Selection and Comparative Advantage in Technology Adoption

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ABSTRACT

This paper examines a well known empirical puzzle in the literature on technology adoption: despite the potential of technologies to increase returns dramatically, a significant fraction of households do not use these technologies. I study the use of hybrid maize and fertilizer in Kenya, where there are persistent cross-sectional differences in aggregate adoption rates with a large fraction of households switching in and out of adoption. By allowing for selection of farmers into technology use via comparative advantage differences, I examine whether the yield returns to adopting hybrid maize vary across farmers. If so, high average returns can coexist with low returns for the marginal farmer. My findings indicate the existence of two interesting subgroups in the population. A small group of farmers has potentially high returns from adopting the technologies. Yet, they do not adopt. This lack of adoption appears to stem from supply and infrastructure constraints, such as the distance to fertilizer distributors. In addition, a larger group of farmers faces very low returns to adopting hybrid maize, but chooses to adopt. This latter group might benefit substantially from the development of newer hybrid strains to increase yields. On the whole, the stagnation in hybrid adoption does not appear to be due to constraints or irrationalities.

1   Introduction

Food security is currently at the forefront of the policy agenda across many Sub-Saharan African economies. Agricultural yields have fallen in the last decade across many of these economies, despite the widespread availability of technologies that increase yields. Governments and policy makers need to understand why yields of agricultural staples are low across parts of Africa in order to find ways to enhance food production and incomes. Table 1 shows the falling yields of staple crops over the last decade in Kenya, compared with increasing yields in India and Mexico. These are worrisome trends: it seems as if Kenya has not yet been able to take the same advantage of improvements in agricultural technologies as have India and Mexico during their Green Revolutions.

   This paper examines adoption decisions faced by farmers in rural Kenya with respect to agricultural technologies, in particular hybrid maize and fertilizer. What agricultural technologies are households using and are these technologies actually increasing yields for all farmers? Why are some farmers not adopting, even though others in the same community adopt and seem to receive significant yield increases? Understanding how and why households decide what technologies to adopt is crucial for understanding the trends in agricultural yields in Sub-Saharan Africa, where risk and incomplete factor markets are potentially important.

   Field trials at experiment stations across Kenya show that hybrid maize and fertilizers can increase yields of maize significantly, increases ranging between 40 and 100% (see Gerhart (1975), Kenya Agricultural Research Institute, KARI (1993), Karanja (1996)). The Fertilizer Use Recommendations Project (FURP) conducted in Kenya in the early 1990's also shows high returns to these technologies in field trials (see Hassan et al (1998)) - results confirmed in the small sample of Duflo, Kremer and Robinson (2003). However, aggregate adoption rates of hybrid maize and fertilizer remain far below 100% across Kenya, with large variations in individual adoption status from year to year. This has posed an empirical puzzle: why are aggregate adoption rates low and stagnating when returns to the technologies are so high? The literature has put forth a number of explanations from models of learning and informational barriers, credit constraints, taste preferences to the lack of effective commitment devices (see Duflo, Kremer and Robinson (2003)).

   My approach to these questions of technology adoption is very different from the standard literature. I examine whether the yield returns to adopting hybrid maize vary across a random sample of maize farmers, such that high average returns to the technologies are accompanied by low returns for the marginal farmer. Allowing heterogeneity in returns to play a role in the adoption decision implies that the knowledge of average returns is not enough to understand the adoption decisions across a sample of farmers. I study the adoption of agricultural technologies in Kenya within a framework of heterogeneous returns where a farmer's expected benefits from the technology are allowed to be correlated with his decision to adopt the technology. I therefore model technology adoption as a selection process where yields may be heterogeneous and expected benefits to the technology may drive adoption decisions in each period. This allows

for household-specific heterogeneity in returns and hence controls for selection via comparative advantage differences across households.

I use an extensive panel dataset representative of maize-growing Kenya, covering the period from 1996 to 2004. I helped design and collect the 2004 round of this panel survey. I first document the adoption patterns of households over the period 1996 to 2004, for both hybrid maize and fertilizer. I find that aggregate adoption over the period is stable over time, even when I look across regions or asset/wealth quintiles. What is striking in my data is that I observe very different adoption rates across regions and asset quintiles, but these adoption rates are stable over time. What is even more surprising is that at least 30% of my households switch into and out of use of hybrid seed over my sample period.

I then turn towards estimating and testing models with homogeneous returns, as well as models with specific forms of unobservable heterogeneity, i.e. household fixed effects models. These serve as a baseline for my later contributions. I look at some empirical tests of these models and in general, such models are rejected in my data. So, I present a more general model of heterogeneous returns and selection. In a methodological contribution, I generalize Chamberlain's (1982, 1984) approach to the fixed effects model to accommodate not just heterogeneous intercepts, but also heterogeneous slopes (here, returns to hybrid). Overall, I find strong evidence of heterogeneity and selection of farmers into the use of technologies. There is evidence of farmers responding to their expected benefits by selecting into the use of high yielding varieties. I find that even though these agricultural technologies have high average returns, the marginal farmer has low returns and switches easily in and out of adoption when subject to idiosyncratic shocks.

The empirical strategy I use allows me to estimate the distribution of returns in my sample (under certain assumptions). The joint distribution of returns and adoption decisions displays some extremely interesting features. In particular, I observe a small group of farmers with high returns from hybrid seed, yet they choose not to adopt. The lack of adoption for this small set of households appears to stem from supply and infrastructure constraints, such as distance to seed and fertilizer distributors. On the flip side, I also find a comparatively large group of households for whom the returns are extremely low, almost zero, yet they adopt hybrid maize. These results point to the need for focused interventions for policy to be cost effective. For the constrained farmers, alleviating their constraints by improving infrastructure and distribution would improve yields dramatically. The unconstrained farmers, however, may benefit greatly from the development of new hybrid strains.

The rest of this paper is structured as follows. In Section 2, I outline some of the relevant literature, focusing on empirical studies. Section 3 describes the data I use and some background and history of maize cultivation in Kenya. Section 4 discusses models of adoption decisions, focusing on the economics motivating my model of heterogeneous returns. Section 5 discusses the results for the standard household fixed effects model, a test of this model, as well as some evidence for selection and heterogeneity in returns. Section 6 describes estimation of the

heterogeneous returns model and the associated distribution of returns. In Section 7, I cover some robustness checks, in particular the Heckman two-step estimator as well as treatment effects under non-random assignment, i.e. the average treatment effect (ATE), the treatment on the treated (TT), the marginal treatment effect (MTE) and the local average treatment effect (LATE) or IV estimator. Section 8 discusses the implications of my results for households and policy makers in Kenya. I discuss why a framework like mine is needed for a country like Kenya, which has widely varying agronomic conditions. Section 9 concludes.

2   Literature Review

I briefly summarize some of the empirical literature on technology adoption[2] in developing countries, with a focus on the studies that have been conducted in Sub-Saharan Africa. Gerhart (1975) is the most relevant study for my paper so I discuss his research first. He tracks the adoption of hybrid maize in Western Kenya in the late 1960's and early 1970's. Gerhart highlights the fast diffusion of hybrid maize in this region and identifies constraints to the use of hybrid maize. He finds that risk is extremely important: if farmers had other means of dealing with risk (such as other drought resistant crops, cash crops or off farm income), then they were far less likely to use hybrid maize. In addition, education of the farmers, credit availability, extension services were all important in determining hybrid use. Finally, farmers who used hybrid maize were also more likely to use other improved farming technologies, such as fertilizer use, manure use, planting in rows, etc.

I split the rest of this review into four main areas, first discussing studies that relate to heterogeneity, then looking at research on learning externalities and credit constraints and ending with the recent experimental research. The seminal empirical paper on new agricultural technology adoption is Griliches (1957)[3]. He looks at the heterogeneity across local conditions in the adoption speeds of hybrid corn in the Midwestern US. Griliches emphasizes the role of economic factors like expected profits and scale in determining the variation in diffusion rates. He also notes how the speed of adoption across geographical space depends on the suppliers of the technology and when the seed was adapted to local conditions. Other researchers have looked at heterogeneity along other dimensions, focusing on describing what forms of heterogeneity drive the decisions of households to adopt new technologies. This covers quite a range of papers: from Schultz (1963) and Weir and Knight (2000), who emphasize the role of education, to the various CIMMYT (The International Wheat and Maize Improvement Center) studies[4] that collect data

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[2]The literature on technology adoption is too vast to review here, excellent reviews can be found in Sunding and Zilberman (2001), Sanders, Shapiro and Ramaswamy (1996), Rogers (1995), and Feder, Just and Zilberman (1985). There is a large theoretical literature, for example, Besley and Case (1993), Banerjee (1992) and Just and Zilberman (1983). For other fields of economics, Hall (2004) reviews well the social, economic and institutional determinants of diffusion rates. I do not discuss studies that focus on livestock or land management practices (Mugo et al (2000)), agricultural extension (Evenson and Mwabu (1998)), or property rights (Place and Swallow (2000)).

[3]Also see David (2003).

[4]See Doss (2003) and De Groote et al (2002) for a review of all the CIMMYT micro surveys in Kenya. Also,

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on what underlies adoption decisions across different parts of Kenya. For example, Makokha et al (2001) look at the determinants of fertilizer and manure use in Kiambu district in Kenya, focusing on measuring soil quality and showing that farmers' perceptions of soil quality are reasonably accurate. The main (self-reported) constraints to using fertilizer were high labor costs, high prices of inputs, unavailability of demanded packages and untimely delivery. Ouma et al (2002) look at the adoption of improved seed and fertilizer in Embu District in Kenya where they find that gender, agroclimatic zone, manure use, hiring of labor and extension services are significant determinants of adoption. Similarly, Wekesa et al (2003) look at the adoption of the Coast Composite, Pwani 1 and Pwani 4 hybrids and fertilizer in the Coastal Lowlands of Kenya where the non-availability and high cost of seed, unfavorable climatic conditions, perceptions of sufficient soil fertility, and lack of money/credit are cited as reasons for low use.

Much of the recent literature on technology adoption has focused on the learning externality, described well by Besley and Case (1993), which relates to the literature on social interactions. Foster and Rosenzweig (1995) look at the adoption of high yielding varieties in post Green Revolution India, allowing for learning by doing, learning from others, and costly experimentation. They find that farmers with more experienced neighbors are more profitable than those without. Munshi (2003) looks at the same question and finds that the impacts are heterogeneous: wheat growers respond strongly to their neighbors' experiences while rice farmers experiment. He finds greater variations in yields in rice growing areas and notes that rice high yielding varieties, unlike those for wheat, tend to be sensitive to soil characteristics and managerial inputs, which are difficult to observe. Conley and Udry (2003) study the adoption of fertilizer in the small-scale pineapple industry in Ghana. They collect information on farmers' sources of information and find evidence of learning, not only from own experiences, but also within information neighborhoods. Bandiera and Rasul (2003) look at decisions to plant sunflower in the Zambezia province of Mozambique. They find that adoption decisions are correlated within networks of family and friends and that this effect is stronger for disadvantaged farmers. Moser and Barrett (2003) look at a high yielding low external input rice production method in Madagascar, analyzing decisions to adopt, expand and disadopt. They find seasonal liquidity constraints and learning effects from extension agents and other households to be important.

A hypothesis that is often raised in the literature is that credit constraints explain the lack of adoption. For example, Croppenstedt, Demeke and Meschi (2003) estimate a double hurdle fertilizer adoption model for Ethiopia, using self-reported information on why farmers did not purchase fertilizer. They find that credit is a major supply side constraint to adoption. Most of the CIMMYT studies also cover self-reported credit constraints; for example, Salasya et al (1998) look at the role of credit in adoption decisions in Western Kenya.

The final strand of literature on Kenya I describe is experimental. There are several impact assessment studies[5] and field trials at experiment stations which show large increases in yields

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see http://www.cimmyt.org/research/economics/map/impact%5Fstudies/impstudea%5Flist/ for all the impact studies done by CIMMYT in East Africa.

    [5]Some studies use survey data to understand the welfare impacts of improved technology use. For example,

from using hybrid maize and fertilizer. Other than the work done by the Kenya Agricultural Research Institute on experiment stations, one of the earlier experimental studies was the Fertilizer Use Recommendations Project (FURP), conducted across 70 sites in the early 1990's in conjunction with the Kenya Maize Database Project (MDBP). FURP recorded yields about half of those on experimental stations (KARI (1993)). The focus of these experiments was to understand optimal rates of fertilizer use in comparison to survey data on actual use from the MDBP (see Corbett (1998)). Hassan et al (1998) use these data and find that both adoption of hybrid maize and varietal turnover rates are higher (and diffusion faster) in high potential areas. They blame poor extension services, bad infrastructure and poor seed distribution for the low adoption rates in the marginal areas. Hassan, Murithi and Kamau (1998) combine the data from the surveys and trials and find that farmers apply less fertilizer than is optimal, leading to an estimated 30% gap between current and optimal yields.

A more recent example is De Groote et al (2003) who look at an ex-ante impact assessment of the Insect Resistant Maize for Africa (IRMA) project that develops GM maize varieties that are more resistant to stem borers. They estimate the surplus from a shift in supply due to the decreased crop loss (measured experimentally) as a result of introducing this maize variety that is more resistant to stem borers. Estimated crop losses amounted to 13.5% with an estimated value of $80 million. The results imply high returns to such genetic technologies[6]. Similarly, Duflo, Kremer and Robinson (2003) run controlled experiments in the field to measure returns from fertilizer use. They find that the average net rate of return for investing in top-dressing fertilizer is between 28% and 134% for an eight month investment. They study diffusion and find a significant negative impact on neighbors of the program. They find that farmers learn via demo trials, distributed kits, but not through announcements of government endorsement. They started the Savings and Fertilizer Initiative (SAFI) as a commitment device for farmers and find that farmers take up this program when it is offered at harvest time, but not later, pointing to these farmers being hyperbolic discounters.

3 Survey Data and Maize Cultivation in Kenya

Maize is the main staple in Kenya[7], accounting for approximately 3.7 million acres of cropped land with main season maize production ranging between 2.3 and 2.7 million MT, of which

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Karanja, Renkow and Crawford (2003) look at differential impacts across high potential and marginal areas in Kenya, in terms of efficiency and distribution. They find that adoption of technologies in high potential areas, relative to those in marginal areas, have large aggregate gains at the expense of poor distributional effects. Sserunkuuma (2002) looks at a partial equilibrium model of adoption of improved maize and fertilizer in Uganda. He uses price elasticities of demand and supply from secondary sources to estimate large consumer gains and large producer losses of a shift in supply due to the adoption of hybrid maize.

[6]See http://www.cimmyt.org/ABC/InvestIn-InsectResist/htm/InvestIn-InsectResist.htm and Smale and De Groote (2003) for more information on the CIMMYT IRMA and GM projects in Kenya.

[7]McCann (2005) describes the fascinating history of maize in Africa pointing out how maize not only gives more food per unit of land and labor, but also has the largest set of alternative uses compared to other grains. Nyameino, Kagira and Njukia (2003) cite that about 90% of Kenya's population depends on maize for income generation.

75% is through small-scale farming. Average maize yields are on the order of 0.8 MT per acre, although there is considerable cross-sectional diversity.

I use data from the Tegemeo Agricultural Monitoring and Policy Analysis (TAMPA) Project (April 1996-June 2005) between Tegemeo Institute at Egerton University, Kenya and Michigan State University[8]. This is a household level panel survey, representative of rural maize-growing areas, which are geographically very diverse. Figure 1 shows a map of Kenya with the location of the villages covered.

Different modules of data were collected in different years of the survey, with a common core set. I have data for 1997, 1998, 2000, 2002 and 2004. The 1997, 2000 and 2004 surveys are similar, containing detailed agricultural input and output data (plus retrospective data for 1995-1996), household consumption (not complete), income, demographics (individual age, gender, education and health), infrastructure, location, and some basic credit information. The panel sample covers about 1400 households, with an additional 800 households in the 2004 sample. The 1998 survey is similar, but covers only a sub-sample of about 612 households. Kenya was strongly affected by El Nino in 1998 and so the 1998 sample is very different from other years. The 2002 survey was a short proxy survey, but it collected detailed data on hybrid maize use. I restrict myself mostly to 1997, 2000 and 2004 data.

To motivate my research questions, I outline some trends in my data over the period 1996-2004 on the use of hybrid maize and fertilizer. Figure 2 shows the trends in adoption of hybrid maize for the two seasons, defined here as the fraction of maize seed planted that is hybrid. Figure 3 looks at main season adoption patterns by province over the same period. Both Figures 2 and 3 illustrate the stability in aggregate adoption patterns over time and the persistence of cross-sectional differences. An identical pattern is evident if I look across wealth/asset or acreage quintiles. The use of inorganic fertilizer during the main season follows similar trends. Figure 4a shows the trends across provinces in the fraction of households that use inorganic fertilizer for maize production and Figure 4b shows the total value (in constant Kenyan shillings) of inorganic fertilizer used, by province. There is a lot more variation over time in the total value of inorganic fertilizer used, but both figures illustrate the familiar persistent cross-sectional differences. Finally, for an idea of the more general patterns in my data, Figures 5a and 5b show main season yields of maize and the acreage planted to maize respectively over the same period. Yields are not stable over time, with the sharp drop in yields around 1997/1998 the result of El Nino floods.

Maize policy in Kenya has an interesting history over this period. Smale and Jayne (2003) provide an excellent review. In terms of technology releases, both hybrid seed and fertilizer have been around since the 1960's. More than twenty modern maize varieties of seed have been released by the government since 1955 (Ouma et al. (2002)). The period from 1965 to 1980 was impressive in terms of yields and hybrid variety 611 diffused in Western Kenya "at rates as fast as or faster than among farmers in the US corn belt during the 1930's-1940's" (Gerhart

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[8]See http://www.aec.msu.edu/agecon/fs2/kenya/index.htm for more information on the TAMPA project.

(1975)). Smale and Jayne (2003) and Karanja (1996) attribute this impressive performance to good germplasm, effective research, strong extension services, good seed distribution/enterprise and coordinated marketing of inputs and outputs. However, this quickly changed in the 1990's as the earlier policies of large subsidies, strong price supports, pan-territorial seed/output pricing and restrictions on cross district trade, resulted in large fiscal deficits[9]. Reform of the cereal sector began in 1988, followed by a wide liberalization in 1994[10], though the government retained some control policies, probably to benefit politically important areas (Smale and Jayne (2003)).

The government recommendations for the types and quantities of hybrid seed and fertilizer to be applied vary by region (Appendix Table A1). The agriculture is all rain fed, with large variations in rainfall that make input use more risky and complicate plant breeding (see Hassan, Onyango and Rutto (1998)). The commonly held wisdom is that the later releases in hybrid technology in Kenya, compared to the early releases, have not shown big improvements in yields[11]. This, along with increases in agricultural intensification and shifting of maize to more marginal areas, is often blamed for stagnating yields.

Table 1b shows summary statistics for my sample of households for 1997, 2000 and 2004. There are interesting trends in fertilizer use. There are 26 different types of fertilizer reported as being used. Table 1b shows only four types (di-ammonium phosphate (DAP), calcium ammonium nitrate (CAN), nitrogen phosphorus potassium (NPK) and mono-ammonium phosphate (MAP)). Table 1c breaks out some of these variables by hybrid/non-hybrid use for the three periods of data. Yields are lower across the board in the non-hybrid sector (the p-values on the t-tests are 0.000 in each period). However, a lot of the other variables look quite similar in means (p-values on the t-tests are often above 5%), except for fertilizer use and main season rainfall.

4   Modeling Adoption Decisions

In this section, I outline a model of adoption decisions that allows for both absolute and comparative advantage in the selection process determining who uses the hybrid maize technology. Throughout this section, I refer to hybrid maize as the relevant technology, though the empirical model will allow for generalizations to this, mostly with respect to the use of fertilizer.

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[9]Kenya National Cereals and Produce Board, the marketing board supporting these policies, managed to accrue losses on the order of 5% of the country's GDP in the 1980's (Smale and Jayne (2003)).

[10]There are numerous studies of the impacts of the cereal sector reforms and liberalization, see Jayne et al (2001). Karanja, Jayne and Strasberg (1998) look at the productivity impacts and Jayne, Myers and Nyoro (2005) at the effect on maize prices over 1990-2004. Hassan, Mekuria and Mwangi (2001) show the five fold increase in private seed companies between 1992 and 1996, also documented by Kamau (2002) who points out important legislative and regulatory constraints during this time. Finally, Nyoro, Kiiru and Jayne (1999) look at the evolution of different types of maize traders post-liberalization and Wanzala et al (2001) describe in detail how the private sector has taken over the supply of fertilizer.

[11]Karanja (1996) states that "newly released varieties in 1989 had smaller yield advantages over their predecessors than the previously released ones... research yields were exhibiting a "plateau effect"". Examples he gives are KSII, which was followed by H611 (40% yield advantage), then H622 (16%) and then H611C (12%). H626 which had a 1% yield advantage over H625 was released eight years later.

There are two technology options available to farmers: to plant either a hybrid maize variety or a traditional (non-hybrid) variety[12]. Say the production functions at any point in time for a farmer are of the Cobb-Douglas form

$$Y_{it}^H = e^{\beta_t^H} \left(\prod_{j=1}^{k} X_{ijt}^{\gamma_j^H} \right) e^{u_{it}^H} \tag{1}$$

$$Y_{it}^N = e^{\beta_t^N} \left(\prod_{j=1}^{k} X_{ijt}^{\gamma_j^N} \right) e^{u_{it}^N} \tag{2}$$

where the outcome variables, Y_{it}^H and Y_{it}^N, are the yields (output per acre) at time t when farmer i uses hybrid or non-hybrid maize respectively[13]. Throughout, H is used to represent the use of hybrid maize and N the use of non-hybrid. The X_{ijt}'s represent various other inputs (where j indexes the input), such as fertilizer, labor, rainfall, etc., as well as province dummies. The indexing of X_{ijt} by both i and t is quite general as some of the inputs may only vary by households (such as average long term rainfall). The production functions for hybrid and non-hybrid maize have different parameters on the inputs, i.e. the X_{ijt}'s have different coefficients in the production functions (indicated by γ^H and γ^N) to allow for complementarity between the maize variety used and the inputs. However, I do assume that the same set of potential inputs are used to grow both hybrid and non-hybrid maize. Finally, the u_{it}^H and u_{it}^N are sector-specific errors that may be the composite of time-invariant household characteristics and time-varying shocks to production. I will consider some specific decompositions of these u_{it}^H and u_{it}^N factors below.

Taking logs of equations (1) and (2) above,

$$y_{it}^H = \beta_t^H + X_{it}'\gamma^H + u_{it}^H \tag{3}$$

$$y_{it}^N = \beta_t^N + X_{it}'\gamma^N + u_{it}^N \tag{4}$$

where y_{it}^H and y_{it}^H are the logs of yields, the X_{it}'s have been redefined to represent the logs of the inputs. The gain in yields per acre from planting hybrid maize is

$$B_{it} = y_{it}^H - y_{it}^N = \beta_t^H - \beta_t^N + X_{it}'(\gamma^H - \gamma^N) + u_{it}^H - u_{it}^N \tag{5}$$

In this framework, we can start to think about what drives adoption decisions. The simplest

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[12] In principle, hybrid use could be a continuous variable as farmers plant quantities of hybrid seed. However, in my sample very few farmers actually plant both hybrid and traditional varieties in a given season. For example, in 1997 only 2% of households planted both hybrid and traditional varieties of maize. Since taking hybrid use to be a binary decision simplifies the problem dramatically, I use this framework throughout.

[13] The yield equation that I specify is driven mainly by data constraints since the measurement of farm inputs and their prices is difficult. This does not allow direct estimation of a profit function. However, maize prices are captured by province and year dummies included in the specification of my yield function. As a result, the log yield regression I estimate captures the benefits of hybrid on percentage yields and thus revenues, holding constant my input measures.

decision to adopt would be based on a comparison of the yields under hybrid and non-hybrid maize, such that $h_{it} = 1$ if $y_{it}^H > y_{it}^N$ and $h_{it} = 0$ if $y_{it}^H \leq y_{it}^N$, where $h_{it} = 1$ represents the use of hybrid and $h_{it} = 0$ the use of non-hybrid. This is the basic implication of the Roy (1951) selection model[14] in terms of yields. The Roy model relies on comparisons of wages, or net benefits but the conceptual framework it provides can be applied to productivities (as suggested by Mandelbrot (1962)).

The strict Roy model therefore implies that

$$\frac{y_{it}^H}{y_{it}^N} > 1 \text{ for } h_{it} = 1 \text{ and } \frac{y_{it}^H}{y_{it}^N} \leq 1 \text{ for } h_{it} = 0 \tag{6}$$

More generally, for any two individuals i and j using hybrid and non-hybrid maize respectively,

$$\frac{y_{it}^H}{y_{it}^N}_{h_{it}=1} > \left(\frac{y_{jt}^H}{y_{jt}^N} \right)_{h_{jt}=0} \tag{7}$$

Equation (7) implies sorting based on comparative advantage[15]. The yield maximization rule given by the Roy model in equation (6) therefore imposes comparative advantage.

In the Roy model setup, the adoption decision is based purely on a comparison of yields under hybrid and non-hybrid maize such that

$$h_{it}(y_{it}) = 1\left[y_{it}^H - y_{it}^N \geq 0 \right] = 1\left[(\beta_t^H - \beta_t^N) + X_{it}' \left(\gamma^H - \gamma^N \right) + u_{it}^H - u_{it}^N \geq 0 \right] \tag{8}$$

where $1[.]$ represents an indicator function of whether the expression in brackets holds true.

This model of selection can be generalized whereby yield maximization is replaced by income maximization or even a more general selection rule. This is important as it allows for both observed and unobserved costs as well as other factors like tastes/preferences[16] to drive the adoption decision. This makes sense in the case of hybrid maize, given its properties. For my scenario, it is important to note two properties of hybrid maize. It increases mean yields as well as reduces the variance in yields, as it can be more pest and drought resistant than traditional varieties.

These two characteristics of hybrid maize are illustrated clearly in Figures 6a, 6b and 6c. The figures show the conditional distributions of yields across farmers who use hybrid and those who do not for each of the three periods of data I use. It is clear from these figures that the mean of the hybrid yield distribution lies to the right of that of non-hybrid yields. The hybrid yield distribution also has a lower variance than the non-hybrid yield distribution (the standard

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[14] Also see Heckman and Honore (1990) and Borjas (1987).

[15] The definitions and implications of absolute and comparative advantage as sorting mechanisms have been outlined by various labor economists (see Willis (1986), Green (1991), Sattinger (1993) and Carneiro and Lee (2004)).

[16] One hypothesis for the lack of adoption and the persistence of non-hybrid maize is differing tastes of hybrid and non-hybrid maize, as in Latin America. This is unlikely in Kenya where the different maize varieties have a uniform price and no distinction in the market.

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deviations of the two distributions are significantly different with p-values on the null of equal standard deviations of 0.000 in each period). These figures highlight an important property of hybrid maize: it eliminates the lower tail of the distribution of outcomes under non-hybrid maize. This is the main motivation for my model of heterogeneous returns. It is clear that the farmers who would benefit the most in terms of yields would be those at the lowest end of the non-hybrid distribution of yields - the bad outcomes would be muted under hybrid.

The generalized Roy model allows for maximization of an underlying benefit function that is far more general than that in equation (8) so that $h_{it} = 1$ if $f^H(y_{it}^H, Z_{it}^H) > f^N(y_{it}^N, Z_{it}^N)$ where Z_{it}^j represents sector j ($j \in H, N$) costs and factors that affect adoption, including the covariates in the X_{it}'s. The simplest version of this benefit function would be a profit maximization rule. When output prices are the same for hybrid and non-hybrid maize, yields and profits differ only by (real) input costs. Throughout the empirical work, I will estimate yield functions, usually controlling for complete input use. My data on inputs is not always at the crop level, but at the field level so that calculating maize profits directly is not as straight forward. The specification I use that estimates yield functions controlling for input use is close to estimating profit functions.

The more general version of a hybrid benefit function for risk-neutral farmers allows for unobserved costs and factors that are not in the yield equation to affect the adoption decision. These are the components of the Z_{it}'s over and above the X_{it}'s that are in the yield equation. Examples of variables that may be in this set of Z_{it}'s that are not in the yield equation and are not tastes include the distance from a household to the seed/fertilizer distributor and measures of the availability of seed for a household in any period. Such measures of seed/input availability clearly affect the costs of planting hybrid maize (over and above the observed costs, which are in the X_{it}'s) and can therefore affect the adoption decision from period to period. In the case of this generalized Roy model, any pattern of sorting is possible and the joint distribution $f(y^H, y^N)$ is required to understand the patterns of sorting and comparative advantage (the standard program evaluation problem)[17].

In particular, I can write the selection rule for a generalized Roy model for yields in terms of a binary choice based on the latent variable, h_i^*, as

$$h_{it}(y_{it}) = 1\,[h_{it}^* \geq 0] = 1\left[Z_{it}^{'}\pi + u_{it}^s \geq 0\right] \tag{9}$$

where h_{it} is the binary adoption decision with respect to hybrid maize and h_{it}^* is the latent net benefits of planting hybrid maize. u_{it}^s is the selection error (the unobservable heterogeneity in the adoption selection equation) and the Z_{it} include not just the X_{it}'s from the yield equations, but also the costs and other covariates that may affect the adoption decision. The higher u_{it}^s in equation (9), the more likely the farmer is to plant hybrid maize. Comparing this to the strict Roy model (without costs) where the adoption decision was driven purely by differences in yields, h_{it}^* would just be $y_{it}^H - y_{it}^N$ and u_{it}^s would be $u_{it}^H - u_{it}^N$.

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[17]The generalized Roy model still imposes the restriction that the selection rule can be expressed as a single index function. I consider the appropriateness of this restriction when I discuss my results.

Using a generalized yield function of the form

$$y_{it} = h_{it}y_{it}^H + (1 - h_{it})y_{it}^N \tag{10}$$

I can substitute in equations (3) and (4) to get

$$y_{it} = \beta_t^N + (\beta_t^H - \beta_t^N)h_{it} + X_{it}'\gamma^N + X_{it}'(\gamma^H - \gamma^N)h_{it} + u_{it}^N + (u_{it}^H - u_{it}^N)h_{it} \tag{11}$$

Equation (11) illustrates the standard selection problem. If farmers know all or some part of the errors u_{it}^H and u_{it}^N and act on what they know, then the decision to adopt hybrid, h_{it}, will generally be correlated with these errors (and hence with the composite error $u_{it}^N + (u_{it}^H - u_{it}^N)h_{it}$ in equation (11)). The OLS estimate of $\beta_t^H - \beta_t^N$ (and of the average treatment effect) is therefore biased, with the bias composed of both a selection bias and a sorting bias (see Heckman and Li (2003)). For example, it may be the case that the farmers who plant hybrid may just have higher soil quality land and/or better farm management (all of which are unobservable). Heterogeneity of this fixed unobservables form has been emphasized in the literature, in particular with respect to farm management (see Mundlak (1961)), productivity of farmers, and soil quality (see Conley and Udry (2003) and Tittonell (2003)). In addition, there may even be heterogeneity in returns to hybrid maize such that the farmers with the high returns to hybrid maize are the ones who plant it. The average returns to hybrid maize computed by comparing farmers who plant hybrid to those who do not are therefore overstated. My aim is to present a model that can account for both these ideas.

In equation (11), the correlation of h_{it} with $(u_{it}^H - u_{it}^N)$ is an issue. I will start with a general decomposition of the u_{it}^H and u_{it}^N errors to allow for the possibility that the expected gain to hybrid varies across farmers. The thought experiment is to consider a farmer i who experiences low yields (say in the bottom quartile) when he plants non-hybrid maize. This can be either permanent or transitory low yields - I will be more specific later. For this farmer i, $y_{it}^N < \bar{c}_t$ where $\bar{c}_t$ is the percentile cut-off to be in the bottom quartile of non-hybrid yields. His percentage gain in yields is given by (assuming no X_{it}'s for simplicity) $E\left[y_{it}^H - y_{it}^N \mid y_{it}^N < \bar{c}_t\right] = \beta_t^H - \beta_t^N + E\left[u_{it}^H - u_{it}^N \mid y_{it}^N < \bar{c}_t\right]$. Similarly, for a farmer who experiences high yields under non-hybrid maize (in the upper quartile, say) so that $y_{it}^N > \bar{k}_t$, his expected gains will be $E\left[y_{it}^H - y_{it}^N \mid y_{it}^N > \bar{k}_t\right] = \beta_t^H - \beta_t^N + E\left[u_{it}^H - u_{it}^N \mid y_{it}^N > \bar{k}_t\right]$. I want a structure on the errors, u_{it}^H and u_{it}^N, that allows these two expected gains to be *different* given the return to hybrid looks higher for the farmers in the lowest quartile of the non-hybrid yield distribution.

I therefore consider the following factor structure on the errors[18]:

$$u_{it}^H = \theta_i^H + \xi_{it}^H \tag{12}$$

$$u_{it}^N = \theta_i^N + \xi_{it}^N \tag{13}$$

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[18]This assumption is similar to the factor assumptions made in Carneiro, Hansen and Heckman (2003), except that I exploit the panel nature of the problem and assume the correlated factors are time-invariant.

The ξ_{it}^H and ξ_{it}^N are assumed to be uncorrelated with each other, as well as with the X_{it}'s and Z_{it}'s, unlike the θ_i^H and θ_i^N. This assumption amounts to the transitory errors ξ_{it}^H and ξ_{it}^N not being allowed to affect the farmer's decision to use hybrid, though the θ_i^H and θ_i^N will. The timing of the production of maize and the fact that it is all rain fed is important here. Farmers are assumed to know their θ_i^H and θ_i^N, but not the ξ_{it}^H and ξ_{it}^N. The seed type (hybrid or non-hybrid) is usually fixed before the ξ_{it} shock is realized. Most farmers plant right before the onset of rains or at the onset of rains (though this is late), but the extent of the rains is unknown. Inputs such as labor and fertilizer may be correlated with the shock, for example rainfall, but the key is that I observe rainfall. So, conditional on the covariates affecting yields I have in my data (most importantly, seasonal rainfall), the assumptions underlying the ξ_{it}^H and ξ_{it}^N are more defendable.

The above structure on the errors allows for maize variety specific unobservables, θ_i^H and θ_i^N, to affect yields under hybrid and non-hybrid maize respectively. However, it is only possible to identify a relative relationship between the θ_i^H and θ_i^N unobservables. It is this relative relationship that leads to the idea of comparative advantage in technology adoption and what role this comparative advantage plays, if any, in returns to hybrid technologies.

Substituting the factor structure on the errors into the yield equations in (3) and (4), I get

$$y_{it}^H = \beta_t^H + \theta_i^H + X_{it}\gamma^H + \xi_{it}^H \tag{14}$$
$$y_{it}^N = \beta_t^N + \theta_i^N + X_{it}\gamma^N + \xi_{it}^N \tag{15}$$

Following Heckman and Honore (1991), Lemieux (1998) and others, I use the linear projections of the θ_i^H and the θ_i^N on $(\theta_i^H - \theta_i^N)$ as follows

$$\theta_i^H = b_H(\theta_i^H - \theta_i^N) + \tau_i \tag{16}$$
$$\theta_i^N = b_N(\theta_i^H - \theta_i^N) + \tau_i \tag{17}$$

where, by construction, the projection coefficients are $b_H = (\sigma_H^2 - \sigma_{HN})/(\sigma_H^2 + \sigma_N^2 - 2\sigma_{HN})$, $b_N = (\sigma_{HN} - \sigma_N^2)/(\sigma_H^2 + \sigma_N^2 - 2\sigma_{HN})$ and $\sigma_{HN} \equiv cov(\theta_i^H, \theta_i^N)$, $\sigma_H^2 \equiv Var(\theta_i^H)$, and $\sigma_N^2 \equiv Var(\theta_i^N)$[19]. I define the τ_i to be the absolute advantage as its effect on yields does not vary by the choice of hybrid/non-hybrid. I define $\theta_i^H - \theta_i^N$ to be the comparative advantage gain from growing hybrid, which is orthogonal to the absolute advantage by construction. I can then re-define this comparative advantage gain to be θ_i as follows:

$$\theta_i \equiv b_N(\theta_i^H - \theta_i^N) \tag{18}$$

This is just a redefinition of the sector specific unobservables θ_i^H and θ_i^N. The θ_i serves as a

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[19]The τ_i's in equations (16) and (17) are the same. Subtracting equation (17) from equation (16) implies that $\theta_i^H - \theta_i^N = (b_H - b_N)(\theta_i^H - \theta_i^N)$. For the τ_i's to be equal across sectors, $b_H - b_N$ must be equal to 1, which is easily shown: $b_H - b_N = \frac{\sigma_H^2 - \sigma_{HN} - \sigma_{HN} + \sigma_N^2}{\sigma_H^2 + \sigma_N^2 - 2\sigma_{HN}} = 1$.

measure of comparative advantage in my model. Recall that it is possible to identify only the relative effect of θ_i in the hybrid sector, see Carneiro, Hansen and Heckman (2003). Allowing $\psi \equiv b_H/b_N$, equations (16) and (17) become

$$\theta_i^H = \psi\theta_i + \tau_i \tag{19}$$

$$\theta_i^N = \theta_i + \tau_i \tag{20}$$

Substituting these back into equations (14) and (15),

$$y_{it}^H = \beta_t^H + \tau_i + \psi\theta_i + X_{it}\gamma^H + \xi_{it}^H \tag{21}$$

$$y_{it}^N = \beta_t^N + \tau_i + \theta_i + X_{it}\gamma^N + \xi_{it}^N \tag{22}$$

The expected gain for a farmer from using hybrid is now a function of both observed and unobserved household characteristics:

$$B_{it} = y_{it}^H - y_{it}^H = (\beta_t^H - \beta_t^N) + (\psi - 1)\theta_i + X_{it}'(\gamma^H - \gamma^N) \tag{23}$$

These descriptions of the logarithmic production functions for the case of heterogeneous returns map back into a generalized version of the Cobb-Douglas production functions I started with so that $Y_{it}^H = e^{\tau_i}e^{\theta_i^\psi}e^{\beta_t^H}\left(\prod_{j=1}^{k} X_{ijt}^{\gamma_j^H}\right)e^{\xi_{it}^H}$ and similarly for Y_i^N except without the $e^{\theta_i^\psi}$ term. The motivation for this structure of production functions comes from the fact that hybrid maize increases mean yields and reduces the variance in yields. We would expect individuals who are in the lower tail of the non-hybrid distribution (who have bad outcomes) to benefit the most from the use of hybrid maize. The production functions illustrate these properties directly: when $\psi < 1$, farmers with $\theta_i < 0$ will have high rewards from hybrid maize (and low rewards if $\psi > 1$), while farmers with $\theta_i > 0$ will have lower rewards from hybrid maize (vice versa if $\psi > 1$).

I can substitute equations (19) through (22) into the generalized yield equation (10) to derive

$$y_{it} = \beta_t^N + \alpha_i + (\beta_t^H - \beta_t^N)h_{it} + X_{it}'\gamma^N + \phi\theta_i h_{it} + X_{it}'(\gamma^H - \gamma^N)h_{it} + \varepsilon_{it} \tag{24}$$

where $\phi \equiv (\psi - 1)$ is the coefficient on the household specific comparative advantage component θ_i and $\alpha_i \equiv \theta_i + \tau_i$. ε_{it} is assumed to be the unanticipated component of yields where $\varepsilon_{it} = \xi_{it}^N + (\xi_{it}^H - \xi_{it}^N)h_{it}$. The coefficient on h_{it}, $\phi\theta_i$, depends on the unobserved household-specific effect θ_i, implying a random coefficient model.

The coefficient on h_{it}, $\phi\theta_i$, is correlated with decisions to adopt (i.e. h_{it} itself). Thinking in terms of the generalized Roy model framework, the household-specific expected gain B_{it} is allowed to enter the latent index determining sector choice, h_{it}. Hence, the coefficient $\phi\theta_i$ is generally correlated with the dummy variable h_{it} if agents use their expected gains from growing hybrid in deciding whether or not to plant hybrid. This framework implies a correlated random

coefficient (CRC) model, which I show in the empirical work is a generalization of Chamberlain's (1984) correlated random effects (CRE) model where household-specific intercepts are allowed to be correlated with h_{it}. The CRC model allows both the household-specific intercepts as well as household-specific slopes/returns to be correlated with h_{it}. As I discuss in detail, this model can be estimated via methods similar to those introduced by Chamberlain (1984).

θ_i and τ_i are uncorrelated by construction, and since the household-specific slope is $\phi\theta_i$, the covariance between individual specific slopes and intercepts in the yield function is:

$$cov(\alpha_i, \phi\theta_i) = \phi\sigma_\theta^2 \tag{25}$$

The structural coefficient ϕ therefore determines whether high intercept households also have the higher returns to hybrid maize. If $\phi > 0$, then $\psi > 1$, and the use of hybrid inflates the role of comparative advantage in the hybrid sector. In the long run, this would lead to greater inequality in yields in the overall economy.

Equation (24) is a generalization of the household fixed effects model. To illustrate this, let $\psi = 1$ so that there is now the same fixed unobservable heterogeneity (for example, due to farm management, farmer productivity or soil quality) that affects yields irrespective of the type of maize seed planted. This imposes very specific assumptions on the error structure, in particular that $u_{it}^H = \alpha_i + v_{it}^H$ and $u_{it}^N = \alpha_i + v_{it}^N$ and that the difference $(v_{it}^H - v_{it}^N)$ must be independent of the selection rule. This implies that the timing of the decision to use hybrid maize at any point in time is independent of the yield difference facing a farmer at that time.

The yield function corresponding to this error structure is the fixed effects version of equation (24):

$$y_{it} = \beta_t^N + \alpha_i + (\beta_t^H - \beta_t^N)h_{it} + X_{it}'\gamma^N + X_{it}'(\gamma^H - \gamma^N)h_{it} + \varepsilon_{it} \tag{26}$$

where $\varepsilon_{it} = v_{it}^N + (v_{it}^H - v_{it}^N)h_{it}$. The expected gain to growing hybrid is therefore:

$$B_{it} = (\beta_t^H - \beta_t^N) + X_{it}'(\gamma^H - \gamma^N) \tag{27}$$

In this fixed effects model, the expected gain from hybrid in equation (27) can vary across households as long as it is a function of the observable X_{it}'s. But, the unobservable heterogeneity or fixed effect α_i is restricted to affect yields identically whether or not a farmer uses hybrid. The fixed effect therefore does not appear in equation (27). The fixed effects yield function can be estimated from two periods of panel data on the same farmers under the assumption that, conditional on the α_i, the error in the yield function is uncorrelated with the decision to adopt hybrid maize. This requires that the source of heterogeneity driving the endogeneity must manifest itself in an α_i that is fixed across households and that does not vary by the hybrid/non-hybrid choice.

The main contribution of this paper is to relax the assumption that the return to hybrid maize varies by only observable dimensions across households. I draw on recent empirical studies in labor economics that allow for generalizations to the fixed effects model, and use the framework

described above that allows for comparative advantage in the adoption decision. Advances in techniques have been made in the context of experimental data (for example, Heckman, Smith and Clements (1997)) and in cross sectional data where the covariate of interest is a stock variable like schooling. I use the panel nature of my data and build upon the approaches of Lemieux (1993, 1998) and Card (1996)[20]. To estimate the model in equation (24), I generalize the multivariate regression/minimum distance approach of Chamberlain (1984) to allow for heterogeneous coefficients.

5 Baseline Results

I begin the empirical work by looking at the OLS and household fixed effects specifications as a baseline to the heterogeneous returns model. Table 3 shows these OLS and household fixed effects results for specifications with and without covariates. The OLS and household fixed effects results reported here are for a simplified version of equation (26):

$$y_{it} = \delta + \beta h_{it} + X'_{it}\gamma + \alpha_i + u_{it} \qquad (28)$$

Comparing this to equation (26), allowing $\beta_t^H - \beta_t^N \equiv \beta_t$, I have assumed that $\beta_t = \beta \; \forall t$. In addition, I have assumed that $\gamma^H = \gamma^N = \gamma$. I will relax the latter of these assumptions in later results. The former can be relaxed but relaxing it is empirically unimportant - the results from the more complicated model that allows for time-varying β's are similar so I report results for the simpler model throughout.

The OLS estimates in the first column of Table 3 are extremely large and positive: households that plant hybrid maize tend to have much higher maize yields, on the order of 100% higher. Also note the strong time trends in yields for my sample of households over this period. Adding province dummies in the second column of Table 3 decreases the coefficient on hybrid, as there are strong differences across provinces in both yields and hybrid use. In the third column, I add covariates to the specification. The purpose of these covariates is to control for other household variables that could affect yields, and that may be correlated with the use of hybrid maize, mostly inputs. They include land acreage, fertilizer (results are robust to whether quantities or total expenditure are used), land preparation costs, seed quantity, variables that measure labor inputs (both hired and family labor where possible), long term mean seasonal rainfall, current seasonal rainfall, year dummies and province dummies. Adding these covariates decreases the OLS coefficient further, though it is still quite large at 56%. The fourth and fifth columns of Table 3 report the household fixed effects results. The coefficient on hybrid decreases dramatically, though with covariates the difference between the OLS and fixed effects is less substantial. There is still a substantial return to hybrid maize even within households, controlling for fixed unobservable heterogeneity and a wide set of covariates, on the order of 15%.

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[20]Some of these issues have been debated in the literature on the return to unionization, see Vella and Verbeek (1998), Green (1991) and Robinson (1989) for examples.

This household fixed effects framework is restrictive in the assumptions it imposes on the adoption process and the comparison of the adopters and non-adopters. A consequence of the restrictions it imposes is that there is assumed to be no difference between farmers who switch into the use of hybrid and those that switch out of the use of hybrid. The α_i allows some farmers to be more productive overall (higher α_i), but the difference across the hybrid and non-hybrid sectors is the same for all farmers, irrespective of their transition histories. Apart from the permanent component in the outcome equation, α_i, the adoption decision cannot depend on observed outcomes except under restrictive assumptions on the transitory component (see Ashenfelter and Card (1985)). Such assumptions can be motivated by myopia or ignorance of the potential gains from planting hybrid, but they are unrealistic here[21]. In addition, as emphasized by Card (1998), the fixed effects model requires that the selection bias for a given characteristic, such as farmer experience or soil quality, must be of the same sign for all individuals. It does not allow, for example, selection into hybrid to be positive for people with low education, say, but negative for those with high education.

For various agronomic and economic factors, such as the slow spread of information and the credit constraints that are alluded to in the literature, it is reasonable to allow for a distribution of returns to the technology that relies on both observed and unobserved factors. The household fixed effects model may therefore not be appropriate for the question at hand. The rest of this section describes tests of the household fixed effects model, and some intuitive evidence for selection and heterogeneity in returns.

5.1 Two Period CRE Model

The household fixed effects estimates are consistent only under the assumption of strict exogeneity of the errors. Chamberlain's CRE approach provides a basis for testing this assumption (see Chamberlain (1984) and Jakubson (1991)). I illustrate the simple two period, no covariates CRE model, for which the data generating process is given by

$$y_{it} = \delta + \beta h_{it} + \alpha_i + u_{it} \tag{29}$$

The assumption of strict exogeneity of the errors is:

$$E(u_{it}|h_{i1}, ..., h_{iT}, \alpha_i) = 0 \tag{30}$$

CRE illustrates how the fixed effects model is overidentified. Replace the fixed effect, α_i, by its linear predictor based on the history of the covariates:

$$\alpha_i = \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + v_i \tag{31}$$

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[21]Hybrid maize was introduced in the 1960's, with widespread use of extension services to promote the technology. See Evenson and Mwabu (1998).

where the projection error v_i is uncorrelated with h_{i1} and h_{i2} by construction, and the λ's are the projection coefficients. Substituting this linear projection into the yield equation,

$$y_{it} = \delta + \beta h_{it} + \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + v_i + u_{it} \tag{32}$$

Let $\epsilon_{it} = v_i + u_{it}$ where $E[\epsilon_{it} h_{i1}] = E[\epsilon_{it} h_{i2}] = 0$. For each time period, therefore:

$$y_{i1} = (\delta + \lambda_0) + (\beta + \lambda_1) h_{i1} + \lambda_2 h_{i2} + \epsilon_{i1} \tag{33}$$

$$y_{i2} = (\delta + \lambda_0) + \lambda_1 h_{i1} + (\beta + \lambda_2) h_{i2} + \epsilon_{i2} \tag{34}$$

These are the structural yield equations for each period. I estimate reduced form yield functions for each period of the form

$$y_{i1} = \delta_1 + \gamma_1 h_{i1} + \gamma_2 h_{i2} + \eta_{i1} \tag{35}$$

$$y_{i2} = \delta_2 + \gamma_3 h_{i1} + \gamma_4 h_{i2} + \eta_{i2} \tag{36}$$

Equations (33) through (36) show how the fixed effects model is overidentified. From the four reduced form coefficients, $\gamma_1, \gamma_2, \gamma_3$ and γ_4, I can estimate the three structural parameters, λ_1, λ_2 and β using minimum distance. It is important to note that estimating the CRE model does not require a specification of the conditional expectation of the α_i. Neither does it require knowledge of the *true* conditional expectation of the α_i.

The intuition behind the identification of the CRE model comes from the underlying assumption of the strict exogeneity of the errors. If the fixed effects model is valid, then the only way the history of h_{it} (both past and future) affects the current outcome is through the household level unobservable, α_i. The identification of β comes from those individuals who switch hybrid status h_{it} during the course of the panel. Conditional on α_i and the included regressors, the switching behavior is taken to be exogenous and driven by transitory factors uncorrelated with the rest of the model. This is testable with panel data as described above. The structural estimates are overidentified even in the two period case. The minimum distance estimator of the structural parameters is also the minimum χ^2 estimator if the weight matrix used is the inverse of the variance covariance matrix of the reduced form coefficients. This is called the optimal minimum distance (OMD) estimator. If the identity matrix is used as the weight matrix instead, the estimates are referred to as equally weighted minimum distance (EWMD) estimates. The OMD estimates are efficient, but they can be biased in small samples and can therefore be out-performed by EWMD (see Altonji and Segal (1996)). Throughout, I report both sets of estimates, as well as the χ^2 statistics on the OMD problem, which are just the value of the minimand in the OMD problem.

Estimates of the CRE model for three periods, both with and without covariates are shown in Table 4. In the CRE model, covariates can be treated as either exogenous or endogenous. Exogenous covariates enter the model in equation (29), but are assumed to be uncorrelated with the fixed effect so that they do not enter the projection in equation (39). Endogenous

17

covariates, on the other hand, are correlated with the fixed effect and enter the projection. The CRE model therefore allows tests of whether covariates are endogenous. I report estimates where all covariates (other than the choice to plant hybrid) are assumed to be exogenous, though allowing for endogenous covariates does not change the results.

Table 4 shows both the reduced form and structural estimates for various specifications. The reduced forms in the upper panel of Table 4 give nine reduced form parameters (not including the constants or covariates), from which I use minimum distance to estimate the four structural estimates, shown in the lower panel of the table. Three of these structural estimates are the λ's from the linear projection of the fixed effects and the fourth is the estimate of the return to hybrid, β. The CRE estimates of β in all cases are very close to the household fixed effects estimates in Table 3, as expected. The OMD and EWMD estimates of β are quite similar, all within sampling error of each other. The last column in the lower panel of Table 4 shows the χ^2 values on the overidentification test. In all cases, I can reject the null that the minimum distance restrictions hold. This overidentification test is an omnibus test. It has low power against any specific alternative, but it does have power against many alternatives. It is therefore not surprising that I am able to reject the overidentifying restrictions.

5.2 Preliminary Evidence of Heterogeneity

To motivate my framework of heterogeneous returns, I report some tests for heterogeneity (see Heckman, Smith and Clements (1997)). These are *purely* for illustrative purposes, as they ignore the role of selection and assume that the data is experimental, i.e. that farmers using hybrid and non-hybrid maize are the same on average. This is an extremely strong assumption. Let the conditional yield distributions for the adopters and non-adopters of hybrid be $F^H(y^H|h = 1)$ and $F^N(y^N|h = 0)$ respectively (shown in Figures 6a, 6b and 6c). The conditional distributions allow us to bound the unknown joint distribution of interest, $F(y^H, y^N|h = 1)$, via the Frechet-Hoeffding bounds[22] which also bound the variance, $Var(y^H - y^N)$. A test of whether the lower bound of $Var(\Delta y)$ is significantly different from zero is a test for heterogeneity in returns. I can look at whether each percentile of the hybrid and non-hybrid yield distributions differs by a common constant with the null hypothesis $H_0 : q(y^H) - q(y^N) = k$ for all q such that $0 \leq q \leq 100$[23]. Figures 7a, 7b and 7c show the differences in percentiles of the returns distributions, assuming perfect positive dependence, and Figures 8a and 8b show similar plots for my samples of joiners (farmers who do not use hybrid one period but do the next) and leavers (vice-versa). Appendix Table A2 shows the full set of results where I can reject the null hypothesis above.

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[22]The Frechet-Hoeffding bounds are given by:

$$\max \left[F^H(y^H|h = 1) + F^N(y^N|h = 1) - 1, 0 \right] \leq F(y^H, y^N|h = 1) \leq \min[F^H(y^H|h = 1), F^N(y^N|h = 1)]$$

[23]I need to make assumptions about the dependence in the hybrid and non-hybrid conditional yield distributions. The two extreme dependence assumptions are perfect positive dependence (the individual at the 99th percentile in the hybrid distribution would be at the 99th percentile of the non-hybrid distribution had he not planted hybrid) and perfect negative dependence, where the percentile rankings are assumed to be reversed.

5.3 Evidence of Selection

Assuming away selection is hardly tenable; in Table 5, I look for evidence of selection. I split the adoption history into dummies describing the transitions of households across technologies over the three periods. The idea is to look at whether households with different transition histories have different returns in terms of yields to planting hybrid (see Card and Sullivan (1988)). To understand transition histories, I define a "joiner" to be a farmer who does not plant hybrid the first period, but does the next, and a "leaver" to be a farmer who plants hybrid one period, but not the next. Similarly, I define a "hybrid stayer" to be a farmer who plants hybrid in both periods and a "non-hybrid stayer" to be one who plants traditional varieties in both periods. Under a household fixed effects model, the selection is reflected by the coefficients on the stayers and leavers in the periods in which they are not growing hybrid.

I look at each pair of periods in my data and compare yields for the hybrid and non-hybrid stayers, the joiners, and the leavers in each of the two periods separately to learn about the extent of selection. For example, the first two columns in Table 5 look at the transitions of households over 1997-2000, with the omitted group being the non-hybrid stayers. The first and second columns of this table compare the yields in 1997 and 2000 for hybrid stayers, joiners and leavers in 1997 and 2000 separately. If there was no selection at all (not even via a household fixed effect), we would expect the coefficient on the leavers in the yield equation for 1997 to be no different from the coefficient on the stayers, and also no different from the coefficient on the joiners in the yield equation for 2000. Similarly, the coefficient on joiners in the yield equation for 1997 would be no different from zero, as should the coefficient on the leavers in the yield equation for 2000. Hence, the coefficient on the leavers and joiners across the two yield equations illustrates the extent of selection. Table 5 reports similar estimates for 2000-2004 and 1997-2004. The hybrid stayers uniformly get the largest yields and the leavers and joiners get very different changes in yields when they switch their adoption status.

In Table 6, I look for heterogeneity in returns to hybrid seed along observable dimensions. This relaxes the assumption that $\gamma^H = \gamma^N = \gamma$ in the OLS and FE estimations reported above. Table 6 reports results for yield functions estimated separately for hybrid and non-hybrid households. I report both the OLS as well as household fixed effects specifications. The returns to observables differ by the use of hybrid, especially in the cases of fertilizer and rainfall. This holds for both the OLS as well as the household fixed effects specifications. The last row of Table 6 reports estimates of the return to hybrid (evaluated at the mean X_{it}'s) for the case where the returns to observables are allowed to vary across hybrid and non-hybrid use. There is a significant return to hybrid for both the OLS and fixed effects specifications, even after allowing for returns to vary by the observables.

6 Estimating a Model with Heterogeneous Returns

The model of heterogeneous returns outlined earlier implies the following econometric model in maize yields for the simple two period, no covariates case:

$$y_{it} = \delta + \beta h_{it} + \alpha_i + \phi \theta_i h_{it} + \epsilon_{it} \tag{37}$$

For simplicity, I focus only on hybrid maize and leave out other inputs to explain the empirical strategy and then discuss extensions. The model above[24] can be estimated as per Lemieux (1998), using non-linear 2SLS. Instead, I extend the basic Chamberlain CRE approach to a scenario of correlated random coefficients. This may be somewhat easier and allows a χ^2 overidentification test, similar to that described above. The next sections are devoted to describing my estimation and identification strategy, keeping in mind the intuition of the CRE approach. I then describe extensions to this basic model and the estimation results.

6.1 Two Period CRC Model

For the simple two period, no covariates case, the yield function is given by equation (37) above. The key identifying assumption here is that, conditional on the comparative advantage component $\phi \theta_i h_{it}$ (and the covariates in the more general specifications), the unanticipated component of yields, ε_{it}, is not correlated with the decision to adopt. Remembering that $\alpha_i \equiv \theta_i + \tau_i$, where θ_i and τ_i are orthogonal, I re-write equation (37) as

$$y_{it} = \delta + \theta_i + \beta h_{it} + \phi \theta_i h_{it} + \tau_i + \varepsilon_{it} \tag{38}$$

Using the same idea as CRE, I linearly project the θ_i's onto the history of the hybrid decisions, as well as their interactions so that the projection error is orthogonal to h_{i1} and h_{i2} individually as well as to their product, $h_{i1}h_{i2}$ by construction[25]. The projection is given by

$$\theta_i = \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i1} h_{i2} + v_i \tag{39}$$

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[24] This empirical model is similar to models of individual specific heterogeneity in Heckman and Vytlacil (1997), Card (2000, 1998), Deschênes (2001), Carneiro, Hansen and Heckman (2001), Carneiro and Heckman (2002), and Wooldridge (1997). Lemieux (1998) has a very similar model to look at whether the return (in terms of wages) to both observables and unobservables varies by union sector membership.

[25] The projection I use here is different from what CRE uses. If I use the simple CRE projection, $\theta_i = \lambda_1 h_{i1} + \lambda_2 h_{i2} + v_i$, and substitute this into the yield function,

$$y_{it} = \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \beta h_{it} + \phi \lambda_0 + \phi \lambda_1 h_{i1} h_{it} + \phi \lambda_2 h_{i2} h_{it} + v_i + \phi v_i h_{it} + u_{it}$$

Even though v_i, the projection error, is linearly uncorrelated with h_{i1} and h_{i2} individually, it is generally correlated with their product, $h_{i1}h_{i2}$, so that $E[v_i h_{i1} h_{i2}] \neq 0$. The projection I use must therefore include the interactions of the hybrid histories.

In addition, I normalize the θ_i's so that $\sum \theta_i = 0$. Since h_{it} is a dummy variable, substituting the above projection into the yield equations gives:

$$y_{it} = \delta + \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i1} h_{i2} + \beta h_{it} + \phi \lambda_0 h_{it} + \phi \lambda_1 h_{i1} h_{it} + \phi \lambda_2 h_{i2} h_{it} + \phi \lambda_3 h_{i1} h_{i2} h_{it} + v_i + \phi v_i h_{it} + u_{it} \tag{40}$$

For each of the two time periods, the yield functions are:

$$y_{i1} = (\delta + \lambda_0) + [\lambda_1(1+\phi) + \beta + \phi \lambda_0] h_{i1} + \lambda_2 h_{i2} + [\lambda_3(1+\phi) + \phi \lambda_2] h_{i1} h_{i2} + (v_i + \phi v_i h_{i1} + u_{i1}) \tag{41}$$

$$y_{i2} = (\delta + \lambda_0) + \lambda_1 h_{i1} + [\lambda_2(1+\phi) + \beta + \phi \lambda_0] h_{i2} + [\lambda_3(1+\phi) + \phi \lambda_1] h_{i1} h_{i2} + (v_i + \phi v_i h_{i2} + u_{i2}) \tag{42}$$

The corresponding reduced forms are:

$$y_{i1} = \delta_1 + \gamma_1 h_{i1} + \gamma_2 h_{i2} + \gamma_3 h_{i1} h_{i2} + \xi_{i1} \tag{43}$$

$$y_{i2} = \delta_2 + \gamma_4 h_{i1} + \gamma_5 h_{i2} + \gamma_6 h_{i1} h_{i2} + \xi_{i2} \tag{44}$$

Equations (43) and (44) give six reduced forms coefficients ($\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5$ and γ_6), from which I can estimate the five structural parameters ($\lambda_1, \lambda_2, \lambda_3, \beta$ and ϕ) using minimum distance[26]. The structural parameters are clearly overidentified and the restrictions for the minimum distance problem are:

$$
\begin{aligned}
\gamma_1 &= (1+\phi)\lambda_1 + \beta + \phi \lambda_0 \\
\gamma_2 &= \lambda_2 \\
\gamma_3 &= (1+\phi)\lambda_3 + \phi \lambda_2 \\
\gamma_4 &= \lambda_1 \\
\gamma_5 &= (1+\phi)\lambda_2 + \beta + \phi \lambda_0 \\
\gamma_6 &= (1+\phi)\lambda_3 + \phi \lambda_1
\end{aligned}
\tag{45}
$$

I now discuss extensions to this basic model and whether the θ_i's themselves can be recovered from this estimation.

6.2 Extensions

I consider the following extensions:

1. Covariates: all the identification arguments presented above generalize when the model includes covariates. Covariates in the CRE model can be thought of as either exogenous or endogenous, the latter implying that they are correlated with the fixed effects. Allowing for

---

[26] There may seem to be six structural parameters, given the presence of λ_0 in equations (39) and (45). However, given the normalization that $\sum \theta_i = 0$, then λ_0 is just a function of the hybrid histories, their interactions and the other λ's. In particular, $\lambda_0 = -\lambda_1 \overline{h_{i1}} - \lambda_2 \overline{h_{i2}} - \lambda_3 \overline{h_{i1} h_{i2}}$ where $\overline{h_{i1}}$ and $\overline{h_{i2}}$ are the averages of the adoption decisions of households in periods one and two, and $\overline{h_{i1} h_{i2}}$ is the average of the interaction.

endogenous covariates in CRE is straight forward: all the leads and lags of the endogenous covariates are included in the projection. The CRC model is slightly more complicated and can become cumbersome. Endogenous covariates are defined similarly - they are correlated with the θ_i's. I allow for fertilizer to be an additional endogenous covariate so that the CRC projection generalizes to

$$
\begin{aligned}
\theta_i \;=\; & \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i1} h_{i2} + \lambda_4 h_{i1} f_{i1} + \lambda_5 h_{i2} f_{i1} + \lambda_6 h_{i1} h_{i2} f_{i1} \\
& + \lambda_7 h_{i1} f_{i2} + \lambda_8 h_{i2} f_{i2} + \lambda_9 h_{i1} h_{i2} f_{i2} + \lambda_{10} f_{i1} + \lambda_{11} f_{i2} + v_i
\end{aligned}
\tag{46}
$$

where f_{it} for $t = 1, 2$ represents the use of fertilizer in each period. The other covariates enter the problem in such a way that they are exogenous (uncorrelated with the θ_i's)[27].

2. Three periods: this is a simple extension. For space considerations, I do not show the restrictions for the three period model. The problem becomes heavily overidentified with only 9 structural parameters to estimate from the 21 reduced form coefficients for the base case with no other endogenous covariates. However, as covariates are allowed to be endogenous, the model becomes cumbersome.

3. Joint choice variables: the two-sector model presented above (hybrid/non-hybrid) can be extended to multiple sectors. An additional technology use sector, like fertilizer, can be incorporated by thinking of a four sector model (farmers use either both hybrid and fertilizer, neither, one or the other). I simplify it further. In 1997, for example, 76% of households fit into one of two of the possible four sectors, namely using both hybrid maize and fertilizer or neither. So, I estimate an easier model that redefines sectors to this joint decision (using both hybrid and fertilizer or not) and looks at the heterogeneity in returns across these two sectors.

6.3 CRC Estimates

This section describes various estimates of the CRC model. I report estimates for the pure hybrid model described in detail above (with and without covariates) for both the two and three period cases. In addition, I report results for the endogenous covariate and joint hybrid-fertilizer extensions to the basic model that I described in the previous section. Recall that a covariate is described as endogenous if it is assumed to be correlated with the θ_i's and therefore enters the projection in equations (39) or (46) (similarly, a covariate is exogenous if it is assumed to be uncorrelated with the θ_i's).

Tables 7, 8a, 8b and 9 present the CRC model reduced form and structural estimates. These tables report both the EWMD and OMD estimates for cases with and without covariates, as

---

[27] There is some justification for this. Using the estimates from the pure hybrid problem in Tables 7 and 8, I am able to look at the distribution of predicted θ_i's and correlate this with the covariates. Of all the covariates, only the correlations between the θ_i's and fertilizer are important in magnitude and significance.

well as the χ^2 statistics on the overidentification tests for the OMD cases. The coefficient of interest is ϕ, i.e. the coefficient on the individual specific comparative advantage components, θ_i. Table 7 presents the two period reduced forms for the CRC model, both with and without covariates, using data for 1997 and 2004. These are the reduced form estimates for the most basic specification described above where hybrid is the only endogenous variable and the projection used is given by equation (39). Table 8a reports the structural estimates for this specification: the OMD and EWMD results, along with the χ^2 statistics, all with and without covariates. The estimates of ϕ are consistently negative, though with quite large standard errors in the EWMD cases.

Table 8b presents two sets of structural estimates of ϕ that account for fertilizer possibly entering the household's decision making process regarding hybrid maize instead of restricting it to be exogenous. I do this in two ways. In the upper panel of Table 8b, I allow for the fertilizer covariate to be endogenous in the sense of being correlated with the θ_i's, as in equation (46). Again, the estimates of ϕ in this panel of Table 8b are consistently negative, both with and without covariates as well as across OMD and EWMD. The lower panel in Table 8b reports results for the case where there is a joint hybrid-fertilizer decision on the part of the farmer so that he is in the so called technology sector if he uses both hybrid maize and fertilizer, otherwise he is not. This is similar to the original hybrid model, except the dummy variable for technology is no longer a dummy variable for the use of hybrid maize, but instead it is a dummy variable for whether the farmer is in the technology sector or not. The reason for estimating this model is that in the three period case allowing fertilizer to be directly correlated with the θ_i's as in equation (46) makes the model too cumbersome. Hence, I settle for a simpler model and account for the endogeneity of fertilizer use by describing the joint hybrid-fertilizer decision. I also estimate this model for the two periods case to have comparable results. The results in Table 8b for two periods are consistent with the previous estimates reported for ϕ.

Table 9 shows the structural estimates (the reduced forms are available upon request) for the three period CRC models for two cases: pure hybrid decision and the joint hybrid-fertilizer decision. Recall that there are three reduced forms here, one for each period, that contain all the possible interactions of the three hybrid histories. This implies a total of 21 reduced form estimates that can be mapped onto the 9 structural estimates: 7 λ's from the projection of the θ_i's, the average return to hybrid, β, and the comparative advantage coefficient, ϕ. These results are shown in Table 9; all the the estimates reported allow for the full set of exogenous covariates (acreage, real fertilizer expenditure, land preparation costs, seed, labor variables and rainfall variables). The estimate of ϕ varies across the specifications, though the OMD estimates are consistently negative. For the joint fertilizer-hybrid problem, both the OMD and EWMD are negative and significant.

6.4 Recovering the Distribution of $\widehat{\theta}_i$

Before I move on to the conceptual discussion of my model and estimates, I look briefly at the distribution of the predicted θ_i's. Given the CRC structural estimates of the λ's and the form of the projection given by either equations (39) or (46), I can predict the θ_i's for a given history of hybrid use. However, I must assume that the projections describe the *true* conditional expectation of the θ_i's. This is essentially an assumption only for the case of equation (46) as in the case of equation (39) since h_{it} is binary and each history is accounted for, the projection is saturated. Once I have the predicted distribution of comparative advantage, θ_i, I can derive the distribution of the predicted τ_i's via the yield function.

Figure 9a shows the distribution of the predicted θ_i's in my sample for the two period model with the full set of exogenous covariates (the estimates come from the last column in Table 8a). Since the predicted θ_i's are obtained from the projection in equation (39), the distribution of the predicted θ_i's is just four mass points: think of these as averages of the individual underlying θ_i's for each history and interaction of histories of hybrid use. There are only four possible hybrid histories: hybrid stayers, non-hybrid stayers, leavers and joiners. Hence, there are only four possible values of $\widehat{\theta}_i$: $0.069, -0.369, 0.227$ and 0.403 for the four histories respectively. The non-hybrid stayers have the negative (and lowest) predicted θ_i's and hence the highest returns to hybrid, since $\phi < 0$. Meanwhile the joiners and leavers have the lowest returns (indicating they are the more marginal farmers) and the hybrid stayers have almost zero returns. Figure 9a shows these four mass points in the $\widehat{\theta}_i$ distribution by farmers hybrid use status in 1997. The mass point at the extreme left corresponds to the non-hybrid stayers, the next (moving from left to right) are the hybrid stayers, followed by the leavers and then the joiners.

Figure 9b shows the distribution of the $\widehat{\theta}_i$'s for the case where both hybrid maize and fertilizer use are endogenous (the estimates come from the last column in the upper panel of Table 8b). Here, the distribution of the predicted $\widehat{\theta}_i$'s is continuous since the predicted $\widehat{\theta}_i$'s come from the projection in equation (46). Again, Figure 9b splits out the distribution by hybrid use in 1997. From Figure 9b it is not clear where the four different types of farmers lie in this distribution, but I can look at the mean of the predicted $\widehat{\theta}_i$'s for each hybrid transition history. I find that the mean $\widehat{\theta}_i$ for the non-hybrid stayers is the lowest at -0.236, the hybrid stayers are next at -0.015, followed by the leavers (0.253) and then the joiners (0.437). Finally, Figure 9c shows the corresponding distribution of the predicted τ_i's (which were constructed to be orthogonal to hybrid choice) for 1997 adopters and non-adopters.

7 Robustness Checks

This section presents some robustness checks. As the first robustness check, I look at the standard control function and treatment effect estimates of the yield returns to hybrid maize. This is a broad set of approaches that includes the familiar Heckman two-step estimator, more general control function estimators (see Garen (1984) and Deschênes (2001)), as well as a description of

treatment effects under non-random assignment, i.e. the ATE, TT, MTE and LATE (see Björk-lund and Moffitt (1987), Heckman (2001), Heckman, Tobias and Vytlacil (2001) and Carneiro and Heckman (2002)).

I rewrite equation (11) for one time period,

$$y_i = \left(\beta + X_i'(\gamma^H - \gamma^N) + (u_i^H - u_i^N)\right)h_i + X_i'\gamma^N + u_i^N \equiv \beta_i h_i + X_i'\gamma^N + u_i^N \qquad (47)$$

Estimates of β_i would illustrate whether the average returns of farmers selecting into using hybrid maize are higher than the returns for the farmers at the margin. The reverse is possible such that the marginal return is greater than the average when costs are sufficiently positively correlated with returns (i.e. the farmers with high returns are the farmers that also face high costs). With assumptions of normality on this model, it is possible to estimate the standard cross sectional selection parameters. However, these selection correction procedures are cross sectional in nature and impose distributional assumptions. They do not fully address the issues I am interested in, nor do they fully exploit the panel nature of my data.

The yields in the hybrid and non-hybrid sectors are given by equations (3) and (4), and the selection equation is given by equation (9). Drawing on Heckman, Tobias and Vytlacil (2001), I look at the following treatment effects:

$$ATE(x) = E(\Delta|X = x) = x(\gamma^H - \gamma^N) \qquad (48)$$

$$TT(x, z, h(Z) = 1) = x(\gamma^H - \gamma^N) + (\rho_H\sigma_H - \rho_N\sigma_N)\frac{\phi(z\pi)}{\Phi(z\pi)} \qquad (49)$$

$$MTE(x, u^s) = x(\gamma^H - \gamma^N) + (\rho_H\sigma_H - \rho_N\sigma_N)u^s \qquad (50)$$

where $\Delta = y^H - y^N$ is the yield gain from hybrid, $\rho_H\sigma_H$ and $\rho_N\sigma_N$ correspond to the coefficient on the selection term in a two-step selection model. I assume $Var(u^s) = 1$ so that $\sigma_H^2 = Var(u_i^H)$, $\sigma_N^2 = Var(u_i^N)$, $\rho_H = Corr(u_i^H, u_i^s)$ and $\rho_N = Corr(u_i^N, u_i^s)$. $\phi(.)$ and $\Phi(.)$ represent the normal probability and cumulative distribution functions respectively where $\frac{\phi(z\pi)}{\Phi(z\pi)}$ is the Inverse Mills ratio/selection correction term for the hybrid yield function (a similar selection term is computed for the non-hybrid yields).

These treatment effects in the case of joint normality are simple to compute. They involve a two-step control function procedure: I first run a probit of selection and control for estimates of the selection (Inverse Mills ratio) terms in the second step that looks at sector specific yield functions. The ATE uses the estimates of the coefficients on the X_i's from this second step. The TT adjusts this estimated ATE for the selection into planting hybrid. The MTE looks at the treatment effect as a function of the unobservables in the selection equation: it describes whether people who are more likely to use hybrid for unobservables reasons (the u_i^s) have higher or lower returns from planting hybrid. If the coefficient on u^s in equation (50) is negative, it implies that farmers with unobservables that make them the least likely to use hybrid have the highest yield return to planting hybrid. The MTE is needed to understand whether heterogeneity is

important and the role of unobservables that make farmers more or less likely to use hybrid.

These treatment effects are shown in Table 10 for every cross-section of my data. I need an exclusion restriction (or instrument), i.e. a variable that enters the selection equation (9), but not the yield functions in (3) and (4). I use a variable that describes a household's access to fertilizer and hybrid seed. The survey question that households are asked is what the distance between their homestead and the closest stockist of fertilizer is (not the distance to where fertilizer is actually purchased). This distance measure gives an idea of the access and availability of the technologies. The results are similar if I use the interaction of the same distance variable with asset quantiles as the exclusion restrictions, while allowing the main effects of both asset quantiles and distance to enter the yield equations.

The ATE's (evaluated at the mean of the X_i's) are all extremely large and positive, ranging from 0.756 in 2000 to 2.097 in 1997. The TT estimates are consistently smaller, ranging from 0.677 to 1.374. The MTE slope, meanwhile, is consistently negative across all three samples: –1.769 (with a standard error of 0.775) in 1997, -0.222 (0.370) in 2000 and -0.911 (0.251) in 2004. In two of these cases, the slope of the MTE function with respect to u^s is negative and significantly different from zero. This implies that farmers with unobservables that make them most likely to use hybrid get the lowest returns from hybrid. In addition, I can estimate the instrumental variable (i.e. the LATE) estimate using the same exclusion restriction. The IV estimates of the return to hybrid, reported in the lower panel of Table 10 are extremely large, on the order of 150%, especially when compared to the earlier OLS and household fixed effects estimates.

Next, I look at how the predicted fixed effects, the $\widehat{\alpha}_i$'s from the fixed effects model, and the predicted $\widehat{\theta}_i$'s from the CRC model correlate with farmers' decisions to adopt hybrid maize. I consider only the $\widehat{\theta}_i$'s from the two period model with both hybrid and fertilizer as endogenous decisions (estimates reported in the last column of the upper panel of Table 8b). These results are reported in Table 11. The first two columns in Table 11 examine how the predicted fixed effects affect the probability of adopting hybrid maize. Note that the sign on $\widehat{\alpha}_i$ changes across columns (1) and (2). Without covariates, the higher the $\widehat{\alpha}_i$ the lower the probability of adoption hybrid maize. However, this reverses once I control for covariates. Columns (3) through (5) of Table 11 show how the predicted $\widehat{\theta}_i$'s affect the probability of adopting hybrid maize. They correlate positively with the probability of adoption, which is consistent with the distributions I discussed in Figures 9a and 9b (the hybrid stayers had higher $\widehat{\theta}_i$'s and hence lower returns than the non-hybrid stayers).

Finally, In Table 12, I look at the OLS and household fixed effects estimates of the return to hybrid and the prevalence of hybrid use across what I refer to as predicted fertility quartiles (similar to Card (1996)). Using only the 1997 sample of non-hybrid farmers, I estimate their yield functions based on my set of covariates. I then predict what the expected yield under traditional varieties would be for my entire sample of farmers in 1997. I call this predicted yield an index of fertility. I look across quartiles of this estimated fertility index and compare

the OLS and FE estimates of the hybrid return and the prevalence of hybrid. The results are reported in Table 12. It is clear that across these quartiles, the selection biased OLS estimates of the return to hybrid fall: the highest return is for the farmers in the lowest predicted fertility quartile. However, there is still a significant return even amongst the farmers in the highest fertility quartile. The fixed effect estimates of the return do not change across the quartiles as consistently as the OLS estimates. The estimate of the return for farmers in the upper fertility quartile is essentially zero, while the farmers in the lower fertility quartile still see significant returns. What is puzzling is that the prevalence of hybrid in the upper fertility quartile is actually the highest. I discuss all these results in the next section.

8 Extensions and Discussion

How do the results from the various estimations related to each other and inform the underlying correlations of returns, costs and adoption decisions? In this section, I relate my estimates of ϕ to the estimates from the standard selection model to understand what the estimates of ϕ mean and what the policy relevance of these results is. Recall that I am interested in the parameter ϕ as it signs the relationship between household-specific returns to hybrids and household fixed effects. The ϕ tells us whether the households that do better on average, irrespective of the technology they use, also have the highest returns to hybrid.

I rewrite the factor structure in equations (12) and (13) above for the one period case:

$$
\begin{aligned}
u_i^H &= \psi\theta_i + \tau_i \\
u_i^N &= \theta_i + \tau_i
\end{aligned}
$$

I suppress the transitory components, ξ_i^H and ξ_i^N, for this cross-sectional discussion. To relate this to the selection model described in the previous section, I need expressions for $\rho_H\sigma_H$ and $\rho_N\sigma_N$ in terms of the parameters of these factor structures. Recall that $\rho_H\sigma_H = Cov(u_i^H, u_i^s)$ and $\rho_N\sigma_N = Cov(u_i^N, u_i^s)$ since $Var(u_i^s) = 1$. Using these, I derive an expression for $\rho_H\sigma_H - \rho_N\sigma_N$:

$$
\begin{aligned}
\rho_H\sigma_H - \rho_N\sigma_N &= Cov(u_i^H, u_i^s) - Cov(u_i^N, u_i^s) = Cov(\psi\theta_i, u_i^s) - Cov(\theta_i, u_i^s) \\
&= \phi Cov(\theta_i, u_i^s) \tag{51}
\end{aligned}
$$

In the strict Roy model without costs, $u_i^s = u_i^H - u_i^N = \theta_i$. From equation (51), $\rho_H\sigma_H - \rho_N\sigma_N = \phi\sigma_\theta^2$. Hence, a negative MTE slope must imply that $\phi < 0$. However, in the generalized Roy model with costs $u_i^s = \theta_i - C_i$ where C_i is a measure of relative costs in the hybrid sector that are not in the yield equation. This implies

$$
\rho_H\sigma_H - \rho_N\sigma_N = \phi\sigma_\theta^2 - \phi Cov(\theta_i, C_i) \tag{52}
$$

From the negative slope of the MTE, $\rho_H\sigma_H - \rho_N\sigma_N < 0$. If $\phi > 0$ it implies that $Cov(\theta_i, C_i)$

27

needs to be quite large and positive (enough to outweigh the σ_θ^2). On the other hand if $\phi < 0$, then $Cov(\theta_i, C_i)$ can be either positive and small, or negative. In terms of a generalized Roy model, the sign of ϕ describes something about the covariance between the household level unobservable comparative advantage and the relative costs of planting hybrid maize that are not in the yield equation.

To get an idea of what these costs may be, Table 13 looks at what observables correlate with the predicted $\widehat{\theta}_i$'s. All the results are reported are for the two period model which has endogenous hybrid and fertilizer use (using the estimates in the last column of the upper panel of Table 8b). The observables I consider include the distance from the household to the closest fertilizer seller, the fraction of adult household members with no education, a set of dummies for education of the household head, the distance to the closest tarmac road, the distance to the closest matatu (public transport) stop, the distance to the closest motorable road, a dummy for whether the household tried to get credit, a dummy for whether the household received any credit and province and year dummies. As can be seen from Table 13, the infrastructure and education variables correlate strongly with the predicted $\widehat{\theta}_i$'s, results that hold up even in the presence of finer regional dummies. In addition, the credit variables are not at all correlated with these predicted $\widehat{\theta}_i$'s.

Both from the agronomy of hybrid maize, as well as the kernel density plots in Figure 6, it is clear that hybrid increases productivity, but this increase declines as you move rightward through the distribution, such that the expected return from hybrid is almost zero in the right tail. When $\phi < 0$, the marginal gain is negative, so that the farmers in the left tail have the largest gain. This is seen from the estimates of ϕ as well as the negative selection estimates. If selection is only as per the Roy Model, we would see the largest adoption rates in the left tail, but this ignores the possibility of larger costs and greater constraints for these farmers. The LATE estimates using distance suggest that distance *is* a constraining factor, at least for the lower yielding households. The mirror image of this result is that there seems to be "over-adoption" for the farmers in the right tail, shown by the high prevalence of hybrid in the upper fertility quartile in Table 12. This is also borne out in my estimates of ϕ and the distributions of the $\widehat{\theta}_i$'s in Figures 9a and 9b. This indicates that risk may be an important factor in the adoption decision, since the mean gross returns to hybrid in the upper quartile are close to zero. To account for risk, it would be necessary to allow the variance of the transitory component in yields to play a role in the adoption decision. I leave this to future work.

9   Conclusion

This paper examines the adoption decisions and benefits of hybrid maize in Kenya in a framework that is in stark contrast to the empirical technology adoption literature of the past two decades. Rather than think of adoption decisions as based on learning and information externalities, I focus on a framework that recognizes the large disparities in farming and input

supply characteristics across the maize growing areas of Kenya. Within this framework, I find that returns to hybrid maize vary greatly. Furthermore, those farmers who are on the margin of adopting and disadopting (and who do so during my sample period) experience very little change in yields, a finding consistent with my framework, yet harder to reconcile with a pure learning model.

The experimental evidence points to average high, positive returns to these agricultural technologies. However, these experiments say little else about the returns, sometimes hypothesizing irrationality in decision making to account for patterns of low, non-increasing adoption rates. My framework of heterogeneous returns allows me to estimate not just average returns accounting for selection, but also to have an idea of what the distribution of returns looks like across my sample of farmers. I find extremely strong evidence of heterogeneity in returns to hybrid maize, with comparative advantage playing an important role in yield determination.

The most important findings of my work are the policy implications of heterogeneity in returns. Since I am able to look at a distribution of returns across my sample of farmers, I can separate out farmers with low returns from those with high returns. I find that for a small group of farmers in my sample, returns from hybrid maize would be extremely high, yet they do not adopt hybrid maize. For these farmers, it seems that the important constraints that prevent them from adopting hybrid maize are related to access and infrastructure constraints, measured by the distance to seed/fertilizer distributors. In terms of policy, alleviating these constraints would greatly increase yields for these farmers. However, this is only a small fraction of my sample. For a large fraction of my sample, the returns to hybrid maize are close to zero, yet these farmers choose to adopt. While I do not build risk into the choice framework used in this paper, farmers that are well off can afford to use hybrid maize, even when the mean returns to hybrid are low, since it helps insure them again bad outcomes. For these farmers, since they do not seem to be constrained, they would benefit greatly from new and improved hybrid strains, even if they were costlier than the currently available hybrid varieties. Allowing for the riskiness of yields to affect the adoption decision is left to future work.

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