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The Sahel's Silent Maize Revolution
Analyzing Maize Productivity in Mali at the Farm Level

Jeremy Foltz, Ursula Aldana, and Paul Laris

N'i ti kaba séné, e ti balo
If you are not growing maize, you cannot feed your family.
—Malian Farmer (2010)

3.1 Introduction

According to aggregate data, since 1961 total maize production in Mali has increased more than tenfold, bringing maize from being a minor crop to one on par with traditional Sahelian crops of millet and sorghum (see figure 3.1). This tenfold increase in production has come about through both a major increase in acreage and impressive improvements in yields. Maize yields in Mali have doubled in this period while those in Burkina Faso have tripled; in contrast, yields in Senegal, Mauritania, and Niger have barely increased. The maize revolution in the Sahel has gone relatively unnoticed in research circles. Recent work on productivity growth of agriculture in Africa has indeed identified significant increases in productivity in the last decade after some decades of stagnation (Block 1994, 2010) and increases in maize production have led the way in many parts of Africa (Smale, Byerlee, and Jayne 2011). But commentators such as Smale, Byerlee, and Jayne (2011) point out a number of disappointing results in maize production across the continent and suggest a key role of fertilizer in determining yield increases and the potential for maize to jump-start a green revolution.

While the current yields in Mali of around two tons per hectare are still

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low by world standards, the rate of yield increase over the last forty-five years (~2 percent) is equal or better than that of maize production in Iowa, Wisconsin, and India. The maize yield increases in the Midwest of the United States have been the work of hundreds of scientists and garnered many laurels, and yet similar yield increases in the Sahel have gone mostly unnoticed and unexplained. In addition, these great increases in yields go in the opposite direction of most of the rest of sub-Saharan Africa where maize yields have stagnated since the mid-1970s.

Such a success suggests Mali has succeeded in at least partially solving exactly the issues that most bedevil agricultural development projects in the Sahel and most of Africa: farmers bought inputs such as fertilizer, farmers changed their agronomic techniques, farmers paid for new seeds, farmers found markets for their production, and farmers responded to price signals. The large increases in yields in Mali would also not have been possible without research, extension, and marketing. It is evidence of successful extension work that brought to farmers information that induced them to add more fertilizer, invest in new plowing techniques (i.e., animal traction), purchase improved quality seeds, and change their eating habits.

What has pushed the great expansion of maize production in Mali? How much is due to expanded use of inputs such as fertilizer versus technical

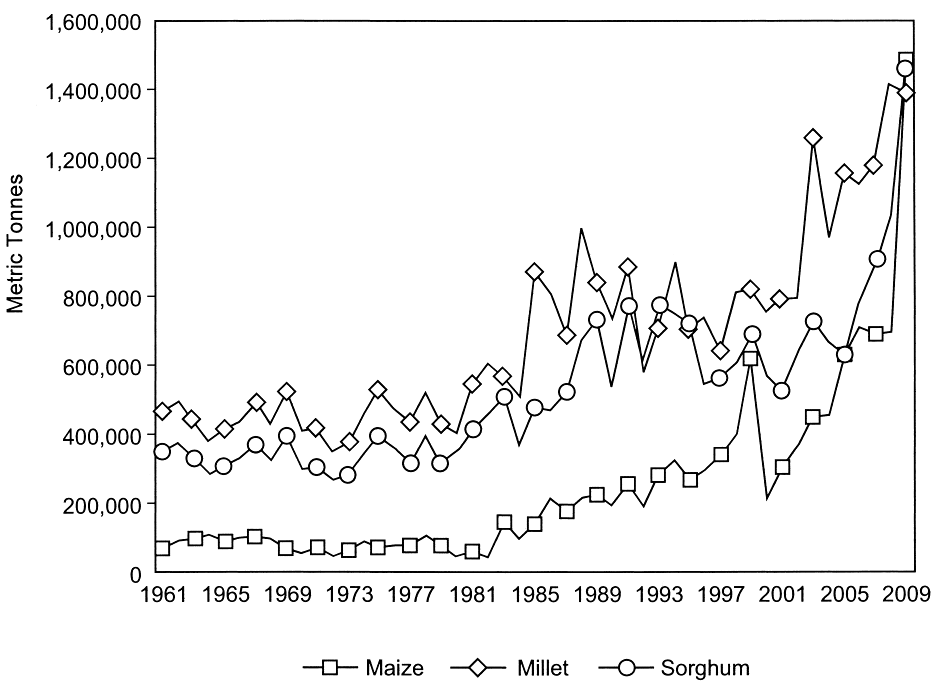

Fig. 3.1 The growth of maize production 1961–2009

changes in seeds and management? What are the key elements of this technical change? This work analyzes these questions by documenting and analyzing the growth of maize production in southern Mali using a novel panel data set that spans the last twenty years. In order to disentangle the different factors behind the increase in maize production, we focus our efforts on generating a consistent and nonbiased estimate of the impact of fertilizer use on yields.

Generally the economics literature shows estimates of high returns to fertilizer in Africa, but that farmers do not adopt fertilizer or they use too little of it (Crawford, Jayne, and Kelly 2006). Standard estimates of the average fertilizer use in Africa is one-tenth of the levels used in the rest of the world. The literature has explained this puzzle through the presence of high levels of heterogeneity in the returns to fertilizer use.

Duflo, Kremer, and Robinson (2008) use a randomized controlled trial (RCT) to find high but heterogeneous returns to fertilizer in maize production in Kenya. They find that the optimal fertilizer use is less than recommended levels, and that the heterogeneity in returns seems related to length of use (i.e., knowledge in how to use fertilizer). Duflo, Kremer, and Robinson (2011) find that helping farmers save for fertilizer can nudge them into using more on their maize. Marenya and Barrett (2009) show that returns to fertilizer in Kenya are a function of soil qualities, in particular the amount of organic matter in the soil. Xu et al. (2009) find substantial variability in the yield response of fertilizer based on a number of observable agronomic (timelines of application) and household factors (access to complementary production factors). In the scientific literature Sileshi et al. (2010) find similar variability in maize yields across the African continent.

In the work closest in spirit to our work, Suri (2011) also finds high but heterogeneous returns to fertilizer and hybrid corn in Kenya. Suri's methodology accounts for unobserved heterogeneity in choice of fertilizer and hybrid econometrically through a control function approach where farmer choice of fertilizer/hybrid is a function of future and past period's fertilizer/hybrid use. While robust to some heterogeneity, the Suri methodology does not allow for unobserved heterogeneity to change through time, nor does it adequately address potential dynamics in soil fertility. Suri concludes that farmers do not use fertilizer where it is not available or expensive, even though returns are high. Overall these studies identify a large amount of heterogeneity in returns to fertilizer and that the sources of heterogeneity are both observable (price of and experience with fertilizer) and unobservable to most econometric efforts (soil organic matter, knowledge).

The presence of heterogeneity in the impact of fertilizer use poses a problem for the estimation of this impact. While Suri's method allows for control of unobserved heterogeneity, her assumption that heterogeneity does not change through time is not applicable to our data set and context. During the years covered by our data set, new seeds where continuously appearing in the market, changing the impact of fertilizer use. Since we do not observe the seeds used by the farmers, this technological innovation could generate a time-varying unobserved heterogeneity.

The current work estimates the impact of fertilizer use and explores the heterogeneity in these returns for the Sikasso region in Mali. It focuses on analyzing technological change as both a disembodied technological change and one due to observed as well as unobserved heterogeneity in the returns to fertilizer use. With regard to observed heterogeneity, we test whether the impact of fertilizer use on yields varies with literacy levels and with the use of organic fertilizer. In order to address unobserved heterogeneity, we apply a control function method first presented by Garen (1984). He developed the method to test for unobserved heterogeneity and control for the bias that it brings. Such a control-function method allows us to control also for the endogeneity that might exist even in the absence of unobserved heterogeneity in the impact of fertilizer use. This last type of endogeneity is the more classic one and it is related to the potential bias that could come from the correlation between unobserved determinants of yields and fertilizer use. All of these efforts allow us to consistently estimate the impact of fertilizer use and, consequently, to analyze the importance of increases in fertilizer use versus generalized technological change in the yield increases in Mali.

The work proceeds as follows: Section 3.2 describes the data and farmer interviews that form the basis for the analysis presented in this work and provides a descriptive analysis of the success in maize production in Mali. Section 3.3 develops a theoretical and econometric model to estimate the determinants of maize yields with a focus on farmer heterogeneity and the returns to fertilizer. Specifically, it develops a model of fertilizer choice based on farm profit functions with heterogeneity in farm returns and builds an econometric technique based on control functions to account for farmer heterogeneity in fertilizer responsiveness. Section 3.4 estimates and provides results for fertilizer-demand functions and then maize-yield functions that account for farmer heterogeneity. Section 3.5 concludes and points to open questions for future research.

3.2 Description of the Data

We use a twelve-year-panel data set (1994–2006) for over 100 farm households from nine villages located in Mali's southern maize belt. The Malian agricultural research organization Institut d'Economie Rurale (IER) started collecting these data in 1988 from 149 farmers spread across twelve villages in three different communes in the Sikasso region. The data set starts with 149 farmers in 1988 and ends with 84 in 2008 due to sample attrition. The IER researchers chose the villages to represent different agroecological zones within the Sikasso region and the farmers to represent different types of farms stratified by farm assets.[1]

The IER researchers collected the data primarily for agronomic studies and they most closely resemble the kind of data one might get from farm trials, except that they come from individual farmers. With their level of agronomic detail and long time series, these microlevel panel data can answer questions that aggregate and cross-sectional data are unable to tackle. They have details such as daily rainfall data that can solve a number of the econometric problems that cause difficulties for many productivity studies. The data set contains disaggregated fertilizer and chemical input data by input type and by crop.

3.2.1 Sikasso Region Context

The Sikasso region is the best-watered region of Mali (800–1,200 mm of rainfall) and the zone best adapted to maize and cotton cultivation. Yet the Sikasso region is reputed to be the location of the greatest poverty in the country (Delarue et al. 2008).[2] The data comes from three of the primary ecological zones within the region (see figure 3.2). Koutiala is where the farmers are the most sophisticated and have a long tradition of growing cotton. Kadiolo subregion is the traditional maize growing area, but with less progressive farmers. Bougouni started the 1990s as the least developed of these regions with farmers least touched by extension services among the subregions, but has developed in the last twenty years into a major maize and cotton growing area through a combination of extensification along with improved techniques (intensification).

In terms of the agronomy of maize production in Mali, there are significant dynamics between years since soil quality can change from one year to the next. That change in soil quality can be a function of the previous year's crop, especially because maize is typically grown in rotation on a field that had cotton the previous year. In addition, maize varieties in Mali have proliferated from one or two to eight to ten in the decade of the data set and seed varieties are unobserved in this data set. The main differences between varieties are related to their suitability to soils and weed conditions, not maximum yield potential. Thus we expect there to be significant unobserved heterogeneity in the impact of fertilizer use in this data set.

Figure 3.3 shows the increases in maize productivity in the sample and across the three surveyed regions. Overall it shows a 17 percent increase in maize yields, but that hides a near flat change in yields in Bougouni to a nearly 35 percent increase in yields in Kadiolo. The figure is suggestive

1. Most of the analysis is conducted using data from 1994–2006 because of problems matching the data from 1988–1993 with later years.

2. Many scholars knowledgeable in the economics of Mali dispute this finding in private conversations, but no refutation of the data has yet appeared in the literature.

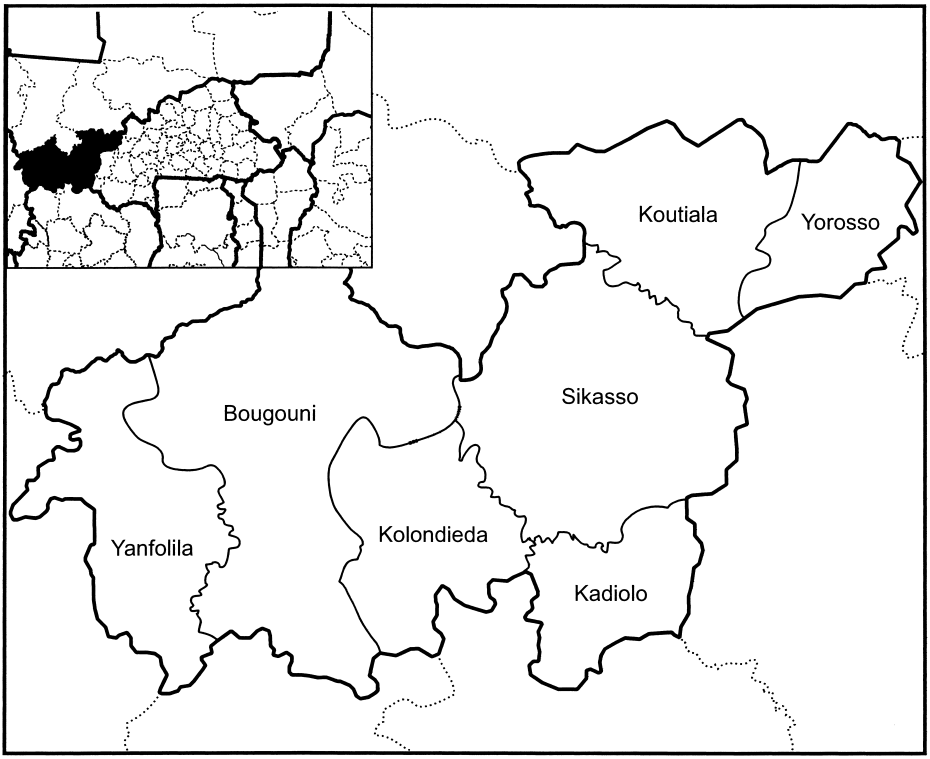

Fig. 3.2 Map of the Sikasso region and research sites in the Bougouni, Kadiolo, and Koutiala districts

of reasonably high levels of technological change that could be either in the form of better seeds, management, or more use of inputs, in particular fertilizer.

Figure 3.4 shows the relationship between fertilizer use, its price, and the price of maize. What is obvious is the great increase in fertilizer use (left axis) of about 25 percent at the same time that its price increased 175 percent (right axis) and maize prices increased only marginally in the same period. This suggests that there has been a secular increase in fertilizer use that is more akin to the adoption of a new technology rather than to marginal calculations of the price/cost margins that would drive the use of a well-known variable input.

This pattern of adoption of fertilizer in maize production is well demonstrated by the regional fertilizer data in figure 3.5. There one sees that Koutiala, the region with the most progressive and informed farmers, has fairly consistent fertilizer use across time and in a pattern reminiscent of a variable input that obeys price signals. Meanwhile, both Bougouni and

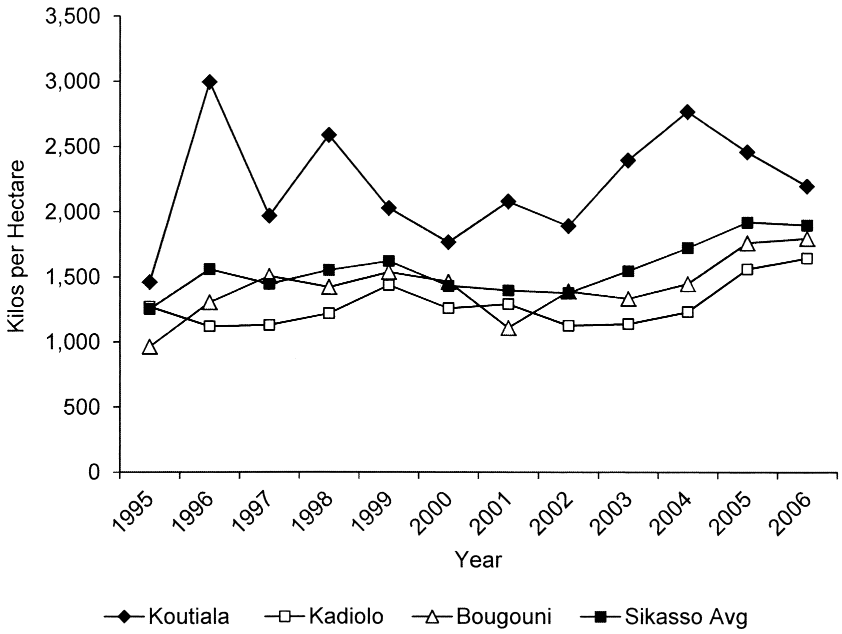

Fig. 3.3 Maize yields by Sikasso region zone

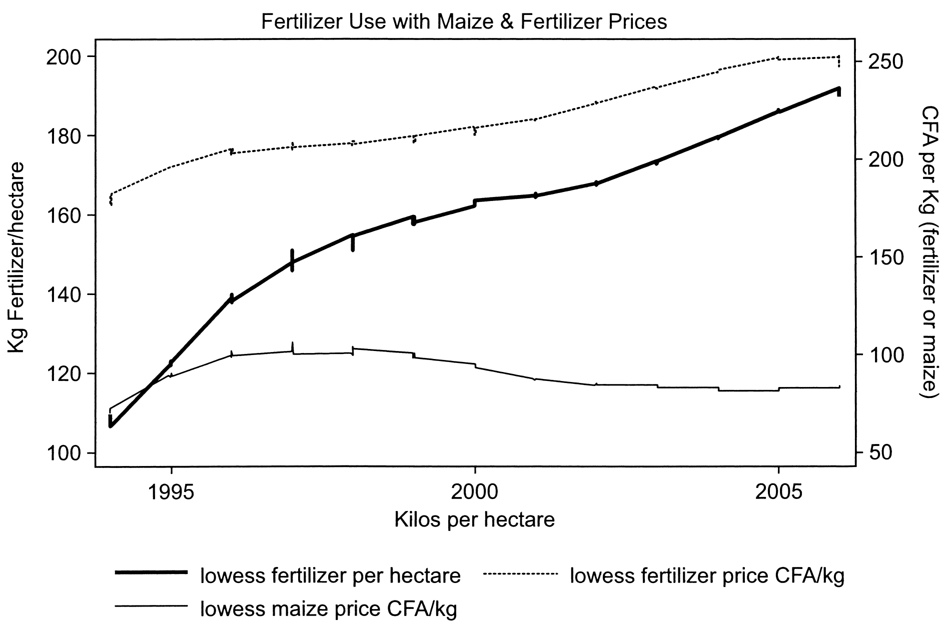

Fig. 3.4 Fertilizer use with maize and fertilizer prices, Lowess curves

Kadiolo exhibit a pattern of fertilizer use increase that mimics the S-curves of standard technology adoption models.

Fok et al. (2000) argue that maize is a risky crop and that the farmers' widespread adoption of maize could be related to a change in their risk aversion. They argue that maize is risky due to the use of expensive inputs such as fertilizers and herbicides. Nevertheless, as explained in Laris and Foltz (2014), maize also reduces risk because it matures quickly, providing a good harvest in years with a short rainfall season. In addition, as shown in figure 3.6, the distribution of yield outcomes of maize production has changed over the last twenty years, reducing the risk farmers face in growing maize. Figure 3.6 shows the distribution of yields in the Sikasso farm data over different time periods. The distributions show a distinct pattern of technological change with the distribution on average moving up in a steady fashion over the twelve years of the data. The mean of the distribution increases and one sees for almost all quantiles of the distribution that yields increase close to 500 kg per hectare, which is suggestive of broad-based participation in the benefits of maize yield increases. In addition, the downside risk of maize production in terms of yields is greatly reduced, with many fewer farmers below 500 kg/ha.

Laris and Foltz (2014) argue that an important factor behind the increase in fertilizer use is the provision of credit for fertilizer. As the authors point out, in the area that corresponds to the data we use, the credit for fertilizer is obtained through the parastatal CMDT (Compagnie Malienne pour le Developpment des Textiles). This company provides fertilizer at the beginning of the season in exchange for the cotton that this company will receive at the time of the harvest. In some cases, the farmers use, in their maize plots, some of the fertilizer they claim that will be used for growing cotton.

Laris and Foltz (2014) provide evidence of this link between cotton and the access to fertilizer for maize. Their interview and quantitative evidence shows, for example, that farmers who grow cotton get higher yields in their other field crops. The estimations that we present below support the idea presented in Laris and Foltz, as they show that the percentage of land under cotton is positively associated with the amount of fertilizer used for growing maize, which contrasts somewhat with Benjaminsen, Aune, and Sidibé's (2010) finding of declining soil fertility in cotton growing areas.

Taken together, the graphical data in figures 3.3, 3.4, 3.5, and 3.6 show increases in maize yield at the same time that there are major increases in fertilizer use. Below we test whether the increase in maize yield is solely attributable to the increased use of fertilizer or whether there is an element of disembodied technological change such as improvements in seeds and or management.

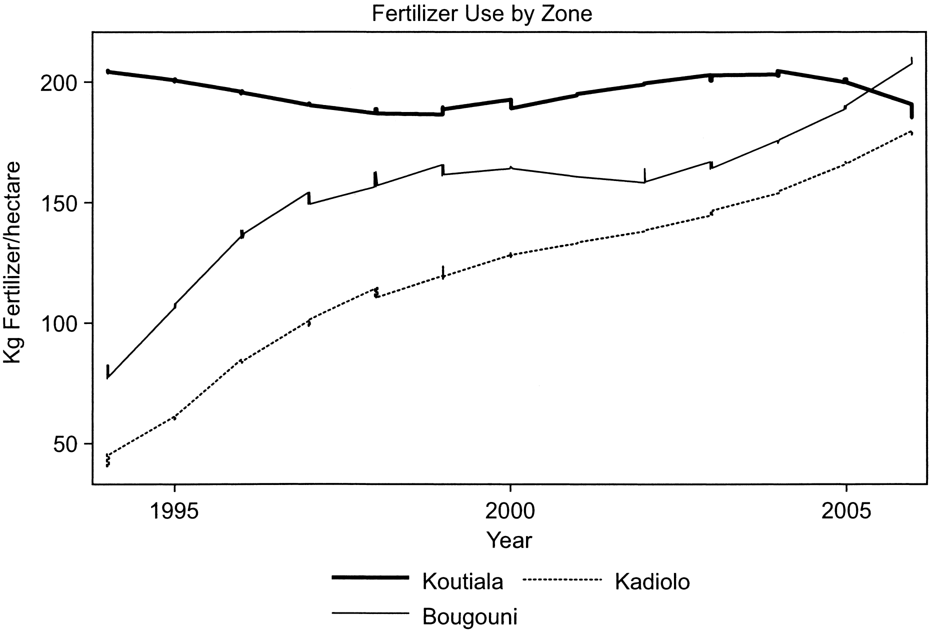

Fig. 3.5 Fertilizer use by Sikasso region zone, Lowess curves

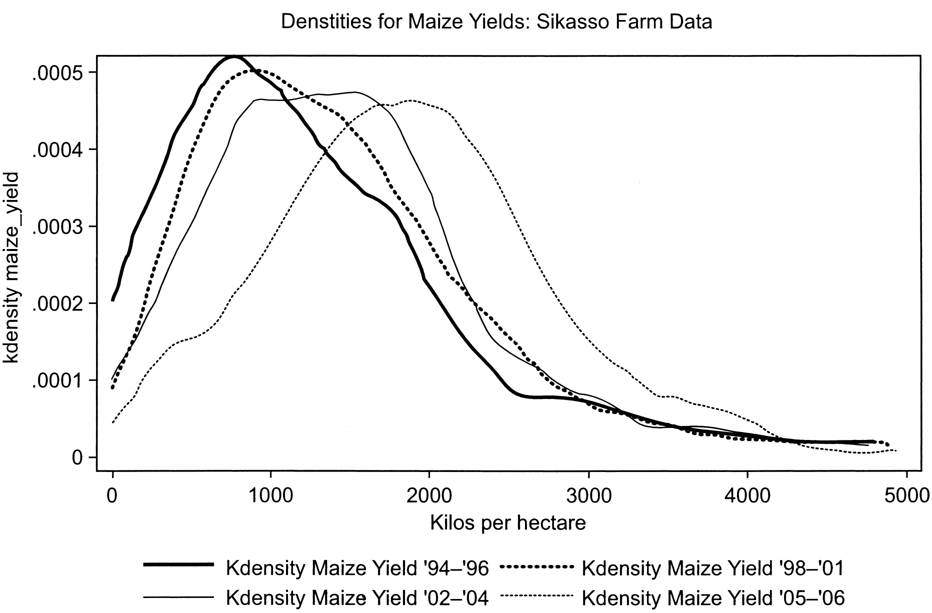

Fig. 3.6 Maize yield distributions over time, Sikasso farm data

3.3 Conceptual Framework

The conceptual framework for analyzing the determinants of maize yields starts with a farmer maximizing profits on his farm: $\Pi = \pi T$ where T represents total land area and π is per hectare profits. Assuming that land is fixed or that the production function exhibits constant returns to scale the farmer can maximize per hectare profits, which setting the price of output to 1, can be described as:

$$\pi = g(\alpha, f, x, r) - p_f f - p_x x, \tag{1}$$

where $g(.)$ reflects the yield function, α represents the level of technology, f reflects the amount of fertilizer per hectare, x reflects other variables that affect yields, r reflects those unobserved variables, such as soil quality that affect yields, and the relative input prices are p_f and p_x. The first-order conditions to maximize profits with respect to fertilizer will produce the following first-order condition for optimality: $\delta\pi/\delta f = \partial g/\partial f - p_f = 0$, which when solved for fertilizer will give the following fertilizer demand function for the optimizing farmer:

$$f = h(\alpha, f, x, r, p_f). \tag{2}$$

Note if the unobserved component, r, is additive in equation (1), then it does not enter into equation (2). But if heterogeneity and the observed differences, x, enter the production function $g(.)$ in a nonadditive way, as they would in a Cobb-Douglas, generalized quadratic, or translog production function, then they will appear in the fertilizer demand function $h(.)$. We use a Cobb-Douglas and allow unobserved variables to appear not only as factors of production (multiplying fertilizer use), but also in the exponent associated to fertilizer use.

This simple maximization problem has a number of immediate implications for the observability of different levels of fertilizer use in real-world data. First, assuming that r is not additive, optimal levels of fertilizer chosen by farmers will be a function of both observable, x, and unobservable, r, differences between farms. Second, the returns to fertilizer will be a function of both observable and unobservable variables. The dependence of fertilizer use and of fertilizer's impact on unobservable variables poses an econometric problem in that these unobservables could bias our estimates of the returns to fertilizer.

3.3.1 Econometric Framework

This section presents the econometric framework that will be used to estimate technological change in maize yields (the Solow residual) and the impact of fertilizer use on yields. While the level of technological change is a straightforward parameter estimation, that of the impact of fertilizer is more complex due to the maximization problem outlined above. The estimation method we use is based on a fixed effect estimation that allows the demeaned error to be correlated with the demeaned fertilizer variable and that also allows for heterogeneity in the impact of fertilizer use. Specifically, the marginal effect of fertilizer on yields can change according to both observables and unobservables that can be different for observations across time and farms.[3]

Our basic yield specification is a standard one, where the impact of fertilizer on yields is the same for all the households in all the periods.

$$y_{it} = \alpha A_t + \beta_x x_{it} + \beta_f f_{it} + \mu_{it}, \tag{3}$$

where y_{it} is the log of yield per hectare, A_t is a time variable whose coefficient, α, is the standard Solow residual measuring disembodied technological change, f_{it} is log of fertilizer per hectare, and x_{it} is a vector that contains other variables that determine yields. We are interested in estimating both the rate of disembodied technical change and the marginal product of fertilizer, α and β_f. The estimate of α is straightforward, while that of β_f requires careful attention to both observable and unobservable determinants, whose econometric properties are delineated below.

In a panel data context it is useful to decompose the unobservable component, μ_{it}, into a time invariant and a time variant component. That is:

$$\mu_{it} = \eta_i + \varepsilon_{it}.$$

As it is well known, access to a panel data allows for a fixed effect estimation, which controls for the potential correlation between the independent variables and the farm or plot specific error term, η_i. Nevertheless, it is likely that a fixed effect will not fully capture or control for the farm-level heterogeneity we seek to measure. Specifically, we expect the effects of fertilizer use to be nonuniform across time, since it can change with seeds used and time-varying differences in soil and other agronomic conditions. We therefore use a modified fixed effect estimation that allows the impact of fertilizer to change for different individuals and at different periods. The heterogeneity in marginal returns to fertilizer is likely to have both observable and unobservable (to the econometrician) elements.[4] Thus, we specify β_{ft} as:

$$\beta_{fit} = \gamma + \gamma_0 x_{it}^0 + \gamma_{it},$$

where x_{it}^0 is a vector of observable variables that affect the impact of fertilizer use on yields and γ_{it} reflects unobservable heterogeneity on the impact of fertilizer on yields. The parameter γ_{it} can be considered as an element from

3. Note this focus on unobservables that affect the marginal returns to a factor of production differs from the methods proposed by Levinsohn and Petrin (2003) for capturing unobservables in a measurement of overall productivity.

4. We assume that farmers know, observe, and act on the elements that are unobservable to the econometrician.

r, the unobserved variables in the production function. We assume that the unobservable element, γ_{it}, has an expected value of zero: $E(\gamma_{it}) = 0$.

Taking into account this specification of β_{fit}, and ignoring A_t to simplify the exposition, the new yield equation will be given by:

$$(4) \qquad y_{it} = \beta_x x_{it} + \gamma f_{it} + \gamma_0 x_{it}^0 f_{it} + \gamma_{it} f_{it} + \mu_{it}.$$

Equation (4) provides a less restrictive specification of the impact of fertilizer on yields.

The presence of unobserved heterogeneity will bring a bias in the estimation of the average impact of fertilizer use (γ). In the current work, we apply Garen's (1984) control function method to account for unobserved heterogeneity in an estimation based on fixed effects, which is to our knowledge the first application of control functions to a panel data setting.[5]

A fixed effects estimation controls for the potential correlation between f_{it} and μ_{it}, through η_i. This method estimates the demeaned dependent variable as a function of the demeaned independent variables:

$$(5) \quad y_{it} - \overline{y_i} = \beta_x\left(x_{it} - \overline{x_i}\right) + \gamma\left(f_{it} - \overline{f_i}\right) + \gamma_0 x_{it}^0\left(f_{it} - \overline{f_i}\right) + \gamma_{it} f_{it} - \overline{\gamma_{it} f_{it}}. \\ + \left(\mu_{it} - \overline{\mu_i}\right)$$

Given that γ_{it} is not observable, the new error of the estimation, μ_{it} will include the terms related to this unobserved heterogeneity. That is:

$$u_{it} = \gamma_{it} f_{it} - \overline{\gamma_{it} f_{it}} + \left(\mu_{it} - \overline{\mu_i}\right).$$

The first two terms of this compounded error come from the unobserved heterogeneity γ_{it}. These two terms are likely to be correlated with $f_{it} - \overline{f_i}$, creating a bias in the estimation of γ. Assuming that $\left(\mu_{it} - \overline{\mu_i}\right)$ is not correlated with $\left(f_{it} - \overline{f_i}\right)$, the linear projection of the error μ_{it} over $\left(f_{it} - \overline{f_i}\right)$ will be given by:

$$u_{it} = \theta\left(f_{it} - \overline{f_{it}}\right) + r_{it},$$

where $\theta = \text{cov}((f_{it} - \overline{f_i})(\gamma_{it} f_{it} - \overline{\gamma_{it} f_{it}})) \,/\, Var((f_{it} - \overline{f_i}))$. Thus the estimated coefficient γ^{hat} will be given by: $\gamma^{\text{hat}} = \gamma + \theta$. Theta is expected to be positive given that an increase in γ_{it} is likely to be correlated with an increase in f_{it}.[6]

As argued by Garen (1984), one can recover γ_{it} from the residual of an estimation where the dependent variable is f_{it}. The idea, which comes from the first-order conditions of a firm profit function that produces the fertilizer factor demand function, equation (2), is that if the impact of fertilizer use

5. The control function used here is similar in spirit to Suri's (2011) method for controlling for heterogeneous returns, but avoids the problem of using past choices to identify current choices, which could be biased in a situation with crop rotations across years on a single plot. In general, panel data should obviate the need for a control function approach with its multiple years of data to account for individual heterogeneity. In this case the heterogeneity is independent-variable specific and changes through time, which means a simple fixed effect cannot fully control for the heterogeneity.

6. This implies a positive correlation between $\left(f_{it} - \overline{f_i}\right)$ and $\gamma_{it} f_{it} - \overline{\gamma_{it} f_{it}}$.

on yields is higher, farmers will respond by using more fertilizer. Thus, the error from estimation of f_{it} will be positively correlated with γ_{it}.

A second potential problem of the fixed effects estimator is that even after eliminating the time invariant component from the error, the demeaned error, $(\mu_{it} - \overline{\mu_i})$, might still be correlated with the dependent variable, $(f_{it} - \overline{f_i})$. This might happen if, for example, the use of fertilizer responds to conditions that change over time, and, simultaneously, these changing conditions affect yields. For example, if the use of fertilizer responds to unobservable changes in the fertility of the soil, there will be a correlation between $(\mu_{it} - \overline{\mu_i})$ and $(f_{it} - \overline{f_i})$. We consider the presence of unobservables in the exponent of fertilizer, and also as an additional production factor that multiplies fertilizer use. The presence of unobservables as an additional production factor imply a correlation between $(\mu_{it} - \overline{\mu_i})$ and $(f_{it} - \overline{f_i})$. This correlation will further bias the estimates of the impact of fertilizer on yields. The control function method that we deploy allows us to overcome these two potential problems.

The coefficient γ_{it} has two components, one component that is observed by the farmer before deciding how much fertilizer to use (γ_{it}^0) and another that is not observed early enough in the growing season (γ_{it}^u) and, consequently, does not affect the farmer's choice of the amount of fertilizer. If we assume a standard production function, the factor demand equation for fertilizer in equation (2), which describes the optimal amount of fertilizer per hectare (in logs), will depend negatively on the price of fertilizer, positively on the log of the other inputs used in production (per hectare), and positively on the observable component of γ_{it}. Using a first-order approximation of the fertilizer demand equation, we have:

$$f_{it} = \Omega_f x_{it} + \Omega_{p_f} m_{it} + \Omega_{x^0} x_{it}^0 + z_{it} \tag{6}$$

where m_{it} includes variables that determine the price of fertilizer and z_{it} is equal to the derivative of f_{it} with respect to γ_{it}^0 multiplied by γ_{it}^0. If we estimate equation (6) including the relevant production inputs that determine fertilizer demand and an exhaustive list of the variables that determine the price of fertilizer, z_{it} can be recovered by estimating equation (4) and capturing the residuals of such estimation.

Expressing individual heterogeneity γ_{it} as well as the error of equation (4) as functions of z_{it}, we have:

$$\begin{aligned} \gamma_{it} &= \lambda_\gamma z_{it} + \nu_{it} \\ \mu_{it} &= \lambda_\mu z_{it} + w_{it} \end{aligned} \tag{7}$$

where v_{it} is equal to γ_{it}^u.

Plugging equation (7) in equation (5), we have:

$$\begin{aligned} y_{it} - \overline{y_i} = {} & \beta_x\left(x_{it} - \overline{x_i}\right) + \gamma\left(f_{it} - \overline{f_i}\right) + \gamma_0 x_{it}^0\left(f_{it} - \overline{f_i}\right) \\ & + \lambda_\gamma\left(z_{it} f_{it} - \overline{z_{it} f_{it}}\right) + \lambda_\mu\left(z_{it} - \overline{z_{it}}\right) + \omega_{it} \end{aligned} \tag{8}$$

where $\omega_{it} = (\nu_{it} f_{it} - \overline{\nu_{it} f_{it}}) + w_{it} - \overline{w_i}$.

The term $\lambda_\gamma(z_{it} f_{it} - \overline{z_{it} f_{it}})$ controls for unobserved heterogeneity, or the presence of unobservables in the exponent associated with fertilizer use. The term $\lambda_\mu(z_{it} - \overline{z_{it}})$ controls for the more classical endogeneity, that will be brought about by the presence of unobservables as additional inputs. Under the assumption that $E(v_{it} | z_{i1}, z_{i2}, z_{iT}, x_{it}) = 0$ (assumption 1), we will have that $E(\omega_{it}(f_{it} - \overline{f_{it}})) = 0$, which will allow us to consistently estimate γ.[7]

For Assumption 1 to hold, we need to include the relevant other factors of production that determine fertilizer demand and all potential determinants of the price of fertilizer. If this is not the case, v_{it} will include not only γ_{it}^u, but also the determinants of fertilizer use that have been excluded from the estimation. If Assumption 1 holds, including the interaction of the log of fertilizer and the residual will take care of unobserved heterogeneity. At the same time, the inclusion of the residual, by itself, will take care of the potential time-varying correlation that might exist between fertilizer use and the error, even after controlling for unobserved heterogeneity.

3.4 Econometric Estimations and Results

3.4.1 Specification of the Equations

The current section estimates the impact of fertilizer use on yields at the plot level where each observation is a specific plot in a particular year. We will use the control function method described above, which uses the residuals from the estimation of the fertilizer demand equation in order to account for two potential biases. The first one originates in unobserved heterogeneity while the second one comes from the potential correlation between the demeaned fertilizer variable and unobservables, a correlation that might exist even after controlling for unobserved heterogeneity.

As shown in the previous section, the use of fertilizer can be estimated as a function of the other factors of production, the factors linked to observed heterogeneity, and the price of fertilizer. We consider as potential factors linked to observed heterogeneity: organic fertilizer and the percentage of adult members (members with more than sixteen years old) who are literate.[8]

7. If $E(v_{it} | z_{i1}, z_{i2}, \ldots z_{iT}, x_{it}) = 0$ then $E(v_{it} | f_{i1}, f_{i2}, \ldots f_{iT}, x_{it}) = 0$ given that f_{it} and z_{it} are one-to-one functions of each other given x_{it}. Using the law of iterated expectations it can be shown that: $E((v_{it} f_{it} - \overline{\gamma_{it} f_{it}}) | f_{i1}, f_{i2}, \ldots f_{iT}, x_{it}) = 0$. Since $\left(f_{it} - \overline{f_i}\right)$ is a function of $f_{i1}, f_{i2}, \ldots f_{iT}$, we can say that $E((v_{it} f_{it} - \overline{v_{it} f_{it}}) | f_{i1}, f_{i2} - \overline{f_i}, x_{it}) = 0$. Using the law of iterated expectations, then: $E((v_{it} f_{it} - \overline{v_{it} f_{it}})(f_{it} - \overline{f_i})) = 0$.

Additionally, if the observable determinants of fertilizer use are not correlated with the error and since $z_{it} - \overline{z_i}$ is, by construction, not correlated with $f_{it} - \overline{f_i}$, we can conclude that $E((w_{it} - \overline{w_i})(f_{it} - \overline{f_i})) = 0$.

Thus, we can conclude that $E((\omega_{it} - \overline{\omega_i})(f_{it} - \overline{f_i})) = 0$.

8. Literacy of household members is likely to improve the productivity of fertilizer in two important ways. First it can help farmers understand the instructions in how to use fertilizer,

We use two types of measures for the price of fertilizer, one for the relative price and the other for the availability of capital to finance fertilizer purchases. For the relative price we use the log of the price of fertilizer divided by the average price for maize in the household's village. To measure capital availability we measure with proxy variables the two main ways villagers access capital: remittances and cotton-based loans. Households that have higher remittances face a more relaxed budget constraint, which should affect fertilizer demand and use. As a proxy for remittances, we use the number of permanent migrants from the household. In the Sikasso region, producers can acquire fertilizer on credit from CMDT, the cotton parastatal, under the promise of paying for it with cotton after the harvest. We therefore use the percentage of land under cotton in the current year as a determinant of access to credit to buy fertilizer.

In addition to the variables describing heterogeneity and costs/access to fertilizer, we include key determinants of production from the yield equation: adult family labor per hectare, a dummy for having grown cotton last year on the plot, and a time trend. We expect that maize grown on fields that in the previous year grew cotton are likely to require more fertilizer and have lower yields because cotton is well known for depleting the soil. Table 3.1 shows the descriptive statistics of the variables used in the estimations of fertilizer use and of yields.

In order to capture z_{it} from the estimation of equation (6), we need the coefficients of the determinants of fertilizer use to be estimated consistently. Nevertheless, some of the independent variables included in equation (6) are likely to be correlated with z_{it}. To avoid a potential inconsistency in the estimation of these coefficients, we exploit the panel structure of the data and estimate the coefficients of the variables that are not constant through time, through a fixed effects method. Thus, we run the following estimations:

$$f_{it} - \overline{f_i} = \Omega^1\left(\kappa_{it}^1 - \overline{\kappa_{it}^1}\right) + \xi_{it} \tag{9.1}$$

$$f_{it} - \Omega^{1\text{hat}}\kappa_{it}^1 = \Omega^2\kappa_{it}^2 + z_{it}. \tag{9.2}$$

where κ_{it}^1 denotes the subset of variables included in equation (4) that change through time, Ω^1 denotes the coefficients associated with these variables, $\Omega^{1\text{hat}}$ denotes the estimated coefficients of Ω^1, κ_{it}^2 denotes the subset of variables that do not change through time, and Ω^2 the coefficients of these variables. That is, we first run a fixed effects estimation of the use of fertilizer, including only those variables that change through time. Afterward, we run

and second it likely increases farmers' ability to learn from extension agents and other knowledgeable outsiders. Interviews in the study villages identified the latter effect as quite important, in that literate farmers were much more likely to have the local extension agents and school teachers as part of their social networks. One can also think of the literacy variable in the context of a target input model (e.g., Foster and Rosenzweig 1995, 2010) in which higher levels of literacy improves farmer accuracy in hitting the optimal level of fertilizer.

Table 3.1 **Descriptive statistics**

Variable	Measurement unit	Mean	Std. dev.
Yield estimation variables			
Log (maize yields)	log (kg per ha)	7.11	0.69
Maize yields	kg per ha	1,494.5	942.38
Log (area of the plot)	log (hectares)	–0.07	0.95
Area of the plot	hectares	1.33	1.04
Time trend (1995 = 1)	year (1995 = 1)	6.65	3.07
Previous yr. cotton dummy	0–1	0.23	0.42
Number of adults per cultivated hectare		0.66	0.27
Log (number of adults/ha)		–0.498	0.44
Log (rain in June)		5.00	0.33
Rain in June	millimeters	157.24	53.74
Log (rain August)		5.74	0.34
Rain in August	millimeters	328.83	111.81
Log (organic fert. per ha)	log (150 kg per ha)	–6.14	2.70
Organic fert. per hectare (150 kg)	150 kg per ha	4.55	37.72
Log (fertilizer per ha)	log (kg per ha)	3.39	3.94
Percent lit members * log (fertilizer per ha)		0.35	0.73
Log (fertilizer per ha) * log (organic fert. per ha)		–20.52	28.24
Fertilizer demand additional variables			
Percent of land under cotton	(from 0 to 1)	0.29	0.13
Relative per kg price of fertilizer/price of maize		2.53	0.88
Number of migrants in the household		4.14	4.18
Percent of adult members that are literate	(from 0 to 1)	0.10	0.12

a standard estimation of the error of the first estimation against the variables that do not change through time. The residuals of this last estimation will be used in the estimation of yields as shown in equation (8).

The fertilizer (6) and maize yield equations (8) are estimated as fixed effect models at the plot level with robust standard errors clustered at the farm household level. There are up to eight observations per plot with an average just below three observations per plot across 120 households in twelve years. The panel is unbalanced and the number of observations varies between 733 and 675 depending on the variables included in the model. In all models the fixed effects are tested to be significant.

Yield estimates will have log maize yields as a function of key production variables, a time trend to capture disembodied technological change and observable and unobservable determinants of fertilizer returns. For key production variables we include adult labor in the household, rainfall in June during planting, rainfall in August during maize flowering, and the area of the plot. Labor inputs are only available at the household, rather than the plot level, and only measures household adult labor available to farm, rather than actual labor inputs. Because farmer interviews identified hired labor as being rare in the survey villages and representing only a small proportion of labor inputs, this measure is likely reasonably well correlated with total labor use. We measure labor in per hectare terms. We chose the two key periods of rainfall for maize production, planting and harvesting, rather than total rainfall, which includes rainfall outside of the growing season, in order to get a more precise estimate. Lack of June rainfall often leads to plants not sprouting and farmers having to replant maize, while lack of August rainfall can affect whether the maize will pollinate and is the most common reason for crop failures. We include the area of the plot to control for any potential increasing or decreasing returns to scale as is sometimes found in peasant agriculture (e.g., Chayanov 1986; Benjamin 1995), although yield estimations implicitly assumes constant returns to scale.

We estimate the yield model two ways to measure the returns to soil fertility both observed and unobserved. The first basic model includes an observable related to knowledge acquisition, the percent literate household members as an interaction with fertilizer. Following the findings of Marenya and Barrett (2009) as well as many agronomic studies (e.g., Chikowo et al. 2010; Sileshi et al. 2010; Wopereis, Vanlauwe, and Mando 2008) that higher levels of soil organic matter improves the efficiency of chemical fertilizer use, the second model includes measures of the amount of organic fertilizer (cow manure) applied to the fields. Soils in Mali are particularly low in organic matter and cow manure is the primary method available, aside from long-term fallowing, that Malian farmers can use to improve soil organic matter. Organic fertilizer is measured as the log of 150 kg donkey cartloads. The first version of model 2 includes organic fertilizer alone, while the second also includes the interaction of organic fertilizer with chemical fertilizer.

In addition, as a robustness check we provide estimates of the yield function in both model 1 and 2 versions without controlling for endogeneity through the residuals of the control function. These estimates provide the baseline from which we can understand the importance of controlling for the endogeneity of chosen inputs in yield functions.

3.4.2 Fertilizer Function Estimates

Table 3.2 shows the estimation of the fertilizer equation in two specifications. The difference between the specifications is the inclusion of the use of organic fertilizer as an independent variable for model 2. The model is a fixed-effects estimation with robust standard errors to correct for the correlation of the error across plots that belong to the same household.

The estimations show no time trend in fertilizer demand once one controls for other factors that influence fertilizer demand. There is a strong association between previous cotton production on a plot and the following year's fertilizer use, with an 82–86 percent higher rate of application on plots that previously grew cotton. In addition, the model 2 specification shows farmers applying lower levels of chemical fertilizer to plots that received higher

Table 3.2 Estimation for fertilizer demand

Dep. variable: log (fertilizer per ha)	Model 1 coefficient	S. E.	Model 2 coefficient	S. E.
Time trend	0.087	0.06	0.067	0.07
1 if cotton plant previous year	0.861***	0.24	0.821***	0.25
Log(organic fert. per ha)			–0.116*	0.06
Log fert. price/maize price	–1.074*	0.6	–0.788	0.56
Number of migrants in the household	0.222	0.19	0.286	0.18
Percent land under cotton	3.832***	1.41	4.426***	1.41
Log (number of adults/ha)	0.176	0.66	0.479	0.64
Percent of adults that are literate in hh	2.5793**	1.21	2.622**	1.34
Constant	1.782**	0.82	0.597	0.77
Number of observations	733		675	

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

levels of organic fertilizer, suggesting farmers see these as at least partial substitutes. These two results suggest that Malian farmers apply chemical fertilizer to improve fields with lower natural or applied fertility, which implies that a naïve regression of the effects of fertilizer that did not control for the endogeneity of its use would produce biased estimates.

We do not find a statistically significant effect of labor availability, but see a strong effect in terms of labor quality in our measure of the number of literate adults in the household. As seen below in the yield equations, levels of household literacy increase the productivity of fertilizer (likely through learning and management effects) and it stands to reason that this would also increase fertilizer demand.

In terms of price variables, the estimates show a weakly significant but negative effect of fertilizer prices on fertilizer demand. We find much stronger effects on fertilizer demand from our proxies for access to capital. While the number of migrants is not significant, the percentage of land devoted to cotton in the household shows a large and significant effect on the ability of farmers to purchase chemical fertilizer for their maize fields.

3.4.3 Yield Function Estimates

Table 3.3 presents the fixed-effects yield estimations for the baseline model and model 1. Both estimates include a time trend to capture disembodied technical change and a set of yield determinants including land, labor, rainfall, and fertilizer. The baseline estimation does not include the terms associated with the residuals of the fertilizer estimation, while the second includes the residuals and their interaction with the log of fertilizer as specified in equation (8).

The baseline estimation demonstrates a number of the pitfalls of not addressing farm and farmer heterogeneity in the demand for fertilizer. It shows a negative and statistically nonsignificant impact of the use of chemical fertilizer on yields. The only positive relation between fertilizers and maize yields is through the interaction with the percentage of adult members that are literate in the household. In addition the baseline estimation shows a strong time trend, suggesting a nearly 4 percent per year level of technical change in maize yields.

In contrast the model 1 estimates, which control for the potential endogeneity of fertilizer use, show much stronger effects of chemical fertilizer on yields and a much more modest and marginally significant level of technical change of ~2 percent. The model 1 estimate of a yield elasticity of 0.2 for fertilizer when combined with the literacy premium of 0.36, yields a substantial effect of fertilizer on yields especially for the most educated households. The positive impact of the interaction between literacy and the use of fertilizer is consistent with the importance of adequate management in fertilizer application. At the same time, this coefficient might reflect other variables such as a higher presence of extension agents in areas that are more developed and that consequently present a more educated population.

The model 1 estimates show significant effects of farmer heterogeneity in their optimal fertilizer application and that this heterogeneity does effect yields. This second specification shows a negative and statistically significant relationship between the demeaned residuals of fertilizer use and the demeaned yields: our estimate of λ_{μ} (in equation [7]) is negative. At the same time, the estimation shows a positive and statistically significant impact of

Table 3.3 **Maize yield estimations: Model 1**

Dep. variable: Log (maize per ha)	Baseline coefficient	S. E.	Model 1 coefficient	S. E.
Time trend	0.039***	0.01	0.019*	0.01
Log(area of the plot)	–0.006	0.05	0.038	0.06
One if cotton plant prev. year	–0.031	0.07	–0.173*	0.09
Log (number of adults/ha)	–0.077	0.15	–0.115	0.16
Log (rain in June)	–0.048	0.10	–0.02	0.10
Log (rain August)	0.005	0.13	0.014	0.13
Log (fertilizer per ha)	–0.015	0.01	0.232***	0.05
Percent lit members * log (fertilizer/ha)	0.343**	0.14	0.364***	0.12
Residuals of fert. demand equation			–0.208***	0.05
Residuals * (log [fertilizer per ha])			0.010***	0.001
Constant	6.971***	0.56	5.941***	0.61
N	733		733	

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

the interaction between fertilizer use and the residuals of the fertilizer equation: our estimate of λ_γ (in equation [7]) is positive.

A positive and statistically significant estimation of λ_γ implies that households that use more fertilizer are households that benefit more from the using it. These results confirm the presence of unobserved heterogeneity in the sample under analysis. On the other hand, the negative and statistically significant estimate of λ_μ, implying a negative correlation between the residuals of the fertilizer equation and yields, suggests that fertilizers might compensate for the declining soil fertility. The residuals alone having a significant and negative coefficient suggest that the unobservables in the fertilizer equation that tend to increase fertilizer demand have a negative effect on maize yields (for example, unobserved low soil fertility). Meanwhile, the interaction of the unobservables with fertilizer use suggests that those unobservables increase the marginal productivity of fertilizer. If one takes the unobservables from the fertilizer equation to be related to soil fertility, one sees that it reduces maize yields but produces a higher marginal return to fertilizer application as one would expect across low ranges of soil fertility common in West African soils.

We find no effect of either rainfall or household labor on maize yields. The lack of a rainfall result may be due to farmer's ability to do ex post farm management of the crops in which they can make up for poor rain in June by replanting, and poor rain in August by extra effort in other farm tasks such as weeding. The household labor variable is likely not measured accurately enough to demonstrate an effect on yields.

A second factor that might influence yields, as well as the impact of fertilizer on yields, is the use of organic fertilizer, which we control for in our model 2 estimates. The next set of estimations includes the use of organic fertilizer as an additional determinant of yields as well as a determinant of the use of chemical fertilizer. Table 3.4 shows yield estimations that include the use of organic fertilizer. The first specification shows the baseline model, which has a positive and statistically significant impact of organic fertilizer use on yields. The second specification corrects for the residuals of the fertilizer use equation, where this equation includes the use of organic fertilizer as an independent variable. The results for either fertilizer, its residual, or other variables do not change much from the results shown in table 3.3. The third specification includes the interaction between the use of organic fertilizer and the use of chemical fertilizers. The estimated coefficient on this interaction is not statistically significant, suggesting no significant complementary interaction between organic and chemical fertilizer. While this result contrasts with that of Marenya and Barrett (2009), this lack of significant complementarity matches well with the fertilizer demand equation, which shows chemical and organic fertilizer to be substitutes rather than complements.

Table 3.4 Maize yield estimates: Model 2 with organic fertilizer

Dep. variable: Log (maize per ha)	Baseline coeff.	S. E.	Model 2A coeff.	S. E.	Model 2B coeff.	S. E.
Time trend	0.036***	0.01	0.009	0.01	0.008	0.01
Log(area of the plot)	–0.006	0.05	0.025	0.05	0.029	0.05
One if cotton plant prev. year	–0.052	0.08	–0.227**	0.10	–0.228**	0.10
Log (number of adults/ha)	–0.111	0.16	–0.22	0.16	–0.22	0.16
Log (rain in June)	–0.038	0.10	–0.026	0.10	–0.024	0.10
Log (rain August)	0.059	0.12	0.064	0.12	0.062	0.12
Log(organic fert. per ha)	0.027**	0.01	0.054***	0.01	0.061***	0.02
Log (fertilizer per ha)	–0.014	0.01	0.255***	0.05	0.247***	0.05
Percent lit members * log (fertilizer/ha)	0.377***	0.13	0.397***	0.12	0.407***	0.12
Log (fert./ha).*.log (organic fert./ha)					–0.002	0.003
Residuals of fert. use equation			–0.238***	0.05	–0.243***	0.05
Residuals * l(og [fertilizer/ha])			0.009**	0.004	0.009**	0.004
Constant	6.775***	0.55	5.977***	0.59	5.998***	0.59
N	675		675		675	

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

3.4.4 Econometric Results Discussion

The estimations presented here have demonstrated the importance of controlling for the endogeneity of fertilizer use. The results indicate that in the absence of controlling for endogeneity, the impact of fertilizer use on yields would not be consistently estimated due to the correlation between the unobservables and the use of chemical fertilizer. In addition, we find that there is evidence of heterogeneity in the impact of fertilizer on yields. First, this impact is higher for households with a higher percentage of members in the household that are literate. Secondly, we find strong evidence of unobserved heterogeneity, which affects both the choice of fertilizer amounts and the marginal returns to fertilizers.

The estimations show much stronger evidence for the growth in maize yields having been driven by farmer adoption of higher levels of fertilizer use rather than improvements in seeds and management, disembodied technical change. This is not to say that farmers did not adopt new technologies, but rather the maize revolution came as a sequential adoption process (e.g., Aldana et al. 2010) in which farmers adopted parts of a package in succession: seed first, appropriate levels of organic and chemical fertilizer later.

The importance of controlling for endogeneity in fertilizer use goes beyond a correct decomposition of the determinants of corn yields. The naïve model ignoring this endogeneity would have decided that most of the technical change was in seeds and management and seriously underestimated the return to fertilizer. Such an underestimate of the returns to fertilizer could seriously call into question public policies such as the Malian government's current program to subsidize fertilizer. Once one controls for both observed and unobserved heterogeneity in the returns to fertilizer, one sees yield elasticities of about 0.2–0.3 for fertilizer. In addition, farmers seem to respond to reduced fertility of their soils, as happens with cotton cultivation (Benjaminsen, Aune, and Sidibé 2010), with increased applications of fertilizer. This suggests a sophistication in African farmer knowledge that goes beyond that commonly suggested in the economics literature. Malian farmers are using fertilizer application rates to make both temporally and dynamically rational decisions about the fertility of their soils.

3.5 Conclusions

The success of Mali's farmers in adopting technologies and intensifying their maize production has created a green revolution in maize production in the region. In part through the adoption of improved maize seeds, farming techniques, and the growing use of fertilizer on maize fields, farmers in southern Mali have helped turn Mali from being a food-deficit country to a regional bread basket. This success has been fostered by a combination of research efforts, extension and diffusion of ideas especially by the cotton parastatal CMDT, and a farmer willingness to adopt new seeds and inputs. The success is not unique, as Alene et al. (2009) show that a number of other countries have had similar improvements in maize production.

Adoption of improved maize varieties in Mali in the late 1980s to early 1990s led first to a growth in maize production, which was followed by a sharp growth in the use of fertilizer in maize production from the late 1990s to early in the twenty-first century. This later growth in fertilizer use (adoption of fertilizer for maize cultivation) is primarily responsible for the growth in maize yields one sees in the last decade, as opposed to better management or seeds. Counter to the situation one sees in many African countries, Malian farmers adopted fertilizer for maize in growing numbers despite an increasing price for fertilizer relative to the flat price of maize. This suggests that recent efforts to subsidize fertilizer for maize production could have an increasing knock-on effect.

It is important to highlight that the high estimates of the impact of fertilizer do not mean that the adoption of new seed varieties has had no impact on yields. Based on our results, we can assert that the adoption of new seed varieties needs to be complemented by increased use of fertilizers. This finding is aligned with Smale, Byerlee, and Jayne (2011) who assert that yields in many African countries have remained stagnated, in spite of the generalized adoption of new seeds, due to the low levels of fertilizer use.

The results presented in this chapter also highlight the importance of cash and credit constraints in the adoption and use of fertilizer. The results show that an important determinant of fertilizer use is given by the percentage of land under cotton. Since the fertilizer used in corn plots is financed with the promise of delivering cotton to the parastatal textile company CMDT, our results confirm the argument presented in Laris and Foltz (2014) and in Tefft (2010) that cotton production contributes to food security through the credit it provides for fertilizer use.

There remains room for a great deal of improvement in maize yields in Mali and the West African region in the future. Most of the last decade's growth in yields is due to improved use of inputs, but higher performing varieties of maize seed, including hybrids, are already available on the market in Mali and could lead to a next jump in maize yields and production. In addition, new maize varieties that are drought resistant have the potential to spread maize production into lower rainfall regions of Mali and give those farmers the potential to access the higher fertilizer responsiveness of maize compared to sorghum or millet. There is also room for more work on the silent green revolution in maize in Mali. First, Mali is not alone in experiencing this growth, and work that compared and analyzed the similarly large growth of maize in Burkina Faso would provide a comparative perspective that might help identify key institutional factors that promoted this revolution. Expanding the analysis to the whole region could be particularly important in identifying institutional factors, since other neighboring countries such as Senegal, Gambia, Guinea, and Niger have been left out of the growth in maize.

Appendix

Table 3A.1 **Available maize varieties in Mali, 2008**

Maize variety	Maximum farmer yields	Origin	Type	Minimum rainfall	Date of intro.	Other quality
Kogoni B	2–3 T/HA	Mali IER	OPV	800 mm/yr.	1970	90-day variety, resists leaf disease
Tzersw	2–3 T/HA	Mali IER	OPV	800 mm/yr.	1983	90-day variety, resists leaf disease
Tiémantié	3.5–4 T/HA	Mali IER	OPV	800 mm/yr.	1983	100–120 day, sensitive to leaf disease
SR22 (EV8422SR)	4–5 T/HA	Mali IER	OPV	800 mm/yr.	1984	100–120 day, resists leaf disease
Sotubaka	4–5 T/HA	Mali IER	OPV	800 mm/yr.	1985	100–120 day, resists leaf disease
Niéléni	3 T/HA	Mali IER	OPV	600 mm/yr.	1996	90-day variety, resists leaf disease
Appolo	2 T/HA	Mali IER	OPV	500 mm/yr.	1996	70-day variety, resists leaf disease
Dembanyuman	4–5 T/HA	Ghana	OPV	800 mm/yr.	1998	100–120 day, resists leaf disease
Jorobana	2–3 T/HA	Mali IER	OPV	600 mm/yr.	2008	80-day variety, resists leaf disease
Mali Hybride 7	6–7 T/HA	Mali IER	Hybrid	800 mm/yr.	2008	100–120 day, resists leaf disease

Source: Coulibaly (2008). “Fiche Technique sur Les Variétés de Mais au Mali” IER-Mali.

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