega Z}_{ict} + \boldsymbol{\theta}_t + \boldsymbol{\gamma}_c + f(A_{ict}) + \boldsymbol{\theta}_t \times f(A_{ict}) + \varepsilon_{ict} \qquad (2.1)$$

where y_{ict} is log of output per ha for farm i in community c in year t and x_{ict} is log of input per ha for the $k = 1, \dots, 5$ non-land inputs: purchased intermediate inputs, physical capital, draft animals, family labor, and non-family labor. The variable of interest, $f(A_{ict})$, is a measure of farm size, A_{ict}, taking various functional forms including linear, quadratic, cubic, and a flexible dummy variable structure. Community-level fixed effects, $\boldsymbol{\gamma}_c$, allow for the inclusion of household-level explanatory variables, $\boldsymbol{Z}_{ict}$.[3] We use survey year dummies, $\boldsymbol{\theta}_t$, and interact survey year with the measurement of farm size to allow the farm size – productivity relationship to vary over time. Omitting survey year interactions with inputs effectively assumes that the technology is time-invariant, forcing any changes

[3] A model with household-level fixed effects is estimated as a robustness check.

in technology into the TFP term. The standard normal error term is given by ε_{ict}, clustered at the community level.

Additionally, production functions interacting household explanatory variables with farm size are estimated. These models explore the potential for heterogeneity in the farm size-productivity relationship across important subgroups:

$$y_{ict} = \beta_0 + \boldsymbol{\beta x}_{ict} + \boldsymbol{\omega Z}_{ict} + \boldsymbol{\theta}_t + \boldsymbol{\gamma}_c + f(A_{ict}) + \boldsymbol{\theta}_t \times f(A_{ict}) + \boldsymbol{Z}_{ict} \times f(A_{ict}) + \varepsilon_{ict} \tag{2.2}$$

The second approach complements the average production function by estimating a stochastic *production frontier*. We take an output-oriented perspective, measuring technical inefficiency as the difference between what is actually produced by a farm, Y, and the maximum possible production given the inputs used, $f(\boldsymbol{X})$:

$$Technical\ Inefficiency = \frac{f(\boldsymbol{X})}{Y} \tag{2.3}$$

Rearrangement of the log of technical inefficiency generates the following relationship:

$$lnY = lnf(\boldsymbol{X}) - \ln\,(Technical\ Inefficiency) \tag{2.4}$$

Stochastic production frontier analysis differs from the estimation of an average production function because of the use of a two-part error term – a standard idiosyncratic error term, v, coupled with a one-sided error term, u, that measures inefficiency or deviations from the production frontier:

$$lnY = lnf(\boldsymbol{X}) + v - u \tag{2.5}$$

Econometric estimation requires the assumption of a functional form for the frontier, a distributional assumption for v, and a distributional assumption for u. Functional forms for the frontier are typically Cobb-Douglas or the more general translog functional form, and the standard normal distribution is generally assumed for v. Common assumptions for the distribution of u include the exponential distribution, the half normal distribution, and a more general truncated normal distribution.

Stochastic frontier models allow for the simultaneous estimation of the frontier and heterogeneity in the inefficiency as a function of explanatory variables, and are estimated with maximum likelihood methods. We employ Greene's (2005) "true" fixed effects model with community-level fixed effects using the *sfpanel* command in Stata.[4] Working with community level fixed effects has the advantage of allowing the inclusion of household-level explanatory variables. A half-normal distribution is used for the inefficiency component of the error term, allowing for estimation of the variance of the inefficiency term simultaneously with the stochastic frontier.[5] A Cobb-Douglas functional form is assumed for the production frontier with inputs and output measured in logs per unit of land. The idiosyncratic component of the error term is assumed to follow a normal distribution and standard errors are clustered at the community level. More formally, the model is given by equations (2.6) through (2.9).

$$y_{ict} = \beta_0 + \boldsymbol{\beta} \boldsymbol{x}_{ict} + \boldsymbol{\omega} \boldsymbol{Z}_{ict} + \boldsymbol{\theta}_t + \delta A_{ict} + \boldsymbol{\gamma}_c + v_{ict} - u_{ict} \tag{2.6}$$

$$v_{ict} \sim N(0, \sigma_{v,c}^2) \tag{2.7}$$

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[4] See Belotti et al. (2012) for a discussion of *sfcross* and *sfpanel*.

[5] We attempted to estimate a frontier with a more flexible truncated normal distribution for the inefficiency term, allowing us to estimate its mean and/or variance (Wang, 2002). These models failed to converge with the MxFLS data.

$$u_{ict} \sim N^{+}(0, \sigma^2_{u,ict}) \quad (2.8)$$

$$\sigma^2_{u,ict} = \alpha_0 + \alpha_1 A_{ict} + \boldsymbol{\theta}_t + \boldsymbol{\varphi V}_{ict} + \epsilon_{ict} \quad (2.9)$$

where $\boldsymbol{x}_{ict}$ are inputs per ha in logs, A_{ict} is log farm size, $\boldsymbol{Z}_{ict}$ and $\boldsymbol{V}_{ict}$ are vectors of household level controls used in the frontier and inefficiency equations, respectively, $\boldsymbol{\theta}_t$ are time dummies, $\boldsymbol{\gamma}_c$ are community dummies, v_{ict} is the standard normal idiosyncratic component of the error term, u_{ict} is the half normal inefficiency component of the error term, and ϵ_{ict} is a standard normal error term used in the inefficiency equation. For simplicity, we assume farm size (A_{ict}) enters linearly in the frontier model.[6]

The current analysis of the farm size – productivity relationship in Mexico using the MxFLS takes a similar approach to that of Kagin et al. (2016). An important difference is that we assess how the relationship may have changed over time as it has done in the modernizing agricultural regions of Brazil. This extension is important for the case of Mexico in the wake of NAFTA and other significant reforms to Mexican agricultural policy.

2.4 Data

The Mexican Family Life Survey (MxFLS) is a longitudinal survey of Mexican households, representative of the Mexican population at the national, urban, and rural levels.[7] The MxFLS is a rich source of data for this analysis, as controlling for unobservable farm and community level characteristics using fixed effects is potentially important for

[6] The results with farm size dummies are largely equivalent.
[7] MxFLS was designed, implemented, and is managed by the Iberoamerican University and the Center for Economic Research and Teaching in Mexico, in conjunction with Duke University researchers.

determining the farm size – productivity relationship. Further, the decade long span of the surveys allows for a careful analysis of how the size-productivity relationship has evolved in the wake of NAFTA and contemporaneous reforms affecting the Mexican agricultural sector.

The three survey rounds – 2002, 2005-06, and 2009-12[8] – tracked a broad range of individual, family, and community characteristics for the 8,437 initial households. The second (2005) and third (2009) waves of the survey successfully re-interviewed 90% and 94% of first wave households, respectively. Individuals from the first wave formed new households at annual rates of 3.6% and 4.7% between the first and second and the second and third waves, with 83% of newly formed households being re-interviewed in the third survey wave.

While not representative of the Mexican agricultural sector per se, the MxFLS is representative of both rural and non-rural Mexican households. As such, the use of the dataset to study Mexican agriculture has the important caveat that it underrepresents the larger, commercial agricultural operations to the degree that they are not family farms.[9] A comparison with the 2007 Agricultural Census reveals that both the census and MxFLS have less than 5% of farms that are greater than 50 ha. However, it is important to note that these "large" farms are not necessarily the same as those in the census because they are family-run farms and do not include corporate-run, commercial agricultural

[8] The vast majority of third wave interviews, 95%, were conducted in 2009 and 2010.
[9] This is similarly true of the Mexico National Rural Household Survey (ENHRUM) used by Kagin et al. (2016), which is representative of rural communities in Mexico with between 500 and 2,500 inhabitants.

operations. In comparison to the 2007 census, the MxFLS over-represents farms less than 2 ha and under-represents farms between 20 ha and 50 ha. This is true for each survey wave, highlighting that while the MxFLS is not representative of the Mexican agricultural sector in its entirety, it is appropriate for studying household farms in Mexico.

We employ a farm (i.e. household) level analysis using all MxFLS households engaged in agricultural production. A plot-level analysis is not feasible because agricultural input data is recorded at the household level and is therefore not plot specific. However, as we are primarily concerned with documenting the farm size – productivity relationship in Mexico and how it has changed over time, and we are less concerned with fully explaining its determinants, a farm level analysis will suffice. Households in the MxFLS move in and out of agricultural production between survey waves. An unbalanced panel is constructed through two stages of restricting the MxFLS data: first, cross-sections of households with complete farm data are identified and cleaned to eliminate outliers, and second, the unbalanced panel is formed out of all households that appear in two or more MxFLS survey waves.[10]

Table 2.1 shows all households using plots for agricultural production in a given survey wave are referred to as agricultural households, whereas all households with plot size and output data for all non-fallow plots are referred to as complete farms. The intermediate group, farms with farm size data, includes all farms with complete farm size

[10] Some households have incomplete data on plot size or output. After removing such households, we eliminate outliers by trimming the extremes of the farm size and land productivity distributions.

data but not necessarily complete production data – this less restricted dataset increases the sample size at the expense of potentially introducing some measurement error, and is an alternative treatment of the data that is pursued below. Lastly, the number of farms in the panel includes the number of households with complete farm data in two or more of the survey years. These restrictions on the data leave us with a sample of 566 farms reappearing in two or more survey years. Table 2.2 describes these farms according to the combination of survey years in which they appear.

2.4.1 Input and Output Variables

Farms are classified into one of 7 farm size groups, as shown below in Table 2.3. The distribution of farms across these bins is roughly constant over time and across treatments of the data, although the share of farms between 0 and 0.5 ha is falling over time while the share of farms between 0.5 and 1 ha is increasing. Importantly, with the exception of the share of farms between 0.5 and 1 ha in 2002, the distribution does not change in any notable way as we restrict the cross section to form the panel, an indication that use of the panel has not introduced bias along this dimension. There is a considerable range in farm sizes in the sample, ranging from less than one hundredth of a hectare to 45,000 hectares. The median farm size in the panel is 2.5, 2.1, and 3.0 hectares in 2002, 2005, and 2009, respectively, with mean farm sizes of 101, 232, and 218 hectares. Around 75 percent of farms utilize only one plot for production in any given year.

The preferred measure of agricultural output is a Fisher quantity index that includes all crop and livestock production for each farm in the MxFLS panel. Crop prices from the Food and Agriculture Organization of the United Nations are used to aggregate crop output. Together with a measure of the value of livestock production, an output index is constructed as detailed in Appendix B.1.

The MxFLS offers data on five agricultural inputs other than land: physical capital, draft animals, purchased intermediate inputs, family labor, and non-family labor. Physical capital is measured as the value of tractors and other machines and equipment owned and draft animals is the value of horses, donkeys, and mules owned by each household in each survey year, deflated to 2002 values. Purchased intermediate inputs are measured using reported expenditures on each of nine agricultural inputs over the course of the previous year, again deflated to 2002 values. An index of family labor is constructed using household members' time use and employment data in the MxFLS, and is an estimate of annual hours worked on the farm by all household members. In contrast, the non-family labor index is a measure of the number of non-household individuals that worked on each farm in each year, measured in workers and not labor hours. Appendix B.2 provides a detailed discussion of the source and construction of the family labor and non-family labor indices, including a set of alternative family labor indices.

Table 2.4 shows the share of panel households using the different input categories in each year, with purchased intermediate inputs shown both collectively and further disaggregated into their nine components.[11] For all of the inputs there exist at least some,

[11] A comparison of input usage and patterns over time between the cross section and the panel shows broad consistency across the treatments of the data, again showing that use of the panel does not appear to bias the sample along this dimension.

if not a majority, of households that have zeros for that input category. This is expected, as farms in the sample are expected to span a range from low technology subsistence agriculture to more modern and input intensive operations. Furthermore, many inputs may be substitutes for each other, and farms can access these inputs by owning them or by purchasing them in factor markets. Tractor services, for example, may be substituted for with draft animals. Households can either own some combination of these capital stocks or purchase their services from the market. We follow Battese (1997) to estimate production functions with observations having zero inputs.[12]

Of principle importance is any relationship between inputs per hectare and farm size, as systematic relationships between input intensity and farm size potentially drive a wedge between the farm size – land productivity and farm size – total factor productivity relationships (see chapter 1). We calculate the correlation coefficients between logged input per hectare and logged farm size for those farms with non-zero values of usage of each input. These correlations are shown in Table 2.5. Conditional on using the input, the intensity (per hectare) of all inputs used declines with farm size, emphasizing the importance of moving from partial measures of productivity to a comprehensive measure such as TFP.

[12] For each input, k, for each farm in each survey year, we generate a dummy variable, D_{ict}, equaling 1 if there is zero input for that farm in that survey year and zero otherwise. We then define a new measure of the input, x^{*}_{ict}, equaling 0 if $D_{ict} = 1$ and the log of that input per ha (x_{ict}) otherwise. The inclusion of the dummy variables and newly constructed inputs allows for unbiased estimation of the production function's parameters in the presence of zeros while using the full sample.

2.4.2 Additional Household Controls

The vast majority of plots are either privately owned property or are part of an *ejido* – a piece of communally held land where plots are farmed by designated households.[13] It is commonly accepted that ejidos are less productive than privately held farms, although there is little empirical evidence comparing the TFP of these farms using micro data. At least 91% of privately held plots in the MxFLS have some form of formal documentation in any given year, while just 75-84% of MxFLS ejido properties do. Privately held plots primarily have a formal deed or title to the land as documentation, whereas ejido plots primarily have a certificate of ejido status or agricultural rights. Formal documentation of property rights is important for accessing credit and is expected to be positively correlated with TFP. How property rights are formally documented matters, however, as a certificate of ejido status is often not acceptable to private financial institutions for use as collateral whereas formal deeds are. We control for both separately in the core empirical analysis. Because ejidos may function differently than privately owned parcels, we control for ejido status. Ejido farms make up 58% of the panel, and the ejido status of farms does not change for almost all farms in the panel.

Panel farms are located in 92 distinct communities and are grouped into five regions in Mexico: the North, Center, Pacific, South, and Gulf. In the first survey wave, 26% of panel farms are in Northern states where agriculture is characterized by having larger commercial farms with greater importance of the commercial production of maize.

[13] Other ownership categories include rented land, borrowed land, sharecropped land, and other.

In comparison, 50% of first wave farms are in Southern and Central states where agriculture is characterized by more traditional, smallholder maize producers and the commercial production of fruits and edible vegetables (Prina, 2013). The distribution of farms in the panel is stable across both states and regions. In tests of heterogeneity, we introduce regional interactions with farm size in estimations of equation (2.2), allowing the farm size – TFP relationship to vary across agricultural regions.

Additional household level controls are grouped into two broad categories: variables describing agricultural practices that are mostly endogenous, and demographic variables that are largely exogenous. Household demographic variables are based on pre-determined characteristics of the household head. The panel farms predominantly have male, married, and Spanish speaking heads of household, with little differences across farm sizes or ejido status. Table B.3.5 in Appendix B.3 shows that farms larger than about 5 ha appear to be less likely to have an indigenous household head and more likely to have a literate household head than do smaller farms. Literacy is just one way to measure educational attainment of the household head, and it captures a rather low bar. We measure the education of household head by creating indicator variables for the highest level of formal schooling attended, from no formal education to elementary school, secondary school, high school, or college education. With little variation across survey years, Table B.3.6 in Appendix B.3 shows educational attainment by farm size for 2002 only, showing that a majority of farms have household heads with no more than an elementary school education, while almost one quarter of the panel's household heads have no formal education at all.

The following variables describing agricultural practices of farms are potentially endogenous, and for this reason are not included in the base specifications. They are introduced to shed light on potential channels affecting TFP and the farm size – TFP relationship. Any farm that does not bring any of its crop to market is classified as a subsistence farm, identifying farms that may behave differently than those who do. There is little difference in the prevalence of subsistence farming between ejido and non-ejido farms. As shown in Table B.3.1 in Appendix B.3, subsistence farming decreases with farm size, as expected. We calculate the share of each farm's crop that is marketed – on average, those farms in the sample that do participate in the market sell around 75% of their production. This appears relatively constant across farm size bins.

Alongside subsistence farming practices, Table B.3.1 in Appendix B.3 shows the share of farms engaged in monocropping. The farms in the sample that monocrop do so on the vast majority of their farm, not just on specific plots. In each survey year over half of the plots being monocropped are growing maize, with approximately 10% each growing beans and coffee. As shown in Table B.3.1 of Appendix B.3, there is no discernible difference in monocropping across farm sizes, although ejido farms are marginally more likely to employ monocropping than non-ejido farms. The MxFLS asks households about crop and livestock loss in recent years. To account for potentially persistent negative productivity shocks we generate a dummy variables for whether the household suffered crop or livestock loss in either of the previous two years.

The MxFLS asks households about their participation in a variety of government programs. The two most important programs are Progresa/Oportunidades and Procampo. Procampo is an income transfer program designed to support agricultural producers of staple crops. Progresa, later renamed Oportunidades, is a conditional cash transfer program designed to combat poverty and incentivize investments in children. Data limitations do not allow us complete information on participation in Progresa[14] so we focus exclusively on participation in Procampo. Table B.3.1 in Appendix B.3 shows the share of farms participating in Procampo by year and farm size. With the exception of the largest farms, participation increases with farm size. In addition, we consider participation in Alianza, a government-run program designed to aid farmers' transition into crops for export. While less than 3% of the sample participated in this program in any survey round, we consider participation in this program for its potentially important impact on farmers.

Having access to credit is an important determinant of agricultural productivity, and the existence of credit constraints and differential access to credit is one theoretical source of a relationship between farm size and productivity. Table B.3.3 in Appendix B.3 shows "access to credit" by farm size, where a household is considered to have access if the household head knows where they can go to borrow or ask for a loan. This is a crude measure as it does not account for credit rationing and the likelihood that a household

[14] In the MxFLS, data is available for participation in 2005 only.

could succeed in obtaining a loan. A follow up question regarding the source of that credit allows us to identify if access is through a formal or an informal financial institution.[15] There are no clear relationships between farm size and this measure of access to credit. We introduce an indicator variable to control for access to formal lines of credit.

2.5 Empirical Results

As with much of the literature, we begin the discussion of the farm size – productivity relationship using land productivity, measured as output per hectare. Figure 2.1 shows the non-parametric relationship between the log of farm size and the log of output per hectare in 2002, where output is measured using the Fisher quantity index.[16] There is a clear inverse relationship between farm size and land productivity over the entire range of farm sizes, and while not shown here this relationship is strikingly consistent across the three survey waves. Land productivity falls rapidly up to approximately 1 ha, at which point the relationship levels before resuming a dramatic decline in land productivity after approximately 20 ha.

2.5.1 Production Function Analysis

As shown in chapter 1, an inverse relationship between farm size and land productivity is neither necessary nor sufficient for the existence of an inverse relationship between farm size and total factor productivity. For reference, the linear relationship

[15] Formal sources of credit include banks, cooperative savings funds, and government credit programs.
[16] Estimated using the default local polynomial regression in Stata.

between land productivity and farm size is estimated. Farm size is inversely related to land productivity at the 1% level of significance, as shown in column 1 of Table 2.6, where we estimate the elasticity of land productivity with respect to farm size to be -0.82. We then estimate the average production function identified by equation (2.1) assuming four alternate specifications of the farm size – productivity relationship that vary in their flexibility. These regressions measure output using the quantity index, weight observations by the expansion factors provided by MxFLS, use the preferred measure of the family labor index, employ community fixed effects, and cluster standard errors at the community level. Coefficients for the farm size variables, the primary variables of interest, are displayed in Table 2.6. Table 2.7 displays the coefficients for additional household controls, and technology coefficients are included as Table B.4.1 of Appendix B.4.

The results indicate an inverse relationship between farm size and TFP, as shown by the negative and statistically significant coefficient on the linear Farm Size variable in model 2. In the sample, a 1% increase in farms size is associated with a 0.81% decrease in output per hectare, *ceteris paribus*. The farm size coefficient is slightly less negative than in model 1, but not statistically different, indicating that the relationships between farm size and land productivity and farm size and TFP are almost identical in this sample.

Models 3 and 4 allow for a quadratic and cubic relationship between farm size and TFP, but the coefficients on the higher ordered terms are either not statistically significant or do not have a noticeable impact on the linear model. Model 5 captures some non-linearity in the farm size – TFP relationship by using dummy variables for 7 farm size bins.

The smallest of farms, those less than one half of a hectare, are significantly more productive than all other farms, while the largest, those greater than 20 hectares, are significantly less productive than all smaller farms. Productivity between these two extremes, however, appears relatively stable. This closely mirrors the non-parametric relationships between farm size and land productivity shown in Figure 2.1, highlighting the need to assume a flexible functional form to fully understand the farm size – productivity relationship. The linear relationships identified in the parametric specifications 2 through 4 do not capture these subtleties.

We see little change in the inverse relationship over time across all models, as none of the farm size and survey year interaction terms are statistically significant. The finding of a time invariant inverse relationship between farm size and productivity – when using both land productivity and TFP – suggests that the IR is alive and well in Mexico. There is, however, evidence for a decline in average productivity over time in this sample, as the 2009 dummy variable is negative and statistically significant.

Results for the household explanatory variables, displayed in Table 2.7, show that monocropping and operating as a subsistence farm have a consistently negatively relationship with TFP. In contrast, participating in Procampo is positively associated with productivity (as is participation in Alianza, although the relationship is not statistically significant). It is important to reiterate that these are potentially endogenous explanatory variables, and we should not interpret the coefficients as identifying causal relationships.

Having more education is positively related to TFP, but with the exception of a college education these results are not consistently statistically significant at standard levels.

Estimates of equation (2.2) explore heterogeneity in the farm size – productivity relationship across different groups of Mexican family farms by interacting indicator variables for those groups with farm size. For simplicity, we assume the farm size – TFP relationship to be linear and time invariant.[17] Table 2.8 displays the results from interacting farm size with being located in the more commercially oriented agricultural region of Northern Mexico, participation in Procampo, practicing monocropping, operating as a subsistence farm, and whether or not the household head has any education beyond secondary school. Overall, the farm size – TFP relationship remains stable, as none of these additional interactions contribute to explaining the farm size – TFP relationship that we have identified. [18]

In addition, we interact controls for farms having ejido status, various forms of property rights, and access to credit in Table 2.9. These are of special interest given the reforms of the ejido system and rural credit markets. Again, the IR is unaltered across these subgroups as these interactions are not statistically significant. The relationship between farm size and TFP is the same for ejido farms as for non-ejido farms, is the same regardless of how property rights are documented, and is the same whether or not farms have access to formal credit markets.

[17] Relaxing the assumption of a linear relationship does not qualitatively alter the results presented here.
[18] In addition, we estimate separate regional models using household fixed effects, resulting in the same conclusion of a homogenous farm size – TFP relationship across regions.

2.5.2 Robustness Tests

The farm-size – TFP relationship is subjected to a series of robustness tests. We assume the farm size – TFP relationship is best captured by the linear and dummy variable models used above, as the quadratic and cubic models provide little additional information. Table 2.10 contains the results from the linear models and Table 2.11 from the dummy variable specification.

First, model 1 introduces household-level fixed effects to control for time-invariant, unobserved, household heterogeneity. The model omits time-invariant household controls, clusters standard errors at the household level, and provides a superior approach to addressing potential omitted variable bias relative to the model with community level fixed effects. Second, model 2 tests the sensitivity of the relationship to decisions regarding the construction of the family labor index by using an alternative index of family labor described in Appendix B.2. Third, we test the impact of choice of weighting of the observations. Whereas the core results apply the MxFLS weights designed to make the sample statistically representative of Mexican households in each survey year, model 3 shows results when we apply no weighting at all. We explore sensitivity to the use of weights because (a) we are interested in Mexican agriculture, not rural Mexican households, and (b) the treatment of the data reduces the sample size; therefore, it is not clear that these weights remain appropriate. Fourth, model 4 uses an alternative measure of the dependent variable – farm output. Whereas the core results uses the preferred approach of calculating a quantity index for each household (see

Appendix B.1 for more detail), model 4 deflates the nominal value of production in each year for each household and uses the real value of output (in 2002 Mexican pesos). Lastly, model 5 uses the real value of output as in model 4, but estimates the relationship over the repeated cross-sections. This final robustness check speaks to the potential for households to be selecting into or out of the unbalanced panel.

Overall, these alternative treatments of the data generate qualitatively similar results to the core regressions in Table 2.6 for our primary variables of interest. This is true in terms of the coefficient signs and orders of magnitude. The exception is model 2 using the alternative index of family labor, for which the farm size coefficients are diminished in magnitude although negative and still statistically significant. The consistency across models is reassuring that treatment of the data is not driving the core results regarding the farm size – TFP relationship. In similar fashion, estimated coefficients on household explanatory variables are quite robust. The coefficients identifying farms engaged in monocropping and operating as subsistence farms remain negative and statistically significant in almost all of the robustness exercises, while the coefficients for participation in Procampo and college education remain positive and statistically significant. In results not shown here, we estimate the core models using crop production only in measuring output and the conclusions regarding the farm size – productivity relationship are robust to this dimension as well.

2.5.3 Frontier Analysis

Estimating a stochastic frontier complements analysis of the average production function by identifying productivity at the frontier and production inefficiencies. Together, these components determine average TFP identified with the average production function. In similar fashion, whereas the estimation of the average production function allows us to assess the relationship between farm size and average productivity, stochastic frontier analysis allows us to assess any relationships between farm size and productivity at the technical frontier and between farm size and technical inefficiency.

The results of five specifications of the stochastic production frontier are shown in Table 2.12, with the top and bottom panels displaying the results from the frontier and variance of inefficiency equations, respectively. Model 1, the baseline model, has no additional household controls in either the frontier (**Z**) or the inefficiency equations (***W***). Model 2 includes dummy variables for the household head's level of education in the frontier equation and includes a dummy variable for the household head being of indigenous ethnicity in the inefficiency equation. Model 3 alternatively assumes that education of the household head should be included as a control in the inefficiency equation but not the frontier equation. Model 4 assumes that education belongs in both equations. Model 5 includes education in the frontier equation only, adding interaction terms between farm size and the survey year dummies in both the frontier and the inefficiency equations. The models all use community fixed effects and, for simplicity, have farm size entering linearly.

The estimated coefficients from models 1 – 5 are largely consistent. They indicate a strong inverse relationship between farm size and frontier TFP and that the frontier is increasing over time, reflecting positive technical change. The coefficients on inputs are positive and stable across specifications, with family labor and purchased intermediate inputs being significant. The variance of the inefficiency term σ_u^2 is roughly double the size of the variance of the noise σ_v^2 in all models, and lambda – the ratio of the two variances – indicates that estimation of a stochastic frontier is appropriate with the MxFLS data.[19]

The models indicate an inverse relationship between farm size and productivity at the technological frontier of the same order of magnitude as the farm size-TFP relationship estimated in the preceding analysis of the average production function. The coefficients on survey year dummies in Table 2.12 are all positive and significant, indicating that the frontier is increasing over time. Thus, in contrast to the results from the average production function analysis where evidence of declining average TFP over time was found, here we find evidence of positive technical change at the frontier. The interaction between farm size and the survey year dummies in model 5 identifies a positive and significant relationship between farm size and technical change, suggesting that technical change has been biased towards larger farms and that the inverse relationship along the frontier became less steep over time.

[19] In models estimated with a constant variance of the inefficiency distribution (σ_u^2), and thus no explanatory variables, Stata provides a p-value for the test of lambda equal to zero. This hypothesis is rejected at greater than the 1% level of significance, providing evidence in support of the stochastic frontier model.

Models 1 through 4 show that, while the variance of the inefficiency distribution increased over time, there is no relationship between farm size and inefficiency. The inclusion of interactions between farm size and survey year dummy variables in model 5, however, reveals a more nuanced dynamic relationship between farm size and technical inefficiency. Larger farms were indeed more efficient than smaller farms in 2002 (i.e. they operated closer to the frontier) but inefficiency is increasing faster for larger farms. These differential changes in inefficiency across the farm size distribution have caused the farm size - inefficiency relationship to disappear in the latter waves of the MxFLS.[20] Model 5 reveals that rising technical inefficiency has accompanied technological change, suggesting that the majority of farms have been unable to keep up with the TFP growth of the most productive farms. This is particularly true for larger farms, who have experienced faster growth in both frontier productivity and technical inefficiency.

Having secondary or college education reduces the variance of the one-sided inefficiency term when education is included in the inefficiency equation. When education of the household head is included in the frontier specifications but not in the explanation of inefficiency (models 2 and 5), having secondary education or a college education is positively associated with higher levels of productivity among frontier producers. When education is included in both the frontier and inefficiency equations (model 4), almost none of the education dummies are significant as the model appears to

[20] This can be seen by adding the farm size coefficient (-0.32) in model 5 with the year*size interaction from 2005 (0.37) or 2009 (0.42). In either case, the sum of the two coefficients is not statistically significantly different from zero.

struggle to identify the separate relationships with education. In models not shown here, we estimate a stochastic frontier including the household controls from Table 2.8 as explanatory variables of the inefficiency term. In addition to educational attainment of the household head, technical inefficiency is lower among Procampo participants and higher among farms practicing monocropping. When interacted with farm size, none of the interaction terms are statistically significant, suggesting that they do not fundamentally change the relationships observed in Table 2.12.

2.5.4 Discussion

The analysis of Mexican data reveals an inverse and time-invariant relationship between farm size and TFP. Underlying this IR is a negative relationship between farm size and frontier productivity that has diminished over time and a positive relationship between farm size and technical efficiency that disappeared over the sample period. This evidence suggests that, in the wake of NAFTA era reforms, the IR is weakening for the most productive farms along the production frontier but that this change is not widespread. Although frontier productivity is increasing most rapidly for larger farms, the higher growth of inefficiency for large farms leaves the farm size – TFP relationship unchanged over the period. The evolving relationships between farm size and frontier productivity and technical efficiency cast doubt on the ability to exploit the existing inverse relationship between farm size and TFP to generate productivity gains.

These results are complemented by previous work on the farm size – productivity relationship in Brazil. Whereas the Brazilian experience suggests a dynamic farm size –

TFP relationship, with an inverse relationship in traditional agriculture becoming flat and potentially positive with modernization, we observe no such dynamics in the Mexican sample. The relationship observed in the MxFLS is time invariant and persistently negative, contrasting with the emerging U-shaped relationship observed in the modernizing regions of Brazil. It is quite similar, however, to the more traditional agricultural regions in Brazil that display a persistent inverse relationship between farm size and TFP. The lack of corporate-run commercial farms is one limitation of using the MxFLS data, inhibiting analysis of the farm size-productivity relationship across all sectors of Mexican agriculture. This is especially true in light of findings that, in Brazil, larger commercial farms (along with the smallest of family farms) exhibit distinct advantages in achieving productivity growth (Rada et al., 2019).

The frontier analysis using MxFLS data finds that technical change has been biased towards larger farms, weakening the farm size – productivity relationship at the frontier. This indicates that if inefficiency had not increased, the average inverse relationship between farm size and productivity would have weakened with modernization of the agricultural sector. This analysis indicates the potential for larger farms to be the key drivers of future productivity growth in Mexico. Policies geared towards smaller family farms may not have large returns in terms of increasing overall agricultural productivity, but they are likely very important for poverty reduction. Even if small farms generate an increasingly smaller share of agricultural output, they are likely here to stay because of their roles in generating livelihoods for rural households. Increasing their productivity remains an important component of facilitating poverty reduction in rural areas.

These findings are largely consistent with earlier empirical work by Kagin et al. (2016), who estimate both an average production function and a stochastic production frontier using a different panel of Mexican family farms. They find that both technical change and technical inefficiency increased over time and, as with the current analysis, their fixed effects estimates show inverse relationships between farm size and both TFP and frontier productivity. Similarly, they find that smaller farms are more efficient than larger farms. In addition to highlighting the non-linearity in the farm size – TFP relationship, we provide evidence of a more nuanced and dynamic relationship between farm size and technical inefficiency and between farm size and productivity at the frontier. Larger farms have both more rapidly growing frontier productivity and technical inefficiency than their smaller counterparts, and these considerations are important for effective policy.

We find evidence of declining average TFP over the period of analysis for the MxFLS sample of family farms. This appears to be driven by increasing average technical inefficiency offsetting the positive technical change and expansion of the productivity frontier. The largest farms in the sample and their relatively rapidly growing technical inefficiency are an important factor here, indicating a growing advantage for some large farms in harnessing more modern agricultural practices that has not been widespread enough to translate into sector-wide average TFP growth. Policies enabling broader inclusion in the benefits from technical change would both increase average TFP and likely further diminish the IR. Whereas policies promoting technical change are more relevant for smaller farms, policies improving technical efficiency, such as extension services, are exceptionally important for larger farms. The growing technical inefficiency observed in Mexico indicates the potential for policies designed to promote and support the adoption and efficient use of best practices to achieve gains in agricultural productivity.

The finding of declining average TFP over time is a curious result, running counter to both the body of long-run country-level analyses and the micro-level analysis of Kagin et al. (2016) over similar time periods. One important caveat is the MxFLS sample does not include corporate run commercial farms as do national-level studies such as an agricultural census. To the extent that such farms have more effectively harnessed the gains from technological change, as with larger family farms on the frontier, the potentially heightened productivity of such large farms is not included in the current evaluation of the farm size – TFP relationship in Mexican agriculture or growth in average TFP over time. This has important policy implications for the development impacts of agriculture productivity gains – if these gains are experienced primarily by corporate-run commercial farms and not by family-run farms, the potential impacts on poverty and broader rural economic development will not be fully realized. Productivity gains for smaller family farms not only reduce poverty directly but are also likely to contribute more to local development because of how they interact with the local economy. To be most effective, policy directed at spurring development and poverty reduction through agricultural productivity gains should be inclusive of smaller family farms.

The lack of commercial farms does not, however, reconcile this finding with that of Kagin et al. (2016), who find rising average TFP over a similar period in a different sample of rural households. One difference is the MxFLS includes more larger family farms, and these farms are experiencing the most rapid increase in technical inefficiency. The inclusion of more large family farms may be the source of this result. One possible explanation of the finding of declining average TFP over the first decade of the 21st century is that the productivity of Mexican family farms has declined in the wake of the NAFTA era reforms. This interpretation is consistent with claims that NAFTA era reforms were insufficient for generating positive change in Mexico's agricultural sector, and that these reforms may have been detrimental to some segments of Mexican agriculture.

Participation in Procampo and increased education are found to be positively correlated with the agricultural productivity of Mexican family farms, whereas the practices of monocropping and operating as a subsistence farm are found to be negatively correlated with TFP. We are tentative in drawing stronger conclusions about the causal impact of these variables, as they are likely endogenous. However, the frontier analysis suggests how these controls relate to productivity. Education appears to increase the efficiency with which inputs are used on family farms, and monocropping is found to be an inefficient use of inputs. In this light, farmer education – particularly in methods such as intercropping – is expected to increase technical efficiency on family farms. Procampo is primarily an income support program it is unclear how participation would affect agricultural productivity. On the one hand, participation may relax income constraints and allow for adopting more productive methods because payments are distributed prior to planting season. This would suggest an emphasis on improving access to credit to improve the efficiency of Mexico's family farms. On the other hand, the historical production requirements of Procampo participation may mean that participants are simply more experienced producers.

A significant share of farms do not have formal documentation of property rights. Policies to ensure that farms have the necessary documentation could potentially help provide farms with the opportunity to keep abreast of technical change, as documented property rights are an important condition for accessing credit and thus facilitating adoption. This is especially true for ejido farms transitioning into participation with private credit and land markets. Nevertheless, we find no correlation here between agricultural TFP and property right documentation, access to credit, or ejido status, as we would have expected.

2.6 Conclusions

Working with a sample of family farms from the Mexican Family Life Survey (MxFLS), we document a persistent inverse relationship between farm size and land productivity over the period 2002 to 2009. Similarly, when estimating an average production function we find a time-invariant inverse relationship between farm size and

TFP, driven by the relatively high productivity of the smallest farms relative to those in the middle, and relatively low productivity of the largest farms. This is complemented by a stochastic frontier analysis, allowing for estimation of the relationship between farm size and frontier productivity and between farm size and technical inefficiency. Analysis of the production frontier reveals a dynamic inverse relationship between farm size and frontier productivity, where technical change has increased the frontier for larger farms at a faster rate than for smaller farms, weakening the inverse relationship along the frontier of productivity. Despite these changes at the frontier, the farm size – average TFP relationship has remained constant due to technical inefficiencies growing faster for larger rather than smaller farms. In essence, many of the larger farms were not able to keep up with technical change at the frontier, suggesting that successfully reducing technical inefficiency for this group could mediate, if not reverse, the farm size - productivity relationship.

To the extent that the inverse relationship between farm size and TFP has flattened along the frontier for Mexican family farms, it suggests that size may fade as one of the key determinants of productivity differences as agricultural sectors modernize. Policies that help family farms keep abreast of improvements in agricultural technology, such as farmer education, will be needed to reduce growing technical inefficiency. These findings support the claim that family farms have struggled in the wake of NAFTA era market liberalization, and we echo the calls of Pérez et al. (2008) that investment in rural infrastructure and assistance for smallholder transition into niche markets would support productivity growth for family farms.

Robust agricultural TFP growth is also important for poverty reduction. By growing the food supply more rapidly than demand, falling prices benefit poor consumers wherever they may live. And for the small farms that continue to exist, either because they are competitive or because they have few other opportunities, TFP growth helps to boost income. Where farms are too small, as in many parts of Mexico, increased productivity may still be insufficient to lift households out of poverty. Households in regions with access to non-agricultural employment may persist, and some will escape poverty, but migration is likely to continue. An important extension of this work would assess the potential impact of productivity growth on rural economic development and poverty alleviation.

An important limitation of analysis conducted here is the absence of non-family commercial farms in the Mexican sample. Future research should extend this analysis to a nationally representative sample of farms, such as the 2007 Mexican Agricultural Census, which would include family and non-family agricultural operations. Extending the analysis to the entire range of farm sizes and farm types would allow for a more complete analysis of the farm size – productivity relationship. Together with a theoretical analysis of a dynamic farm size – TFP relationship, such extensions would inform policy efforts to increase agricultural productivity.

Chapter 2 Tables and Figures

Table 2.1: Agricultural Households and Complete Farms by Survey Year

	2002	2005	2009
N Households	8,440	8,437	10,119
N Agricultural Households	1,586	1,303	1,410
N with Farm Size Data	1,042	713	696
N Complete Farms	887	626	596
N Farms in Panel	483	412	359

*Note that *N Complete Farms* and *N Farms in Panel* are after respective rounds of cleaning for outliers.

Table 2.2: Panel Sample Size for Complete Farms

	N
All Survey Years	*122*
First and Second Surveys Only	207
First and Third Surveys Only	154
Second and Third Surveys Only	83
Total	*566*

Table 2.3: Sample Size by Farm Size Group for Complete Farms

	Cross Sections			Panel		
Farm Size Group	2002	2005	2009	2002	2005	2009
0 to 0.5 ha	199 (22%)	116 (19%)	110 (18%)	103 (21%)	66 (16%)	55 (15%)
0.5 to 1 ha	108 (12%)	102 (16%)	101 (17%)	45 (9%)	60 (15%)	57 (16%)
1 to 2 ha	141 (16%)	109 (17%)	96 (16%)	83 (17%)	75 (18%)	58 (16%)
2 to 5 ha	182 (21%)	133 (21%)	122 (20%)	108 (22%)	88 (21%)	75 (21%)
5 to 10 ha	143 (16%)	93 (15%)	91 (15%)	79 (16%)	76 (18%)	65 (18%)
10 to 20 ha	65 (7%)	34 (5%)	40 (7%)	39 (8%)	23 (6%)	27 (8%)
> 20 ha	49 (6%)	39 (6%)	36 (6%)	26 (5%)	24 (6%)	22 (6%)
Total	*887*	*626*	*596*	*483*	*412*	*359*

Table 2.4: Percent of Households Using Selected Intermediate Inputs

	Panel		
Input Category	*2002*	*2005*	*2009*
Family Labor	94%	94%	91%
Non-family Labor	52%	49%	39%
Physical Capital	13%	12%	14%
Draft Animals	35%	30%	27%
Purchased Intermediate Inputs	70%	70%	71%
Fertilizer	51%	48%	46%
Manure	17%	17%	18%
Pesticides	33%	26%	27%
Seeds	24%	23%	25%
Tractor Services	32%	25%	36%
Animal Power	3%	10%	11%
Labor	5%	25%	27%
Water	3%	16%	20%
Fuel	2%	10%	15%

Table 2.5: Correlation Coefficients between Logged Farm Size and Logged Inputs per ha

	Farms with Non-zero Values		
Input Category	*2002*	*2005*	*2009*
Family Labor	-0.93*	-0.90*	-0.89*
Non-family Labor	-0.90*	-0.91*	-0.89*
Physical Capital	-0.34*	-0.20	-0.28*
Draft Animals	-0.84*	-0.84*	-0.62*
Purchased Intermediates	-0.69*	-0.65*	-0.68*

*Note: * indicates statistical significance at the 10% level*

Figure 2.1: Non-parametric Relationship between Farm Size and Productivity, 2002

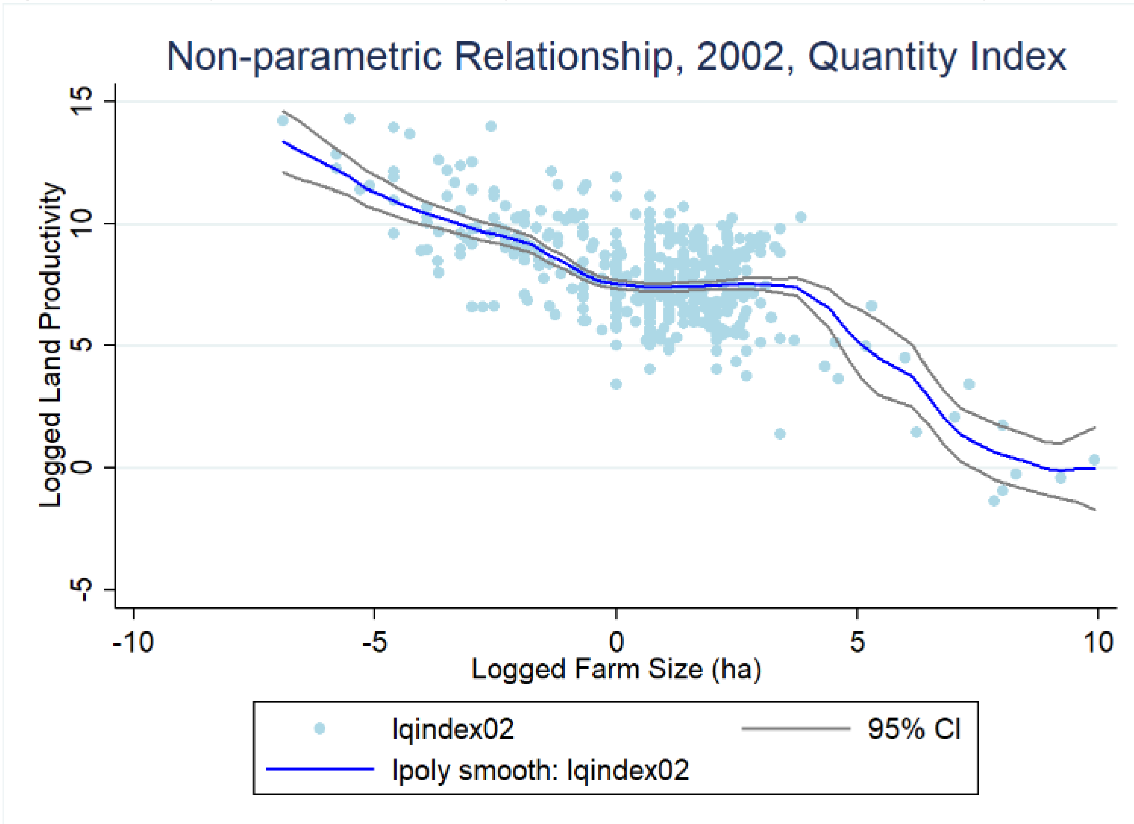


Table 2.6: Farm Size Coefficients, Community Fixed Effects with Household Controls

	(1) Linear w/o Inputs	(2) Linear	(3) Quadratic	(4) Cubic	(5) Dummies
Farm Size	-0.822***	-0.814***	-0.795***	-0.773***	
	(0.039)	(0.068)	(0.060)	(0.073)	
0.5 to 1 ha					-1.583***
					(0.265)
1 to 2 ha					-2.185***
					(0.226)
2 to 5 ha					-2.150***
					(0.269)
5 to 10 ha					-2.542***
					(0.402)
10 to 20 ha					-2.387***
					(0.539)
20+ ha					-5.264***
					(0.950)
2005 Dummy	-0.298*	-0.208	-0.264	-0.289	-0.192
	(0.168)	(0.158)	(0.190)	(0.220)	(0.209)
2009 Dummy	-0.677***	-0.551***	-0.639***	-0.672***	0.199
	(0.130)	(0.121)	(0.155)	(0.190)	(0.517)
2005*Farm Size	0.018	0.031	0.014	0.049	
	(0.043)	(0.050)	(0.046)	(0.084)	
2009*Farm Size	-0.073	-0.069	-0.093	-0.067	
	(0.070)	(0.074)	(0.072)	(0.109)	
Farm Size^2			-0.018*	-0.015	
			(0.009)	(0.013)	
2005*Farm Size^2			0.013	0.016	
			(0.012)	(0.017)	
2009*Farm Size^2			0.020	0.024	
			(0.013)	(0.020)	
Farm Size^3				-0.001	
				(0.002)	
2005*Farm Size^3				-0.001	
				(0.003)	
2009*Farm Size^3				-0.001	
				(0.003)	
2005*Bin 2					-0.224
					(0.566)
2005*Bin 3					0.564
					(0.484)
2005*Bin 4					-0.402
					(0.302)

2005*Bin 5					0.137
					(0.268)
2005*Bin 6					0.083
					(0.593)
2005*Bin 7					-0.424
					(0.841)
2009*Bin 2					-0.855
					(0.667)
2009*Bin 3					-0.921
					(0.729)
2009*Bin 4					-0.854
					(0.622)
2009*Bin 5					-1.053
					(0.779)
2009*Bin 6					-1.286
					(0.797)
2009*Bin 7					-1.554
					(1.353)
Constant	8.004***	9.289***	10.000***	10.494***	6.309***
	(0.466)	(1.067)	(1.287)	(1.473)	(1.193)
Community FE	Yes	Yes	Yes	Yes	Yes
R^2	0.69	0.72	0.72	0.72	0.68
N	1235	1235	1235	1235	1235

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 2.7: Coefficients on Household Controls

	(1) None	(2) Linear	(3) Quadratic	(4) Cubic	(5) Dummies
Monocrop	-0.397**	-0.386**	-0.381**	-0.368**	-0.451***
	(0.155)	(0.159)	(0.156)	(0.160)	(0.146)
Subsistence	-0.562***	-0.439***	-0.435***	-0.431***	-0.279
	(0.182)	(0.156)	(0.157)	(0.161)	(0.183)
Crop Loss	0.032	0.031	0.024	0.021	-0.041
	(0.243)	(0.206)	(0.200)	(0.203)	(0.200)
Procampo	0.478***	0.397**	0.384**	0.378**	0.283*
	(0.147)	(0.158)	(0.159)	(0.159)	(0.163)
Alianza	0.544	0.328	0.377	0.383	0.307
	(0.339)	(0.325)	(0.334)	(0.331)	(0.330)
Formal Credit	0.100	0.054	0.045	0.039	0.125
	(0.264)	(0.252)	(0.259)	(0.257)	(0.239)
Ejido	0.047	0.039	0.003	0.009	-0.103
	(0.163)	(0.162)	(0.155)	(0.157)	(0.169)
Documentation	-0.084	-0.041	-0.038	-0.052	-0.065
	(0.270)	(0.222)	(0.219)	(0.223)	(0.227)
Age	0.001	-0.002	-0.002	-0.002	-0.001
	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)
Male	0.043	0.016	0.027	0.029	-0.003
	(0.245)	(0.209)	(0.213)	(0.215)	(0.203)
Married	0.236	0.174	0.171	0.159	0.170
	(0.210)	(0.185)	(0.185)	(0.187)	(0.189)
Indigenous	-0.082	-0.099	-0.106	-0.125	-0.169
	(0.199)	(0.211)	(0.209)	(0.212)	(0.233)
Elementary School	0.097	0.018	-0.001	0.005	0.034
	(0.175)	(0.168)	(0.167)	(0.167)	(0.182)
Secondary School	0.632*	0.404	0.361	0.379	0.181
	(0.355)	(0.413)	(0.415)	(0.412)	(0.479)
High School	0.383	0.314	0.331	0.367	0.079
	(0.336)	(0.334)	(0.347)	(0.342)	(0.404)
College	1.359**	1.348**	1.329**	1.374**	0.833
	(0.533)	(0.548)	(0.561)	(0.556)	(0.517)
Community FE	Yes	Yes	Yes	Yes	Yes
R^2	0.69	0.72	0.72	0.72	0.68
N	1235	1235	1235	1235	1235

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 2.8: Community Fixed Effects with Household Control Interactions

	(1) North	(2) Procampo	(3) Monocrop	(4) Subsistence	(5) Higher Education
Farm Size	-0.813***	-0.841***	-0.819***	-0.816***	-0.812***
	(0.067)	(0.076)	(0.090)	(0.081)	(0.069)
Farm Size*North	-0.013				
	(0.196)				
Farm Size*Procampo		0.090			
		(0.068)			
Farm Size*Monocrop			0.009		
			(0.074)		
Farm Size*Subsistence				0.004	
				(0.057)	
Farm Size *Education					-0.038
					(0.083)
2005 Dummy	-0.208	-0.214	-0.208	-0.209	-0.209
	(0.158)	(0.157)	(0.160)	(0.157)	(0.158)
2009 Dummy	-0.550***	-0.575***	-0.553***	-0.551***	-0.555***
	(0.121)	(0.125)	(0.115)	(0.121)	(0.121)
Community FE	Yes	Yes	Yes	Yes	Yes
R^2	0.72	0.72	0.72	0.72	0.72
N	1235	1235	1235	1235	1235

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 2.9: Community Fixed Effects with Credit/Property Rights Interactions

	(1) Ejido	(2) Deed or Title	(3) Ag. Rights Certificate	(4) Any Document	(5) Access to Credit
Farm Size	-0.820***	-0.805***	-0.815***	-0.799***	- 0.814***
	(0.076)	(0.073)	(0.076)	(0.115)	(0.069)
Farm Size*Ejido	0.025				
	(0.069)				
Farm Size*Deed		-0.016			
		(0.047)			
Farm Size*Certificate			0.004		
			(0.055)		
Farm Size*Documentation				-0.018	
				(0.079)	
Farm Size*Credit					0.016
					(0.078)
2005 Dummy	-0.199	-0.203	-0.207	-0.208	-0.208
	(0.166)	(0.157)	(0.163)	(0.157)	(0.158)
2009 Dummy	-0.548***	-0.548***	-0.550***	-0.554***	- 0.550***
	(0.121)	(0.120)	(0.125)	(0.126)	(0.122)
Community FE	Yes	Yes	Yes	Yes	Yes
R^2	0.72	0.72	0.72	0.72	0.72
N	1235	1235	1235	1235	1235

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 2.10: Farm Size Coefficients, Linear Robustness Checks

	(1) Household FE	(2) Alt. Labor Index	(3) No Weights	(4) Alt. Output	(5) Alt. Output Cross Section
Farm Size	-0.825***	-0.602***	-0.732***	-0.814***	-0.668***
	(0.103)	(0.085)	(0.054)	(0.069)	(0.060)
2005 Dummy	-0.241	-0.135	-0.130	-0.290*	-0.313**
	(0.175)	(0.096)	(0.095)	(0.160)	(0.126)
2009 Dummy	-0.388*	-0.328***	-0.318***	-0.324**	-0.380***
	(0.213)	(0.112)	(0.110)	(0.126)	(0.126)
2005* Farm Size	0.089	0.041	0.038	0.035	-0.030
	(0.089)	(0.043)	(0.043)	(0.050)	(0.037)
2009* Farm Size	-0.110	0.012	0.007	-0.069	-0.084
	(0.118)	(0.052)	(0.053)	(0.074)	(0.052)
Constant	11.437***	6.507***	7.062***	9.385***	7.042***
	(2.010)	(1.090)	(1.136)	(1.064)	(1.160)
Household FE	Yes	No	No	No	No
Community FE	No	Yes	Yes	Yes	Yes
R^2	0.86	0.67	0.67	0.71	0.68
N	1235	1235	1235	1235	2090

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 2.11: Farm Size Coefficients, Dummy Variable Robustness Checks

	(1) Household FE	(2) Alt. Labor Index	(3) No Weights	(4) Alt. Output	(5) Alt. Output Cross Section
0.5 to 1 ha	-1.801***	-0.653**	-1.433***	-1.598***	-1.329***
	(0.648)	(0.262)	(0.248)	(0.268)	(0.178)
1 to 2 ha	-2.405***	-0.860***	-1.895***	-2.192***	-1.863***
	(0.582)	(0.225)	(0.195)	(0.224)	(0.220)
2 to 5 ha	-2.126***	-0.801***	-1.954***	-2.139***	-1.746***
	(0.591)	(0.232)	(0.236)	(0.266)	(0.199)
5 to 10 ha	-2.869***	-0.974***	-2.403***	-2.547***	-2.326***
	(0.745)	(0.299)	(0.305)	(0.403)	(0.216)
10 to 20 ha	-2.295**	-0.722**	-2.401***	-2.383***	-2.593***
	(1.056)	(0.305)	(0.337)	(0.553)	(0.344)
20+ ha	-6.191***	-1.842***	-4.230***	-5.270***	-5.568***
	(1.356)	(0.546)	(0.648)	(0.961)	(0.638)
2005 Dummy	-0.184	-0.296	-0.112	-0.287	-0.082
	(0.448)	(0.253)	(0.263)	(0.206)	(0.194)
2009 Dummy	0.080	-0.093	0.295	0.418	0.120
	(0.635)	(0.314)	(0.402)	(0.504)	(0.299)
2005*Bin 2	-0.178	0.025	-0.147	-0.199	-0.490
	(0.704)	(0.376)	(0.381)	(0.571)	(0.386)
2005*Bin 3	0.646	0.265	0.156	0.589	-0.057
	(0.671)	(0.390)	(0.411)	(0.492)	(0.468)
2005*Bin 4	-0.453	0.117	-0.119	-0.401	-0.657**
	(0.608)	(0.329)	(0.329)	(0.294)	(0.285)
2005*Bin 5	0.406	0.496	0.252	0.161	-0.079
	(0.591)	(0.316)	(0.316)	(0.274)	(0.233)
2005*Bin 6	-0.536	0.505	0.296	0.148	0.118
	(0.853)	(0.358)	(0.399)	(0.591)	(0.514)
2005*Bin 7	0.186	-0.016	-0.697	-0.407	0.002
	(1.059)	(0.623)	(0.722)	(0.842)	(0.773)
2009*Bin 2	-0.629	-0.717	-1.073**	-0.891	-0.656
	(0.867)	(0.449)	(0.532)	(0.687)	(0.424)
2009*Bin 3	-0.510	-0.341	-0.754	-0.884	-0.625
	(0.796)	(0.451)	(0.522)	(0.724)	(0.543)
2009*Bin 4	-0.675	0.004	-0.460	-0.866	-0.632
	(0.886)	(0.426)	(0.505)	(0.607)	(0.472)
2009*Bin 5	-0.785	-0.160	-0.651	-1.031	-0.926*
	(0.851)	(0.439)	(0.488)	(0.774)	(0.525)
2009*Bin 6	-0.847	-0.099	-0.470	-1.227	-0.543
	(1.069)	(0.463)	(0.560)	(0.795)	(0.566)
2009*Bin 7	-1.756	-0.433	-0.972	-1.596	-1.072
	(1.689)	(0.684)	(0.900)	(1.359)	(1.003)
Constant	11.031***	4.359***	4.720***	6.427***	7.549***

	(2.662)	(1.089)	(1.288)	(1.170)	(0.833)
Household FE	Yes	No	No	No	No
Community FE	No	Yes	Yes	Yes	Yes
R^2	0.85	0.66	0.63	0.68	0.67
N	1235	1235	1235	1235	2090

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 2.12: Stochastic Frontier Production Function Results

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Frontier Equation					
Farm Size	-0.642***	-0.653***	-0.638***	-0.646***	-0.805***
	(0.051)	(0.050)	(0.052)	(0.053)	(0.062)
2005 Dummy	0.477**	0.475**	0.458**	0.446**	0.400**
	(0.186)	(0.177)	(0.186)	(0.174)	(0.201)
2009 Dummy	0.790***	0.799***	0.765***	0.769***	0.711***
	(0.212)	(0.207)	(0.210)	(0.201)	(0.223)
2005*Farm Size					0.192***
					(0.064)
2009*Farm Size					0.204*
					(0.108)
Family Labor	0.077**	0.077**	0.074**	0.072**	0.068**
	(0.032)	(0.033)	(0.034)	(0.034)	(0.033)
Physical Capital	0.008	0.012	0.019	0.016	0.037
	(0.047)	(0.042)	(0.045)	(0.044)	(0.046)
Draft Animals	0.028	0.026	0.023	0.022	0.006
	(0.034)	(0.032)	(0.033)	(0.032)	(0.030)
Purchased Intermediates	0.148***	0.139***	0.148***	0.146***	0.145***
	(0.038)	(0.038)	(0.039)	(0.040)	(0.041)
Non-family Labor	0.045	0.041	0.053	0.051	0.024
	(0.034)	(0.034)	(0.034)	(0.034)	(0.033)
Elementary School		0.044		-0.048	0.057
		(0.090)		(0.142)	(0.094)
Secondary School		0.517**		0.293	0.531**
		(0.205)		(0.332)	(0.209)
High School		0.008		-0.069	0.083
		(0.204)		(0.344)	(0.207)
College		0.703**		-0.334	0.699**
		(0.307)		(0.494)	(0.302)
Inefficiency Equation					
Farm Size	0.037	0.031	0.040	0.035	-0.317***
	(0.062)	(0.060)	(0.061)	(0.060)	(0.119)
2005 Dummy	1.152***	1.163***	1.146***	1.112***	1.198***
	(0.377)	(0.361)	(0.403)	(0.359)	(0.430)
2009 Dummy	1.838***	1.878***	1.871***	1.840***	1.870***
	(0.407)	(0.387)	(0.431)	(0.379)	(0.401)
2005*Farm Size					0.368**
					(0.149)
2009*Farm Size					0.417**

					(0.167)
Indigenous		0.001	-0.046	-0.038	0.001
		(0.230)	(0.245)	(0.238)	(0.233)
Elementary School			-0.142	-0.193	
			(0.193)	(0.271)	
Secondary School			-0.882**	-0.499	
			(0.411)	(0.549)	
High School			-0.118	-0.190	
			(0.579)	(0.819)	
College			-1.603***	-1.680*	
			(0.480)	(0.451)	
$E(\sigma_u^2)$	1.679	1.666	1.641	1.661	1.620
σ_u^2	0.846	0.840	0.852	0.838	0.853
λ	1.985	1.983	1.926	1.982	1.899
N	1235	1235	1235	1235	1235

Standard errors in parentheses
** p<0.10, ** p<0.05, *** p<0.01*

CHAPTER 3

Agricultural Productivity and Poverty: A Counterfactual Analysis of Mexican Family Farms

3.1 Introduction

Poverty in Mexico has proven stubborn and, as in many developing countries, poverty alleviation remains an important policy objective. Indeed, combatting poverty was a central tenet of the policy platform sweeping Andrés Manuel López Obrador to victory in the 2018 presidential elections. With over 52 million Mexicans impoverished, or almost 42% of the Mexican population (World Bank, 2020), poverty is most prevalent in rural Mexico where, as in many developing countries, poverty rates are significantly higher than in urban areas.

The work of Iniguez-Montiel (2014) exemplifies these conditions, assessing Mexican poverty over the period 1992-2008. Using the official income-based poverty thresholds, Iniguez-Montiel finds that overall poverty rates are consistently 20 percentage points higher in rural than in urban communities, driven largely by differences in the prevalence of extreme poverty. While poverty rates fell over the period of study, over 66% of rural Mexicans lived in poverty in 2008, with roughly half of those living in extreme poverty. With the exception of the share living in extreme poverty, this picture mirrors what is found when using Mexico's official multidimensional measure of poverty (Ornelas, 2019).

Agricultural workers are disproportionately poor, emphasizing the need for pro-poor growth strategies in Mexico and an emphasis on the agricultural sector. The case for poverty alleviation through agricultural policy is reflected in the World Bank's *World Development Report for 2008* (World Bank, 2007), and this perspective partly explains a resurgent emphasis on the role of agriculture in economic development (Wiggins et al., 2010). In fact, recent studies have identified growth in agriculture as being uniquely suited for achieving rural economic development goals, including economic growth and poverty alleviation. Cross-country macroeconomic studies such as Valdés and Foster (2010), for example, estimate that agriculture is 2.5 times as effective than other sectors in improving incomes of the poor. Christiaensen et al. (2011) find that agricultural growth is 3.2 times more effective, and Diao et al. (2010) draw similar conclusions.

Improving agricultural productivity is one source of growth for the agricultural sector, and a large literature documents the links between agricultural productivity and poverty reduction (for example, see de Janvry and Sadoulet (2010) or Schneider and Gugerty (2011) for thorough reviews and discussions). Productivity gains affect poverty through multiple channels, including by reducing food prices, increasing demand in the non-agricultural rural economy, and expanding employment opportunities in the rural economy. Most directly, improved productivity on farms has the potential to reduce on-farm poverty of agricultural households themselves. A limitation of much of the literature, however, is that it relies on macroeconomic or cross-country empirical evidence.

The microeconomic empirical investigations that do assess the poverty reduction potential of agricultural productivity are largely in the context of Asia. Datt and Ravallion (1998) estimate short-run and long run rural poverty – land productivity elasticities in India, finding that whereas the direct effects of agricultural productivity gains dominate in the short run, the indirect effects dominate in the long run, where the relationship is stronger. Foster and Rosenzweig (2004) add nuance to this discussion, finding that while land productivity positively increased rural incomes, per capita incomes of the poorest were increased most importantly by the non-agricultural rural sector and that, in India, this sector grew faster where agricultural productivity did not. Christiaensen et al. (2013) find evidence in China that improved labor productivity in the agricultural sector has greater poverty reducing effects than other pathways out of poverty. Dzanku (2015) draws similar conclusions in Ghana, where on-farm labor productivity is found to be more important than off-farm labor productivity for poverty alleviation when using a multidimensional measure of poverty.

Using a 2002-2009 panel of family farms in Mexico drawn from the Mexican Family Life Survey, this paper contributes to understanding these linkages by estimating the direct contribution of changing agricultural productivity to changes in the distribution of income, and their impact on on-farm poverty. Further, by decomposing changing agricultural productivity into five sources – technical change, the farm size-frontier productivity relationship, technical efficiency, input intensification, and farm size – the analysis seeks to inform policy on the potential contribution of these productivity sources to poverty alleviation. In short, this study addresses the following research questions: (i) what direct contribution did agricultural productivity make towards poverty alleviation in Mexico in the early 21st century; and (ii) what were the relative contributions of the constituent sources of productivity?

This paper does not evaluate any particular policy, nor does it identify causal determinants of agricultural productivity and poverty alleviation. Rather, this paper relies on decomposition methods pioneered in labor economics to construct counterfactual distributions of agricultural productivity, assessing the potential contributions of changing agricultural productivity to the alleviation of poverty. Estimating a stochastic production frontier generates estimates of technical change and technical (in)efficiency change, enabling parametric decompositions of land productivity. Counterfactual productivity distributions are generated from these decompositions, and the contribution of changing sources of agricultural productivity to poverty alleviation are estimated.

The study finds evidence of a decline in land productivity over the study period, driven primarily by decreasing technical efficiency and changes to the farm size distribution. Whereas poverty rates among family farms increased over the period, the severity of poverty saw a decline. Further, the counterfactual analysis suggests that raising land productivity through intensification and technical change would be a more pro-poor approach to improving productivity in the agricultural sector than would increasing technical efficiency, as those sources of land productivity have more pronounced contributions to the direct alleviation of on-farm poverty. The remainder of the paper is organized as follows. Section 2 provides context for understanding agricultural policy and poverty in Mexico. Section 3 lays out the empirical methodology for the decomposition and counterfactual analysis. This is followed by a description of the data source and key descriptive statistics in section 4. Section 5 presents the empirical results, and section 6 concludes.

3.2 The Context of Mexico

Mexico is an interesting case study for this exercise, in part because of the persistence of rural poverty and the importance of agriculture in the rural economy, but also because of its rich and active history of agricultural policy and efforts to alleviate poverty. Land reform and the establishment of *ejido* communities under the Cárdenas presidency in the 1930s is a hallmark of the agricultural sector in Mexico. As *ejidos* have long been characterized by high poverty rates and relatively low agricultural productivity, the reform of property rights and land markets in the 1990s aimed, in part, to increase productivity of the *ejido* sector (World Bank, 2001). Mexico was also the birthplace of the Green Revolution when the Mexican Agricultural Program, funded by the Rockefeller

Foundation in the 1940s, introduced improved seed varieties, input intensification, mechanization, and advanced cultivation practices, transforming and modernizing segments of Mexican agriculture (Sanderson, 1986).

A competitive, commercial agricultural sector exists alongside the *ejido* sector, historically enjoying government subsidization of key agricultural inputs. This includes the national water system and irrigation districts established in the mid-1950s, federally controlled agricultural credit programs and the rural credit bank (BAN-RURAL), low fuel prices maintained by a national petroleum pricing system (PEMEX), and the subsidization of fertilizers through the national fertilizer company (FERTIMEX). These support programs were rolled back considerably as part of liberalization efforts in the early 1990s (UNCTAD, 2014), but price support, agricultural credit, and fertilizer subsidization programs have recently resurfaced as part of the López Obrador administration's efforts to increase productivity and reduce poverty among Mexico's poor and marginalized farmers (USDA, 2019).

Mexico has a long history of extension services, including the continuation of the Mexican Agricultural Program that launched the Green Revolution and the National Institute for the Development of the Rural Sector, a federal institution established in the 1970s. The liberalization efforts of the 1990s under the North American Free Trade Agreement (NAFTA), and the recent update under the United States-Mexico-Canada Agreement (USMCA) significantly altered the competitive landscape for Mexican farmers, liberalizing agricultural input and output markets. Mexico's anti-poverty efforts are perhaps best exemplified by Oportunidades (formerly Progresa), the widely celebrated conditional-cash-transfer program that targeted poverty through cash transfers while incentivizing educational attainment, medical care, and nutrition for impoverished children.

Despite this history, and in contrast to Southeast Asia's experience with the Green Revolution, poverty reduction through agriculture led growth has not been widely successful in Mexico (de Janvry and Sadoulet, 2010; Dzanku, 2015). This echoes Sanderson (1986), who noted that by the late 20th century the transformed agricultural sector of Mexico was failing to generate livelihoods for many in rural communities, where poverty and malnutrition were common and migration out of rural Mexico was necessary to generate an economic livelihood. Shedding light on the direct link between agricultural productivity and on-farm poverty is one step towards improving policy effectiveness.

3.3 Empirical Methodology

3.3.1 Poverty Analysis

Adopting an income-based measure of poverty, income of household i in period t, Y_{it}, is the sum of agricultural income, Y_{it}^{A}, and non-agricultural income, Y_{it}^{NA}:

$$Y_{it} = Y_{it}^{A} + Y_{it}^{NA} \tag{3.1}$$

Comprehensive assessment of household income includes both the monetary income derived by the household and the flow of non-monetary goods and services received by the household. As such, agricultural income is measured as the value of total farm output, which includes output reserved for household use along with output sold to market. Monetary non-agricultural income includes labor income – from wage labor and/or self-employment – and non-labor income, including sources such as profits from business operations, government transfers, remittances, and pensions. Normalizing household income by household size, H_{it}, income-per-capita, y_{it}, is given by:

$$y_{it} = \frac{Y_{it}}{H_{it}} \tag{3.2}$$

Following Foster, Greer, and Thorbecke (1984), poverty of a given household in a given period, P_{it}^{α}, is measured as:

$$P_{it}^{\alpha} = I(y_{it} < z_t)\left(\frac{z_t - y_{it}}{z_t}\right)^{\alpha} \tag{3.3}$$

where z_t is the poverty line in period t, $I(y_{it} < z_t)$ is an indicator taking the value of 1 if income-per-capita is below the poverty line and 0 otherwise, and α is a parameter governing how poverty is measured. Three poverty measures are calculated: poverty *incidence*, or the headcount ratio, corresponding to $\alpha = 0$; poverty *depth*, or the poverty gap, corresponding to $\alpha = 1$; and poverty *severity*, or the squared poverty gap, corresponding to $\alpha = 2$. The associated poverty rates for the sample, p_t^{α}, are then given by:

$$p_t^{\alpha} = \frac{\sum_{i=1}^{N_t} P_{it}}{N_t} \tag{3.4}$$

where N_t is the number of individuals in the sample in period t.

3.3.2 Agricultural Productivity

Agricultural productivity affects poverty through agricultural income. Agricultural output, Q, is the product of farm size, A, and land productivity, q, defined as output per unit of land:

$$Q = Aq \tag{3.5}$$

Improving livelihoods through agriculture can potentially be achieved on the extensive margin by expanding and increasing scale (through A), or on the intensive margin by enhancing the productivity with which existing land holdings are used (through q). While providing opportunities on the extensive margin is much of the logic behind land reform and efforts to improve the functioning of land markets, much of agricultural policy targets productivity.

For a given farm, land productivity is a function of the intensity with which other agricultural inputs are used in production, $\boldsymbol{x}$, the technology characterized by the production function parameters, $\boldsymbol{\beta}$, the (in)efficiency with which the farm utilizes the agricultural technology, v, and random productivity shocks, u. In addition, the literature on the relationship between farm size and productivity has consistently shown an inverse farm size-productivity relationship. Changes in farm size, A, or a changing farm size – productivity relationship, δ, also influence land productivity:

$$q = f(\boldsymbol{x}, \boldsymbol{\beta}, v, u, A, \delta) \tag{3.6}$$

Changes in these determinants affect land productivity, agricultural output, and the livelihoods of farming households, and with the exception of random productivity shocks, these determinants are potential policy targets. For example, input subsidization and market reform affect access to inputs and the intensity with which inputs are used, $\boldsymbol{x}$. Research and development and the adoption of modern technology affect agricultural production through $\boldsymbol{\beta}$, while extension services and farmer education influence technical (in)efficiency, u, and land reform, property rights, and market reform affect A and δ. Decomposing land productivity into these sources using farm-level data enables a counterfactual analysis of their contributions to changes in the land productivity distribution and poverty alleviation.

3.3.3 Stochastic Frontier Analysis

Estimation of a stochastic production frontier provides the foundation for the decomposition, generating an estimate of the frontier technology, a measure of technical change, and technical (in)efficiency scores. Closely following the stochastic frontier analysis in chapter 2, an output-oriented approach is taken for measuring technical inefficiency. Defining $f(\boldsymbol{X})$ as the maximum that can potentially be produced with input levels, $\boldsymbol{X}$, technical inefficiency is the ratio of potential production and actual production, Q:

$$Technical\ Inefficiency = \frac{f(\boldsymbol{X})}{Q} = \frac{f(\boldsymbol{x})}{q} \tag{3.7}$$

where $f(\boldsymbol{x})$ is the maximum output per unit of land. As shown in chapter 1, normalization of the production frontier by farm size is expressed as:

$$f(\boldsymbol{x}) = \frac{f(\boldsymbol{X})}{A} = A^{1-\tau} f\left(\frac{\boldsymbol{X}}{A}\right) \tag{3.8}$$

where τ captures returns to scale along the frontier, and the normalized production frontier is expressed as the product of two terms: (i) the frontier expressed as a function of input intensities, $f\left(\frac{\boldsymbol{X}}{A}\right)$, and (ii) any deviation from constant returns to scale (CRS) along the frontier, $A^{1-\tau}$.

Taking the log of (3.7), defining u as the log of technical inefficiency, and redefining q and $f(\boldsymbol{x})$ as the log of land productivity and logged frontier production per unit of area, respectively, the stochastic production frontier can be expressed as:

$$q = f(\boldsymbol{x}) - u \tag{3.9}$$

Estimating (3.9) econometrically requires assumptions on the frontier's functional form, the distribution of the technical inefficiency term, and the distribution of a standard idiosyncratic error term. A Cobb-Douglas functional form is assumed for the frontier.[1] Substituting the natural log of (3.8) into (3.9) generates an expression for the stochastic production frontier in period t:

$$q_t = \beta_{0t} + \delta_t A_t + \boldsymbol{\beta_t x}_t + v_t - u_t \tag{3.10}$$

where $\delta_t = 1 - \tau$ captures the farm size – frontier productivity relationship.

Standard distributional assumptions are adopted for the two-part error term, with a normally distributed idiosyncratic error term, v_t, and an exponential distribution for the one-sided inefficiency term, u_t.[2] The assumption of an exponential distribution for the

[1] While a more general functional form such as a translog would be preferable, attempts to estimate such a model failed to converge with the present data.
[2] Alternative assumptions of an exponential or truncated normal distribution are also common in the literature. Attempts to estimate a model assuming the more general truncated normal distribution failed to converge.

inefficiency term allows for simultaneous estimation of the stochastic frontier and determinants of the variation of u_t. Community-level fixed effects, $\boldsymbol{\gamma}_c$, are included in the final model estimated and, because this study is interested in technical change along the frontier and a (possibly) changing farm size – frontier productivity relationships, the frontier technology coefficients, $\boldsymbol{\beta}$, and coefficient on farm size, δ, are allowed to vary over time through interactions with a time dummy, θ_t. The complete model for farm i in community c in period t, estimated with maximum likelihood estimation and standard errors clustered at the community level, is:

$$q_{ict} = \beta_0 + \theta_t + \delta_t A_{ict} + \boldsymbol{\beta_t x}_{ict} + \boldsymbol{\gamma}_c + v_{ict} - u_{ict} \tag{3.11}$$

$$v_{ict} \sim N(0, \sigma_{v,c}^2) \tag{3.12}$$

$$u_{ict} \sim exp(\sigma_{u,ict}^2) \tag{3.13}$$

$$\sigma_{u,ict}^2 = \alpha_0 + \theta_t + \boldsymbol{\varphi V}_{ict} + \epsilon_{ict} \tag{3.14}$$

where $\boldsymbol{V}_{ict}$ is a vector of exogenous controls explaining the variance of technical inefficiency and ϵ_{ict} is a standard normal error term.

3.3.4 Counterfactuals and Decompositions

A decomposition similar to that of Oaxaca (1973) and Blinder (1973) illustrates the usefulness of the stochastic frontier to conduct a parametric decomposition of changing land productivity, providing the basis for generating counterfactual land productivity distributions. Denoting subscript 0 to refer to the base year and subscript 1 to denote the later survey year, the change in average land productivity between the two periods, $\Delta E(q) = E(q_1) - E(q_0)$, can be decomposed as follows:

$$\Delta E(q) = \Delta\delta E(A_0) + \delta_1 \Delta E(A) + \theta_1 + \Delta\boldsymbol{\beta} E(\boldsymbol{x}_0) + \boldsymbol{\beta_1} \Delta E(\boldsymbol{x}) - \Delta E(u) \qquad (3.15)$$

This approach to a parametric decomposition of productivity growth closely resembles that of Chatzimichael and Liasidou (2018), who decompose total factor productivity growth for the hotel sector in Europe. (See Appendix C.1 for more detail on the decomposition). Interpreting expression (3.15), the first term on the right-hand side, $\Delta\delta E(A_0)$, captures the contribution to the observed change in average land productivity of a changing farm size – frontier productivity relationship, including changes to the returns to scale along the frontier. Similarly, the second term, $\delta_1 \Delta E(A)$, captures the contribution of changing farm size, while the third and fourth term, $\theta_1 + \Delta\boldsymbol{\beta} E(\boldsymbol{x}_0)$, capture the contribution of technical change. The fifth term, $\boldsymbol{\beta_1} \Delta E(\boldsymbol{x})$, captures the contribution of changing average input intensities of family farms, and the final term, $\Delta E(u) = E(u_1) - E(u_0)$, is the change in average technical inefficiency between periods. In expression (3.15) above, the second, fifth, and sixth terms are equivalent to the "explained" portion of an Oaxaca-Blinder decomposition, whereas the remaining terms containing changes in parameters are equivalent to the "unexplained" portion of the difference.

While (3.15) provides the foundation for a counterfactual analysis of the average contributions of these channels to observed changes in average land productivity, it is often the case that the incidence of these contributions along the entire distribution of farms is of policy interest. The objective of poverty alleviation is one such case, where changes in average productivity are neither necessary nor sufficient for poverty alleviation – for average productivity changes to affect poverty, they must affect the poor or cause families to fall into poverty. One possible extension of (3.15) conducts the decomposition by decile, d, illuminating differences in changing productivity and the contribution of its constituent channels along the land productivity distribution in an interpretable albeit crude manner:

$$\Delta E(q_d) = \Delta\delta E(A_{d0}) + \delta_1 \Delta E(A_d) + \theta_1 + \Delta\boldsymbol{\beta} E(\boldsymbol{x}_{d0}) + \boldsymbol{\beta_1} \Delta E(\boldsymbol{x_d}) - \Delta E(u_d) \qquad (3.16)$$

To estimate the potential contribution of these productivity channels towards alleviating poverty, however, counterfactual simulations of the entire land productivity distribution are required. These counterfactual distributions can be derived parametrically using estimates from the stochastic frontier analysis and replacing values from the later survey wave for values from the base year survey for each observation. For example, to generate a counterfactual distribution of land productivity if inefficiency had not changed during the sample period, land productivity is estimated for each farm in 2009 using observed inputs and farm size from 2009, the estimated technology parameters for 2009, but the technical inefficiency scores from 2002. This provides one counterfactual estimate of the land productivity distribution that would have prevailed if technical efficiency had not changed.

This approach is akin to the counterfactual analysis on income and poverty of Azevedo et al. (2012) and Brito and Kerstenetzky (2019), and can be used to decompose the observed change in productivity distributions into its constituent parts. Let the land productivity distribution in the base period be given by $g(q_0)$ and its distribution in the later survey wave be given by $g(q_1)$:

$$\Delta g(q) = g(q_1) - g(q_0) = [g(q_1) - \hat{g}(q_1|u_0)] + [\hat{g}(q_1|u_0) - g(q_0)] \qquad (3.17)$$

In (3.17), the first bracketed term on the right-hand side, $[g(q_1) - \hat{g}(q_1|u_0)]$, provides a counterfactual estimate of the marginal contribution of changing technical inefficiency to changing land productivity, whereas the second bracketed term, $[\hat{g}(q_1|u_0) - g(q_0)]$, is the portion of the observed change in the distribution attributable to other factors. This can be further decomposed by sequentially changing to base year input levels and parameter estimates:

$$\Delta g(q) = \Delta g(q|u) + \Delta g(q|\boldsymbol{\beta}, \theta) + \Delta g(q|\boldsymbol{x}) + \Delta g(q|A) + \Delta g(q|\delta) \qquad (3.18)$$

where

$$\Delta g(q|u) = g(q_1) - \hat{g}(q_1|u_0) \qquad (3.19)$$

$$\Delta g(q|\boldsymbol{\beta}, \theta) = \hat{g}(q_1|u_0) - \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \theta) \qquad (3.20)$$

$$\Delta g(q|\boldsymbol{x}) = \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \theta) - \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \theta, \boldsymbol{x}_0) \qquad (3.21)$$

$$\Delta g(q|A) = \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \theta, \boldsymbol{x}_0) - \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \theta, \boldsymbol{x}_0, A_0) \qquad (3.22)$$

$$\Delta g(q|\delta) = \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \theta, \boldsymbol{x}_0, A_0) - g(q_0) \qquad (3.23)$$

Expressions (3.19) – (3.23) are counterfactual estimates of the contribution of changing technical inefficiency, technical change, input intensification, changing farm size, and a changing farm size – frontier productivity relationship to changes in the land productivity distribution over time. This parametric decomposition of observed land productivity changes provides the basis for counterfactual analysis of functions of land productivity, such as agricultural output or poverty. The change in poverty measures defined in (3.4) are decomposed using these counterfactual estimates of land productivity, illuminating the contribution of each component to changes in poverty in farm households.

It is important to note that the decomposition in (3.18) is path dependent – the order of decomposition matters. For example, changing technical inefficiency first, $g(q_1) - \hat{g}(q_1|u_0)$ is the counterfactual contribution of changing technical inefficiency given the changes in the other determinants of land productivity. In contrast, changing technical inefficiency last, $\hat{g}(q_1|\boldsymbol{\beta}_0, \boldsymbol{x}_0, A_0, \delta_0\,) - g(y_0)$, would provide the counterfactual contribution of changing technical inefficiency given that none of the other determinants had changed. These counterfactuals are not the same. With no priors regarding what order ought to be used in this decomposition, all possible decomposition paths are conducted and then summarized with three measures. As the literature suggests that the counterfactual contribution of any channel increases with the position in the decomposition, the marginal impact of the first and last are considered as bounds. The preferable approach, suggested by Shorrocks (2013), is akin to a Shapley decomposition, averaging over the marginal contribution of each component from all possible decomposition paths. With five channels of interest, each channel potentially follows any of 16 unique decomposition paths. These counterfactual contributions – first, last, and mean of all 16 possible paths – are calculated for the changing land productivity distribution and for changes in poverty measures.

3.4 The Data

The panel of family farms is drawn from the Mexican Family Life Survey (MxFLS), a nationally representative sample of Mexican households asking detailed information on households' assets, incomes, consumption patterns, and well-being with survey waves in 2002, 2005-2006, and 2009-2012. For those households engaging in agriculture, MxFLS gathers plot level information on plot size and the most important crops produced and household information on asset ownership, on farm labor, and expenditures on other inputs. These farming households are the focus of the analysis, and the nature of the survey make it a rich source of data for analyzing the relationships between agricultural productivity and poverty.

3.4.1 Agricultural Variables

Drawing from the MxFLS sample of family farms identified in chapter 2 as having complete data on their agricultural operations, this study uses farms engaging in agricultural production in both the 2002 and 2009 survey waves.[3] Due to concern over measurement error in the income measure, the top and bottom 5% of the income per-capita distribution were dropped from the sample, resulting in a final sample of 224 farms. The sample contains a broad range of family farms: while the median and mean farm sizes in 2002 were 2.45 ha and 113.0 ha, respectively, the largest farms are over 1,000 ha. Median farm size fell to 2.1 ha and mean farm size grew to 179.3 ha by 2009,

[3] See chapter 2 for a more complete discussion of the agricultural data in the MxFLS.

suggesting that while small farms are getting smaller, large farms are growing in size. Figure 3.1 below displays kernel density estimates of the distribution of farm size (in logs) for 2002 and 2009.

Construction of the measure of agricultural output closely follows that of chapter 2, with the exception that the current analysis does not construct an output quantity index. Rather, the current analysis uses the real value of output, valued in 2002 Mexican pesos. Although an output quantity index is often preferable for productivity analysis, the use of an output variable measured in value terms provides a direct link between land productivity and household income, facilitating the current analysis. Average land productivity fell over time, with the mean logged land productivity falling from 7.71 in 2002 to 7.56 in 2009. Figure 3.2 shows the kernel density estimates of the land productivity distributions (in logs) for 2002 and 2009, revealing that most of this decline occurred in the bottom half of the land productivity distribution. Given the inverse relationship found between farm size and productivity, this increase in average farm size is likely contributing to the observed decline in land productivity.

Factors of production other than land include measures of physical capital, draft animals, purchased inputs, family labor, and non-family labor. Physical capital is measured as the real value of tractors and other machinery owned, and draft animals is similarly measured as the real value of horses, donkeys, and mules owned by the household. Purchased inputs are the real value of aggregate reported expenditures on nine inputs, including fertilizer, manure, pesticides, seeds, tractor services, animal power, wage labor, water, and fuel. As with output, these inputs are measured in 2002 prices. Non-family labor is measured as the number of non-family workers working on the farm over the course of the year, and family labor is an index of the hours worked on the farm by household members during the year. Figures 3.3 and 3.4 show the distributions of family labor per ha and purchased inputs per ha in each period, as these are the most commonly used agricultural inputs in the sample, and were found to be the two most significant inputs in chapter 2. While the intensity with which family labor is used falls during the sample period, the share of farms using purchased inputs is increasing. As with changes in farm size, these changing input intensities are potentially contributing to the changing land productivity distribution.

3.4.2 Income, Livelihoods, and Poverty

No complete measure of household income is included by MxFLS, but detailed questions on income sources and economic livelihoods throughout the individual and household level components of the survey are used to construct a measure of total household income. As introduced in section 3.3 above, income is comprised of agricultural income and non-agricultural income. Whereas agricultural income is measured as the value of agricultural output, whether brought to market or used on the farm, non-agricultural income includes both labor and non-labor components. Labor income includes that derived from wage labor and/or self-employment, whereas non-labor income includes profits from businesses, government transfers, rental income, non-agricultural household production, remittances, and pensions, among other sources. See Appendix C.2 for a detailed discussion of the construction of total household income.

Where possible, labor income is grouped into non-agricultural and agricultural related activities. Table 3.1 shows the share of households deriving income from each income source by year, alongside the average share of total household income derived by that source (excluding households that do not derive any income from that particular source). The first group of income sources includes labor income derived from participation in labor markets. Agricultural households increasingly have adult household members participating in wage labor, in both agricultural and non-agricultural occupations, while the participation of household children in wage labor is on the decline. For those family farms with adult household members engaging in wage labor, such wages are important components of total household income – income from non-agricultural wage labor, for example, makes up half of the household incomes of participating households.

The second group includes income from entrepreneurial activities, including agricultural production and non-agricultural businesses, self-employment in agricultural and non-agricultural industries, and home production. On average, agricultural income accounts for 26-29% of total household income for this sample of Mexican family farms – the economic livelihoods of these family farms are diverse, with the majority of household incomes being generated by activities other than agricultural production. Further, whereas fewer households are participating in agriculture related entrepreneurial activities, households are increasingly participating in non-agricultural activities. The non-agricultural sector of the rural economy appears to be increasingly prevalent in the livelihood strategies of Mexico's family farms.

The third and final group include non-labor sources of income, where participation in Oportunidades and other government programs are increasingly prevalent. On average, these programs are important for family farms – households receiving payments through Oportunidades, for example, receive a fifth of their household income from the program. Overall, the livelihood strategies of this sample of family farms are consistent with previous findings from Mexico. In their study of ejido households in 1997, de Janvry and Sadoulet (2001) found that off-farm income generated half to three-fourths of ejido household incomes, that self-employment activities and non-agricultural wage labor were more common than agricultural labor for households participating in off-farm employment, highlighting the importance of the rural non-agricultural sector for the economic livelihoods of Mexican family farms.

Real monthly income per-capita fell in the sample, from a mean of 1,147 to 1,016 Mexican pesos over the span of the panel. Despite this, income per-capita grew for the poorest quartile of the income distribution. These changes had heterogenous impacts on the income-based poverty measures used in this study. For reference, Table 3.2 displays the urban and rural overall and extreme poverty lines for 2002 and 2009, adopted from Mexico's National Council for the Evaluation of Social Development Policy (CONEVAL). Table 3.3 shows the poverty measures introduced in (3.4) using the rural poverty and rural extreme poverty lines, for both survey years. The final two columns calculate the percentage change. As both mean and median incomes fell over this period, the poverty rate increased. While this change in overall poverty incidence was marginal, increasing by just 0.8%, the extreme poverty rate saw a notably large 6 percentage-point increase, equivalent to a 15% increase in the prevalence of extreme poverty for this sample of family farms.

A more complex picture unfolds in light of poverty depth and poverty severity, measured by the poverty gap and the poverty gap squared, respectively. The overall poverty gap index experienced a 1.2% increase as farmers slipped into extreme poverty. However, the extreme poverty gap index fell by 1.0% and the squared poverty gap index declined by 2.2% when using the overall poverty line and by 1.7% when using the extreme poverty line. To summarize, although the incidence of overall poverty increased marginally and the overall poverty gap increased, poverty severity showed declined. Movement in these poverty measures is primarily driven by changes to the extremely poor – as poverty deepened for some, as reflected in the 15% increase in the incidence of extreme poverty. Rising incomes in the bottom quartile of the income distribution meant that the extreme poverty of the poorest of the poor was partially mediated, leading to a reduction in overall poverty severity.

3.5 Empirical Results

As a starting point for unpacking the direct poverty reduction potential of agricultural productivity, Table 3.4 displays the counterfactual poverty measures that would have prevailed if land productivity had not changed over time, alongside the observed poverty measures in 2009 and the percentage difference. In short, the counterfactual poverty measures answer the question, *what would have been the change in poverty if farm income generating activities had evolved as observed, but agricultural productivity had remained at observed 2002 levels*? Similarly, the percentage difference provides an estimate of the reduction in poverty that would have been achieved if base year land productivity had been maintained. Results from the poverty rate suggest that if land productivity had been held at 2002 levels, poverty incidence on family farms would have been more than 4% lower. This would amount to a 4.1-4.6% reduction in poverty given a 16% increase in land productivity, for a point elasticity of approximately -0.26 to -0.29. Irz et al. (2001), in comparison, find that poverty falls by 5-7% given a 10% increase in land productivity, for a point elasticity of -0.5 to -0.7. This is reasonable, given that the current approach assesses only the direct links between land productivity and poverty, whereas Irz et al. (2001) assess the linkages more comprehensively.

While maintaining base year land productivity would have reduced the number of people in both poverty and extreme poverty, the depth and severity of poverty relative to the extreme poverty line would have increased. The counterfactual increase in poverty severity indicates that observed changes in land productivity over the period of study were beneficial for the poorest of the poor. More generally, the impacts of changing land productivity on poverty are heterogeneous, affecting the moderate and extremely poor in distinct ways.

3.5.1 Technical Efficiency Estimates

Estimating a stochastic production frontier according to (3.11) through (3.14) forms the basis for the decomposition of land productivity. The model is estimated using the *sfcross* command in Stata, with community-level fixed effects and standard errors clustered at the community level. The lambda, or the ratio of the variance of the inefficiency term to the variance of the error term, is 1.52, indicating that a stochastic frontier model is appropriate. The model is consistent with that of chapter 2, in that it finds evidence of positive technical change in the frontier and increasing technical inefficiency over time. See Appendix C.3 for further details of the model results. Figure 3.5 shows kernel density estimates for the technical inefficiency scores for each year, showing the growth of technical inefficiency over time.

3.5.2 Counterfactual Land Productivity Analysis

Table 3.5 begins to unpack the change in land productivity into its constituent sources by displaying the results of the decomposition described in (3.15). Again, this decomposition is akin to that of Oaxaca and Blinder, expressing changes in average land productivity as changes in average observable characteristics and differences in model parameters.[4] When evaluated at the mean, technical change had a positive contribution to changes in land productivity during the period. Growing average technical inefficiency and the growth in average farm size largely offset that contribution, contributing most to the decline in land productivity. In comparison, changing average input intensities and a changing farm size – frontier productivity relationship contributed relatively little to the observed decline in average land productivity. From a productivity perspective, this suggests that policy helping family farms with the adoption of new technologies and the efficient use of existing resources poses a significant opportunity.

The average decompositions, however, do not speak to the heterogeneity with which these productivity sources influence the productivity of family farms. Table 3.6 displays the average change in land productivity attributable to each source, by decile of land productivity in the base year. The changes in land productivity are based upon the counterfactual land productivity distributions generated according to (3.18), and follow Shorrocks (2013) in using the average change across all possible orders of decomposition. These average changes for each farm from each productivity source are then averaged over deciles. The corresponding counterfactual land productivity distributions associated with each productivity component can be seen in Appendix C.4.

An immediate implication of this approach is that the observed change in land productivity exhibits considerable heterogeneity across deciles. As shown in the final

[4] As the frontiers for each period are estimated in a single model, the expected error terms will not cancel and the decomposition will not be exact

column of Table 3.6, those farms with the lowest land productivity in 2002 realized notable gains in land productivity on average, whereas the most productive deciles averaged pronounced losses in productivity. Whereas changes in farm size and inefficiency were contributing to productivity losses for the most productive farms, they contributed to productivity gains among the least productive farms. Technical change, in contrast, had a relatively homogenous and positive relationship with land productivity. It is clear that going beyond the mean is necessary to assess the links between agricultural productivity and on-farm poverty, and that the channel for productivity gains will likely matter.

3.5.3 Counterfactual Poverty Analysis

Tables 3.7 and 3.8 display the counterfactual estimates of the contribution of productivity sources to poverty, in terms of percentage and percentage point changes, respectively. These counterfactual estimates are the average changes to poverty if the productivity source maintained their 2002 levels, averaged over all possible paths of decomposition. For example, the results for technical change are interpreted as the counterfactual estimates of the difference in poverty that would have been realized if there were no technical change during the period – regardless of poverty measure or poverty line used, poverty would have been 4-16% higher absent technical change, depending upon the measure. The changes to the farm size distribution, i.e. the fall in small farm size and the rise in large farm size, contributed to increasing poverty. Absent these changes, poverty would have been 5-9% lower. In conclusion, whereas technical change contributed positively to growth in land productivity and poverty alleviation, changes to the farm size distribution detracted from average land productivity and contributed to an increase in poverty.

The relationship between changing technical inefficiency, land productivity, and poverty, appears more nuanced. Yes, productivity would have been higher, on average, and poverty lower in the absence of growing technical inefficiency, but the contribution to changes in poverty is both mixed and relatively muted. The incidence of changing efficiency clearly matters for its contribution to on-farm poverty. Whereas poverty rates would have fallen absent changes to the technical inefficiency distribution, poverty depth and poverty severity relative to the extreme poverty line would have increased. Changes to input intensity on farms made a notably smaller contribution to the decline in average land productivity than did changes to technical inefficiency, but the direct effect on poverty among family farms was more pronounced. This points towards agricultural productivity growth through intensification and technical change being notably more pro-poor than technical efficiency in terms of the direct contribution to on-farm poverty alleviation.

3.6 Discussion and Concluding Remarks

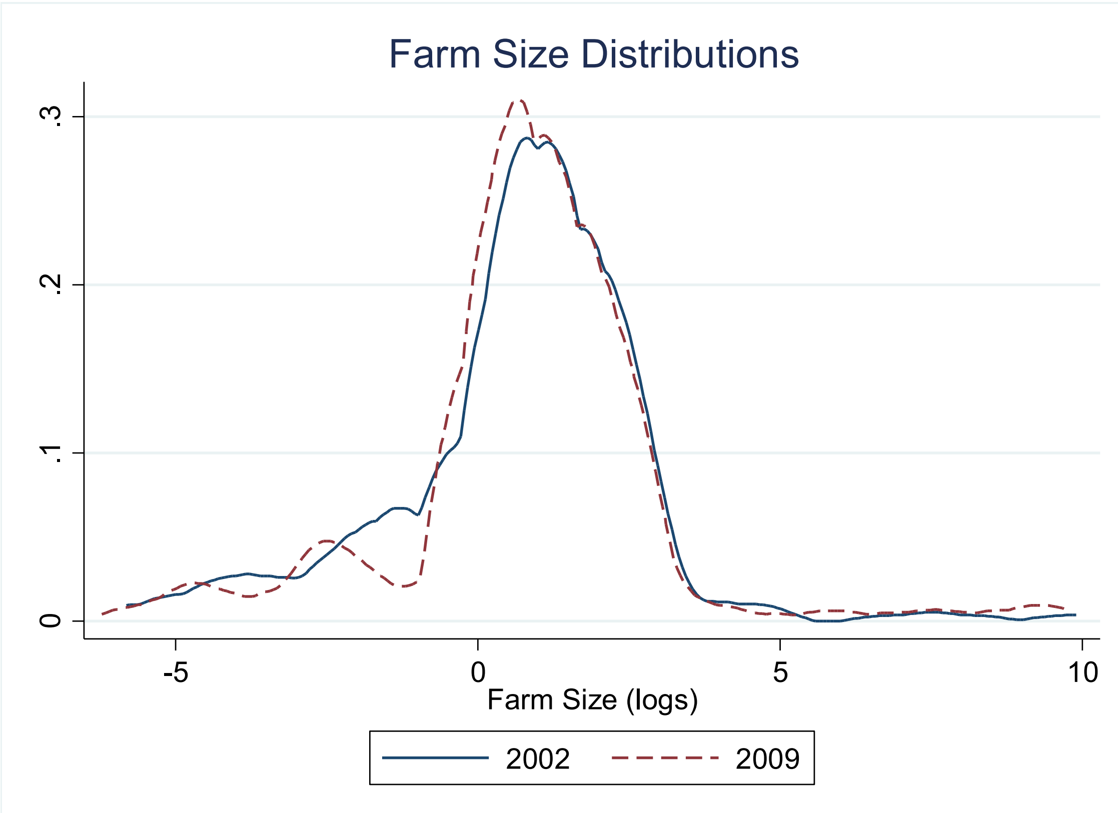
Using a 2002-2009 panel of family farms in Mexico drawn from the Mexican Family Life Survey, this paper contributes to understanding the linkages between productivity and poverty by estimating the direct contribution of changing agricultural productivity to changes in on-farm poverty. The study finds declining average land productivity over the sample period, and while poverty rates increased among family farms, poverty severity declined. Decomposing changing agricultural productivity into five sources – changes in technical efficiency, technical change, input intensification, farm size, and the farm size-frontier productivity relationship – the analysis finds increasing inefficiency and changes to the farm size distribution were driving the decline in land productivity in spite of notable technical change. The counterfactual analysis finds evidence of a land productivity – poverty point elasticity of approximately -0.26 to -0.29; poverty would have been approximately 4% lower if land productivity had not changed. Further, the counterfactual analysis suggests that raising land productivity through intensification and technical change would have a larger direct contribution to alleviating on-farm poverty than would increasing technical efficiency.

This study can be refined and extended in several ways. First, the counterfactual estimates could be improved with further refinement of the sample's income variable. There appear to be several areas where marginal components may not have been included, such as on remittances data and profits from non-agricultural businesses. There are other areas where some double-counting of income may be occurring. Similarly, the prices used to value agricultural output are common, taken from the FAO. Whereas a common set of prices was a boon to productivity analysis, where common prices aid comparability, heterogeneous output prices are likely important when assessing incomes, poverty and livelihoods on family farms.

There are several important extensions of this line of work. First, a third wave of the survey, conducted in 2005, has not been utilized in this study. Leveraging this third survey year may prove interesting, as the literature has shown evidence of a decline in poverty between 2002 and 2005, with an increase in poverty in the following years. Second, the richness and breadth of the survey make it possible to extend the analysis into alternative measures of poverty. An analysis and comparison of consumption-based poverty, nutrition-based poverty, child poverty, and multidimensional poverty are all possible. Third, a methodological extension may involve utilizing the non-parametric decomposition techniques pioneered in labor economics to complement the parametric decomposition presented here. Lastly, this study should be extended to a more general decomposition of poverty into its constituent components.

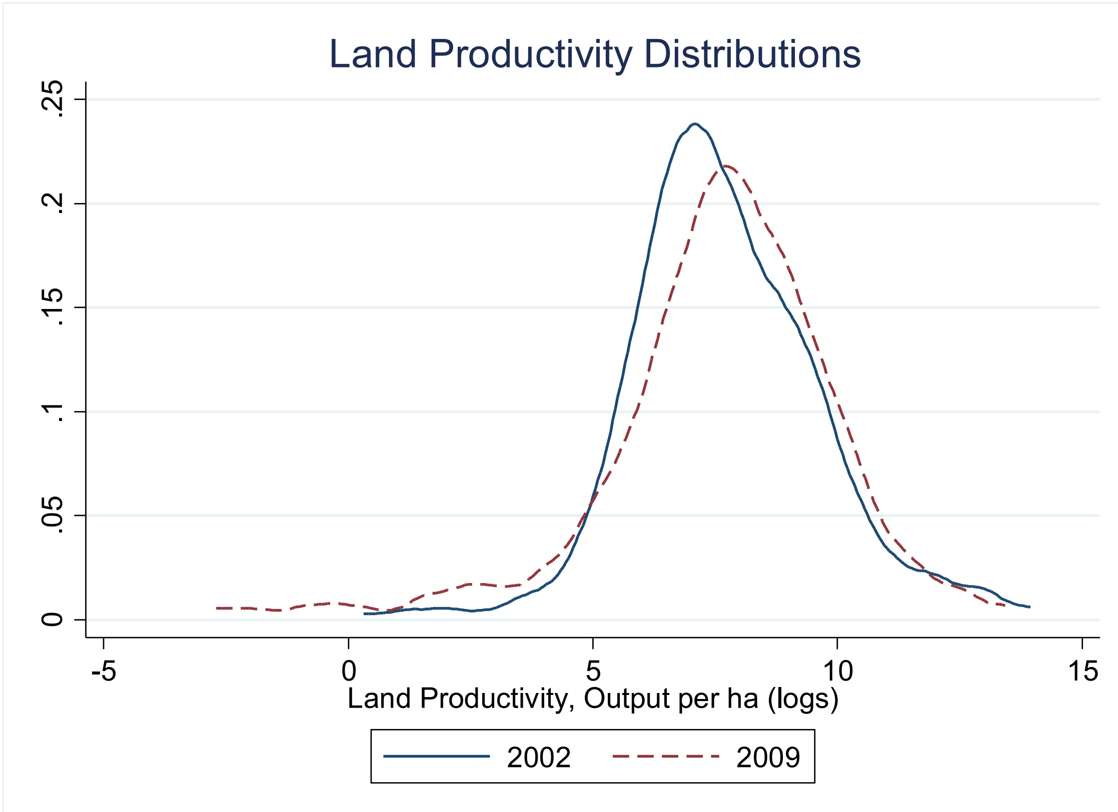
Chapter 3 Tables and Figures

Figure 3.1: Farm Size Kernel Densities for Each Year



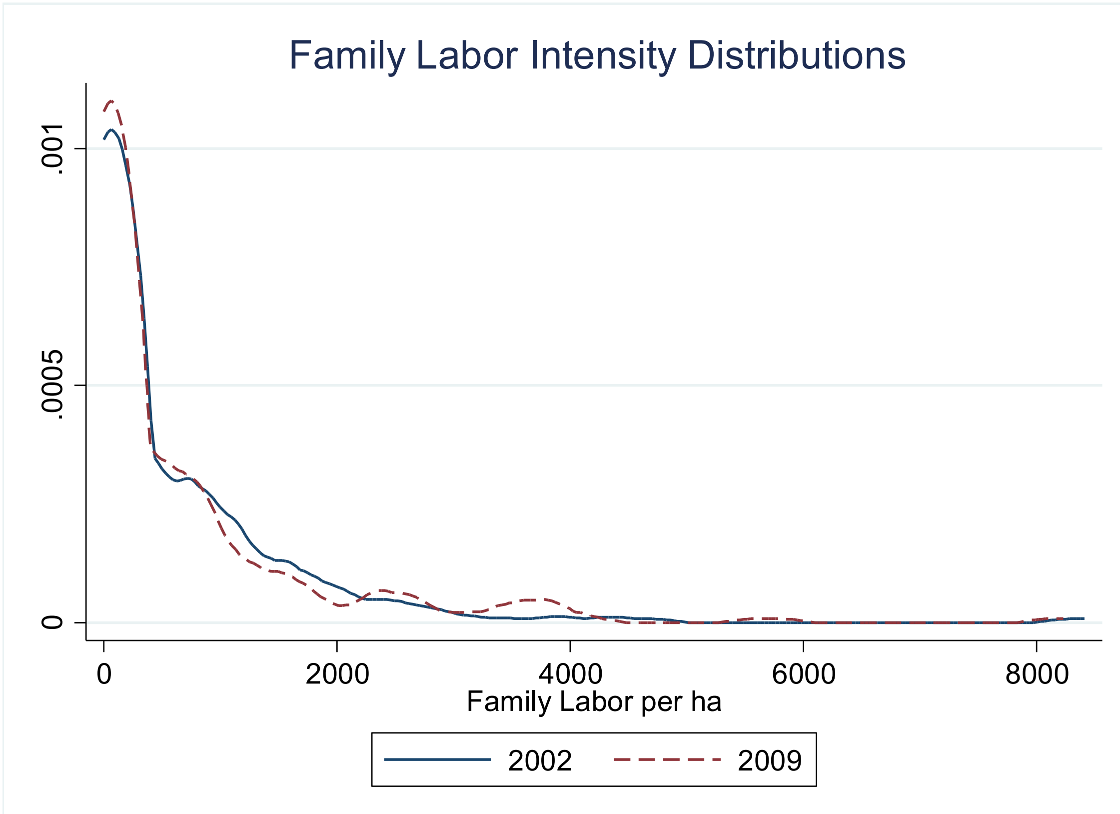
Note: Estimated with the default kernel density command in Stata, using an Epanechnikov kernel

Figure 3.2: Land Productivity Kernel Densities for Each Year



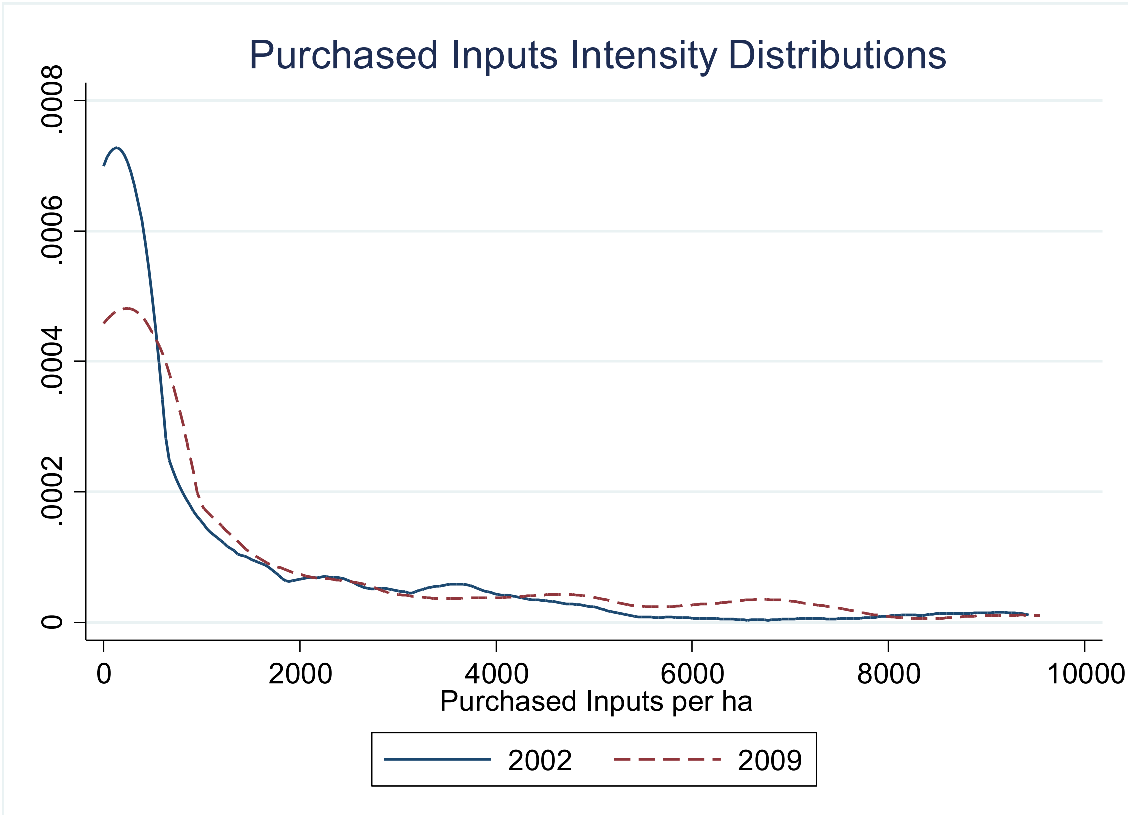
Note: Estimated with the default kernel density command in Stata, using an Epanechnikov kernel

Figure 3.3: Family Labor per ha Kernel Densities for Each Year



Note: Estimated with the default kernel density command in Stata, using an Epanechnikov kernel

Figure 3.4: Purchased Inputs per ha Kernel Densities for Each Year



Note: Estimated with the default kernel density command in Stata, using an Epanechnikov kernel

Table 3.1: Prevalence and Average Share of Income Sources

Income Category		Share of Households with Income		Average Share of Total Income	
		2002	2009	2002	2009
Participation in Labor Markets	Ag Labor Income	15%	20%	46%	33%
	Non-Ag Labor Income	25%	33%	55%	52%
	Child Labor Income	4%	1%	34%	37%
	Other Labor Income	3%	2%	41%	39%
Entrepreneurial Activities	Agricultural Production	100%	100%	26%	29%
	Non-Ag Business	6%	10%	21%	2%
	Farmer Self-Employment	45%	31%	22%	22%
	Ag Self-Employment	50%	36%	23%	24%
	Non-Ag Self-Employment	20%	24%	32%	29%
Other Income Generating Activities	Rental Income	3%	2%	13%	5%
	Household Production	5%	8%	11%	12%
	Oportunidades	37%	45%	21%	20%
	Other Government Transfers	62%	67%	12%	18%
	Other Non-labor Income	19%	12%	26%	16%

Table 3.2: Poverty Lines, Nominal Monthly Mexican Pesos per capita

	2002		2009	
	Overall Poverty	Extreme Poverty	Overall Poverty	Extreme Poverty
Urban	1,468.31	618.94	2,045.82	952.09
Rural	898.99	427.67	1,292.10	673.63

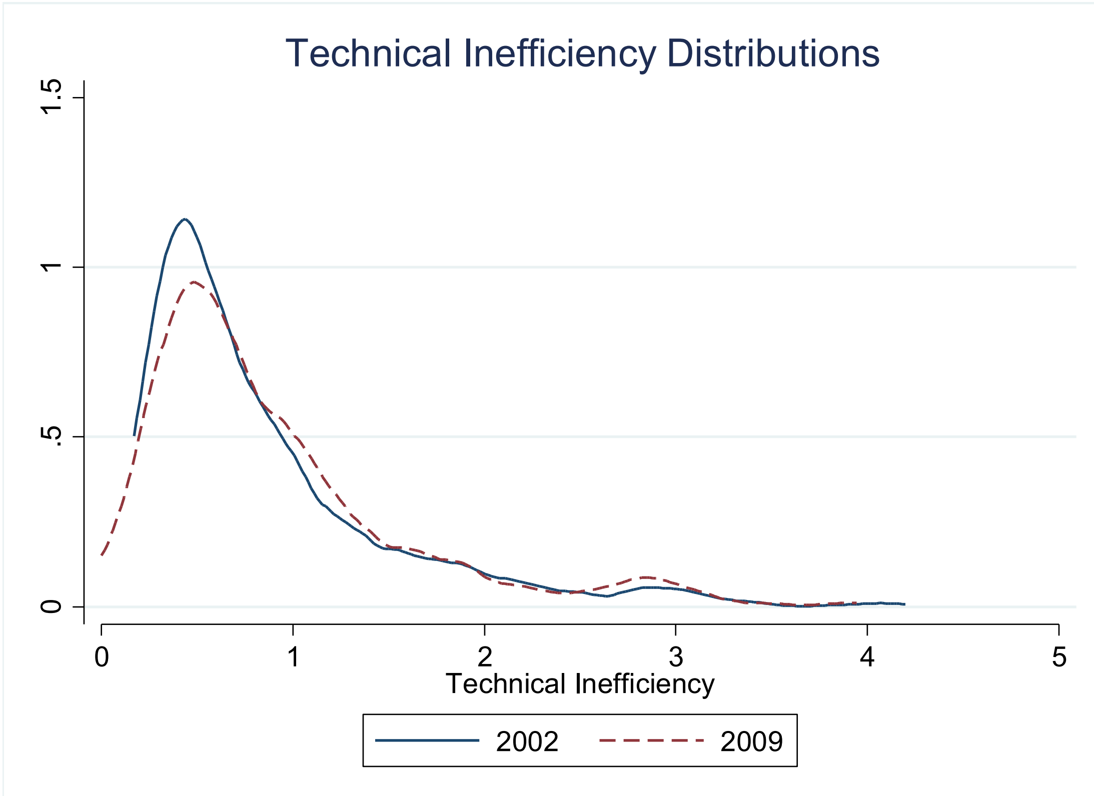
Table 3.3: Observed Poverty Measures

	2002		2009		Percentage Change	
	Overall Poverty	Extreme Poverty	Overall Poverty	Extreme Poverty	Overall Poverty	Extreme Poverty
Poverty Rate	0.715	0.407	0.721	0.469	0.8	15.2
Poverty Gap Index	0.406	0.196	0.411	0.194	1.2	-1.0
Squared Poverty Gap Index	0.276	0.116	0.270	0.114	-2.2	-1.7

Table 3.4: Counterfactual Changes in Poverty Measures, Land Productivity Held Constant

	2009		2009 Counterfactual		Percentage Difference	
	Overall Poverty	Extreme Poverty	Overall Poverty	Extreme Poverty	Overall Poverty	Extreme Poverty
Poverty Rate	0.721	0.469	0.688	0.450	-4.6	-4.1
Poverty Gap Index	0.411	0.194	0.389	0.199	-5.4	2.6
Squared Poverty Gap Index	0.270	0.114	0.261	0.120	-3.3	5.3

Figure 3.5: Technical Efficiency Kernel Densities for Each Year



Note: Estimated with the default kernel density command in Stata, using an Epanechnikov kernel

Table 3.5: Oaxaca Blinder Decomposition of Land Productivity

	Change	% of Total
Total	*-0.132*	*100*
Technical Change	0.395	-298
Input Intensities	-0.012	9
Technical Inefficiency	0.335	253
Farm Size	-0.098	74
Farm Size – Frontier Productivity	-0.011	8
Unexplained Residuals	0.014	-46

Table 3.6: Counterfactual Land Productivity Changes, by Decile

	Inefficiency		Input In		Tech		FS		IR		Actual
	Mean Change	% of Total	Mean Change	% of Total	Mean Change	% of Total	Mean Change	% of Total	Mean Change	% of Total	
Average	-0.361	273	-0.067	51	0.404	-306	-0.090	68	-0.012	9	-0.132
Decile											
1st	0.315	12	0.235	9	0.418	16	1.515	56	-0.025	-1	2.687
2nd	0.330	23	-0.038	-3	0.392	27	0.314	21	-0.014	-1	1.463
3rd	-0.157	-1,570	-0.034	-340	0.397	3,970	-0.186	-1,860	-0.016	-160	0.010
4th	-0.504	-438	0.025	22	0.411	357	0.284	247	-0.014	-12	0.115
5th	-0.729	98	-0.197	26	0.491	-66	-0.177	24	-0.018	2	-0.745
6th	-0.104	-18	-0.073	-13	0.422	74	0.178	31	-0.012	-2	0.568
7th	-0.318	-558	-0.079	-139	0.419	735	-0.144	-253	-0.018	-32	0.057
8th	-0.288	90	0.063	-20	0.391	-123	-0.224	70	-0.007	2	-0.319
9th	-0.790	65	-0.177	15	0.359	-30	-0.595	49	-0.009	1	-1.207
10th	-1.467	36	-0.434	11	0.332	-8	-2.018	50	0.016	0	-4.052

Table 3.7: Counterfactual Changes in Poverty Measures, Percentage Changes

	Poverty Line	Counterfactual Reductions in Poverty Poverty Rate	Poverty Gap	Poverty Gap Squared
Inefficiency	*Overall*	-0.4	-1.4	-1.0
	Extreme	-0.7	0.4	1.6
Input Intensity	*Overall*	-0.4	-2.0	-2.8
	Extreme	0.8	-4.4	-5.7
Technical Change	*Overall*	3.9	6.2	8.9
	Extreme	6.8	13.2	15.5
Farm Size	*Overall*	-5.3	-7.2	-7.7
	Extreme	-6.7	-8.2	-9.0
Farm Size – Frontier Productivity	*Overall*	-0.3	0.1	0.2
	Extreme	-0.4	0.2	0.5

Table 3.8: Counterfactual Changes in Poverty Measures, Percentage Point Changes

	Poverty Line	Counterfactual Reductions in Poverty Poverty Rate	Poverty Gap	Poverty Gap Squared
Inefficiency	*Overall*	-0.3	-0.5	-0.3
	Extreme	-0.4	0.1	0.2
Input Intensity	*Overall*	-0.3	-0.8	-0.8
	Extreme	0.4	-0.9	-0.7
Technical Change	*Overall*	2.7	2.4	2.3
	Extreme	3.1	2.4	1.7
Farm Size	*Overall*	-3.8	-3.0	-2.2
	Extreme	-3.3	-1.7	-1.1
Farm Size – Frontier Productivity	*Overall*	-0.2	0.1	0.1
	Extreme	-0.2	0.1	0.1

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Appendix A.1

Proof of expression (1.14):

$$\frac{\partial TFP}{\partial A} = \left(\frac{\partial q}{\partial A}\right)\left(\frac{1}{\tau(A)}\right) - \frac{\left(\frac{\partial \tau(A)}{\partial A}\right) q}{\tau(A)^2}$$

$$\frac{\partial TFP}{\partial A} = \left(\frac{\partial q}{\partial A}\right)\left(\frac{1}{\tau(A)}\right)\left[1 - \frac{\left(\frac{\partial \tau(A)}{\partial A}\right) q}{\tau(A)\left(\frac{\partial q}{\partial A}\right)}\right]$$

$$\frac{\partial TFP}{\partial A} = \left(\frac{\partial q}{\partial A}\right)\left(\frac{1}{\tau(A)}\right)\left[1 - \frac{\left(\frac{\partial \tau(A)}{\partial A}\right)\left(\frac{1}{\tau(A)}\right)}{\left(\frac{\partial q}{\partial A}\right)\left(\frac{1}{q}\right)}\right] = \left(\frac{\partial q}{\partial A}\right)\left(\frac{1}{\tau(A)}\right)\left[1 - \frac{\left(\frac{\partial \tau(A)}{\partial A}\right)\left(\frac{A}{\tau(A)}\right)}{\left(\frac{\partial q}{\partial A}\right)\left(\frac{A}{q}\right)}\right]$$

$$\frac{\partial TFP}{\partial A} = \left(\frac{\partial q}{\partial A}\right)\left(\frac{1}{\tau(A)}\right)\left[\frac{\varepsilon_{q,A}}{\varepsilon_{q,A}} - \frac{\varepsilon_{\tau(A),A}}{\varepsilon_{q,A}}\right]$$

$$\frac{\partial q}{\partial A} = \left(\frac{\partial TFP}{\partial A}\right)\tau(A)\left[\frac{\varepsilon_{q,A}}{\varepsilon_{q,A} - \varepsilon_{\tau(A),A}}\right]$$

Appendix A.2

Table A.2.1: Data Cleaning and Sample Size, by Region and Farm Size Class

	Farm Size Class (ha)	Observations (N)	Less Farm Size Outliers	Less Land Productivity Outliers	Percent Dropped from Cleaning
North	0-5	315	315	310	1.6
	5-20	420	420	403	4.0
	20-100	459	459	437	4.8
	100-500	443	443	433	2.3
	500 +	323	315	305	5.6
Center-West	0-5	537	537	520	3.2
	5-20	619	619	605	2.3
	20-100	681	681	673	1.2
	100-500	672	672	659	1.9
	500 +	613	595	581	5.2
Southeast	0-5	3,850	3,850	3,805	1.2
	5-20	3,991	3,991	3,927	1.6
	20-100	4,024	4,024	3,944	2.0
	100-500	3,896	3,896	3,871	0.6
	500 +	2,235	2,215	2,195	1.8
Brazil[1]		*47,365*	*47,281*	*46,515*	*1.8*

[1]The sample size in Brazil includes data from the Northeastern and Southern regions.

Table A.2.2: Descriptive Statistics, 2006

	Farm Size Class (ha)	Output (R$ 2006/ha)	Capital (Index/ha)	Family Labor (Adult Male Equivalents/ha)	Purchased Inputs (R$ 2006 per ha)	Share of Farms (%)	Share of Area (%)	Share of Output (%)
	0-5	4,185.02	965.03	1.75	862.4	19.4%	0.3	6.9
	5-20	1,110.46	333.92	0.24	214.4	17.4	1.6	12.0
North	20-100	282.24	129.06	0.05	73.5	43.0	17.4	32.2
	100-500	120.65	88.47	0.01	58.2	16.9	26.4	20.9
	500 +	78.98	54.90	0.01	73.0	3.3	54.3	28.0
	0-5	3,265.49	2,628.76	0.72	1,971.5	8.5	0.1	0.8
	5-20	902.03	851.41	0.16	507.0	20.2	0.7	2.4
Center-West	20-100	444.53	378.38	0.04	231.9	37.8	5.0	8.3
	100-500	276.48	279.76	0.01	210.4	21.2	13.8	14.3
	500 +	247.08	127.28	0.01	246.5	12.3	80.4	74.2
	0-5	4,152.85	3,903.90	0.85	1,892.5	28.8	1.1	5.5
	5-20	1,611.97	1,797.21	0.18	1,061.6	32.1	6.2	11.7
Southeast	20-100	923.89	906.85	0.04	554.7	28.5	21.8	23.5
	100-500	711.38	555.44	0.01	556.7	9.1	32.9	27.2
	500 +	726.50	276.13	0.01	715.4	1.5	37.9	32.1

Appendix A.3

Table A.3.1: Estimated Technology Coefficients

	North	Center-West	Southeast
Capital per ha	0.201***	0.171***	0.121***
	(0.033)	(0.035)	(0.014)
Family Labor per ha	0.267***	0.142***	0.191***
	(0.056)	(0.039)	(0.026)
Purchased Inputs per ha	0.315***	0.430***	0.510***
	(0.035)	(0.042)	(0.019)
Constant	3.862***	3.667***	3.309***
	(0.225)	(0.290)	(0.019)
Weather Shocks	Yes	Yes	Yes
AMC FE	Yes	Yes	Yes
Time-varying Size Dummies	Yes	Yes	Yes
R-squared	0.96	0.90	0.91
N	1,888	3,038	17,742

Dependent variable is logged output; all independent variables are logged; all variables normalized by farm size.

Standard errors in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Appendix B.1

Construction of the Output Index

There are three components to the construction of the output index. First, the valuation of crop production for each farm. Second, the valuation of livestock production. Third, the construction of the quantity index.

Valuing Crop Production

The three most important crops produced on each parcel used in production were aggregated into 90 groups, with a residual group for a set of relatively minor products. The construction of the quantity index requires a price from each of the three periods for each product produced, regardless of whether or not it was produced in all periods. Whereas there was quite good coverage of prices for MxFLS crops produced within any given year, many crops did not have prices in all three years. More importantly, marked fluctuations in the crop prices generated across years raised concerns about using MxFLS generated prices for generating consistent crop valuations. In their place, we use price data from the Food and Agriculture Organization of the United Nations (FAO)[1] which provides Mexican producer prices over the relevant time period for approximately 110 crops, resulting in a near one to one mapping to the MxFLS crop grouping. The FAO prices are a vetted and defensible data series of average Mexican crop prices in each period, allowing for consistent valuation of MxFLS crop production.[2]

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[1] See http://www.fao.org/faostat/en/#data/PP.

[2] For the "Blackberries" and "Nuts" crop groupings the FAO price data is supplemented using prices generated by the Mexican government, found at http://www.economia-

The value of production of each crop on each parcel for each farm is valued using each of the three periods' prices. Value of production is then aggregate across crops for each parcel using each year's prices, and then aggregated across parcels for each farm for each set of prices. The result is three valuations for the crop production of each farm in each year, one using the price from each of the three survey years, providing the basis for construction of quantity indices.

Valuing Livestock Production

The MxFLS records the existence and value of the stock of many household assets. These asset categories include horses, cows and bulls, pigs and goats, and chickens. Whereas horses are most likely an input in the agricultural production process, the latter three categories constitute the production of livestock and their related goods. For the 20% - 25% of households owning cows and/or bulls in any period, the 23% - 28% owning pigs and goats, and the 37% - 46% of households owning chickens, the MxFLS provides a valuation of those asset stocks and some measures of the product of those asset stocks. A final value of nominal livestock production is calculated by summing the value of livestock sales with the value of livestock consumption. Nominal values are deflated to 2002 values, generating the value of livestock production to be used in the calculation of the quantity index.

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sniim.gob.mx/2010prueba/Agricolas.asp. For the "Herbs" crop grouping we generate average prices from the MxFLS data itself. The "Pasture" grouping is not valued, and the "Other" and "Flowers" groupings are not valued either.

The value of product sold is measured as the previous year's sales of dairy products, meat products, and fattened animals. The value of product consumed is calculated as the value of meat, dairy, and other animal products received as gift, as payment, or obtained from crops and animals over the previous week. Aggregating across these categories for each household in each year and then multiplying by 52 generates the value of livestock production consumed. Treating this summation as the annual value of livestock production consumed implicitly assumes that (i) all, or nearly all, of these consumption values come from home production and not gifts or as payment, and (ii) the previous week's consumption patterns are representative of consumption patterns over the course of the year.

Construction of the Quantity Index

In each period, we begin by aggregating the total value of production for each farm in each survey year. For those households that have complete farm data in two or more years (i.e. complete farm size data on all parcels and valuation data of all crops on all parcels) we then construct a Fisher quantity index. Having identified "complete farms" in the panel, we then generate the following Panel IDs:

- 1 if the farm is in the panel in 2002 and 2005 only
- 2 if the farm is in the panel in 2002, 2005, and 2009
- 3 if the farm is in the panel in 2005 and 2009 only
- 4 if the farm is in the panel in 2002 and 2009 only
- 0 otherwise

We generate the quantity index for farm, f, producing crop, i, by first calculating changes in the Fisher quantity index over all relevant pairs of periods. These changes are then applied to base year values. The changes in the Fisher quantity index are calculated as follows:

- $Q^f_{02,05} = \sqrt{\left(\frac{\sum_i p_{i,2002} q_{fi,2005}}{\sum_i p_{i,2002} q_{fi,2002}}\right)\left(\frac{\sum_i p_{i,2005} q_{fi,2005}}{\sum_i p_{i,2005} q_{fi,2002}}\right)}$ … if Panel = 1 or 2

- $Q^f_{02,09} = \sqrt{\left(\frac{\sum_i p_{i,2002} q_{fi,2009}}{\sum_i p_{i,2002} q_{fi,2002}}\right)\left(\frac{\sum_i p_{i,2009} q_{fi,2009}}{\sum_i p_{i,2009} q_{fi,2002}}\right)}$ … if Panel =2 or 4

- $Q^f_{05,09} = \sqrt{\left(\frac{\sum_i p_{i,2005} q_{i,2009}}{\sum_i p_{i,2005} q_{i,2005}}\right)\left(\frac{\sum_i p_{i,2009} q_{i,2009}}{\sum_i p_{i,2009} q_{i,2005}}\right)}$ … if Panel=2 or 3

With changes in the quantity index in hand we then generate the level of the quantity index for each year as follows. Here $Value^f_{year}$ is the value of output in a given year using nominal prices for farm f:

- $QI^f_{2002} = Value^f_{2002}$ *… if Panel = 1, 2, or 4*

- $QI^f_{2005} = \begin{cases} Value^f_{2002} * Q^f_{02,05} & if\ Panel = 1\ or\ 2 \\ Value^f_{2005}/Deflator & if\ Panel = 3 \end{cases}$

- $QI^f_{2009} = \begin{cases} Value^f_{2002} * Q^f_{02,09} & if\ Panel = 4 \\ Value^f_{2005} * Q^f_{05,09} & if\ Panel = 3 \\ QI^f_{2005} * Q^f_{05,09} & if\ Panel = 2 \end{cases}$

Appendix B.2

Construction of Inputs

Family Labor Index

Two approaches are used to generate a measure of family labor as an input to the production process. The first uses categorical variables for whether or not household members helped farm each plot. These measures are plot specific providing a measure of household labor on the extensive margin, but do not include any intensive measure of labor use. The second approach uses time-use data for each household member. While this approach has advantages on the intensive margin, it is less comprehensive and less complete on the extensive margin.

We develop a set of three indicators. The first uses time-use data and is the preferred approach, whereas the second and third use the binary yes/no data regarding family members' participation on each plot. The construction of Family Labor Index 1 is as follows estimates annual hours worked on the farm by each household member. If a core household member indicates that agricultural work on the family farm was either their primary or secondary job then average hours worked per week is the basis for that individual's annual agricultural labor.[3] If not, then hours spent on household agricultural activities in the previous week provides the basis for the individual's annual agricultural

[3] This includes not only those who claim that their job is as a "peasant on your own plot", but also those who work in agriculture as a "family worker in a household owned business, without remuneration" or a "boss, employer, or business proprietor."

labor.[4] For non-core family members the most comprehensive data comes at the plot level - annual hours worked for these family members are estimated using group averages of time spent on household agricultural activities and the number of family members in each group, by type of family member.[5]

Summing hours worked by the core family members and the non-core family members generates Family Labor Index 1. This approach prioritizes employment data over the time use data, avoids double-counting of those two measures, and uses as much of the data as possible. Equation (1) summarizes this preferred Family Labor Index:

$$Family\ Labor\ 1_i = H_i^h * 52 + H_i^s * 52 + \sum_k H_{ik}^c * 52 + \sum_{j=1}^{10} N_{ij} * \bar{H}_j * 52$$

where H_i^h, H_i^s, and H_{ik}^c are the weekly hours worked of household i's household head, household head's spouse, and household head's k[th] children as described above, $\bar{H}_j$ is the average weekly hours worked of non-core family member type *j* (unique for each of the 10 possible categories)[6], and N_{ij} is the number of non-core family members in group j of household i.

The construction of indices two and three creates an indicator for the involvement of family members in household production followed by aggregation across family member types for each household in each year. These measures calculate an indicator for

[4] Individuals are asked about the use of their time on different activities over the previous week, one of which is "make any agricultural activity like weeding hoe[ing], cleaning, sowing, [etc.]."
[5]The average number of hours spent engaged in agriculture in the past week is 18.99 hours for non-core family members.
[6] These family member types are: parents, parents in law, siblings, siblings in law, grandchildren, grandparents, aunts and uncles, nephews and nieces, cousins, and ex-spouses.

each of the $j = 1 \dots 14$ types of family members (identified in relation to the household head).[7] In recognition that for multi-parcel farms a given family member type may not help on all plots, we weight each family member type's indicator by the share of the farm they participated on (measured as the size of the parcels that they participated on divided by the size of the total farm). For family member type j of farm i, the indicator I_{ij} is given by:

$$I_{ij} = \frac{size\ of\ farm\ i's\ parcels\ on\ which\ group\ j\ helped}{total\ size\ of\ farm\ i}$$

When aggregating, we then have the option of summing the indicator functions for each family member type or summing with weights that reflect the number of individuals in each family member type in each household in each survey year. The second index uses the former aggregation procedure, with no weights for the number of members of each family member type. The third index uses the latter aggregation procedure, applying weights that reflect the number of individuals in each family member type, N_{ij}:

$$Family\ Labor\ 2_i = \sum_{j=1}^{14} I_{ij}^2$$

$$Family\ Labor\ 3_i = \sum_{j=1}^{14} I_{ij}^3 * N_{ij}$$

[7] These family member types are: spouse, children, step children, children in law, parents, parents in law, siblings, siblings in law, grandchildren, grandparents, aunts and uncles, nephews and nieces, cousins, and ex-spouses.

Family Labor Indices 1, 2, and 3 are positively correlated with each other. The correlation coefficients between index 2 and 3 range from 0.68 in 2002 to 0.71 in 2005. Family Labor Index 1 is less highly correlated with 2 and 3 than they are with each other, but this is reasonable given that it is based upon time use and is fundamentally different than the other two. Family Labor Index 1 is a measure of annual hours of agricultural labor from family members, capturing the intensity of agricultural labor of those family members included in the individual Adult and Child surveys, whereas indices 2 and 3 measured the extent of family participation in the agricultural process. Family Labor Index 1 is the preferred measure because it is less crude and takes advantage of as much of the data as possible, and it is used in the core regression analysis. Family Labor Indices 2 and 3 provide alternative measures and are used for sensitivity analysis.

Non-Family Labor

The MxFLS records the number of non-household members that worked on each parcel used in agricultural production. This forms the basis of the index of non-family labor. For each parcel, we weight this number of individuals by that parcel's share of the farm. These parcel level indicators are then aggregated across parcels for each household in each survey year to form a final measure.

A second measure of non-family labor is recorded in the household's expenditure on agricultural inputs, one of which is expenditure on laborers. These two measures are potentially very different, the former being unpaid non-family labor and the latter being paid labor. This might be especially true for ejido farms. Prior to including both measures we check for correlation between having both expenditures on laborers and non-family laborers helping out on a farm. For those farms with non-family labor, 92%, 54%, and 39% of farms with such workers recorded no expenditure on labor in 2002, 2005, and 2009, respectively. There is a negative correlation coefficient of -0.39 between having non-household members help with agricultural production and having paid for laborers, suggesting that these are distinct measures of labor and are not redundant. There appears to be no substantive difference between the use of these types of labor across ejido and non-ejido farms.

Appendix B.3

Additional Descriptive Statistics for Household Controls

Table B.3.1: Prevalence of Subsistence Farming, Monocropping, and Procampo Participation, by Farm Size and Survey Year

	Subsistence Farming			Monocropping			Participation in Procampo		
Farm Size	2002	2005	2009	2002	2005	2009	2002	2005	2009
0 to 0.5 ha	70%	53%	73%	76%	89%	75%	39%	38%	25%
0.5 to 1 ha	58%	50%	54%	82%	77%	68%	42%	40%	37%
1 to 2 ha	54%	36%	38%	73%	72%	83%	67%	47%	67%
2 to 5 ha	27%	37%	30%	71%	63%	62%	56%	51%	46%
5 to 10 ha	28%	21%	23%	58%	71%	69%	82%	74%	60%
10 to 20 ha	21%	8%	44%	72%	67%	67%	85%	79%	78%
> 20 ha	24%	25%	18%	72%	67%	82%	44%	42%	68%
Total	43%	36%	41%	71%	73%	71%	45%	42%	39%

Table B.3.2: Share of Farms Suffering Crop and Livestock Loss

	2002	2005	2009
Crop Loss	9%	7%	15%
Livestock Loss	5%	2%	3%

Table B.3.3: Share of Farms with Access to Credit, by Farm Size

	2002		2005		2009	
Farm Size	Credit	Formal	Credit	Formal	Credit	Formal
0 to 0.5 ha	31%	8%	24%	5%	95%	13%
0.5 to 1 ha	36%	7%	33%	12%	93%	7%
1 to 2 ha	27%	6%	39%	20%	90%	14%
2 to 5 ha	47%	22%	34%	19%	92%	23%
5 to 10 ha	47%	20%	26%	11%	91%	23%
10 to 20 ha	46%	21%	33%	21%	89%	15%
> 20 ha	40%	24%	29%	17%	95%	14%
Total	39%	14%	32%	14%	92%	16%

Table B.3.4: Savings and Credit of Panel Households, by Farm Size

	Has Savings			Used Credit		
Farm Size	2002	2005	2009	2002	2005	2009
0 to 0.5 ha	5%	6%	2%	21%	26%	22%
0.5 to 1 ha	4%	8%	5%	13%	22%	14%
1 to 2 ha	7%	7%	7%	17%	26%	26%
2 to 5 ha	3%	5%	12%	27%	23%	26%
5 to 10 ha	15%	9%	11%	39%	22%	23%
10 to 20 ha	18%	13%	22%	23%	21%	30%
> 20 ha	20%	13%	14%	40%	17%	18%
Total	8%	8%	9%	25%	23%	23%

Table B.3.5: Share of Farms with Indigenous and Literate Household Head, by Farm Size

	Indigenous Ethnicity			Literate		
Farm Size	2002	2005	2009	2002	2005	2009
0 to 0.5 ha	28%	29%	29%	75%	76%	76%
0.5 to 1 ha	38%	32%	28%	71%	77%	72%
1 to 2 ha	38%	39%	36%	77%	76%	78%
2 to 5 ha	27%	34%	26%	77%	78%	78%
5 to 10 ha	20%	12%	11%	90%	93%	83%
10 to 20 ha	13%	8%	19%	79%	92%	89%
> 20 ha	24%	13%	32%	80%	79%	91%
Total	28%	27%	25%	79%	81%	79%

Table B.3.6: Share of Last Level of Education Attended, by Farm Size, 2002

Farm Size	None	Elementary or Less	Secondary School	High School	College
0 to 0.5 ha	24%	60%	8%	7%	1%
0.5 to 1 ha	18%	71%	9%	0%	0%
1 to 2 ha	26%	60%	12%	1%	1%
2 to 5 ha	24%	63%	7%	1%	5%
5 to 10 ha	18%	67%	9%	5%	1%
10 to 20 ha	18%	64%	13%	2%	3%
> 20 ha	28%	52%	12%	4%	4%
Total	23%	62%	10%	3%	2%

Appendix B.4

Technology Coefficients Accompanying Tables 2.6 and 2.7

Table B.4.1: Community Fixed Effects with Household Controls

	(1) Linear w/o Inputs	(2) Linear	(3) Quadratic	(4) Cubic	(5) Dummies
Family Labor		-0.026	-0.040	-0.038	0.112**
		(0.044)	(0.047)	(0.047)	(0.051)
Physical Capital		-0.041	-0.044	-0.043	0.078
		(0.079)	(0.080)	(0.082)	(0.070)
Draft Animals		0.034	0.025	0.024	0.065
		(0.040)	(0.044)	(0.048)	(0.046)
Purchased Intermediates		0.071	0.072	0.070	0.194***
		(0.051)	(0.051)	(0.051)	(0.073)
Non-family Labor		0.010	0.016	0.011	0.121**
		(0.045)	(0.054)	(0.052)	(0.046)
Constant	8.004***	9.289***	10.000***	10.427***	6.309***
	(0.466)	(1.067)	(1.287)	(1.505)	(1.193)
Community FE	Yes	Yes	Yes	Yes	Yes
R^2	0.69	0.72	0.72	0.72	0.68
N	1235	1235	1235	1235	1235

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Appendix C.1

Detailed Derivation of Decompositions

Beginning with stochastic production frontiers estimated for both a base period (subscripted by 0) and a later period (subscripted by 1), the expected land productivity in each period is given by:

$$E(q_0) = \beta_0 + \delta_0 E(A_0) + \boldsymbol{\beta_0} E(\boldsymbol{x}_0) + E(\boldsymbol{\gamma}_c) + E(v_0) - E(u_0)$$

and

$$E(q_1) = \beta_0 + \theta_1 + \delta_1 E(A_1) + \boldsymbol{\beta_1} E(\boldsymbol{x}_1) + E(\boldsymbol{\gamma}_c) + E(v_1) - E(u_1)$$

where $E(v_t) = 0$ in each period by assumption if estimated using cross-sections, but may remain if estimated jointly with longitudinal data. The change in average land productivity between the two periods, $\Delta E(q)$, is given by $E(q_1) - E(q_0)$:

$$\Delta E(q) = \theta_1 + \delta_1 E(A_1) - \delta_0 E(A_0) + \boldsymbol{\beta_1} E(\boldsymbol{x}_1) - \boldsymbol{\beta_0} E(\boldsymbol{x}_0) - \Delta E(u) + \Delta E(v)$$

where $\Delta E(u) = E(u_1) - E(u_0)$ is the change in average technical efficiency between periods. Using period $t = 0$ as a reference period, this change in average land productivity can be decomposed as follows by adding and subtracting both $\delta_1 E(A_0)$ and $\boldsymbol{\beta_1} E(\boldsymbol{x_0})$:

$$\Delta E(q) = (\delta_1 - \delta_0) E(A_0) + \delta_1 [E(A_1) - E(A_0)] + \theta_1 + (\boldsymbol{\beta_1} - \boldsymbol{\beta_0}) E(\boldsymbol{x}_0) + \boldsymbol{\beta_1} [E(\boldsymbol{x}_1) - E(\boldsymbol{x}_0)] - \Delta E(u)$$

or

$$\Delta E(q) = \Delta\delta E(A_0) + \delta_1 \Delta E(A) + \theta_1 + \Delta\boldsymbol{\beta} E(\boldsymbol{x}_0) + \boldsymbol{\beta_1} \Delta E(\boldsymbol{x}) - \Delta E(u)$$

Note that, as with Oaxaca-Blinder decompositions, the results are sensitive to choice of reference group and a similar analysis could be conducted using $t = 1$ as a reference period.

Counterfactual productivity distributions are derived by iteratively replacing household attributes and estimated parameters from the later survey wave with values from the base year for each observation, uncovering the contribution of those changing factors to the changing land productivity distribution. This approach can be used to decompose the observed change in productivity distributions into its constituent parts. Let the land productivity distribution in the base period (2002) be given by $g(q_0)$ and its distribution in the later survey wave (2009) be given by $g(q_1)$:

$$\Delta g(q) = g(q_1) - g(q_0) = g(q_1) - \hat{g}(q_1|u_0) + \hat{g}(q_1|u_0) - g(q_0)$$

The first term on the right-hand side, $g(y_1) - \hat{g}(y_1|u_0)$, provides a counterfactual estimate of the marginal contribution of changing technical efficiency to changing land productivity, whereas the second term, $\hat{g}(y_1|u_0) - g(y_0)$, is the portion of the observed change in the distribution attributable to other factors. This can be further decomposed by allowing another determinant of $g(y_1)$ to reflect 2002 values:

$$\hat{g}(q_1|u_0) - g(q_0) = \hat{g}(q_1|u_0) - \hat{g}(q_1|\boldsymbol{\beta}_0, u_0) + \hat{g}(q_1|\boldsymbol{\beta}_0, u_0) - g(q_0)$$

where the first difference is a measure of the marginal contribution of technical change to the changing land productivity distribution, and the latter difference is now the portion of the observed change in the land productivity distribution attributable to factors other than changing technical inefficiency and technical change. Following this logic for each of the other sources of productivity gains – changing input intensities, farm size, and relationship between farm size and frontier productivity – we have:

$$\Delta g(q) = g(q_1) - g(q_0) = g(q_1) - \hat{g}(q_1|u_0) + \hat{g}(q_1|u_0) - \hat{g}(q_1|u_0, \boldsymbol{\beta}_0) + \cdots$$
$$\hat{g}(q_1|u_0, \boldsymbol{\beta}_0) - \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \boldsymbol{x}_0) + \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \boldsymbol{x}_0) - \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \boldsymbol{x}_0, A_0) + \cdots$$
$$\hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \boldsymbol{x}_0, A_0) - \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \boldsymbol{x}_0, A_0, \delta_0)$$

or

$$\Delta g(q) = \Delta g(q|u) + \Delta g(q|\boldsymbol{\beta}, \theta) + \Delta g(q|\boldsymbol{x}) + \Delta g(q|A) + \Delta g(q|\delta)$$

where

$$\Delta g(q|u) = g(q_1) - \hat{g}(q_1|u_0)$$
$$\Delta g(q|\boldsymbol{\beta}, \theta) = \hat{g}(q_1|u_0) - \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \theta)$$
$$\Delta g(q|\boldsymbol{x}) = \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \theta) - \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \theta, \boldsymbol{x}_0)$$
$$\Delta g(q|A) = \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \theta, \boldsymbol{x}_0) - \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \theta, \boldsymbol{x}_0, A_0)$$
$$\Delta g(q|\delta) = \hat{g}(q_1|u_0, \boldsymbol{\beta}_0, \theta, \boldsymbol{x}_0, A_0) - g(q_0)$$

Appendix C.2

Construction of Income Measure

The Mexican Family Life Survey (MxFLS) does not provide a total income measure for households, so an income measure is aggregated from the individual and household-level components of the survey. Income derived from agricultural versus non-agricultural activities are distinguished wherever possible to better understand the role of agriculture and agricultural policy in providing livelihoods and alleviating poverty in Mexico. The construction of a total household income measure in MxFLS is complicated by the facts that (a) the related income information is solicited in a disaggregated fashion, (b) this information comes from both the household-level survey and the individual-level surveys (separate for children and adults), and (c) there are considerable redundancies built into the survey, both within and between the household and individual survey components.

Construction of Household Income in MxFLS

Labor income is taken from the individual-level component of the survey, where income earned by individual household members is recorded in several different places of the survey and in several different ways. Individuals identifying as workers are asked different questions than those identifying as entrepreneurs, business-owners, or otherwise self-employed. A decision-making process is necessary to ensure that this component of income is comprehensive and complete while avoiding any double counting. See Technical Note 1 for details on the construction of wage labor income, and Technical Note 2 for details on the construction of self-employment labor income. In contrast, non-labor income, government transfers, profits from non-agricultural businesses, agricultural production, non-agricultural home production, and rents derived from household assets are taken from the household-level component of the survey.

Non-labor income includes the following forms of income, collected at the household level. All are included in the household income measure:

- Scholarship or donations to support schooling other than through Oportunidades,
- Severance Pay (and payments for labor risk and worker compensation),
- Remittances (money, aid, donations, or gifts to the household by any other relative or friend, living in Mexico or abroad),
- Pension and Retirement Funds,
- Life Insurance Payments,
- and Other non-labor income.

Government transfers includes payments received through participation in *Oportunidades* as well as with a host of other government programs. See Technical Note 3 for details. Profits from non-agricultural businesses are solicited in multiple forms, including "gross" profits, "net" profits, and "revenue." As most businesses include one but not all measures, a consistent measure of "net" profits was constructed. See Technical Note 4 for details. Agricultural production is valued according to chapter 2. The MxFLS provides neither crop prices nor estimates of the value of agricultural output, requiring an alternative means of valuing output. Output is currently grouped by crop type and valued using Mexican producer prices for these crop groupings from FAO. See Appendix B.1 for more detail. The non-agriculture rural income section of the MxFLS household survey records income derived from different home production activities, including the production of canned goods, clothes, craft production, furniture, medical plants, honey, and other. This income is included in total household income. See Technical Note 5 for more details on the prevalence of these activities.

The household component of MxFLS asks households the value of different asset holdings, whether or not rent was derived from those different assets, and the value of the rents received. Incomplete data on valuations of the rents received required imputation, as these rents should be included in household income if they were received. Further, the second and third waves of the survey recorded value of rents for a much more limited set of assets than in the first. For consistency, (a) calculations are restricted to rents generated from the family's home, other real estate, and financial assets, and (b) rents are imputed using asset and survey wave specific median rental rates for those households that record the value of those asset categories, claimed to have generated rents from those assets, but have missing values for the value of rents received. See Technical Note 6 for more details.

Technical Note 1: Construction of Wage Labor Income

Income earned by individual household members is recorded in three distinct places: first, the primary household respondent estimates the incomes earned by each household member; second, adult household members are directly asked a suite of detailed employment questions; and third, for those adults not directly interviewed a set of proxy questions is asked of a household representative. Income derived by the labor of children (those under the age of 15) is recorded separately. There is considerable overlap between the estimated incomes provided by the primary household respondent and the employment data collected through direct or proxy adult interviews. As such, I include the estimates of household members' incomes only in the case where there is no income data from direct or proxied interviews for those household members.

Respondents in the Adult Survey of MxFLS are asked to characterize their employment over the previous year, whether they are:

(i) a "[p]easant on your plot,"
(ii) a "[f]amily worker in a household owned business, without remuneration,"
(iii) a [n]on-agricultural worker or employee,"
(iv) a "[r]ural laborer, or land peon (agricultural worker),"
(v) a "[b]oss, employer or business proprietor,"
(vi) a "[s]elf-employed worker (with or without non-remunerated worker),"
(vii) or a "[w]orker without remuneration from a business or company that is not owned by the hhold."

Individuals who are non-agricultural or agricultural workers ((iii) or (iv) above) are then asked detailed wage information. Individuals who are peasants on their own plot (i), bosses, employers, or business proprietors (v), or self-employed (vi) are then typically asked a separate set of questions that are detailed in Technical Appendix 2.

Workers' incomes are separated into income derived from agricultural labor and from non-agricultural labor to facilitate the study of agriculture, rural livelihoods, and poverty in Mexico. This is done using industry classifications or whether the worker identifies as an "agricultural worker," information solicited separately for each individual's primary and secondary job. I categorize a job as agricultural if:

(i) The Mexican Classification of Occupations (MCO) was 41, “Agricultural, cattle activities, foresting, hunting and fishing wokers,” or
(ii) The North American Industrial Classification System (NAICS) was 11, “Agriculture, cattle ranch, forest advantage, fish and hunt” or
(iii) The individual identified as a “[r]ural laborer, or land peon (agricultural worker).”

Note that the NAICS classification is not generated in the final wave of MxFLS, so in that year I rely solely on the MCO classification.

Wage labor income earned in the Adult survey and Proxy survey asks for annual income, monthly income, a decomposed measure of annual income, and a decomposed measure of monthly income from each individual’s primary job along with the annual and monthly income for the secondary job. The decompositions break down wages into salary, piece-rate, profit-sharing, bonus, and benefits components, amongst others. Most individuals have multiple but not all measures, so decisions on treatment of the data have to be made. I derive two different measures of monthly income:

- Monthly Income Measure 1 = stated total monthly income from primary job
- Monthly Income Measure 2 = sum of monthly income decomposition from primary job

From this I derive four different measures of annual income from workers’ primary job:

- Annual Income Measure 1 = total annual income from primary job
- Annual Income Measure 2 = sum of annual income decomposition from primary job
- Annual Income Measure 3 = 12 * Monthly Income Measure 1
- Annual Income Measure 4 = 12 * Monthly Income Measure 2

As shown in tables C.2.1 through C.2.3 below, in each survey wave most respondents with Measure 1 also have Measure 3. Similarly, most respondents with Measure 2 also have data for calculating Measure 4. In short, respondents typically either state a total income or provide detailed decomposition of their income, but not both.

Table C.2.1: Share of Adults with Different Annual Income Measures, 2002

Has Measure (N)	Measure 1	Measure 2	Measure 3	Measure 4
Measure 1 (2,656)	--	<1%	93%	5%
Measure 2 (2,982)	<1%	--	16%	63%
Measure 3 (3,135)	79%	15%	--	<1%
Measure 4 (2,114)	6%	89%	1%	--

Table C.2.2: Share of Adults with Different Annual Income Measures, 2005

Has Measure (N)	Measure 1	Measure 2	Measure 3	Measure 4
Measure 1 (5,339)	--	0%	97%	3%
Measure 2 (924)	0%	--	38%	61%
Measure 3 (5,823)	90%	6%	--	0%
Measure 4 (753)	20%	75%	0%	--

Table C.2.3: Share of Adults with Different Annual Income Measures, 2009

Has Measure (N)	Measure 1	Measure 2	Measure 3	Measure 4
Measure 1 (6,180)	--	0%	96%	3%
Measure 2 (1,013)	0%	--	22%	77%
Measure 3 (6,569)	91%	3%	--	0%
Measure 4 (1,018)	19%	77%	0%	--

Where observations have multiple measures of wage income, they are consistent on average, but there are some wildly different income measures. It appears to matter which annual income measures is used. Without any priors on which measure is expected to be most accurate, I base my preferences over the four annual wage labor income measures first on which measures are most common and second which minimize assumptions. I assign annual income from the primary job, for both ag and non-ag work, as follows:

- Use the total annual income datapoint if available (Annual 1)
- Use the annualization of total monthly income if needed (Annual 3)
- Use the decomposed/detailed annual income measure if needed (Annual 2)
- Use the annualization of decomposed/detailed monthly income measure if none of the above are available (Annual 4)

To derive annual income from workers' potential secondary jobs, for both ag and non-ag work, I prefer the annual datapoint over the annualized monthly datapoint, but use the annualized monthly datapoint in the few cases where it exists but an annual datapoint does not. For each individual in each household I calculate their total annual agricultural income (annual ag income from primary job plus annual ag income from secondary job) and total annual non-agricultural income (annual non-ag income from primary job plus annual non-ag income from secondary job) in each period.

For those adults where detailed income data from the Adult or Proxy survey does not exist but income estimates are provided by the primary household respondent, that estimated income is used. Because the household respondent is not asked about the nature of other household members' work, that income cannot be binned into agricultural or non-agricultural. As such, there are three potential forms of wage labor income: agricultural, non-agricultural, and other (estimated).

Household members under the age of 15 are not asked detailed employment questions. Rather, they are simply asked how much they earned per week, month, or year over the previous year. These answers are annualized and summed over all children of each household, generating a measure of wage labor earned by children.

Technical Note 2: Construction of Self-Employment Labor Income

According to the survey questionnaire, Self-Employment Income is solicited from those who identify as peasants on their own plot, bosses, employers, or business proprietors, or self-employed, as discussed in Technical Note 1 above. As with wage labor income, the self-employment income of adults' primary and secondary income sources are binned as agricultural or non-agricultural based upon MCO and NAICS industrial classifications. In addition, any income derived from work as a "peasant on your own plot" is automatically binned as being derived from agriculture.

I am concerned that counting income of "peasants" here may double count with the value of production from the household-level agricultural analysis, as some agricultural production is brought to market for many farming households in MxFLS. So, I break self-employment labor income into three categories: farmer self-employment income, agricultural self-employment income, and non-agricultural self-employment income.

Self-employment income from the adult survey asks for gross and net values of profits from these activities from the previous month and from the previous year, and from these a consistent measure of self-employment income for each individual is derived. As with wage labor income, annual measures are prioritized over monthly measures of income. A consistent measure of net profits from self-employment activities is constructed by generating ratios of net to gross profits for those respondents that have both net and gross measures of profits from self-employment activities. I calculate these separately for reported annual income and reported income from the previous month. Theoretically these ratios should all be less than or equal to 1, although in practice they all are not. For all observations with ratios less than or equal to 1, the mean net/gross ratio for each year are shown in TablesC.2.4 and C.2.5.

Table C.2.4: Mean Net/Gross Profit Rates, Annual Income

Survey Round	Mean Net/Gross Profit Rate
2002	78.4%
2005	84.1%
2009	74.5%

Note: calculated using observations with Net/Gross Profit Rates less than or equal to one.

Table C.2.5: Mean Net/Gross Profit Rates, Monthly Income

Survey Round	Mean Net/Gross Profit Rate
2002	80.1%
2005	82.1%
2009	66.8%

Note: calculated using observations with Net/Gross Profit Rates less than or equal to one.

Those individuals with an annual measure of net income from these activities use that measure (Self-Employment Income Measure 1). For those with annual gross income but not net income, net income is estimated using the mean net/gross income ratio for the appropriate year, as shown in Table B4 (Self-Employment Income Measure 2). For those individuals with net monthly income, this measure is annualizee by multiplying by 12 (Self-Employment Income Measure 3). For those individuals with gross monthly income measures, this data is first adjusted to net monthly income using the mean net/gross income ratios of the appropriate year, as seen in Table A2-2, and then annualized (Self-Employment Income Measure 4).

This potentially generates four sets of income measurements from each self-employment activity from each adult. To construct a comparable and consistent measure of self-employment income I use annual net profits data over monthly data if available. I then prefer net data over estimated net data when possible. In short, I use Self-Employment Measure 1 where possible, Measure 2 if needed, followed by Measure 3 and then Measure 4.

Technical Note 3: Payments from Government Programs

Payments through Oportunidades are separated from payments through other government programs. These other government programs include:

- PROCAMPO
- VIVAH Program (Savings and Subsidies Program for Progressive Homes)
- Word (oral) Credit Program
- Social Conversion Program
- PET (Temporary Job Program)
- Alianza Para El Campo (Agricultural Aid)
- Funds for Micro, Small, and Medium Enterprises
- FONAES (National Support Fund for the Solidarity Enterprises)
- Other. While I do not have data on what "Other" programs include, but I do have values of any income received from them.

Note that in 2009 there is no Micro or Word, and VIVAH turned into TU CASA Y VIVIENDA RURAL. The following government programs were added:

- 70 Y Mas (70 and Older)
- Apoyo Alimentario (Food Support)
- and Opciones Productivas (Productive Options)

As shown in Table C.2.6, participation in Oportunidades is most common, followed by Procampo, a program meant to support farmers and help them to remain competitive in the wake of NAFTA-era reforms.

Table C.2.6: Participation in Government Programs

	2002		2005		2009	
Program	N	% of Sample	N	% of Sample	N	% of Sample
Oportunidades	1,177	14.0%	1,496	17.7%	1,662	16.4%
Procampo	692	8.2%	491	5.8%	532	5.3%
Vivah	14	0.2%	2	<0.1%	12	0.1%
Word	57	0.7%	6	0.1%	--	--
Social Conversion	0	0.0%	1	<0.1%	0	0.0%
PET	15	0.2%	1	<0.1%	7	0.1%
Alianza Para El Campo	26	0.3%	15	0.2%	14	0.1%
Funds for Enterprises	6	0.1%	7	0.1%	--	--
FONAES	0	0.0%	7	0.1%	3	<0.1%
70 y Mas	--	--	--	--	584	5.8%
Apoyo Alimentario	--	--	--	--	134	1.3%
Opciones Productivas	--	--	--	--	8	0.1%
Other	99	1.2%	115	1.4%	223	2.2%

Technical Note 4: Profits from Non-Agricultural Businesses

The MxFLS has data on non-agricultural businesses owned by households, including 4 measures of annual “income” from each business: revenue, gross profit, net profit, and loss. No businesses in any period has both of the profit measures, and some contain none, and not all businesses record revenues/losses. In each period, for example, less than 10% of businesses with a measure of profits does not have revenues. In each period, 12-20% of businesses with revenues don’t have any measure of profits. Construction of a consistent and comparable income measure from these non-agricultural businesses is needed, and as with self-employment income the notion of net profits is used, in part for consistency, because it is most commonly recorded, and because it is likely the correct conceptual measure for the contribution of the business to household income. Note that in any period, 21-32% of non-agricultural businesses don't have any revenue or any profit data, so no income from these businesses is included.

Mean net profit rates and net profit/gross profit ratios are used to impute net profits for those businesses that do not provide that data. Ideally these rates would vary by type of business, but this data is not currently available. Table C.2.7 shows average gross and net profit rates (as a percentage of total revenues) in each survey year for those businesses recording both profits and revenues. The table includes profit/revenue rates for each measure of profit in each year that are less than or equal to 100% of the listed revenues because some observations show profits higher than revenues - there must be some measurement error in either revenue and/or profits).

Table C.2.7: Mean (Median) Profit/Revenue Rates, by Survey Year

Year	Gross Profit Rate	Net Profit Rate
2002	85% (100%)	71% (84%)
2005	80% (100%)	64% (63%)
2009	13% (10%)	11% (10%)

Net profits for each are calculated as follows:

- If a business records net profits it is kept.
- If a business has revenues but no measure of profits, the survey year-specific mean net profit rate is used to impute net profits.
- If a business has gross profits but no revenue recorded and no net profit, I impute net profits using the appropriate mean net profit/gross profit ratio for that survey wave.

The mean net profit rates and net profit/gross profit ratios used are shown in Table C.2.8. A small number of businesses record losses from the previous year. While I do not include business losses in the primary measure of income, an alternative measure that accounts for these business losses is generated.

Table C.2.8: Mean Net Profit Rates and Net/Gross Profit Ratios Used for Imputation

Year	Net Profit Rate	Net/Gross Ratio
2002	0.710	0.832
2005	0.641	0.799
2009	0.110	0.863

Technical Note 5: Rural Non-Agricultural Income

The rural non-agricultural income component of MxFLS is conducted at the household-level, soliciting data on income derived from a number of home production activities. Those production activities that have been counted as livestock production (sale of eggs, meat products, dairy products, and fattened animals) and excluded to avoid double-counting, and the rest are aggregated. Table C.2.9 lists the N's and share of households claiming they sold such products that have valuations of sales from the previous year, for each survey year. Note that, for those households that claimed they have sold such products but have no data on the values of annual production, some have values for sales from the previous month. In such cases the monthly data has been annualized.

Table C.2.9: Number of Households with Rural Non-Ag Production and Share with Sales

	2002		2005		2009	
	N	Share with Value	N	Share with Value	N	Share with Value
Canned Goods	4	100%	8	100%	11	100%
Clothes	81	93%	78	94%	88	98%
Craft Production	110	86%	135	96%	104	99%
Furniture	17	88%	20	90%	8	100%
Medical Plants	8	88%	19	95%	13	100%
Honey	13	85%	10	100%	6	100%
Other	167	90%	144	90%	210	90%

Technical Note 6: Rents Earned from Household Assets

The household component of MxFLS asks about the ownership of different asset categories, the valuation of those assets, whether or not those assets were rented out for income, and the value of the rents received over the previous year. There is a considerable amount of missing data for these valuations. Table C.2.10 shows the number of households claiming to have assets and to have rented them (in parentheses), and the share of those households that actually have valuations. For those households that claim to have rented assets for income but do not have data on the value of incomes received, those valuations need to be imputed. Note that in 2005 and 2009, the latter two survey waves of MxFLS, rental of assets is asked for a much smaller set of asset categories. While all asset categories are shown here, for consistency the only rents included in household income in any year are those derived from renting the “Home,” “Real Estate,” and “Financial” assets.

Table C.2.10: Number of Households with Assets and Rents, the Share with Valuations, and the Share of Rentals with Valuations, by Survey Year and Asset

	2002			2005			2009		
	Value	Rent	N	Value	Rent	N	Value	Rent	N
Home	82.9%	90.0%	6197 (30)	81.7%	73.3%	6409 (30)	73.3%	79.2%	7088 (24)
Real Estate	84.2%	91.2%	1982 (159)	81.7%	85.3%	1463 (102)	74.7%	82.3%	1804 (62)
Financial	72.9%	47.6%	1330 (208)	65.2%	35.2%	1117 (142)	56.5%	23.9%	1136 (46)

Average rental rates for each asset category recorded in MxFLS are generated for each survey year using observations that have both valuations of asset holdings and values of rents received from their being rented out. These average values, both mean and median, are shown in Table C.2.11 below. As there appear to be significant outliers skewing the mean, I use median rental rates in each year to impute the rents received from "Home," "Real Estate," and "Financial" assets owned for those households that have valuations of these assets, claimed to have rented them, but provided no values for the rents received. This brings up the broader question of whether or not we should be imputing the flow of services from all of these household assets. The rental rates from 2002 could potentially be used to do this, but are not at this point. Note that, to the degree that some of these assets are already counted (for example the services generated by assets used in agricultural production are already counted) we would have to be careful about double-counting.

Table C.2.11: Mean and Median Rental Rates, by Survey Year and Asset

	2002			2005			2009		
	Mean	Med	N	Mean	Med	N	Mean	Med	N
Home	3.9%	3.6%	24	6.0%	0.9%	14	15.8%	4.0%	17
Real Estate	777.0%	6.0%	137	192.1%	4.0%	67	549.7%	3.8%	41
Financial	6,387.5%	2.93%	98	21.4%	4.2%	50	3.7%	1.0%	9

Appendix C.3

Results from Stochastic Frontier Analysis

Table C.3.1: Stochastic Production Frontier Results

Frontier Equation	
Farm Size	-0.650***
	(0.063)
2009 Dummy	0.237
	(0.271)
2009*Farm Size	-0.016
	(0.083)
Family Labor	0.134***
	(0.046)
Physical Capital	-0.047
	(0.066)
Draft Animals	0.086
	(0.054)
Purchased Intermediates	0.073
	(0.057)
Non-family Labor	0.016
	(0.084)
2009*Family Labor	0.028
	(0.030)
2009*Physical Capital	-0.009
	(0.034)
2009*Draft Animals	-0.010
	(0.039)
2009*Purchased Intermediates	0.016
	(0.023)
2009*Non-family Labor	-0.102
	(0.104)
Inefficiency Equation	
Farm Size	-0.040
	(0.126)
2009 Dummy	0.650
	(0.477)
2009*Farm Size	0.140
	(0.149)
Procampo Participation	-0.958***
	(0.325)
Access to Formal Credit	-0.381
	(0.412)

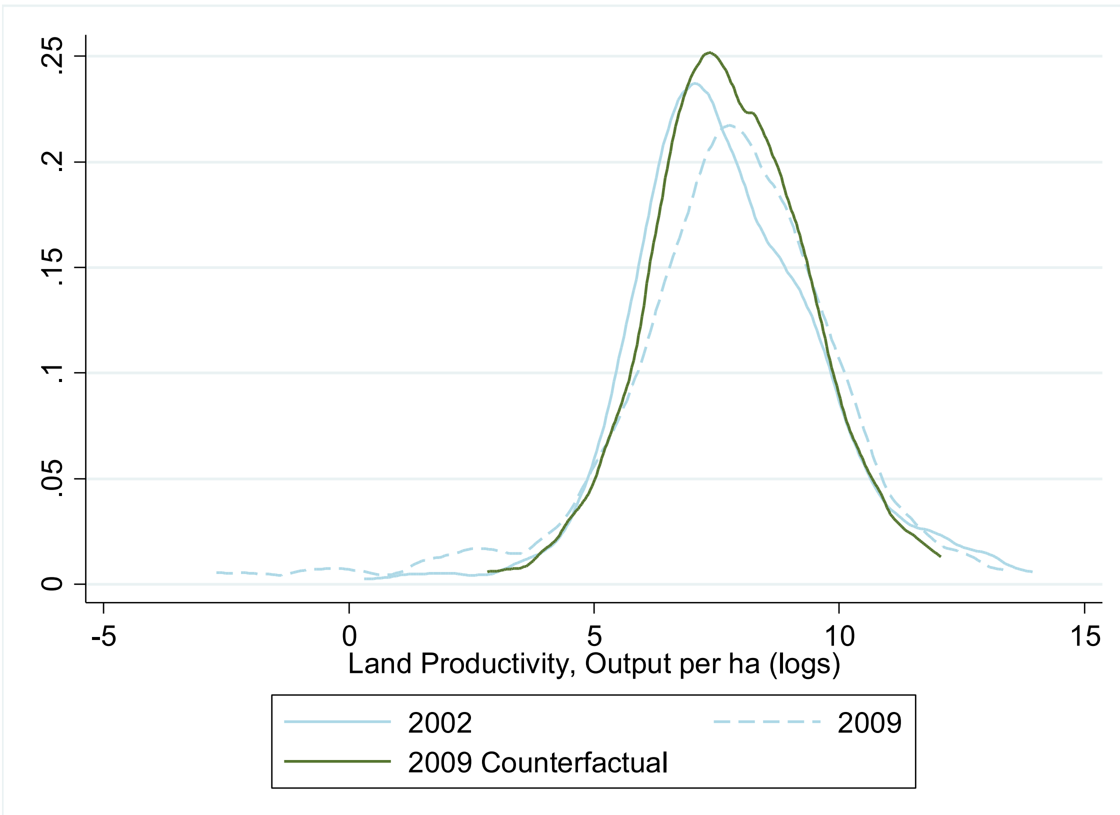
High School	0.338
	(0.686)
College	-6.799
	(0.073)
$E(\sigma_u^2)$	0.945
σ_u^2	0.621
λ	1.522
N	448

Standard errors in parentheses
** p<0.10, ** p<0.05, *** p<0.01*

Appendix C.4

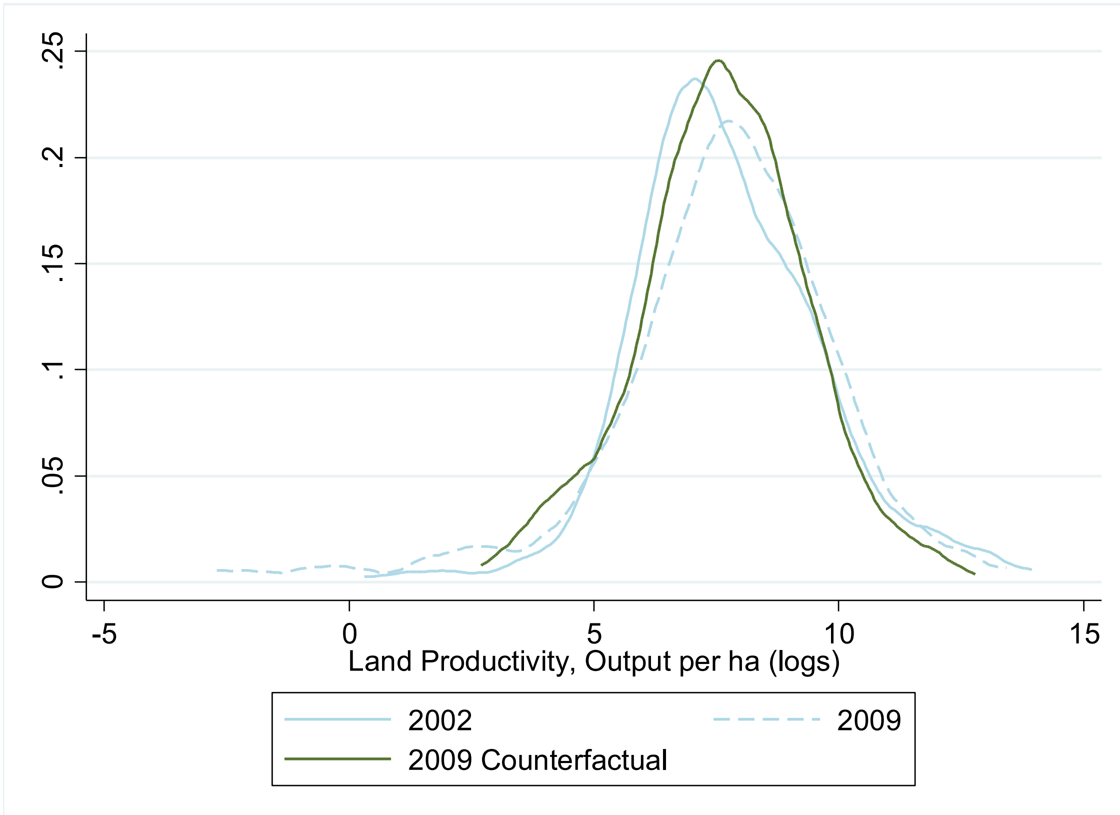
Counterfactual Land Productivity Distributions

Figure C.4.1: Counterfactual Distribution, Changing Technical Inefficiency



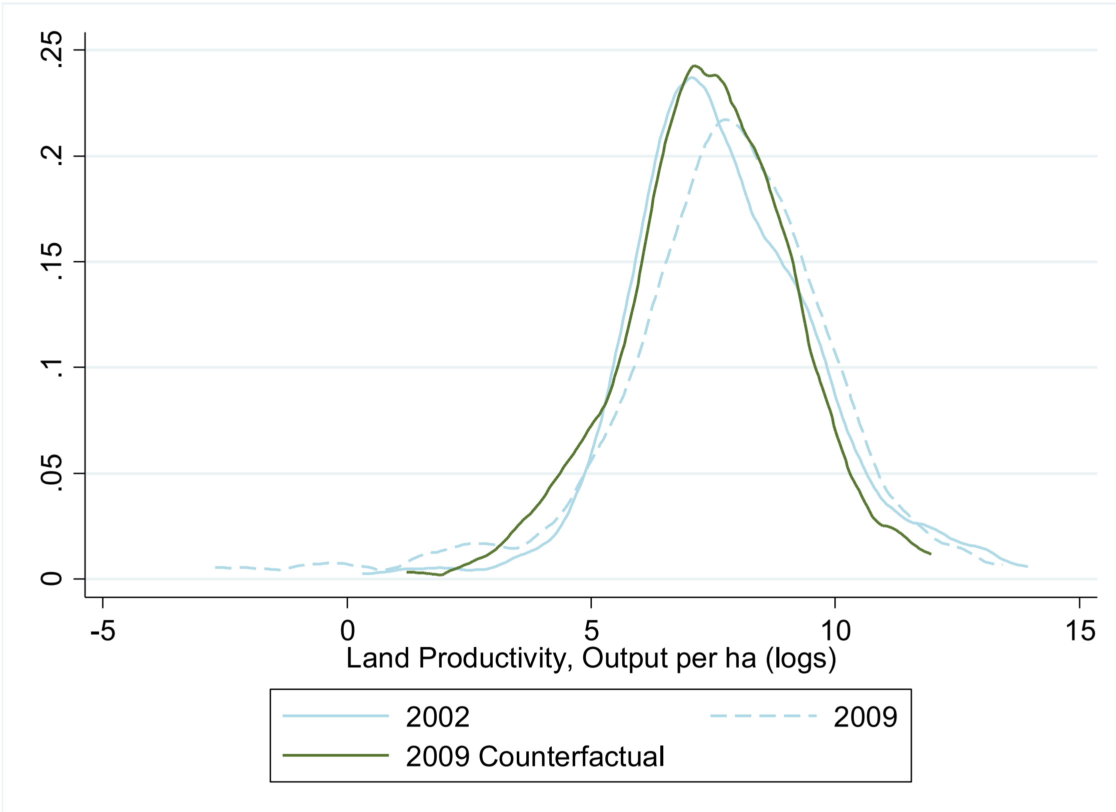
Note: Estimated with the default kernel density command in Stata, using an Epanechnikov kernel

Figure C.4.2: Counterfactual Distribution, Changing Input Intensities



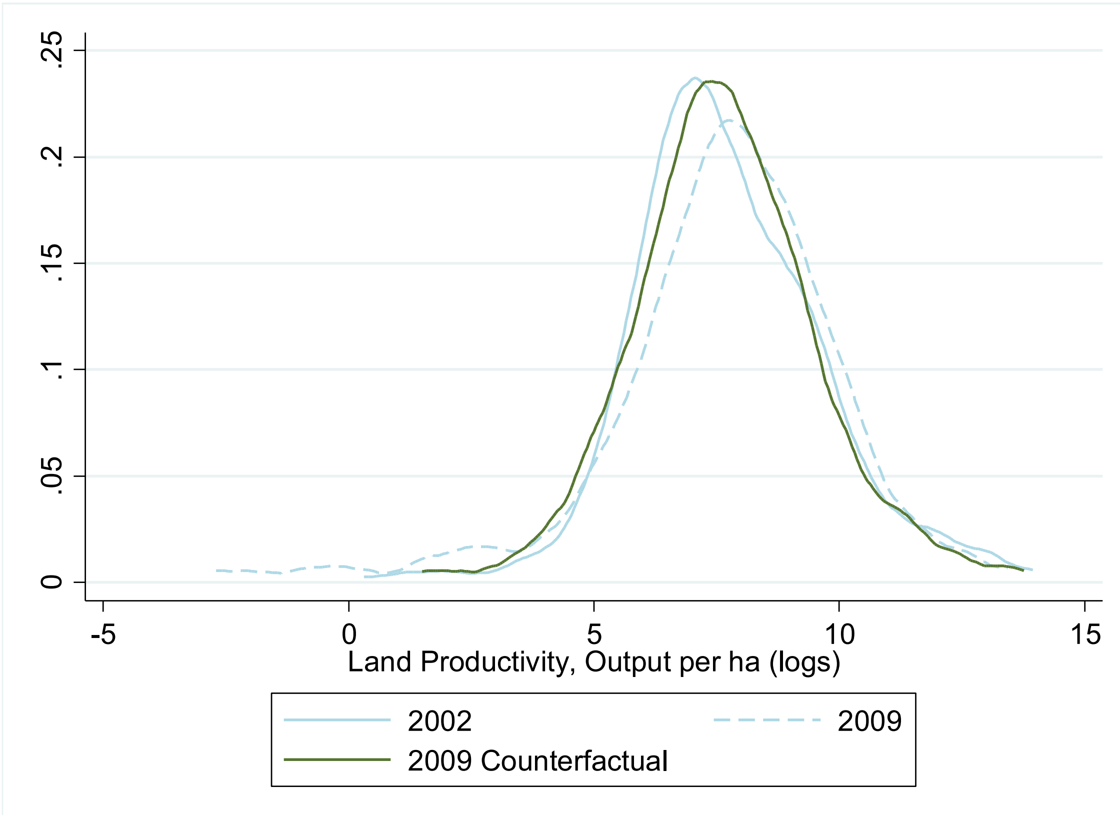
Note: Estimated with the default kernel density command in Stata, using an Epanechnikov kernel

Figure C.4.3: Counterfactual Distribution, Changing Technology



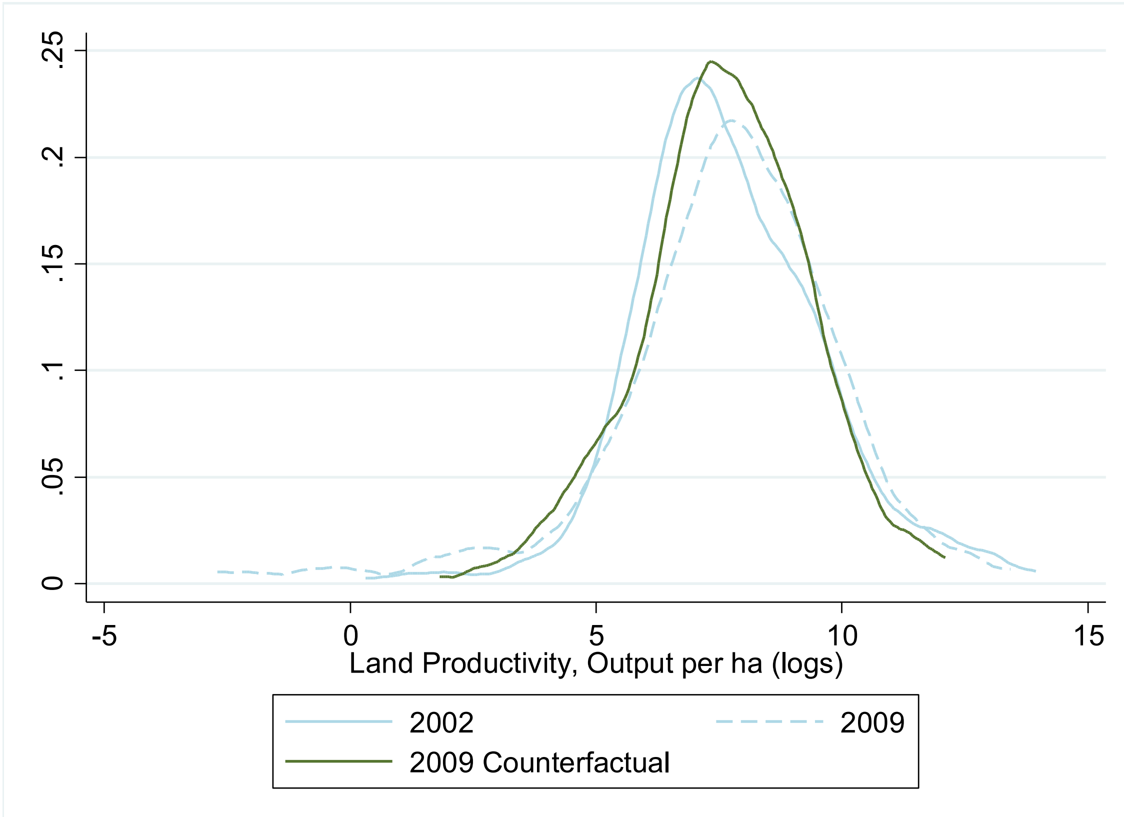
Note: Estimated with the default kernel density command in Stata, using an Epanechnikov kernel

Figure C.4.4: Counterfactual Distribution, Changing Farm Size



Note: Estimated with the default kernel density command in Stata, using an Epanechnikov kernel

Figure C.4.5: Counterfactual Distribution, Changing Farm Size – Frontier Relationship



Note: Estimated with the default kernel density command in Stata, using an Epanechnikov kernel