The Sahel's Silent Maize Revolution: Analyzing Maize Productivity in Mali at the Farm-level[a]

by

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Abstract
Since independence a quiet revolution has taken place in maize production in the Sahel with Mali increasing production more than ten-fold and yields going up ~2% a year. This research work uses farm level panel data from southern Mali's maize growing regions to demonstrate this success in agricultural production and technological change. We analyze the determinants of production to unpack increases in input use from technological change. The estimations show that farmer adoption of increased fertilizer use has driven much of the productivity growth rather than the adoption of improvements in seeds and management. Additionally, we find strong evidence of observed and unobserved heterogeneity, which affects both the choice of fertilizer amounts and the marginal returns to fertilizer use. The results demonstrate the key changes behind this silent maize revolution and point to the importance of taking into account farmer heterogeneity in estimating productivity and returns to fertilizer.

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N'i ti kaba séné, e ti balo

If you are not growing maize, you cannot feed your family (Malian Farmer, 2010)

Introduction

According to aggregate data, since 1961 total maize production in Mali has increased more than ten-fold; bringing maize from being a minor crop to one on par with traditional Sahelian crops of millet and sorghum (see Figure 1). This ten-fold 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. Despite this growth a recent review of maize production by the World Bank (Smale, Byerlee, and Jayne; 2011) concludes that very little progress has been made in achieving the potential maize has for improving cropping systems and diets in Africa.

While the current yields in Mali of around 2 tons per hectare are still low by world standards, the rate of yield increase over the last 45 years (~2%) is equal or better than that of maize production in Iowa, Wisconsin, and India. The maize yield increases in the Midwest of the US 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-1970's.

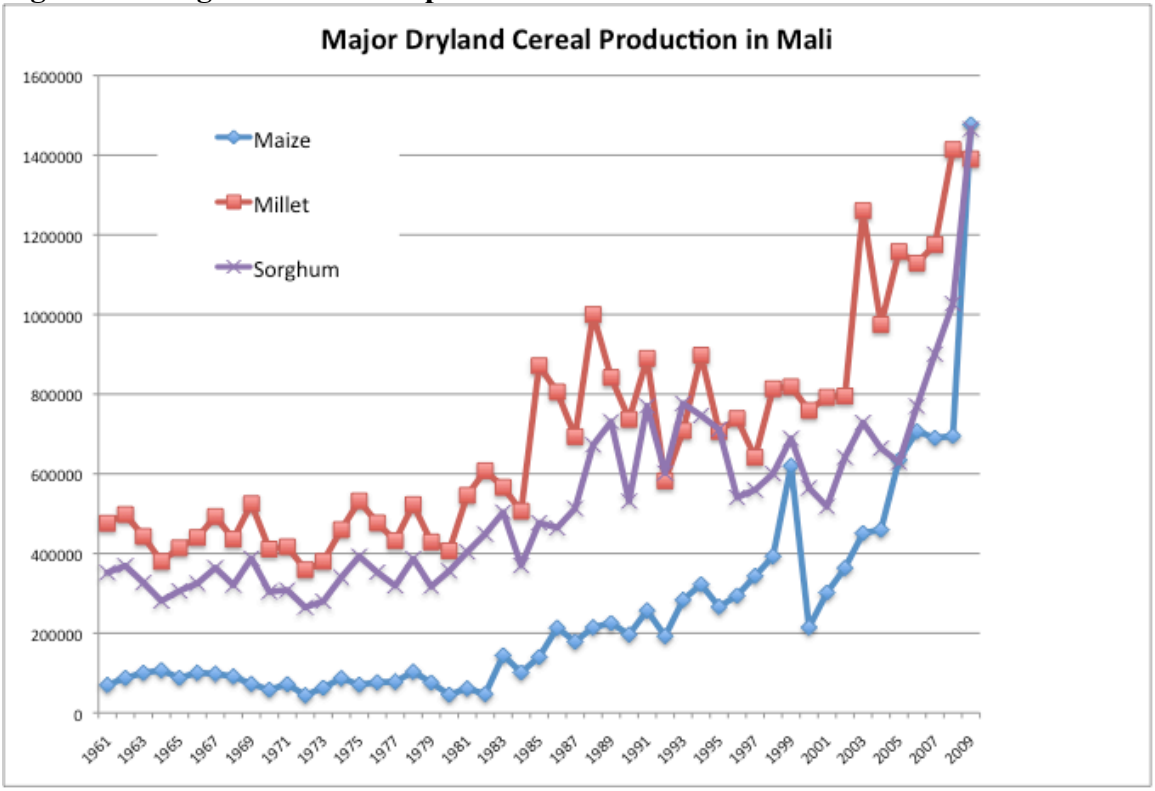
Such a success suggests Mali has succeeded in at least partially solving exactly the issues that most bedevil agricultural development projects in the Sahel and most of Africa: farmers bought inputs such as fertilizer, farmers changed their agronomic techniques, farmers paid for new seeds, farmers found markets for their production, 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 in 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 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 20 years.

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 1/10th of the levels used in the rest of the world. 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.

Figure 1: The growth of maize production 1961-2009



Recent work on productivity growth of agriculture in Africa identifies significant increases in productivity in the last decade after some decades of stagnation (Block, 1994; 2010). Increases in maize production have led the way in many parts of Africa (Smale, Byerlee, and Jayne; 2011), but the revolution in maize is only partially done. Smale et al. (2011) point to the key role of fertilizer in determining yield increases and the potential for maize to jump-start a green revolution.

In terms of recent empirical studies, Duflo et al. (2008) use an 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 et al. (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 (rate and timelines of application) and household factors (recent death). 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's 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).

In order to address this unobserved heterogeneity, we apply a control function method first presented by Garen (1984) in order to test for this heterogeneity and to control for the bias that this heterogeneity brings. This 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. For observed heterogeneity, we test weather the impact of fertilizer use on yields varies with literacy levels and with the use of organic fertilizer. All of these efforts are 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 II 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 III 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; builds an econometric technique based on control functions to account for farmer heterogeneity in fertilizer responsiveness. Section IV estimates and provides results for fertilizer demand functions and then maize yield functions that account for farmer heterogeneity. Section 5 concludes and points to open questions for future research.

II. Description of the data

We draw upon multiple sources of data to trace the history of maize for southern Mali. These sources vary by scale as does our analysis. We begin with a broad-brush approach focusing on the major maize growing regions of southern, Mali (see Figure 2), using available national and regional level data (FAO and IER, 2008).We then shift to a finer-scale quantitative analysis of a 12 year data set (1994-2006) for over 100 household farms from nine villages located in Mali's southern maize belt. Finally, interwoven in the data analysis we explore this linkage further by scaling down to understand farmer perceptions and decision-making logic during the past decade using semi-formal interviews.

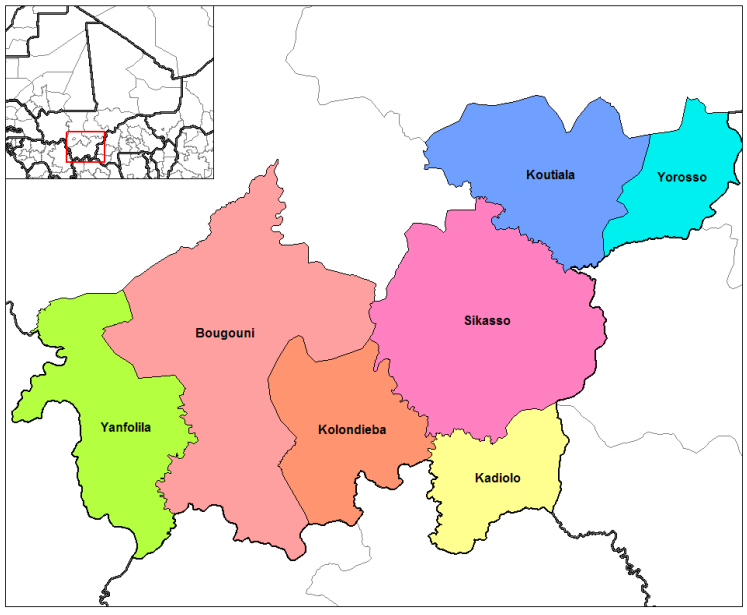
The micro-level panel data set was collected in the region of Mali, Sikasso, which grows most of the country's maize. The data has been collected since 1988 by the Malian

agricultural research organization Institut d'Economie Rurale (IER) from 84 farmers spread across 9 villages in 3 different communes. The data set starts with 149 farmers in 1988 and ends with 84 in 2008 due to sample attrition. The villages were chosen to represent different agro-ecological zones with the Sikasso region and the farmers were chosen to be representative of different types of farms stratified by farm assets.[1]

The data has been collected for agronomic studies and most closely resembles the kind of data one might get from farm trials, except that it comes from individual farmers. With their level of agronomic detail and long time series, these micro-level 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. In addition data on farm implement use (tractors, oxen drawn plows) and some labor data allow us to control for most inputs in production.

In addition to the quantitative data, Jeremy Foltz and Paul Laris conducted interviews in 15 villages in 2010 and 2011. Eleven of the villages were located in the Bougouni area of the Sikasso region. Three of these corresponded to villages also included in the farm data set. Four villages were located in the OHV zone in the Siby area. We conducted both individual and focus group interviews with maize farmers. Farmers were asked a series of open ended questions in the local language of Bambara about farming history and decision-making regarding all crops. Interviews were then transcribed and analyzed for common themes.

Figure 2: Map of the Sikasso region and research sites in the Bougouni, Kadiolo, and Koutiala districts.



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

II.B. Sikasso Region Context

The Sikasso Region is the best-watered region of Mali (800-1200mm 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. Koutiala is where the farmers are the most sophisticated and have a long tradition of growing cotton. Kadiolo sub-region is the traditional maize growing area, but with less progressive farmers. Bougouni started the 1990's as the least developed of these regions with farmers least touched by extension services among the sub-regions, but has developed in the last 20 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 1or 2 to 8 – 10 in the decade of the dataset 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 this dataset.

Figure 3 shows the increases in maize productivity in the sample and across the three surveyed regions. Overall it shows a 17% increase in maize yields, but that hides a near flat change in yields in Bougouni to a nearly 35% increase in yields in Kadiolo. The figure is suggestive 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 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% at the same time that its price increased 175% (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 5. There one sees that Koutiala, the region with the most progressive 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 Kadiolo exhibit a pattern of fertilizer use increase that mimics the S-curves of standard technology adoption models.

[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.

Fok et al. (2000), argue that farmers' choice to grow maize is largely an economic one, that they have responded to high prices for grains which increased following devaluation and reached high levels in the late 2000s (Moseley et al. 2010). They argue that the gross margin per hectare is greater for maize than other crops and that, "Farmers' widespread adoption of sole cropping of maize with greater fertilizer use could be related to an astonishing change in their aversion to risk" (2000: 6). As Fok et al. (2000) point out maize requires investment in expensive inputs such as fertilizers and herbicides—thereby increasing risk. But maize farmers we interviewed in the cotton zone explain that maize also reduces risk because it matures quickly and thus provides a good harvest in years with a short rainfall season. Although maize will fail as a crop if drought occurs during a specific point in the plants growing cycle, it matures more rapidly than millet or sorghum also helping farmers to shorten the "hungry season." Furthermore, maize has been well-integrated into a farming system that includes a variety of different grains assuring that if one crop fails, others will provide a harvest.

In addition as shown below in figure 6 the distribution of yield outcomes of maize production has changed over the last 20 years, reducing the risk farmers face in growing maize. Figure 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 12 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 500kg, 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 500kg/ha.

Taken together the graphical data shows 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.

Figure 3: Maize yields by Sikasso region zone

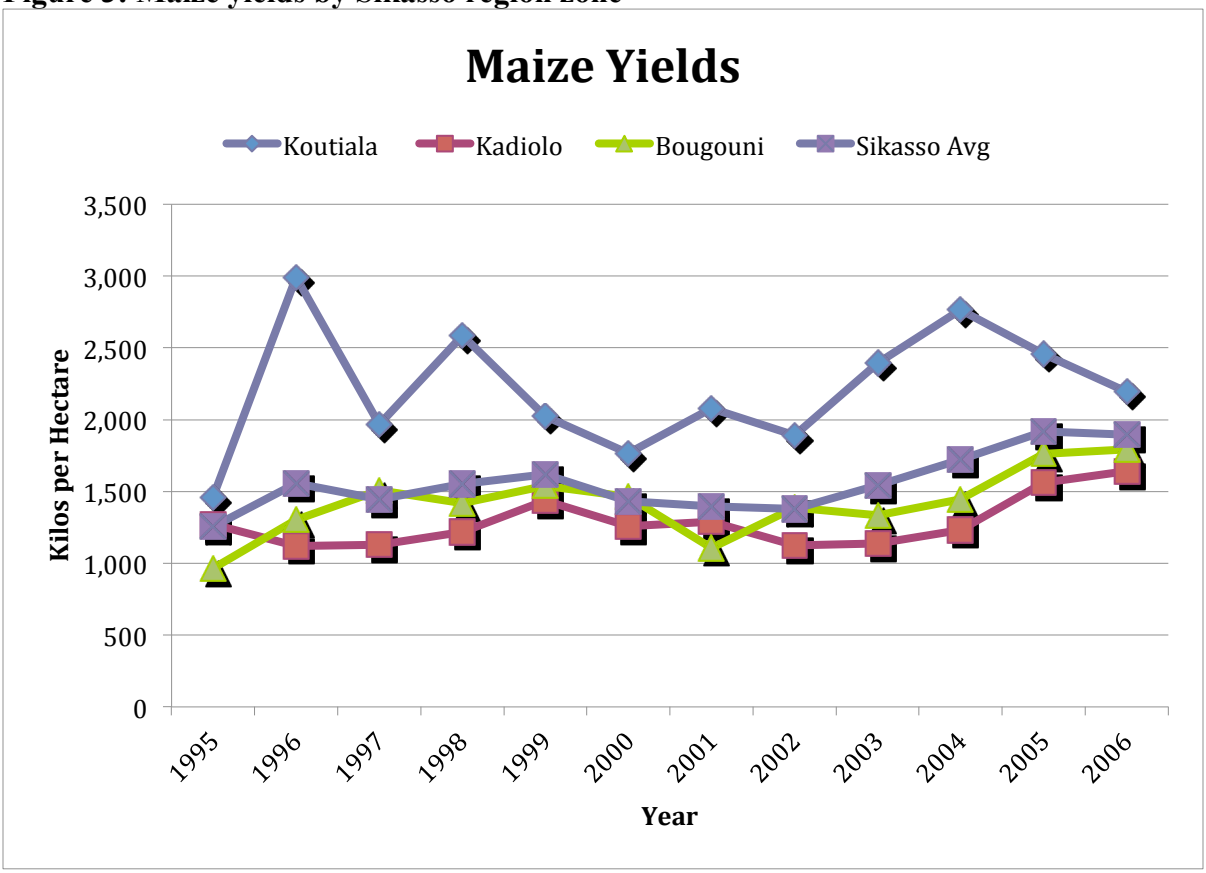


Figure 4: Fertilizer use with maize and fertilizer prices, Lowess curves

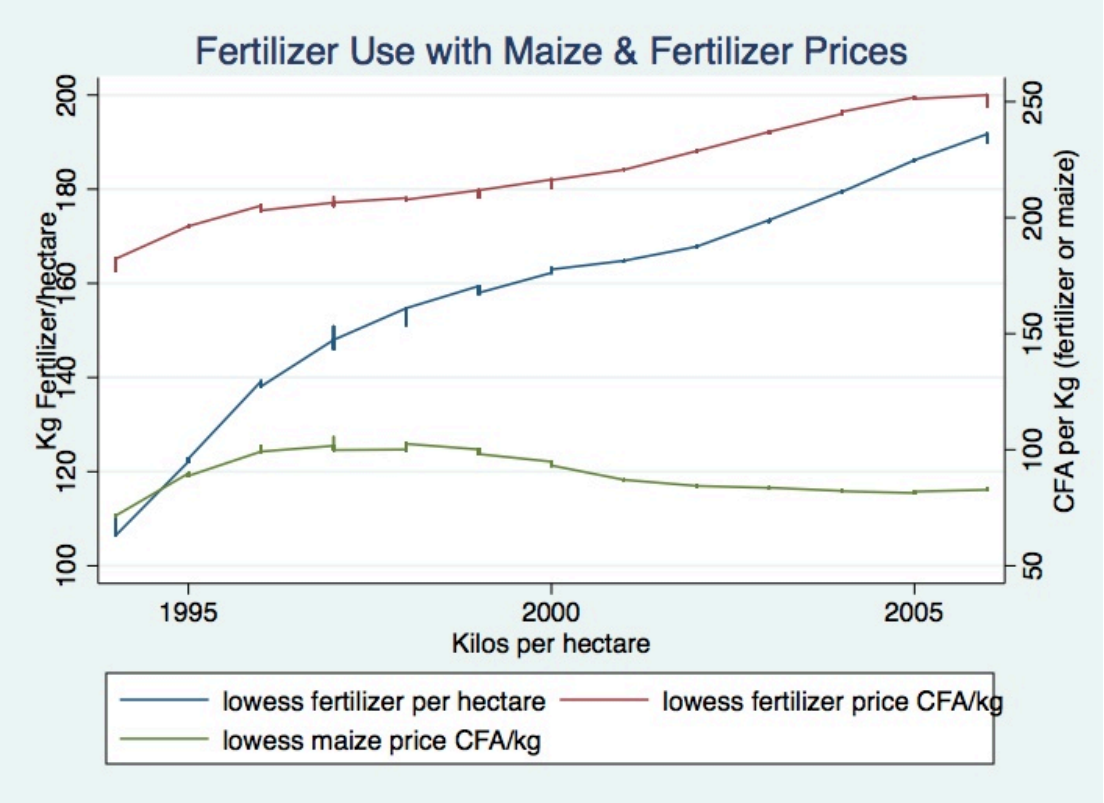


Figure 5: Fertilizer use by Sikasso region zone, Lowess curves

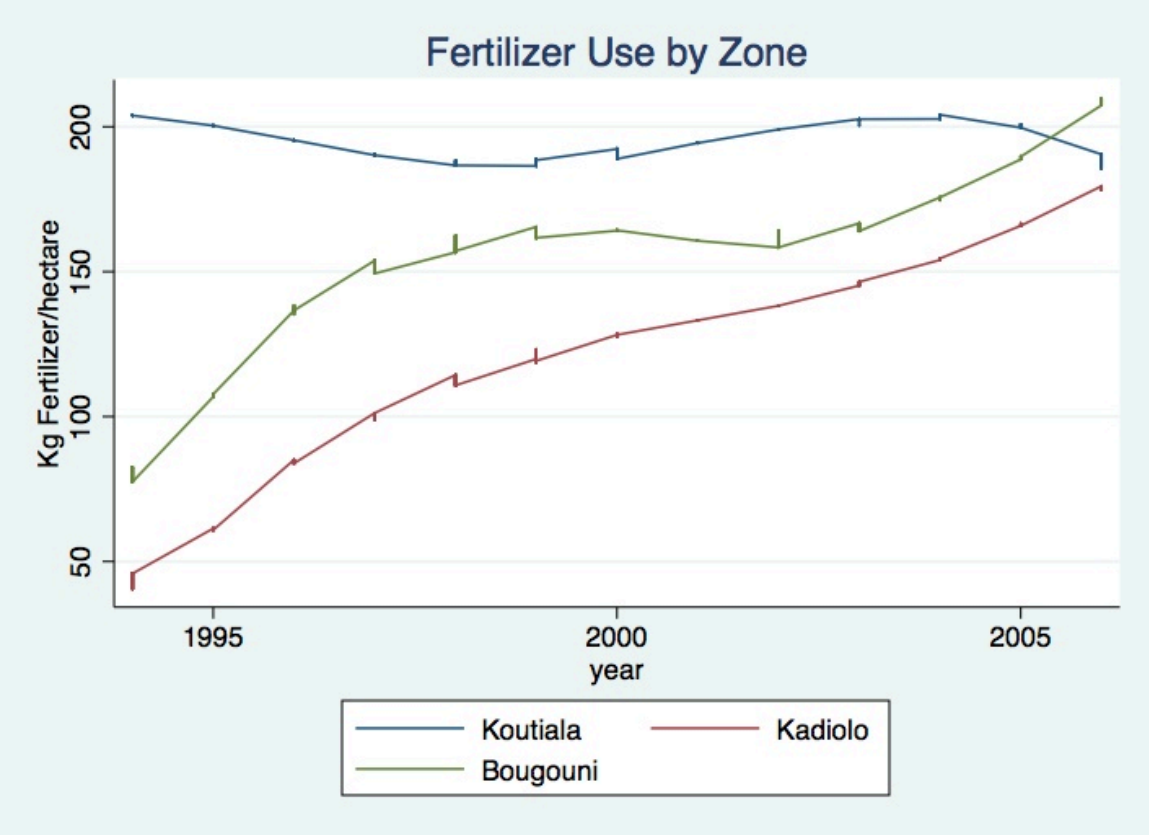
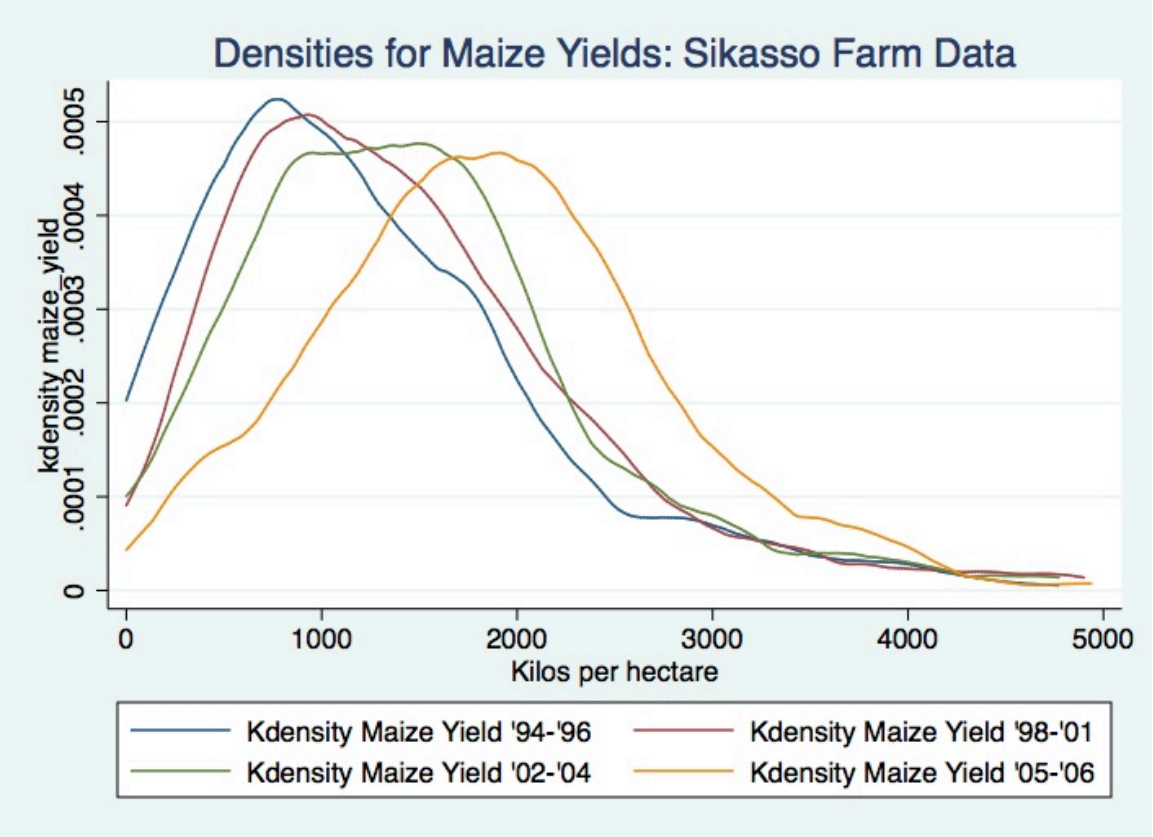


Figure 6: Maize yield distributions over time Sikasso farm data



III. Conceptual Framework

The conceptual framework for our 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:

$$\pi = g(\alpha, f, x, \gamma) - p_f f - p_x x \qquad (1)$$

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, γ is a parameter related to farmer heterogeneity, such as soil quality (unobserved), 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: $\partial\pi/\partial f = \partial g/\partial f - p_f = 0$, which when solved for fertilizer will give the following fertilizer demand function for the optimizing farmer:

$$f = h(\alpha, x, \gamma, p_f). \quad (2)$$

Note if the unobserved heterogeneity, γ, is additive in (1), then it does not enter into equation (2). But if heterogeneity and the observed differences, x, enter the production function $g(.)$ multiplicatively as they would in a Cobb-Douglas, generalized quadratic, or translog production function, then they will appear in the fertilizer demand function $h(.)$.

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 a multiplicative production function, optimal levels of fertilizer chosen by farmers will be a function of both observable, x, and unobservable γ, differences between farms. Second the returns to fertilizer will be a function both observable and unobservable parameters. Third, the use of fertilizer will be positively correlated with the unobservables, such as soil quality, in the fertilizer demand function. This poses an econometric problem in that unobserved heterogeneity could bias our estimates of the returns to fertilizer, such that we might find low or no returns in part because farmers have chosen the optimal level given their knowledge of their farm.

III.A. 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.

$$y_{it} = \alpha A_t + \beta_x x_{it} + \beta_f f_{it} + \mu_{it} \quad (3)$$

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

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

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. If the heterogeneity is non-constant through time, as would be the case if unobserved soil qualities varied across plots and time, the assumption of a uniform impact of fertilizer use is not likely to hold. In the current work, we use a fixed effect estimation and, at the same time, we allow 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:

$$\beta_{fit} = \gamma + \gamma_o x_{it}^o + \gamma_{it}$$

where x_{it}^o is a vector of observable variables that affect the impact of fertilizer use on yields and where γ_{it} reflects unobservable heterogeneity on the impact of fertilizer on yields. 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:

$$y_{it} = \beta_x x_{it} + \gamma f_{it} + \gamma_o x_{it}^o f_{it} + \gamma_{it} f_{it} + \mu_{it} \qquad (4)$$

Equation (4) provides a less restrictive specification of the impact of fertilizer on yields. As we will see below, the presence of unobserved heterogeneity will bring a bias in the estimation of the average impact of fertilizer use (γ). One of the methods that has been developed to account for unobserved heterogeneity is the control function method first laid out in Garen (1984).[5] In the current work, we apply Garen's method to an estimation

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

[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.

based on fixed effects, which is to our knowledge the first application of control functions to a panel data setting.[6]

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:

$$y_{it} - \overline{y_i} = \beta_x(x_{it} - \overline{x_i}) + \gamma(f_{it} - \overline{f}_i) + \gamma_o x_{it}^o(f_{it} - \overline{f_i}) + \gamma_{it} f_{it} - \overline{\gamma_{it} f_{it}} + (\mu_{it} - \overline{\mu_i}) \quad (5)$$

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

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

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 $(\mu_{it} - \overline{\mu_i})$ is not correlated with $(f_{it} - \overline{f}_i)$, the linear projection of the error u_{it} over $(f_{it} - \overline{f_i})$ will be given by:

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

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: $\gamma^{hat} = \gamma + \theta$. Theta is expected to be positive given that an increase in γ_{it} is likely to be correlated with an increase in f_{it}[7].

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 produce the fertilizer factor demand function, equation (2), is that if the impact of fertilizer use on yields is higher, farmers will respond by using more fertilizer. Thus, the error of the 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 form the error, the demeaned error, $(\mu_{it} - \overline{\mu_i})$, might still be

[6] 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.

[7] This implies a positive correlation between $f_{it} - \overline{f_i}$ and $\gamma_{it} f_{it} - \overline{\gamma_{it} f_{it}}$

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 $(f_{it} - \overline{f}_i)$. 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} can be thought as having two components, one component that is observed by the farmer before deciding how much fertilizer to use (γ_{it}^{o}) and another that is not observed on time (γ_{it}^{u}) and, consequently, does not affect the use of fertilizer. If we assume a standard Cobb Douglas production function, the factor demand equation for fertilizer, 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:

$$f_{it} = \Omega_{f} x_{it} + \Omega_{p_f} m_{it} + \Omega_{x^o} x_{it}^{o} + z_{it} \qquad (6)$$

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}^{o} multiplied by γ_{it}^{o}. 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.[8]

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

$$\gamma_{it} = \lambda_{\gamma} z_{it} + v_{it}$$

$$\mu_{it} = \lambda_{\mu} z_{it} + w_{it} \qquad (7)$$

where v_{it} is equal to γ_{it}^{u}.

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

[8] Note that our fertilizer equation must control for all the relevant variables that determine fertilizer demand, but that do not affect yield. The method can accommodate having omitted variables that show up in the error term so long as they

$$y_{it} - \overline{y_i} = \beta_x(x_{it} - \overline{x_i}) + \gamma(f_{it} - \overline{f}_i) + \gamma_o x_{it}^o(f_{it} - \overline{f_i}) + \lambda_\gamma(z_{it}f_{it} - \overline{z_{it}f_{it}}) + \lambda_\mu(z_{it} - \overline{z_{it}}) + \omega_{it} \quad (8)$$

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

Under the assumption that $E(v_{it} \mid z_{i1}, z_{i2}, z_{iT}, x_{it}) = 0$ (*assumption 1*), we will have that

E($\omega_{it}(f_{it} - \overline{f_{it}})$)=0 which will allow us to consistently estimate γ[9].

For *assumption 1* to hold, we need to include the relevant other factors of production that determine fertilizer demand and all potential the 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. This would imply that assumption 1 will not hold.

If *assumption 1* holds, including the interaction of the log of fertilizer and the residual will take care of unobserved heterogeneity. On the other hand, 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.

IV. Econometric Estimations and Results

IV.A. Parameterization 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 according to the econometric method laid out in the previous section. 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 is originated in unobserved heterogeneity while the second one comes from the potential correlation between the demeaned fertilizer variable and unobservables, correlation that might exist even after controlling for unobserved heterogeneity.

If $E(v_{it} \mid z_{i1}, z_{i2}, ..z_{iT}, x_{it}) = 0$ then $E(v_{it} \mid f_{i1}, f_{i2}, ..f_{iT}, x_{it}) = 0$ 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: $E((v_{it}f_{it} - \overline{v_{it}f_{it}}) \mid f_{i1}, f_{i2}, ..f_{iT}, x_{it}) = 0$. Since $f_{it} - \overline{f_i}$ is a function of $f_{i1}, f_{i2}, ..f_{iT}$, we can say that $E((v_{it}f_{it} - \overline{v_{it}f_{it}}) \mid f_{it} - \overline{f}_i, x_{it}) = 0$. Using the law of iterated expectations, then: $E((v_{it}f_{it} - \overline{v_{it}f_{it}})(f_{it} - \overline{f_i})) = 0$

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 16 years old) that are literate.[10] Regarding the price of fertilizer, we use two types of measures, 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 can be thought as behaving as if they faced a lower price of fertilizer, given that they face a more relaxed budget constraint. 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 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:

$$f_{it} - \overline{f}_i = \Omega^1 (\kappa^1_{it} - \overline{\kappa^1_{it}}) + \xi_{it} \qquad (9.1)$$

$$f_{it} - \Omega^{1hat} \kappa^1_{it} = \Omega^2 \kappa^2_{it} + z_{it} \qquad (9.2)$$

[10] 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 and second it likely increases farmer 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 Rosensweig, 1995, 2010) in which higher levels of literacy improves farmer accuracy in hitting the optimal level of fertilizer.

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, Ω^{1hat} 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 trough time. Afterwards, we run 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 8 observations per plot with an average just below 3 observations per plot across 120 households in 12 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, 1966 and Benjamin, 1995), although yield estimations implicitly subsumes 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 et al., 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 maure 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 one and two versions without including the unobserved heterogeneity measured with the residuals of the control function. These estimates provide the baseline from which we can understand the importance of measuring farm and farmer heterogeneity in yield functions.

Table 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	1494.5	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
% 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			
% 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
% of adult members that are literate	% (from 0 to 1)	0.10	0.12

IV.B. Fertilizer function estimates

Table 2 shows the estimation of the fertilizer equation used for two models or 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 estimated as a fixed effects 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% 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 levels of organic fertilizer, suggesting farmers see these as at least partial substitutes. Taken together these two results suggest farmers who apply chemical fertilizer to fields with lower natural or applied fertility.

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.

Table 2 Estimation for fertilizer demand

	Model 1		Model 2	
Dep variable: log (fertilizer per ha)	Coefficient	S.E.	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
% land under cotton	3.832***	1.41	4.426***	1.41
Log (number of adults/ha)	0.176	0.66	0.479	0.64
% 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	

IV.C. Yield Function Estimates

Table 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 non-significant 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% per year level of technical change in maize yields.

In contrast the model 1 estimates, which control for farmer heterogeneity in their optimal choice of fertilizer, show much stronger effects of chemical fertilizer on yields and a much more modest and marginally significant level of technical change of ~2%. 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 the 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 relation between the demeaned residuals of fertilizer use and the demeaned yields. That is, our estimate of λ_μ (in equation (7)) is negative. At the same time, the estimation shows a positive and statistically significant impact of the interaction between fertilizer use and the residuals of the fertilizer equation. That is, 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, our negative and statistically significant estimation of λ_μ indicates that, even in the absence of unobserved heterogeneity, the fixed effects estimation does not preclude a correlation between the residual of the estimation and the demeaned fertilizer variable.

This last estimation of the impact of fertilizer use, which controls for the potential correlation between this variable and unobservables, shows a positive impact of the use of fertilizer on yields.

The 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 (for example unobserved low soil fertility) have a negative effect on maize yields. 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.

Table 3 Maize Yield Estimations: Model 1

	Baseline		Model 1	
Dep. variable: log (maize per ha)	Coefficient	S.E.	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
1 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
% 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	

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 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 regarding the impact of fertilizer as well as the impact of the variables related to the residuals of the fertilizer equation do not change much in comparison with the results shown in Table 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. 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 4 Maize Yield Estimates: Model 2 with organic fertilizer

	Baseline		Model 2A		Model 2B	
Dep. variable: log (maize per ha)	Coefficient	S.E.	Coefficient	S.E.	Coefficient	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
1 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
% 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	0.0000
Residuals of fert use equation			-0.238***	0.05	-0.243***	0.05
Residuals *(log (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	

IV.D. Econometric Results Discussion

In sum, we find that there is evidence of heterogeneity in the impact of fertilizer on yields. First, this impact is higher for households that present a higher percentage of members in the household that are literate. Additionally, we find strong evidence of unobserved heterogeneity, which affects both the choice of fertilizer amounts and the marginal returns to fertilizers. The results indicate that in the absence of controlling for unobserved

heterogeneity, 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.

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 estimations presented here have demonstrated the importance of taking farmer heterogeneity into account when estimating the returns to fertilizer in Africa. The naïve model ignoring farmer heterogeneity 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, 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 making both temporally and dynamically rational decisions about the fertility of their soils.

V. 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 early 1990's led to a first growth in maize production, which was followed by a sharp growth in the use of fertilizer in maize production from the late 1990's to the 2000's. 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.

There is room for lots 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 room for a great deal 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.

Another important line of work to pursue would be investigations of the effects of this increased maize productivity on household food security, risk profiles, farm profits and other well-being measures such as health and education. Alene et al. (2009) make a start in that direction, but more work needs to be done. Development professionals and donors have long been hoping for just such a growth in food crop production in Sub-Saharan Africa in order to address poverty and household food security issues (McIntyre, 2009). But while a large academic literature has analyzed agricultural productivity, that work has typically assumed that higher agricultural production will automatically translate into better household incomes and food security. Future work investigating how and whether increased maize yields translate into better long-term sustainable development outcomes is warranted.

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Appendix

Table A1 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	800mm /yr	1970	90 day variety, resists leaf disease
Tzersw	2 - 3 T/HA	Mali IER	OPV	800mm /yr	1983	90 day variety, resists leaf disease
Tiémantié	3.5 - 4 T/HA	Mali IER	OPV	800mm /yr	1983	100-120 day, sensitive to leaf disease,
SR22 (EV8422SR)	4 - 5 T/HA	Mali IER	OPV	800mm /yr	1984	100-120 day, resists leaf disease
Sotubaka	4 - 5 T/HA	Mali IER	OPV	800mm /yr	1985	100-120 day, resists leaf disease
Niéléni	3 T/HA	Mali IER	OPV	600mm /yr	1996	90 day variety, resists leaf disease
Appolo	2 T/HA	Mali IER	OPV	500mm /yr	1996	70 day variety, resists leaf disease
Dembanyuman	4 - 5 T/HA	Ghana	OPV	800mm /yr	1998	100-120 day, resists leaf disease
Jorobana	2 - 3 T/HA	Mali IER	OPV	600mm /yr	2008	80 day variety, resists leaf disease
Mali Hybride 7	6 -7 T/HA	Mali IER	Hybrid	800mm /yr	2008	100-120 day, resists leaf disease

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