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SELECTION AND COMPARATIVE ADVANTAGE IN TECHNOLOGY ADOPTION

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This paper investigates an empirical puzzle in technology adoption for developing countries: the low adoption rates of technologies like hybrid maize that increase average farm profits dramatically. I offer a simple explanation for this: benefits and costs of technologies are heterogeneous, so that farmers with low net returns do not adopt the technology. I examine this hypothesis by estimating a correlated random coefficient model of yields and the corresponding distribution of returns to hybrid maize. This distribution indicates that the group of farmers with the highest estimated gross returns does not use hybrid, but their returns are correlated with high costs of acquiring the technology (due to poor infrastructure). Another group of farmers has lower returns and adopts, while the marginal farmers have zero returns and switch in and out of use over the sample period. Overall, adoption decisions appear to be rational and well explained by (observed and unobserved) variation in heterogeneous net benefits to the technology.

KEYWORDS: Technology, heterogeneity, comparative advantage.

1. INTRODUCTION

FOOD SECURITY is a major social and economic issue across many sub-Saharan African economies. Agricultural yields (output per acre) have fallen in the last

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The data come from the Tegemeo Agricultural Monitoring and Policy Analysis (TAMPA) Project, which is between Tegemeo Institute at Egerton University, Kenya and Michigan State University, and is funded by USAID. A special thanks to Thomas Jayne and Margaret Beaver at Michigan State University for all their help. I am sincerely grateful to the Tegemeo Institute and Thomas Jayne for including me in the 2004 survey and to Tegemeo for their hospitality during the field work. I would like to thank James Nyoro, Director of Tegemeo, as well as Tegemeo Research Fellows Miltone Ayieko, Joshua Ariga, Paul Gamba, and Milu Muyanga, Senior Research Assistant Frances Karin, and Research Assistants Bridget Ochieng, Mary Bundi, Raphael Gitau, Sam Mburu, Mercy Mutua, and Daniel Kariuki, and all the field enumeration teams. An additional thanks to Margaret Beaver and Daniel Kariuki for their work on cleaning the data. The rainfall data come from the Climate Prediction Center, part of the USAID/FEWS project: a special thanks to Tim Love for his help with these data.

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TABLE I

TRENDS IN YIELDS OF STAPLES: AVERAGE ANNUAL % CHANGES IN YIELDS (HG/HA) BY DECADE[a]

	1961–1970	1971–1980	1981–1990	1991–2004
Kenya				
Maize	0.362	2.373	1.169	−1.198
Wheat	5.646	2.333	−3.078	0.984
India				
Maize	1.502	0.842	1.900	2.572
Wheat	4.876	2.514	3.343	1.235
Rice	0.954	1.714	3.310	0.838
Mexico				
Maize	2.057	4.267	−0.548	1.447
Wheat	4.586	3.204	−0.255	1.664
Zambia				
Maize	−0.267	10.403	1.571	−1.707

[a]Surprisingly, in the 1960's the levels of yields of maize in Kenya, India, and Mexico were comparable and very similar (all ranging between 10,000 and 12,000 hg/ha). The levels of yields in Zambia were slightly lower (about 8000 hg/ha), whereas those in Uganda and Malawi were comparable to those in Kenya. Source: FAOSTAT Online Database.

decade across many of these economies, despite the widespread availability of technologies that increase yields. For instance, Table I shows the falling yields of staple crops over the last decade in Kenya, compared with increasing yields in India and Mexico. Kenya has clearly not been able to take the same advantage of improvements in agricultural technologies as have India and Mexico during their green revolutions. This is not an isolated example, and is very worrisome for economic policies intended to enhance food production and agricultural incomes.

The leading edge of agricultural technology has improved over the past few decades. Field trials at experiment stations across Kenya have shown that hybrid maize and fertilizers can increase yields and profits of maize significantly, with increases ranging from 40% to 100% (see Gerhart (1975), Kenya Agricultural Research Institute (1993a, 1993b), Karanja (1996)).[2] Despite this, the aggregate adoption rates of hybrid maize and fertilizer remain far below 100%, with no sustained increases in adoption over the past decade. This contrasts with the experience in more developed countries; for example, adoption rates

[2]The Fertilizer Use Recommendations Project (FURP) in Kenya also shows high returns to hybrid maize and fertilizer (see Hassan, Njoroge, Njore, Otsyula, and Laboso (1998b)). These results are confirmed for fertilizer in the small sample of Duflo, Kremer, and Robinson (2008a) for western Kenya. In fact, Duflo, Kremer, and Robinson (2008b) analyzed the rates of return to fertilizer and show high, but variable, returns to fertilizer.

of hybrid in the United States are close to 100% (Griliches (1980), Dixon (1980)).

The facts that improved agricultural technologies are not universally adopted and that adoption rates have remained persistently low over a long period of time illustrate the empirical puzzle that motivates this paper. I find that if farmer heterogeneity is properly taken into account, there is no puzzle. The farmers with high net returns to the technology adopt it and the farmers with low returns do not. Persistent lack of adoption is a reflection of the distribution of (observable and unobservable) costs and benefits of the technology. The approach here models households' adoption decisions in an environment with household-specific heterogeneity in the costs and benefits, and hence profits, to the technology. I estimate how the returns to the technology vary across farmers and then compare these returns to the adoption decisions of farmers. I find that farmers with low (or zero) returns to the technology are precisely the farmers who do not adopt it.

In particular, I use a generalized Roy model along the lines of Heckman and Vytlacil (1998), where the expected profits from hybrid maize are heterogeneous and drive adoption decisions. This theoretical model implies a yield function for maize with a correlated random coefficient structure, which is estimated using a generalization of Chamberlain's (1982, 1984) method for fixed effects models, applied here to a correlated random coefficients model. The estimation results imply a distribution of returns that can endogenously affect adoption decisions. I therefore provide an empirical resolution of the puzzle that, despite high average returns to hybrid use, the marginal returns are low, and, given the infrastructure constraints faced by farmers, adoption decisions are on the whole rational.

The estimation strategy in this paper allows for two different forms of household-specific heterogeneity in maize production: absolute advantage (independent of the technology used) and comparative advantage, which measures the relative productivity of a farmer in hybrid over nonhybrid. The novel econometric contribution here is to analyze the role of comparative advantage in adoption decisions, to empirically estimate its importance, and to estimate its distribution. I also discuss why this approach is preferable in development settings to related approaches used to study firms in developed countries, where the evolution of firm efficiencies is more likely to be important in consistently estimating output and investment equations.

I use an extensive panel data set representative of maize-growing Kenya for the period 1996–2004. I first document the adoption patterns of households for both hybrid maize and fertilizer. Aggregate adoption is stable over the period, but, surprisingly, at least 30% of households switch into and out of hybrid use from period to period.[3] The panel structure of the data allows me to identify the distribution of returns to hybrid maize and to estimate the correlated

[3]This lack of a trend with underlying switching of use from period to period is seen in other parts of Africa. Dercon and Christiaensen (2005) found identical patterns for fertilizer use in

random coefficient structure of the underlying yield functions. The panel also allows me to construct counterfactual distributions of returns for all the farmers in the sample, including those who do not use hybrid. It is important for identification that some farmers switch in and out of use of the technology, and also that there are farmers in the sample who use hybrid maize in every period. I discuss how the identification assumptions used are supported by the timing of maize production, other characteristics of the production process, and the fact that shocks to yields like rainfall are observed in the data.

I find strong evidence of heterogeneity in the returns to hybrid maize, especially in the sample excluding the 2 districts (out of a total of 22) with high adult mortality. I estimate the distribution of returns, and compare the mean of this distribution to estimates from standard approaches that fail to take full account of farmer heterogeneity, such as ordinary least squares (OLS), instrumental variable (IV), and fixed effects models.[4] OLS estimates of the average return are in the range of 50–100%, models with fixed effects suggest returns of close to 0%, and IV estimates (using supply constraints as instruments) are on the order of 150–200%. The estimated mean gross return from my approach is 60%, but some farmers have returns as high as 150%, while there are many who have returns either close to zero or (in some cases) negative.

These estimated returns control for input use, but do not account for other costs (such as the costs of accessing the technology) and are therefore gross, rather than fully net returns. The joint distribution of estimated returns and adoption decisions displays some remarkable features. There are three subgroups of farmers in the sample. A small group of farmers has extremely high counterfactual returns to hybrid (about 150%), yet they choose not to adopt. This is rather striking and seems to deepen the initial puzzle, but is well explained by supply and infrastructure constraints, such as long distances to seed and fertilizer distributors. These farmers have higher costs to using hybrid as they have poor access to input suppliers. Their overall net counterfactual returns are therefore rather low. A comparatively larger group of farmers has lower, though still high, returns and they adopt hybrid in every period. Finally, a third group of farmers has essentially zero net returns and they switch in and out of use of hybrid from period to period. These are marginal farmers who switch easily when subject to shocks to the cost of and access to hybrid seed and fertilizer.

The heterogeneity in returns to this technology has important implications for policy. For one, encouraging complete adoption of a technology that has a large average return among existing adopters may be very inefficient due to

Ethiopia. Duflo, Kremer, and Robinson (2008b) also found a lot of switching behavior in fertilizer use in western Kenya.

[4]When there is heterogeneity in returns, IV estimates a local average treatment effect, that is, the returns for only the subpopulation that is affected by the instrument. This could explain why OLS and IV are so different here.

the much lower returns for the nonadopters. In addition, knowing the distribution of returns to a technology allows for focused policy interventions that can be cost effective. For example, for farmers who would have high returns but are constrained on the supply side, alleviating their constraints by targeted distribution of inputs and infrastructure improvements could improve yields dramatically. Similarly, the unconstrained farmers would benefit from the development of new hybrid strains. This research also illustrates the importance of the distributional consequences of policy and sheds light on the "scaling up" of policy (see Attanasio, Meghir, and Szekely (2003)).[5]

The literature provides a number of explanations for low adoption, ranging from learning models (Foster and Rosenzweig (1995) and Conley and Udry (2010)), informational barriers, credit constraints, taste preferences, differences in agroecological conditions, and local costs and benefits to time inconsistency and the lack of effective commitment devices (see Duflo, Kremer, and Robinson (2008a)). The dominant approach has been to frame adoption decisions in a learning environment where benefits and costs to the technologies are homogeneous but unknown, and are learned over time. The approach in this paper is in contrast to much of the literature. Since these technologies have been available for many years, and are well known and understood[6] (as in Duflo, Kremer, and Robinson (2008a, 2008b)), the approach here assumes the benefits and costs are known ex ante, but are spatially heterogeneous across farmers.

The rest of this paper is structured as follows. Section 2 outlines some relevant empirical literature. Section 3 describes the institutional context and the data. Section 4 discusses a theoretical framework for adoption decisions, clarifying the role of comparative advantage and the identification assumptions needed to estimate the yield function. It also describes the empirical model and its estimation.[7] Section 5 discusses some descriptive baseline regressions, such as OLS, fixed effects, IV, various treatment effects, and preliminary evidence that heterogeneity in returns is relevant. Section 6 presents the results from the correlated random coefficient model and the associated distribution of returns. Section 7 discusses implications of the results and a host of alternative models. Section 8 concludes.

[5]The questions posed here cannot be answered with an experiment which randomizes the technology across farmers without specific assumptions. With experimental data, one can test for the presence of heterogeneous returns, but estimating the distribution of returns requires assumptions about the underlying selection process, which is randomized away in such an experiment (see Heckman, Smith, and Clements (1997)).

[6]For example, in my sample, about 90% of households have used hybrid maize at some point in the past. The mean number of years since first use for hybrid maize is 19.4 years and for fertilizer is 20.5 years.

[7]Estimation programs are provided in the Supplemental Material (Suri (2011)).

2. LITERATURE REVIEW

This section briefly summarizes some of the empirical literature on technology adoption, focusing on a few studies in sub-Saharan Africa (see Suri (2006) for a more detailed review).[8] I describe the literature that has looked at the roles of heterogeneity, credit constraints, learning externalities, and, finally, the more recent experimental research on similar technologies in Kenya. The seminal empirical paper on technology adoption is by Griliches (1957), who looked at heterogeneity across local conditions in the adoption speeds of hybrid corn in the midwestern United States and emphasized the role of expected profits and scale. He noted how the speed of adoption across geographical space depended on the suppliers of the technology and when the seed was adapted to local conditions. For Kenya, Gerhart (1975) tracked the adoption of hybrid maize in western Kenya in the early 1970's. He highlighted the fast diffusion of hybrid and identified risk, education, credit availability, extension services, and use of fertilizer as constraints.

There is a vast literature that describes the observable heterogeneity that drives adoption decisions. For example, Schultz (1963) and Weir and Knight (2000) emphasized education. Various CIMMYT (The International Wheat and Maize Improvement Center) studies[9] across Kenya highlighted the unavailability and untimely delivery of the technologies, labor and input use, costs, and unfavorable climactic conditions.[10] There are a number of papers that focus on credit constraints, mostly using self-reports (see Croppenstedt, Demeke, and Meschi (2003) for Ethiopia, Salasya, Mwangi, Verkuijl, Odendo, and Odenya (1998) for western Kenya). Dercon and Christiaensen (2005) showed that the possibility of a poor harvest (and hence very low consumption) can account for the low use of fertilizer in Ethiopia. Their data showed similar adoption patterns to Kenya, with a lot of switching of technology use from period to period.

[8]The literature on technology adoption is too vast to review here: excellent reviews are Sunding and Zilberman (2001), Sanders, Shapiro, and Ramaswamy (1996), Rogers (1995), Feder, Just, and Zilberman (1985), David (2003), and Hall (2004). For the theoretical literature, see Besley and Case (1993), Banerjee (1992), and Just and Zilberman (1983). For studies of land management practices, see Mugo, Place, Swallow, and Lwayo (2000); for agricultural extension, see Evenson and Mwabu (1998); for property rights, see Place and Swallow (2000).

[9]See Doss (2003) and De Groote, Doss, Lyimo, and Mwangi (2002) for a review of all the CIMMYT surveys in Kenya.

[10]For example, Makokha, Kimani, Mwangi, Verkuijl, and Musembi (2001) looked at fertilizer and manure use in Kiambu district. The main (self-reported) constraints to use were unavailability and untimely delivery, high labor costs, and high prices of inputs. Ouma, Murithi, Mwangi, and Verkuijl (2002) found that, in Embu district, gender, agroclimatic zone, manure use, hiring of labor, and extension services were significant determinants of the adoption of improved seed and fertilizer. Wekesa, Mwangi, Verkuijl, Danda, and De Groote (2003) looked at the adoption of various hybrids and fertilizer in the coastal lowlands where the nonavailability and high cost of seed, unfavorable climatic conditions, perceptions of sufficient soil fertility, and lack of money were reasons for low use.

Much of the academic literature has focused on the learning externality described by Besley and Case (1993), which I find little evidence for. These papers mostly studied the green revolution in India, where the learning externality was certainly key in the rapid growth of new hybrid varieties developed for India. Foster and Rosenzweig (1995) considered the adoption of high yielding varieties in India and found that farmers with more experienced neighbors are more profitable than those without. Munshi (2003) found these impacts to be heterogeneous across crops. Conley and Udry (2010) studied the adoption of fertilizer in the small-scale pineapple industry in Ghana and found evidence of social learning within information neighborhoods (defined by farmers as the people they discuss farming with).[11]

More recently, there has been a growing experimental literature. A number of field trials at Kenya Agricultural Research Institute (KARI) experiment stations have shown large increases in yields from hybrid seed and fertilizer. One of the early experimental studies was the Fertilizer Use Recommendations Project (FURP) in the early 1990's to understand optimal rates of fertilizer use (see Corbett (1998)). FURP recorded yields about half of those found at experiment stations (KARI (1993a, 1993b)). Hassan et al. (1998b) showed higher adoption and faster diffusion of hybrid in high potential areas, blaming poor extension, infrastructure, and seed distribution in the marginal areas. Hassan, Murithi, and Kamau (1998a) found that farmers apply less fertilizer than optimal, leading to an estimated 30% yield gap.

De Groote, Overholt, Ouma, and Mugo (2003) considered an ex ante impact assessment of the Insect Resistant Maize for Africa project that develops Genetically Modified (GM) maize varieties that are more resistant to stem borers. They experimentally estimated a 13.5% crop loss, valued at about $80 million, due to these insects.[12] Duflo, Kremer, and Robinson (2008a) ran experiments to understand the returns to fertilizer and the low use of fertilizer in western Kenya. They found that the average rate of return for investing in top-dressing fertilizer is between 52% and 85%, and that learning effects were extremely small. Their most significant contribution was to implement the Savings and Fertilizer Initiative (SAFI) as a commitment device for farmers. They showed that offering SAFI at harvest time (vs. planting) increases adoption by between 11 and 14 percentage points, and they showed that this effect on increasing adoption is about equivalent to a 50% subsidy to the fertilizer price. They concluded that behavioral biases prevent farmers from making profitable investments on their farms and, hence, that small subsidies at the right time (i.e., at harvest) or offering farmers a commitment device to investing in fertilizer at this time can improve adoption rates. Duflo, Kremer, and Robinson

[11] Other studies of learning in sub-Saharan Africa include Bandiera and Rasul (2003) for sunflowers in Mozambique and Moser and Barrett (2003) for a rice production method in Madagascar.

[12] See http://apps.cimmyt.org/english/wpp/gen_res/irma.htm and Smale and De Groote (2003) for more information on the CIMMYT IRMA and GM projects in Kenya.

(2008b) looked at the heterogeneity in the returns to fertilizer. They found an average annual return of about 70%, but zero returns to a combination of fertilizer and hybrid, and some evidence of heterogeneity, stating that "the returns to fertilizer are smaller when the control plot does better." The empirical findings of Duflo, Kremer, and Robinson (2008a, 2008b) on adoption patterns are consistent with the evidence here, although, as the discussion in Section 7 indicates, I find different reasons for the differential returns and, therefore, for the lack of adoption.

3. INSTITUTIONAL CONTEXT AND DATA

I now describe the relevant institutional detail and the data, which help motivate the model and empirical approach used. Maize[13] is the main staple in Kenya, with 90% of the population depending on it for income (Nyameino, Kagira, and Njukia (2003)). Hybrid maize increases yields and can be more resistant to agricultural stress (Hassan et al. (1998b)). Both fertilizer and hybrid have been available since the 1960's: more than 20 modern varieties of seed have been released since 1955, although later releases have not shown large yield improvements.[14] In the data, about 70% of plots are planted with a hybrid variety released in 1986. Government recommendations for the types and quantities of hybrid seed and fertilizer vary across the country,[15] and both must be purchased each season. Hybrid seed replanted from the previous year's harvest (i.e., recycled hybrid seed) has little yield advantage over nonhybrid. Most farmers (about 80% in the sample) use either both hybrid and fertilizer or neither.

From 1965 to 1980, hybrid variety 611 diffused in western Kenya "at rates as fast as or faster than among farmers in the U.S. corn belt during the 1930's–1940's" (Gerhart (1975)), but this changed in the 1990's.[16] The most important

[13]McCann (2005) described the fascinating history of maize in Africa. Smale and Jayne (2003) provided an excellent review of maize policy in Kenya.

[14]Karanja (1996) stated "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 in time by H611 (with a 40% yield advantage), then H622 (16%), and then H611C (12%). H626, which had a 1% yield advantage over H625, was released 8 years later.

[15]See Ouma et al. (2002), Hassan et al. (1998b), Salasya et al. (1998), Wekesa et al. (2003), and Karanja (1996).

[16]Reform of the cereal sector began in 1988, followed by some liberalization in 1994. Smale and Jayne (2003) and Karanja (1996) attributed early successes to good germplasm, effective research, good distribution, and coordinated marketing of inputs and outputs. This changed in the 1990's as earlier policies of large subsidies, price supports, pan-territorial seed/output pricing, and restrictions on cross-district trade resulted in large fiscal deficits. The National Cereals and Produce Board accrued losses of 5% of gross domestic product (GDP) in the 1980's. For more on the reforms, see Jayne, Yamano, Nyoro, and Awuor (2001), Karanja, Jayne, and Strasberg (1998), Jayne, Myers, and Nyoro (2005), Nyoro, Kiiru, and Jayne (1999), and Wanzala, Jayne, Staatz, Mugera, Kirimi, and Owuor (2001).

government policy for this sector has been pan-territorial seed pricing. The hybrid seed was all produced by KARI on research stations and then distributed by Kenya Seed Company. The price of seed was not driven by market forces, shows little variance over time, and was fixed across the country. In the data, only 1% of seed purchases are not from Kenya Seed Company. This pan-territorial seed pricing created poor incentives for suppliers to locate in distant areas or far from markets.[17]

3.1. *Data*

The data set comes from the Tegemeo Agricultural Monitoring and Policy Analysis Project, a joint project between Tegemeo Institute at Egerton University, Kenya and Michigan State University. It is a household level panel survey of Kenya, representative of rural maize-growing areas. Figure 1 shows a map of the survey villages and the population density across the country (darker shades represent greater density). Although data are available for the years 1997, 1998, 2000, 2002, and 2004, for most of the analysis in this paper, I use the

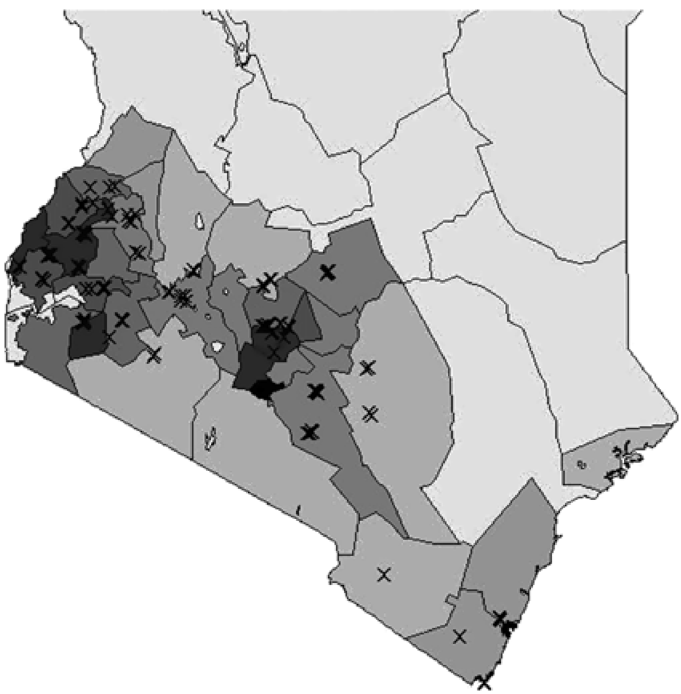

FIGURE 1.—Population density and location of sample villages.

[17]The seed market was liberalized post 2004; in late 2008, fertilizer was subsidized.

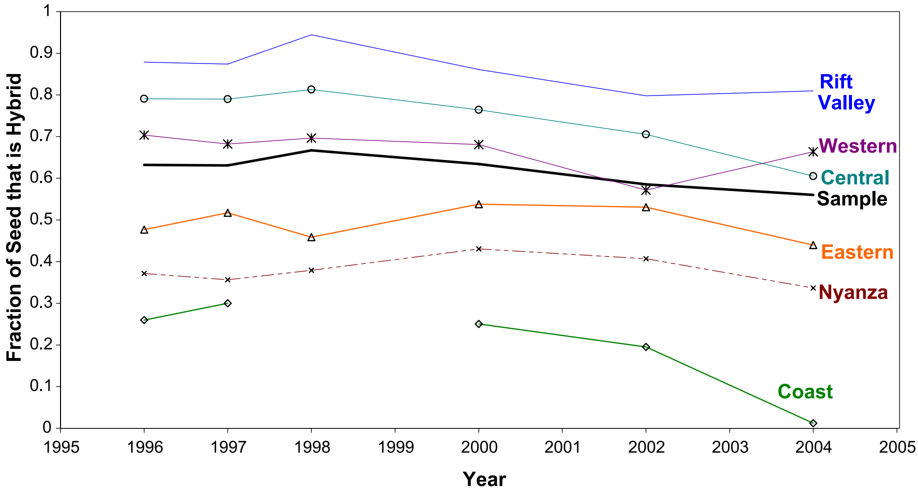

FIGURE 2.—Hybrid maize adoption patterns by province.

1997 and 2004 data. The 1997 and 2004 surveys collect detailed agricultural input and output data, consumption, income, demographics, infrastructure, and credit information.[18] The panel sample covers just over 1200 households.

Figures 2 and 3 show the heterogeneity in hybrid and fertilizer use across provinces and over time. Figure 2 shows the stability in aggregate hybrid maize adoption over time and the persistence of cross-sectional differences.[19] In principle, hybrid use could be a continuous variable as farmers plant quantities of hybrid, but only 2% of farmers in the sample plant both hybrid and nonhybrid in a given season. I therefore take hybrid use to be binary throughout the paper. Figure 3A shows the trends across provinces in the fraction of households that use inorganic fertilizer on maize and Figure 3B shows the total value (in constant Kenyan shillings) of inorganic fertilizer used, both showing similar persistent cross-sectional differences.[20] Figures 4A and 4B show the distribution of yields for 1997 and 2004 by technology, illustrating that mean yields are much higher and the variance of yields lower in the hybrid sector, although

[18]The 2000 and 1998 surveys are similar, but data on family labor were not collected in 2000, and 1998 covers only a subsample of 612 households. The 2002 survey was a short proxy survey.

[19]The Coast province looks rather different in 2004. All the results in the paper are similar if the households in the Coast province are dropped from the sample (59 households). In addition, looking across wealth/asset or acreage quintiles, the pattern is identical, with no systematic temporal variation in average adoption.

[20]Aggregate yields are not stable over time. There is a sharp drop in yields around 1997–1998, the result of El Nino. However, there are no dynamics in any of the main inputs. For example, the acreage farmers plant to maize is constant over this period. For more on these trends, see Suri (2006).

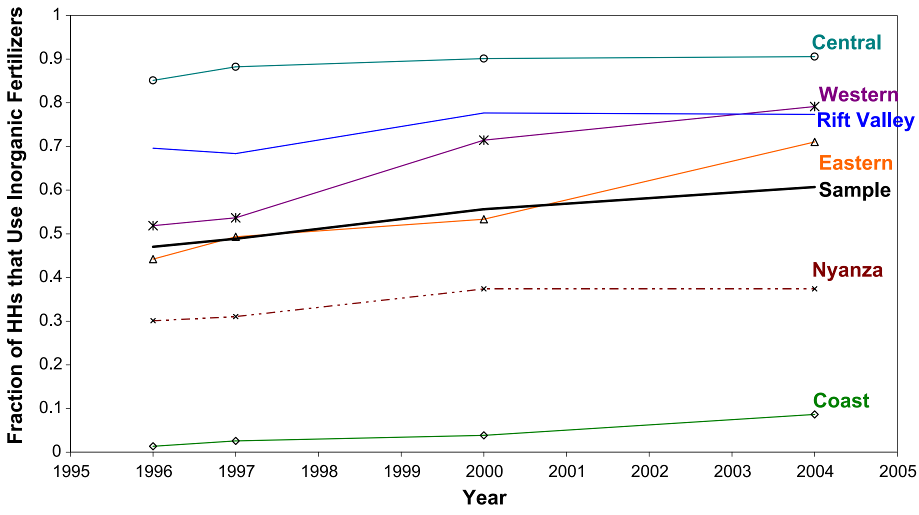

FIGURE 3A.—Fraction of households using inorganic fertilizer by province.

both these summary measures could be artifacts of selection (as I discuss in Section 4).

Table IIA shows summary statistics for my sample of households for 1997 and 2004. Of the 26 different types of fertilizer used, Table IIA shows the three most popular (diammonium phosphate (DAP), calcium ammonium nitrate (CAN), and monoammonium phosphate (MAP)). Table IIB breaks out

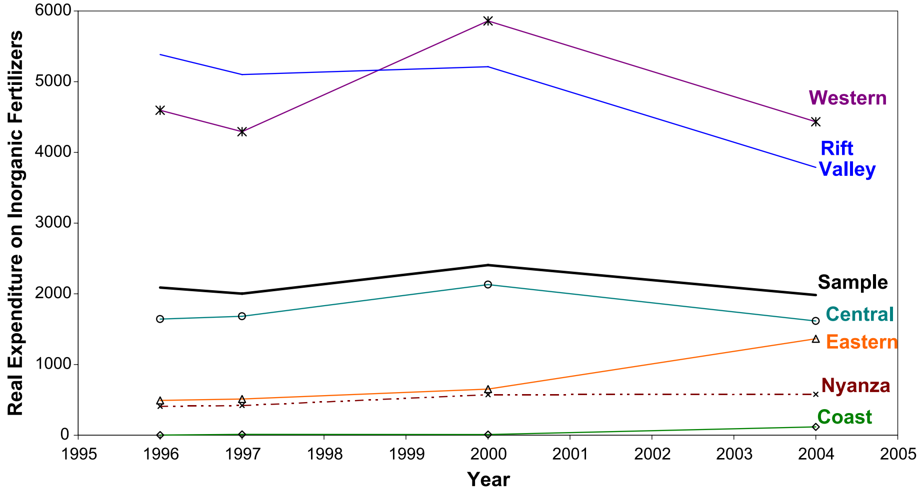

FIGURE 3B.—Real expenditure on inorganic fertilizer by province.

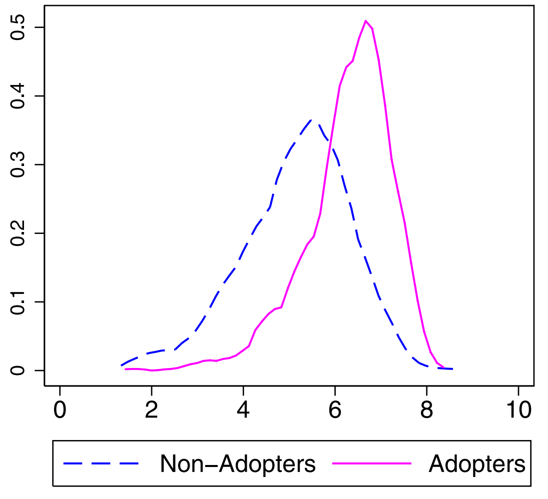

FIGURE 4A.—Marginal distribution of yields by sector, 1997.

some of these variables by hybrid/nonhybrid use for 1997 and 2004. Yields are significantly lower across the board in the nonhybrid sector. Maize acreage and total seed planted are not different across sectors in 1997 and only just in 2004. Fertilizer, land preparation costs, and main season rainfall are different across the two sectors. Finally, hired labor is only barely different in 2004 and family labor is only barely different in 1997.

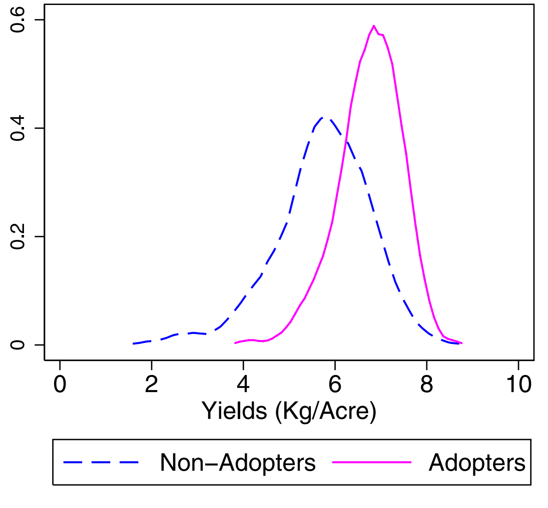

FIGURE 4B.—Marginal distribution of yields by sector, 2004.

TABLE IIA

SUMMARY STATISTICS BY SAMPLE YEAR[a]

	1997 Sample	2004 Sample
Yield (log maize harvest per acre)	5.907 (1.153)	6.350 (0.977)
Acres planted	1.903 (3.217)	1.957 (2.685)
Total seed planted (kg per acre)	9.575 (7.801)	9.072 (6.863)
Total purchased hybrid planted (kg per acre)	6.273 (6.926)	5.080 (5.260)
Hybrid (dummy)	0.658 (0.475)	0.604 (0.489)
Fertilizer (kg DAP (diammonium phosphate) per acre)	20.300 (38.444)	24.610 (34.001)
Fertilizer (kg MAP (monoammonium phosphate) per acre)	1.566 (10.165)	0.308 (4.538)
Fertilizer (kg CAN (calcium ammonium nitrate) per acre)	6.473 (24.727)	8.957 (21.702)
Total fertilizer expenditure (KShs per acre)	1361.7 (2246.3)	1354.6 (1831.2)
Land preparation costs (KShs per acre)	960.88 (1237.1)	541.43 (1022.8)
Family labor (hours per acre)	293.25 (347.49)	354.27 (352.68)
Hired labor (KShs per acre)	1766.0 (3346.4)	1427.4 (2130.3)
Main season rainfall (mm)	620.83 (256.43)	728.11 (293.29)
Distance to closest fertilizer seller (km)	6.288 (9.774)	3.469 (5.964)
Household size	7.109 (2.671)	8.409 (3.521)

[a]Standard deviations are given in parentheses. KShs is Kenyan shillings (exchange rate over this period was KShs 75 = $ 1). All monetary variables are in real terms.

The land preparation costs and labor variables merit some discussion. The land preparation costs variable reported in the summary statistics covers costs that are incurred either before or right at the time of the seed choice and that do not include labor costs. The survey collects the labor data for each component of the production process, separately for hired and family labor. On average, about 75% of the total labor used for maize by these households is family labor, which is difficult to value (it should be valued at the shadow wage, which is not observable).[21] The main production activities that use labor are land preparation (about 23% of total labor), planting (10%), weeding (36%), and harvesting (30%). Harvesting includes all the postharvest activities (threshing, winnowing, bagging, storage), which put the maize into a form fit for sale or consumption. The survey records the harvest of maize in bags, that is, after all postharvest activities.

Table IIC summarizes the labor variables by sector. Planting labor tends to be significantly different across the sectors since it is positively correlated with fertilizer use. Harvest and postharvest labor are also higher in the hybrid sector, unsurprising as the yields of hybrid are higher. In terms of weeding, hired labor is only different across the two sectors in 2004, and family weeding differs only in 1997. Total weeding labor is not different across the sectors in either

[21]When I impute the shadow wage for family labor as the district level hired labor wage, I find that about half my sample has negative profits, implying this is not the correct shadow wage, and that these households tend to undervalue family labor relative to the district level wage rate.

TABLE IIB

SUMMARY STATISTICS BY HYBRID/NONHYBRID USE[a]

	1997 Sample		2004 Sample	
	Hybrid	Nonhybrid	Hybrid	Nonhybrid
No. of households	791	411	726	476
Yield (log maize harvest per acre)	6.296 (0.934)	5.158 (1.167)	6.751 (0.692)	5.738 (1.030)
Total maize acres cultivated	1.982 (3.557)	1.753 (2.428)	2.087 (3.029)	1.758 (2.042)
Total seed planted (kg per acre)	9.669 (6.569)	9.394 (9.750)	8.746 (4.156)	9.569 (9.608)
Fertilizer (kg DAP per acre)	28.755 (44.115)	4.028 (13.266)	37.148 (37.294)	5.488 (13.909)
Fertilizer (kg CAN per acre)	9.087 (29.715)	1.442 (7.152)	12.708 (24.961)	3.235 (13.622)
Land preparation costs (KShs/acre)	1043.9 (1242.7)	801.08 (1211.7)	659.83 (1079.7)	360.83 (901.0)
Expenditure on fertilizer (KShs/acre)	1922.3 (2542.9)	282.64 (740.53)	1893.3 (1964.7)	533.09 (1211.4)
Inorganic fertilizer use (dummy)	0.7421 (0.4378)	0.2311 (0.4221)	0.8994 (0.3009)	0.4055 (0.4915)
Main season rainfall (mm)	651.70 (228.82)	561.44 (293.88)	825.41 (215.20)	579.69 (332.05)
Hired labor (KShs/acre)	1864.3 (2680.6)	1576.7 (4347.8)	1616.5 (2197.4)	1139.0 (1991.6)
Family labor (hours/acre)	260.35 (264.13)	356.57 (461.71)	343.6 (336.1)	370.58 (376.33)
Distance to closest fertilizer seller (km)	4.684 (7.993)	9.374 (11.93)	2.419 (2.420)	5.069 (8.760)
Household size	7.162 (2.616)	7.007 (2.773)	8.457 (3.340)	8.336 (3.783)

[a]Standard deviations are given in parentheses. The mean of yields is higher and the standard deviation of yields is lower in the hybrid sector.

year. If I value family labor at the district hired labor wage, the dominant cost differences between hybrid and nonhybrid production come from seed and fertilizer costs, and not from labor cost differences. Finally, Table IID shows the transitions of hybrid use in the data, with 30% of households switching in and out of use over 1997, 2000, and 2004. Including 2002, this fraction becomes 39%. In the raw data, households that always plant hybrid have the highest average yields, followed by households that switch in and out of use. Those that never use hybrid have the lowest average yields.

4. THEORY AND EMPIRICAL FRAMEWORK

This section first describes the theoretical foundations underlying my empirical model and then the empirical framework. I am interested in estimating a distribution of returns to the hybrid technology to assess if the farmers who do not adopt hybrid are those who do not benefit from it. I do this by estimating the yield (production) function underlying farmers' adoption decisions. The exact structure of the adoption decisions is never estimated, so the adoption model below is for illustrative purposes. I base the model on a comparison of

TABLE IIC

BREAKDOWN OF LABOR COSTS BY HYBRID/NONHYBRID USE[a]

	1997 Sample		2004 Sample	
	Hybrid	Nonhybrid	Hybrid	Nonhybrid
Hired labor (KShs/acre)				
Land preparation	408.4 (1171)	514.2 (3178)	408.2 (869.1)	501.8 (1096)
Planting	159.8 (318.9)	105.4 (293.5)	143.4 (354.1)	76.67 (216.9)
Weeding	678.8 (1149)	651.8 (1484)	635.7 (1088)	403.1 (915.5)
Harvest	365.1 (642.5)	196.6 (766.1)	151.1 (303.5)	96.42 (340.5)
Postharvest activities	236.5 (472.6)	98.65 (308.6)	241.1 (576.7)	47.37 (182.1)
Fertilizer application	15.21 (84.67)	10.02 (156.4)	13.24 (79.32)	2.374 (28.04)
Other	0.501 (9.727)	0 (0)	23.84 (281.6)	11.26 (227.5)
Family labor (hours/acre)				
Land preparation	47.95 (113.5)	102.4 (214.6)	51.93 (98.22)	97.79 (180.1)
Planting	29.12 (31.81)	35.23 (45.19)	38.27 (56.13)	39.55 (49.01)
Weeding	93.75 (107.1)	127.5 (151.6)	120.1 (151.3)	134.6 (160.2)
Harvest	42.45 (46.04)	49.54 (143.0)	58.77 (72.36)	49.60 (62.80)
Postharvest activities	44.07 (55.77)	39.89 (70.00)	68.54 (91.76)	44.69 (59.98)
Fertilizer application	3.171 (8.778)	1.935 (15.09)	3.928 (9.976)	1.510 (6.706)
Other	0.047 (1.313)	0 (0)	2.041 (13.62)	2.814 (24.73)

[a]Standard deviations are given in parentheses. On average, family labor accounts for 75% of total labor use (the rest being hired labor). The main production activities that use labor are listed above. Land preparation accounts for 23% of total labor use on average, planting accounts for 10%, weeding accounts for 36%, and harvesting and postharvesting activities account for 30%. Postharvesting activities include threshing, winnowing, bagging, and storing the maize.

TABLE IID

TRANSITIONS ACROSS HYBRID/NONHYBRID SECTORS FOR THE SAMPLE PERIODS 1997, 2000, AND 2004[a]

Transition in Terms of Technology Used (1997 2000 2004)	Fraction of Sample (%) ($N = 1202$ Households)
N N N	20.38
N N H	2.83
H N H	6.07
N H H	4.91
H N N	5.99
H N H	3.16
H H N	7.15
H H H	49.50

[a]This table shows all the possible three period transitions in my sample of farmers and the fraction of my sample that experiences each of these transitions. The three periods correspond to 1997, 2000, and 2004. In the first column, the three letters represent the transition history with respect to technology, where "H" represents the use of hybrid and "N" represents the use of nonhybrid. For example, the transition "N N N" stands for farmers who used nonhybrid maize in all three periods; they make up about 20.4% of my sample. The survey instrument asks about hybrid use in multiple sections of the questionnaire (since it is a rather large part of household decisions). We check and confirm the coherency of these responses in the field, which greatly reduces the likelihood that the observed switching behavior is appreciably affected by measurement error.

profits under hybrid and nonhybrid, and it clearly illustrates the role of the fixed costs of acquiring hybrid seed and fertilizer in the adoption decision, which is important for identification. The model shows how the unobserved heterogeneity in the yield function is a key determinant in the profit comparison underlying the hybrid decision. The aim of this section is, therefore, to derive the fundamental of the yield function that is of interest: the distribution of farmers' comparative advantage in the production of hybrid maize, which is the correlated random coefficient in the yield function. I then discuss the underlying identification assumptions, their validity, and the estimation of this yield function.[22]

4.1. *Adoption Decisions Under Profit Maximization*

I start with a simplified technology choice model where the farmer decides between hybrid and nonhybrid seed. In reality, the technology choice is a joint decision of using both hybrid and fertilizer or neither, which I elaborate on in Section 4.5. For ease of exposition, I use the hybrid/nonhybrid choice as a parsimonious representation of this joint choice.

The timing of the farmer's decisions is as follows. Each year, the farmer decides on his seed technology at the beginning of the growing season, just before the rains begin. The farmer makes his decision based on all his current information, his forward looking expectations as to the coming year's growing conditions, and the relative costs and benefits (differing productivities) of the two types of seed, which are assumed to be known to him.

The farmer is assumed to be risk-neutral and chooses a seed type to maximize profits per area of land. He compares $\pi_{it}^{*H}(p_{it}, a_{it}, b_{it}, \mathbf{w}_{it})$ and $\pi_{it}^{*N}(p_{it}, c_{it}, \mathbf{w}_{it})$, the maximized profit functions under hybrid and nonhybrid, respectively, where p_{it} is the expected output price of maize for both hybrid and nonhybrid maize,[23] a_{it} represents the (fixed) cost of obtaining hybrid seed (due to availability differences), b_{it} is per-unit cost of hybrid seed, c_{it} is the (very low, if not zero) per-unit costs of replanting nonhybrid seed from the previous year's harvest, and $\mathbf{w}_{it} \equiv (w_{1it}, w_{2it}, \dots, w_{Jit})$ represents the vector of input prices for the inputs X_{jit}^k, $j = 1, \dots, J$ and $k \in H, N$. The profit functions are

$$\pi_{it}^H = p_{it} Y_{it}^H - (b_t s_{it} + a_{it}) - \sum_{j=1}^{J} w_{jit} X_{jit}^H, \tag{1}$$

[22]Note that profit functions themselves are difficult to estimate here due to the widespread use of family labor, which is hard to value. Households do not value family labor in the same way as hired labor. Below, I show that the yield function here is similar to a gross revenue function (as in Levinsohn and Petrin (2003)). As a robustness check, I estimate a model using the value of yields and valuing all the inputs where possible using their prices. The results are extremely similar. Finally, if I assume that family labor is valued at hired labor wages, I can estimate profit functions, which also show qualitatively similar results.

[23]There is no distinction in the output market between hybrid and nonhybrid maize.

$$\pi_{it}^N = p_{it} Y_{it}^N - c_{it} s_{it} - \sum_{j=1}^{J} w_{jit} X_{jit}^N, \tag{2}$$

where Y_{it}^H and Y_{it}^N are the yields of hybrid and nonhybrid maize, respectively, and s_{it} is the quantity of seed used. In addition, I have imposed the following restrictions based on the institutional context in Section 3. First, the quantity of seed used for a given area of land is the same whether it is hybrid or nonhybrid seed.[24] Second, since the seed price is fixed across space, b_t is indexed only by t and not i.

Therefore, the farmer chooses to plant hybrid when $\pi_{it}^{*H} > \pi_{it}^{*N}$ or when

$$\left(Y_{it}^{*H} - \sum_{j=1}^{J} \frac{w_{jit}}{p_{it}} X_{jit}^{*H}\right) - \left(Y_{it}^{*N} - \sum_{j=1}^{J} \frac{w_{jit}}{p_{it}} X_{jit}^{*N}\right) > \frac{a_{it}}{p_{it}} + \frac{(b_t - c_{it})}{p_{it}} s_{it}^*. \tag{3}$$

I can rewrite the second term on the right-hand side of the inequality in (3) as the normalized (by the price of maize) cost difference between hybrid and nonhybrid seed. In fact, it is the case that $s_{it}^* \approx s^*$, as evidenced in Tables IIA and IIB, where both the quantity of seed used for a given area of land and the land area planted to maize are similar over time. This comes from standard seeding rates for maize and since land markets barely exist, there is little change in land ownership and land cropped to maize over time (see Suri (2006)).[25]

From (3), the optimized profits from using hybrid over nonhybrid are greater when

$$\left(Y_{it}^{*H} - \sum_{j=1}^{J} \frac{w_{jit}}{p_{it}} X_{jit}^{*H}\right) - \left(Y_{it}^{*N} - \sum_{j=1}^{J} \frac{w_{jit}}{p_{it}} X_{jit}^{*N}\right) > \frac{a_{it}}{p_{it}} + \frac{\delta_{it}^s}{p_{it}} \equiv A_{it} + \Delta_{it}^s, \tag{4}$$

where $\delta_{it}^s = (b_t - c_{it})s^*$, $A_{it} = a_{it}/p_{it}$, and $\Delta_{it}^s = \delta_{it}^s/p_{it}$. In reality, the value of c_{it}, the cost of nonhybrid, is close to zero (relative to the hybrid cost) and the output price p_{it} does not vary much across space (time by province dummies explain 60% of the variation in p_{it}).

From the evidence on input use in Table IIB, the optimized quantities of inputs apart from fertilizer tend to be about equal under hybrid and nonhybrid. If, in addition, I assume that fertilizer is only used with hybrid (as in the data) and that a fixed amount is used per land allocated to hybrid in each year, then

[24] There are standard seeding rates for maize that do not vary by seed type. This is borne out by the empirical seeding rates not varying much over time and not varying across hybrid and nonhybrid sectors; see Tables IIA and IIB.

[25] Note that the second term on the right-hand side of equation (3) can be ignored if the cost of obtaining hybrid seed, a_{it}, is much greater than the straight cost difference between hybrid and nonhybrid seed, which seems to be borne out in reality.

fertilizer costs are subsumed in b_t in equation (3) and hence in Δ_{it}^{s}.[26] If this is the case, then the farmer chooses hybrid if

$$(5) \qquad (Y_{it}^{*H} - Y_{it}^{*N}) > A_{it} + \Delta_{it}^{s}.$$

It is clear that adoption decisions based on profits depend fundamentally on yield comparisons. The above assumptions simply isolate the components of the adoption decision that are important to the identification and estimation of the yield function, which I now describe.

4.2. *The Underlying Yield Functions*

Underlying the profit functions, assume Cobb–Douglas production functions of the form

$$(6) \qquad Y_{it}^{H} = e^{\beta_t^H} \left(\prod_{j=1}^{k} X_{ijt}^{\gamma_j^H} \right) e^{u_{it}^H},$$

$$(7) \qquad Y_{it}^{N} = e^{\beta_t^N} \left(\prod_{j=1}^{k} X_{ijt}^{\gamma_j^N} \right) e^{u_{it}^N}.$$

These production functions for hybrid and nonhybrid maize have different parameters on the inputs, γ^H and γ^N, to allow for differential complementarity between the seed variety and the inputs (although the same set of potential inputs are used). u_{it}^H and u_{it}^N are sector-specific errors that may be the composite of time-invariant farm characteristics and time-varying shocks to production, and the β's are sector-specific aggregate returns to yields. Taking logs,

$$(8) \qquad y_{it}^{H} = \beta_t^H + x_{it}'\gamma^H + u_{it}^H,$$

$$(9) \qquad y_{it}^{N} = \beta_t^N + x_{it}'\gamma^N + u_{it}^N.$$

I now place additional structure on the unobserved productivities and impose the following factor structure, as in Lemieux (1993, 1998) and Carneiro,

[26]This is purely for expositional purposes, since the decision rule it leads to in equation (25) can be amended to include other input costs. Even if I allow the optimized inputs to differ by hybrid and nonhybrid for a given farmer (such as for harvest labor), this will create no bias in the empirical work since the estimated yield function does not depend on the *counterfactual* input use and conditions on inputs for the *observed* hybrid/nonhybrid choice. The other reason for taking the approach in the text is that for all inputs other than harvest/postharvest labor, the assumptions are empirically true, and valuing labor is problematic in this context. Therefore, departures from the strict assumptions in the text should be thought of as captured in the error term ϑ_{it} in the decision rule in equation (25).

Hansen, and Heckman (2003):

$$u_{it}^H = \theta_i^H + \xi_{it}^H, \tag{10}$$

$$u_{it}^N = \theta_i^N + \xi_{it}^N. \tag{11}$$

Farmers are assumed to know θ_i^H and θ_i^N, but not ξ_{it}^H and ξ_{it}^N, when making their seed choice. The transitory errors, ξ_{it}^H and ξ_{it}^N, are assumed to be uncorrelated with each other and with the X_{it}'s, and do not affect the hybrid decision (as per Heckman and Honore (1990)). It is clear that, in expected terms, $E(u_{it}^H - u_{it}^N) = (\theta_i^H - \theta_i^N)$ plays a role in the hybrid choice. I discuss this further in Section 4.4.

Following Lemieux (1998), since the relative magnitudes of the unobserved θ_i^H and θ_i^N are not identified, I define the relative productivity of a farmer in hybrid over nonhybrid as $(\theta_i^H - \theta_i^N)$, using the decomposition of θ_i^H and θ_i^N,

$$\theta_i^H = b_H(\theta_i^H - \theta_i^N) + \tau_i, \tag{12}$$

$$\theta_i^N = b_N(\theta_i^H - \theta_i^N) + \tau_i, \tag{13}$$

where 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 $\sigma_{HN} \equiv \mathrm{Cov}(\theta_i^H, \theta_i^N)$, $\sigma_H^2 \equiv \mathrm{Var}(\theta_i^H)$, and $\sigma_N^2 \equiv \mathrm{Var}(\theta_i^N)$.[27]

The τ_i is farmer i's absolute advantage: its effect on yields does not vary by technology and it is (by construction of the linear projection) orthogonal to $(\theta_i^H - \theta_i^N)$. The gain, $(\theta_i^H - \theta_i^N)$, can be redefined to be farmer-specific comparative advantage, θ_i, as

$$\theta_i \equiv b_N(\theta_i^H - \theta_i^N). \tag{14}$$

Defining $\phi \equiv b_H/b_N - 1$, equations (12) and (13) become

$$\theta_i^H = (\phi + 1)\theta_i + \tau_i, \tag{15}$$

$$\theta_i^N = \theta_i + \tau_i. \tag{16}$$

I am interested in the structural parameter ϕ and the distribution of θ_i, both fundamentals of the production function. The θ_i's are the key unobservables that determine selection into hybrid.

[27]The τ_i's in equations (12) and (13) are the same. To see this, subtracting equation (13) from equation (12) gives $\theta_i^H - \theta_i^N = (b_H - b_N)(\theta_i^H - \theta_i^N)$. For the τ_i's to be equal across sectors, $b_H - b_N$ must be equal to 1, which is easily shown: $b_H - b_N = (\sigma_H^2 - \sigma_{HN} - \sigma_{HN} + \sigma_N^2)/(\sigma_H^2 + \sigma_N^2 - 2\sigma_{HN}) = 1$.

Using this decomposition of u_{it}^H and u_{it}^N, I can rewrite equations (8) and (9) as[28]

$$(17)\qquad y_{it}^H = \beta_t^H + \tau_i + (\phi + 1)\theta_i + X_{it}\gamma^H + \xi_{it}^H,$$

$$(18)\qquad y_{it}^N = \beta_t^N + \tau_i + \theta_i + X_{it}\gamma^N + \xi_{it}^N.$$

I use a generalized yield equation of the form

$$(19)\qquad y_{it} = h_{it}y_{it}^H + (1 - h_{it})y_{it}^N,$$

and substituting in equations (17) and (18), I get

$$(20)\qquad \begin{aligned} y_{it} = {} & \beta_t^N + \theta_i + (\beta_t^H - \beta_t^N)h_{it} + X_{it}'\gamma^N \\ & + \phi\theta_i h_{it} + X_{it}'(\gamma^H - \gamma^N)h_{it} + \tau_i + \varepsilon_{it}. \end{aligned}$$

Equation (20) is my basic empirical specification; Section 4.5 describes the estimation in detail. Since, the coefficient on h_{it}, $\phi\theta_i$ (the fifth term in the equation), depends on the unobserved θ_i, this is a correlated random coefficient (CRC) model where the θ_i's are correlated with the adoption decision.[29] I estimate two components of this model: the coefficient ϕ that describes how important differences in comparative advantage are in this economy, and, second, the distribution of θ_i and hence the corresponding distribution of the heterogeneous returns to hybrid.

Intuitively, in a specification like equation (20), θ_i measures farmer i's relative productivity in hybrid over nonhybrid, that is, his comparative advantage in hybrid. The θ_i's are a fundamental of the production function, but also play a role in the adoption decision. If the farmers with high θ_i's have *lower* gains to switching to hybrid from nonhybrid, then $\phi < 0$. In that case, relative to the mean θ_i in the population, a farmer would need a small θ_i to meet the adoption criterion. This is the notion of selection on the basis of comparative advantage, in that those with lower baseline productivities have larger gains to switching to the new technology. The coefficient ϕ therefore describes the sorting in the economy. If $\phi < 0$, there is less inequality in yields in this economy as compared to an economy where individuals are randomly allocated to a technology. On the other hand, if $\phi > 0$, then the self-selection process leads to greater inequality in yields. To see this, from equation (20), if we let $\mu_i = \theta_i + \tau_i$, then μ_i is a household-specific intercept (average yield) and $\phi\theta_i$ is the household-specific return to hybrid. Since θ_i and τ_i are uncorrelated by construction, the

[28]Note that this decomposition of u_{it}^H and u_{it}^N implies a more complex Cobb–Douglas production function for hybrid maize, $Y_{it}^H = e^{\tau_i}e^{\theta_i^{\phi+1}}e^{\beta_t^H}(\prod_{j=1}^k X_{ijt}^{\gamma_j^H})e^{\xi_{it}^H}$, and similarly for nonhybrid maize.

[29]Also note that equation (20) is a generalization of the household fixed effects model (see Suri (2006)).

covariance between μ_i and $\phi\theta_i$ is $\phi\sigma_\theta^2$. The sign of ϕ is therefore the sign of the covariance between a household's overall average yield and its return to hybrid. A negative ϕ implies that farmers who do better on average, do worse at hybrid and vice versa for a positive ϕ.

4.3. *The Role of Fixed Costs in the Adoption Decision*

In this section, I discuss the implications of profit maximization to illustrate how changes in infrastructure and access to seed and fertilizer distributors affect adoption decisions. This profit maximization approach is a generalization of the strict Roy model where adoption decisions are based purely on the outcome (yields). I combine the yield function decomposition of Section 4.2 with the profit maximization problem of Section 4.1 to discuss how the farm-specific comparative advantage parameters combine with the costs of acquiring seed and fertilizer to determine the hybrid adoption decision.

Rewriting (4) in log output and using (8) and (9), a farmer chooses hybrid if

$$E(u_{it}^H - u_{it}^N) > A_{it} + \Delta_{it}^s - (\beta_t^H - \beta_t^N) + \sum_{j=1}^{J}(\gamma_j^N x_{jit}^{*N} - \gamma_j^H x_{jit}^{*H}). \tag{21}$$

In the data, the revenue in hybrid is about double that in nonhybrid. 30% of this is due to differential seed and fertilizer costs, 4% is land preparation cost differences, 7% is hired labor cost differences, family labor goes the other way, and the rest is profit differences and costs of acquiring seed over and above the seed price. Apart from fertilizer, the optimized inputs x_{jit}^{*H} and x_{jit}^{*N} are not substantially different, so if $\gamma_j^H \simeq \gamma_j^N$ for all inputs j, then the last term in this expression is zero for all inputs except fertilizer.[30] If for fertilizer, I assume as above that fertilizer is used only with hybrid and in fixed proportions per area of land, then fertilizer is subsumed in the Δ_{it}^s. In this case, the adoption rule reduces to

$$E(u_{it}^H - u_{it}^N) > A_{it} + \Delta_{it}^s - (\beta_t^H - \beta_t^N). \tag{22}$$

Substituting in equations (10) and (11), and using equations (15) and (16),

$$(\theta_i^H - \theta_i^N) > A_{it} + \Delta_{it}^s - (\beta_t^H - \beta_t^N), \tag{23}$$

$$\phi\theta_i > A_{it} + \Delta_{it}^s - (\beta_t^H - \beta_t^N). \tag{24}$$

[30]It is important to emphasize again that the assumption that the term involving the optimized inputs is zero is purely for expositional convenience, in addition to it being roughly true in the data. The estimated yield equation will condition on the observed input intensities. So even without this simplifying assumption, conditional on the observed input intensities, the counterfactual input intensities do not affect the observed outputs, so their role in the adoption decisions does not create bias in the empirical work.

Equation (24) implies that the technology choice will depend on (i) unobserved, farmer-specific, time-invariant comparative advantage θ_i that comes from the underlying production function, (ii) pure macroeconomic factors affecting the differential productivity of hybrid and nonhybrid seed $(\beta_t^H - \beta_t^N)$, (iii) potentially time-varying costs of obtaining hybrid, A_{it}, and (iv) the real relative purchase costs of hybrid seed, Δ_{it}^s. The key aspect of the A_{it} costs is that they affect the demand for hybrid seed, but not production and yields directly.[31]

This framework illustrates how to empirically relate my comparative advantage estimates to observables. Let $\alpha_i \equiv E_t[A_{it}]$ be the population time mean of the real fixed costs of acquiring hybrid seed for each farmer, and let $\vartheta_{it} \equiv A_{it} - \alpha_i$. Rewriting equation (24),

$$\phi\theta_i - \alpha_i > \Delta_{it}^s - (\beta_t^N - \beta_t^H) + \vartheta_{it} \tag{25}$$

where α_i is the permanent component of the fixed costs (that is, the average real fixed costs for a farmer over time) and ϑ_{it} denotes the period to period fluctuations in these costs.

Clearly, $\phi\theta_i$ cannot be separately distinguished from the permanent component of fixed costs, α_i. In the empirics, I relate the estimated comparative advantage to permanent aspects of infrastructure, since both act in an equivalent way to drive adoption decisions *across* farmers. By contrast, the changes in the fixed costs, ϑ_{it}, drive adoption decisions for a *given* farmer over time. Section 4.4.3 discusses the empirical evidence on these costs.

4.4. *Identification of the Generalized Yield Function*

The basic equation I estimate is equation (20):

$$\begin{aligned} y_{it} = {} & \beta_t^N + \theta_i + (\beta_t^H - \beta_t^N)h_{it} + X_{it}'\gamma^N \\ & + \phi\theta_i h_{it} + X_{it}'(\gamma^H - \gamma^N)h_{it} + \tau_i + \varepsilon_{it}. \end{aligned}$$

In this section, I discuss the identification assumptions needed to estimate this and the justifications for them. While the projections in equations (15) and (16) only impose uncorrelatedness of the absolute advantage, τ_i, and the comparative advantage, θ_i, my empirical work does not require this level of generality. So, as in Lemieux (1993), I use the stronger sufficient assumption of mean independence of the composite error $(\tau_i + \varepsilon_{it})$ and the comparative advantage component (θ_i), and the histories of the regressors, that is, that

$$E(\tau_i + \varepsilon_{it} | \theta_i, h_{i1}, \dots, h_{iT}, X_{i1}, \dots, X_{iT}) = 0. \tag{26}$$

[31] Δ_{it}^s, the relative per-unit costs of hybrid seed normalized by the output price also play a role, as equation (24) makes clear. But, as this varies mostly across time and not by individual, it is absorbed by time dummies in the empirical specifications.

With respect to the absolute advantage component, τ_i, the assumption in equation (26) is not restrictive for two reasons. First, by definition, τ_i does not affect the differential return to growing hybrid (it is differenced out of $\theta_i^H - \theta_i^N$ as per equations (15) and (16) above). Second, Heckman and Honore (1990) discussed the identification of the Roy model and showed that if the absolute advantage plays a role in adoption decisions, then the Roy model has no empirical content. This assumption is essentially, therefore, the standard strict exogeneity requirement used in panel data models.[32]

The strict exogeneity assumption on the transitory part of the composite error, ε_{it}, is more restrictive, but since the data include measures of shocks to yields, this assumption is more plausible than if I did not observe such shocks. In terms of the primitives of the model,

$$\varepsilon_{it} \equiv h_{it}\xi_{it}^H + (1 - h_{it})\xi_{it}^N. \tag{27}$$

The mean independence assumption regarding ε_{it} implies that ξ_{it}^H and ξ_{it}^N from equations (17) and (18) do not affect the farmer's decision to use hybrid and, crucially, the farmer's switching behavior. I discuss the various types of possible shocks and how they relate to yields and hybrid decisions in the following two subsections. Given the long lag between planting and harvest (an average of 4 or more months), I consider two "types" of ξ_{it}^j $(j \in H, N)$ transitory shocks to yields: those that occur after the seed choice has been made and those that occur before. I discuss each separately below and then discuss the implications for the switching behavior.

4.4.1. *Shocks Realized After the Technology Choice*

Central to identification is the fact that the hybrid seed choice is made before the farmer experiences most of the agricultural shocks to yields. However, the shocks postplanting may affect optimal input use differentially for hybrid and nonhybrid, and hence pose a problem for identification. So it is key that the most important transitory shock postplanting—rainfall—is observable in the data and can be controlled for. There may be other unobservable shocks to yields that are correlated with inputs, such as weeds, pests, and disease. Hassan, Onyango, and Rutto (1998c) used survey data to rank farmers' perceptions of

[32]The assumption in equation (26) implies that $E(\tau_i|\theta_i) = 0$ by the law of iterated expectations. As shown in Section 4.5.1, θ_i can be written as the linear projection $\theta_i = \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i1} h_{i2} + v_i$. Given the mean independence of τ_i from the adoption history discussed above, the additional assumption that $E(\tau_i|\theta_i) = 0$ only implies $E(\tau_i|v_i) = 0$. This last assumption is not actually needed for the empirical work, as the relationship between these two error components is left unspecified—they can be correlated, for example, and my empirical approach is still consistent. The mean independence assumption in (26) is therefore "overly strong," but is useful for expositional convenience concerning the adoption behavior and the assumptions on the composite error term. However, I do make the strict exogeneity assumption regarding τ_i, as described.

the most important maize production shocks and what options are available to them to deal with these shocks. They found that inadequate and/or erratic rainfall is one of the most widespread and one of the two worst shocks to yields across all zones in Kenya.[33]

In addition, given the timing of production, the inputs that could be adjusted after the technology choice are only a subsample of the labor inputs, since the empirical specification will allow for the joint hybrid–fertilizer decision. The main labor activities are land preparation, planting, weeding, harvest, and postharvest. Land preparation and planting are costs incurred before the technology choice, and harvest and postharvest after all shocks are realized. The only input that could therefore be an issue is weeding labor. Table IIC shows that the use of weeding labor in the sample is not very different across hybrid and nonhybrid farmers. Duflo, Kremer, and Robinson (2008b) compared plots that use hybrid and fertilizer, those that use just fertilizer, and those that use nonhybrid and no fertilizer. Other than the cost of the seed and fertilizer, they stated that farmers reported no differences in the time spent weeding across these plots and their field officers observed no differences in weeding.

Overall, it seems that shocks realized after the hybrid choice are well captured by the variables in my data, since rainfall is observed and postplanting input use is unlikely to be differential across technologies.

4.4.2. *Shocks Realized Before the Technology Choice*

Even though the identification assumptions seem robust to shocks realized after the technology choice, there could be an issue with shocks that happen between 1997 and 2004 and affect the use of hybrid as well as yields. An example may be changes in household structure, for example, the death of adults in the household due to HIV, that affect the quality of labor as well as the decision to use hybrid. In all the empirical results reported, I control directly for household structure (excluding these controls does not affect the results; see Suri (2006)). In addition, all the results in this paper are reported for the

[33] I have also investigated other potential shocks. For example, Hassan, Onyango, and Rutto (1998c) also identified Striga (a weed) as an important issue in three agroecological zones (pests and most diseases do not rank high). Hassan and Ransom (1998) carefully analyzed Striga and stated there is "no conclusive evidence that local vs. improved maize, time of planting, and cropping pattern either encourage or discourage Striga." The occurrence of Striga therefore seems to be uncorrelated with the hybrid decision and should not pose a problem for identification. As a robustness check, where I can match my households to these three zones, I drop these households and the results are extremely similar. Another potential shock is temperature: maize grows best in a temperature range of 24–30°C and has trouble germinating at temperatures above 38°C (see Pingali and Pandey (1999) and McCann (2005)). All the maize areas in Kenya fit within this range of temperatures. Looking at data on monthly temperatures for 1956–2006 by latitude and longitude, the maximum observed temperature is 23°. The warmest part of the country in my sample is probably the Coast province. As a robustness check, I drop the households in the Coast province and the results are similar.

Finally, Tables IIA and IIB show the changes in infrastructure between 1997 and 2004. These have been due to private investment in fertilizer distribution networks; now there are more than 10 importers, 500 wholesalers, and 7000 retailers in the country (see Ariga, Jayne, and Nyoro (2006)). For example, the distance to the closest fertilizer seller fell from 6.3 km in 1997 to 3.5 km in 2004 (a fall from 4.9 km to 2.4 km for hybrid farmers and from 9.3 km to 5.1 km for the nonhybrid).

4.5. *Estimating a Model With Heterogeneous Returns*

I now describe how to estimate the CRC model in equation (20).[37] An alternative estimation framework would be to use contemporary industrial organization methods. However, in the face of the correlated heterogeneity in equation (20), methods such as those of Olley and Pakes (1996) and Levinsohn and Petrin (2003) that focus on unobserved time-varying productivity are inconsistent, since the returns to hybrid are heterogeneous and correlated with the decision to use hybrid. Also, in the contexts those papers examined, productivity shifts for existing firms and the productivities for the firms leaving and entering the industry are of key importance in estimating responses to regulatory or trade environments. In my scenario, given the static but cross sectionally heterogeneous nature of the returns to hybrid and the underlying productivities of Kenyan farmers, it is of less importance to deal with time-varying productivities, since the approach controls for the dominant time-varying shocks to output effectively.

4.5.1. *Empirical Identification of the CRC Model*

The estimation strategy I use is a generalization of the Chamberlain (1982, 1984) correlated random effects approach. It parallels Chamberlain (1984) in how the model is identified and how the parameters of the model are estimated, most importantly ϕ. Later, I describe how to use these estimates to derive a distribution of the predicted θ_i's. For simplicity, I first describe how to estimate the model without covariates,

$$y_{it} = \delta + \beta h_{it} + \theta_i + \phi \theta_i h_{it} + u_{it}, \tag{28}$$

where $u_{it} \equiv \tau_i + \varepsilon_{it}$ and assuming $\beta_t^H - \beta_t^N \equiv \beta \ \forall t$. Relaxing this assumption empirically does not change the results.

To estimate equation (28), I eliminate the dependence of the observed θ_i's on the endogenous input (h_{it}) by following Chamberlain to exploit the linear

[37]This empirical model is similar to models of individual-specific heterogeneity in Heckman and Vytlacil (1998), Card (2000, 1998), Deschênes (2001), Carneiro, Hansen, and Heckman (2003), Carneiro and Heckman (2002), and Wooldridge (1997). Lemieux (1998) used the same model to look at whether the return to union membership varies along observable and unobservable dimensions.

projection of θ_i on the full history of the inputs, although the projection I use is more general. The θ_i's are projected onto not just the history of the hybrid decisions, but also their interactions, so that, in the two period case, the projection error is orthogonal to h_{i1} and h_{i2} individually as well as to their product, $h_{i1}h_{i2}$ by construction.[38] The generalized linear projection used is

$$\theta_i = \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i1}h_{i2} + v_i. \tag{29}$$

In addition, the θ_i's are normalized so that $\sum \theta_i = 0$.[39] This normalization implies that λ_0 can be written as a function of λ_1, λ_2, and λ_3 from equation (29).

Here, the coefficient λ_3 is of crucial importance to the empirical identification and estimation of the model, and is where this is a generalization of Chamberlain's approach. The $h_{i1}h_{i2}$ interaction term is necessary in the projection to ensure that v_i is orthogonal to every possible history of hybrid use. Since all the h_{it} variables describing the use of hybrid are dummies, to estimate λ_3 it is necessary to have farmers in the sample that have planted hybrid in *both* periods. Also note that the projection does not have a behavioral interpretation, but is used purely to purge θ_i of its dependence on the full histories of the inputs.

Substituting the projection into the yield equation for each of the two time periods gives

$$\begin{aligned} y_{i1} = {} & (\delta + \lambda_0) + [\lambda_1(1+\phi) + \beta + \phi\lambda_0]h_{i1} + \lambda_2 h_{i2} \\ & + [\lambda_3(1+\phi) + \phi\lambda_2]h_{i1}h_{i2} + (v_i + \phi v_i h_{i1} + u_{i1}), \end{aligned} \tag{30}$$

$$\begin{aligned} y_{i2} = {} & (\delta + \lambda_0) + \lambda_1 h_{i1} + [\lambda_2(1+\phi) + \beta + \phi\lambda_0]h_{i2} \\ & + [\lambda_3(1+\phi) + \phi\lambda_1]h_{i1}h_{i2} + (v_i + \phi v_i h_{i2} + u_{i2}). \end{aligned} \tag{31}$$

The corresponding reduced forms are

$$y_{i1} = \delta_1 + \gamma_1 h_{i1} + \gamma_2 h_{i2} + \gamma_3 h_{i1}h_{i2} + \varsigma_{i1}, \tag{32}$$

$$y_{i2} = \delta_2 + \gamma_4 h_{i1} + \gamma_5 h_{i2} + \gamma_6 h_{i1}h_{i2} + \varsigma_{i2}. \tag{33}$$

Equations (32) and (33) give six reduced form coefficients ($\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6$), from which the five structural parameters ($\lambda_1, \lambda_2, \lambda_3, \beta, \phi$) can be estimated using minimum distance. The structural parameters are overidentified

[38]Chamberlain's correlated random effects (CRE) model uses the projection $\theta_i = \lambda_1 h_{i1} + \lambda_2 h_{i2} + v_i$, which, when substituted into the yield function, gives $y_{it} = \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \beta h_{it} + \phi\lambda_0 + \phi\lambda_1 h_{i1}h_{it} + \phi\lambda_2 h_{i2}h_{it} + v_i + \phi v_i h_{it} + u_{it}$. Even though v_i is uncorrelated with h_{i1} and h_{i2} individually (by the nature of the projection), it could be correlated with their product, $h_{i1}h_{i2}$, so that $E[v_i h_{i1}h_{i2}] \neq 0$. The CRC projection must, therefore, also include all the interactions of the hybrid histories.

[39]This normalization is used so that β in equation (28) corresponds to the average return to hybrid as in a standard fixed effects model. This normalization fixes the average θ_i in the sample and does not change the ordering of the θ_i's across farmers.

given these minimum distance restrictions:

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

There may seem to be six structural parameters, since λ_0 is in equations (29) and (34). However, given the normalization $\sum \theta_i = 0$, then $\lambda_0 = -\lambda_1\overline{h_{i1}} - \lambda_2\overline{h_{i2}} - \lambda_3\overline{h_{i1}h_{i2}}$, where $\overline{h_{i1}}$ and $\overline{h_{i2}}$ are the averages of the adoption decisions in periods one and two, and $\overline{h_{i1}h_{i2}}$ is the average of their interaction.

From the restrictions above, for example, ϕ could be (inefficiently) estimated as a combination of the reduced form parameters in two ways: $\phi = (\gamma_6 - \gamma_3)/(\gamma_4 - \gamma_2)$ and $1 + \phi = (\gamma_1 - \gamma_5)/(\gamma_4 - \gamma_2)$. Note that if γ_2 and γ_4 are equal, then ϕ is not identified. Requiring γ_2 and γ_4 to be different means that the reduced form effect of the hybrid decision in period two on yields in period one has to be different from the reduced form effect of the hybrid decision in period one on yields in period two. Since these are reduced form coefficients, this could structurally arise from a number of mechanisms. One example directly from the theory would be differential shocks to the costs in each period, that is, different ϑ_{it} (see equation (25)) in each period. In Table VII, the null that $\gamma_2 = \gamma_4$ can clearly be rejected. In addition, in the extension discussed in Section 4.5.2, where the use of fertilizer is endogenized (the preferred model), the problem becomes heavily overidentified and ϕ is a more complicated function of the underlying reduced form parameters.

4.5.2. *Extensions to the Basic Model*

I consider the following extensions to the basic model:[40]

(i) *Covariates*: All the identification arguments presented above generalize when covariates are included. Covariates can be either exogenous or endogenous. Exogenous covariates are uncorrelated with the θ_i's and, therefore, enter only the reduced form equations (32) and (33). Endogenous covariates are correlated with the θ_i's and hence also enter the projection in equation (29). In

[40] An extension to three periods is straightforward. The problem is heavily overidentified with 9 structural parameters to estimate from the 21 reduced form coefficients for the basic case. Models with three time periods are not presented here as the 2000 survey does not collect data on family labor inputs. See Suri (2006) for these results.

the case where fertilizer is the other endogenous covariate, the CRC projection generalizes to

$$\theta_i = \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i1} h_{i2} + \lambda_4 h_{i1} f_{i1} + \lambda_5 h_{i2} f_{i1} + \lambda_6 h_{i1} h_{i2} f_{i1} + \lambda_7 h_{i1} f_{i2} + \lambda_8 h_{i2} f_{i2} + \lambda_9 h_{i1} h_{i2} f_{i2} + \lambda_{10} f_{i1} + \lambda_{11} f_{i2} + v_i, \tag{35}$$

where f_{it} for $t = 1, 2$ represents the use of fertilizer in each period. Adding more endogenous covariates does complicate the CRC model and it can become cumbersome.[41] In this case, there are 22 reduced form coefficients and only 14 structural coefficients to be estimated, so the problem is heavily overidentified.

(ii) *Joint choice variables*: The two-sector model presented above (hybrid/nonhybrid) can be extended to multiple sectors. Since the use of hybrid seed and fertilizer is clearly a joint decision in the data, as a further check, the use of fertilizer is incorporated into the technology sector. I therefore also estimate a model that looks at the heterogeneity in returns in a technology sector, where a farmer is in the technology sector when he uses both hybrid and fertilizer, else he is not in the technology sector.

5. DESCRIPTIVE REGRESSIONS

This section provides estimates of the returns to hybrid from models that assume homogeneity in these returns. I also present descriptive evidence that illustrates the importance of selection and heterogeneity in returns, and that there may be selection on these heterogeneous returns.

5.1. *OLS and Fixed Effects Estimates*

The OLS estimates of the yield functions, controlling for various inputs, are in the first data columns of Table IIIA. The estimates of the average return to hybrid are extremely large: households that plant hybrid have 54–100% higher yields. The last two columns of Table IIIA report the household fixed effects results. The coefficient on hybrid decreases to about 9%, indicating a substantial role for heterogeneity in the production function that is fixed across households.[42] The simple household fixed effects estimates are consistent under the assumption of strict exogeneity. Chamberlain's correlated random effects (CRE) approach illustrates how the fixed effects model is overidentified

[41]There is some justification for treating only fertilizer as endogenous with respect to θ_i. First, the summary statistics by sector in Table IIB show that there are not big differences across sectors in the use of other inputs. Second, using the estimates from the hybrid problem in Table VIIIA, I correlate the predicted θ_i's with the inputs. Only the correlations between the θ_i's and fertilizer are important in magnitude and/or significance.

[42]The fixed effects framework imposes restrictive assumptions on the underlying adoption process. Apart from the fixed effect, the adoption decision cannot depend on observed outcomes except under restrictive assumptions on the transitory component of yields (see Ashenfelter and

TABLE IIIA

BASIC OLS AND FIXED EFFECTS (FE) SPECIFICATIONS: DEPENDENT VARIABLE IS YIELDS (LOG MAIZE HARVEST PER ACRE)[a]

	OLS, Pooled	OLS, Pooled	OLS, Pooled	FE	FE
Hybrid	1.074 (0.040)	0.695 (0.039)	0.541 (0.041)	0.017 (0.070)	0.090 (0.065)
Acres (× 1000)	—	–	0.035 (5.749)	—	−0.509 (0.140)
Seed kg per acre (× 10)	—	–	0.184 (0.024)	—	0.179 (0.032)
Land preparation costs per acre (× 1000)	—	–	0.066 (0.016)	—	0.075 (0.023)
Fertilizer per acre (× 1000)	—	–	0.075 (0.009)	—	0.054 (0.012)
Hired labor per acre (× 1000)	—	–	0.037 (0.006)	—	0.027 (0.008)
Family labor per acre (× 1000)	—	–	0.374 (0.050)	—	0.467 (0.072)
Year = 2004	0.501 (0.038)	0.480 (0.035)	0.566 (0.041)	0.444 (0.032)	0.587 (0.044)
Constant	5.200 (0.038)	4.636 (0.080)	3.954 (0.113)	5.896 (0.051)	−2.383 (5.582)
Province dummies	No	Yes	Yes	—	—
R-squared	0.266	0.400	0.502	0.049	0.089

[a]Standard errors are given in parentheses. All regressions have 2404 observations (two periods). Covariates not reported include household size, controls for the age–sex composition of the household (henceforth this includes variables for the number of boys (aged <16 years), the number of girls, the number of men (aged 17–39), the number of women, and the number of older men (aged >40 years)), the main season rainfall, and the average long term main season rainfall. Results are almost identical if the sample is for three periods without family labor as a covariate. Hired labor is measured in KShs per acre and family labor is measured in hours per acre. The OLS and household fixed effects specifications run are $y_{it} = \delta + \beta h_{it} + X_{it}'\gamma + \varepsilon_{it}$ and $y_{it} = \delta + a_i + \beta h_{it} + X_{it}'\gamma + \varepsilon_{it}$.

and testable with panel data.[43] Intuitively, the CRE model tests the fact that if the fixed effects model is valid, then the only way the history of h_{it} affects the current outcome is through a fixed effect that is the same in every period. Table IIIB shows these tests. It shows both the reduced form and structural estimates for the CRE model. Covariates can be treated as either exogenous or endogenous (the latter are assumed to be correlated with the fixed effects). I report estimates where all the covariates are allowed to be endogenous.[44] The

Card (1985)). Such assumptions can be motivated by myopia or ignorance of the potential gains from planting hybrid. Both of these seem unrealistic here, since hybrid maize was introduced in the 1960's with widespread use of extension services to promote the technology (Evenson and Mwabu (1998)) and data in the survey instrument support this as 90% of farmers have used hybrid seed at some point in the past.

[43]With a data generating process of $y_{it} = \delta + \beta h_{it} + \alpha_i + u_{it}$, the CRE model is based on the assumption of strict exogeneity, that is, $E(u_{it}|h_{i1}, \dots, h_{iT}, \alpha_i) = 0$. For the CRE model, the minimum distance estimator is the minimum χ^2 estimator if the weight matrix used is the inverse of the variance–covariance matrix of the reduced form coefficients. See Suri (2006) for more detail on this approach for the current setting.

[44]If I treat only hybrid as endogenous and all the other covariates as exogenous, the results are similar.

TABLE IIIB

CRE MODEL REDUCED FORMS AND STRUCTURAL ESTIMATES DEPENDENT VARIABLE IS YIELDS (LOG MAIZE HARVEST PER ACRE)[a]

Reduced Form Estimates

	Without Covariates		With Covariates		With Covariates and Interactions of Covariates with Hybrid	
	Yields, 1997	Yields, 2004	Yields, 1997	Yields, 2004	Yields, 1997	Yields, 2004
Hybrid, 1997	0.674 (0.075)	0.538 (0.065)	0.579 (0.064)	0.415 (0.060)	0.467 (0.242)	0.501 (0.228)
Hybrid, 2004	0.809 (0.072)	0.723 (0.062)	0.411 (0.065)	0.563 (0.063)	1.214 (0.259)	0.630 (0.230)

Optimal Minimum Distance (OMD) Structural Estimates

	Without Covariates	With Covariates	With Covariates and Interactions of Covariates With Hybrid
β	0.0322 (0.0701)	0.1588 (0.0653)	−0.3039 (0.2522)
λ_1	0.5795 (0.0621)	0.4166 (0.0570)	0.5683 (0.2103)
λ_2	0.7332 (0.0684)	0.4062 (0.0622)	1.0447 (0.2351)
χ^2_1	44.63	0.193	460.5

[a]Standard errors are given in parentheses. Reduced forms are estimated without covariates, with covariates (acreage, real fertilizer expenditure, real land preparation costs, seed, labor, household size, household age–sex composition variables, and rainfall variables) and with all covariates interacted with hybrid. The covariates are all treated as endogenous. Results are the same if three periods without family labor are used. Results are similar if all covariates except hybrid are treated as exogenous. The reduced form for each t, the projection used to estimate the structural model by minimum distance, and the structural model are, respectively, $y_{it} = \delta_t + \gamma_{1t} h_{it} + \gamma_{2t} h_{i2} + \gamma_{3t} h_{i3} + X_i' \pi_t + \varepsilon_{it}$, $a_i = \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + v_i$, and $y_{it} = \delta + \beta h_{it} + a_i + u_{it}$. Structural coefficients β and projection coefficients (λ's) are reported. OMD are optimal (weighted by inverted reduced form variance–covariance matrix) minimum distance estimates. Equally weighted (using the identity matrix) and diagonally weighted (using only the diagonal elements from the OMD weight matrix) minimum distance results are similar.

CRE estimates of the return to hybrid are close to the household fixed effects estimates in Table IIIA, but the χ^2 values on the overidentification test allow me to reject the fixed effects model.[45] The last column of Table IIIB shows estimates for the case where hybrid is interacted with all the covariates. Although the coefficient on hybrid is negative, when evaluated at the mean input levels, the mean return to hybrid is positive.

5.2. *IV and Treatment Effect Estimates*

This section presents IV and control function estimates of the returns to hybrid, using the Heckman two-step estimator (also see Garen (1984)). In par-

[45]This overidentification test is an omnibus test and has low power against any specific alternative. It is, therefore, not that surprising that I am able to reject the overidentifying restrictions.

ticular, I present estimates of the average treatment effects (ATE), the treatment on the treated (TT), marginal treatment effects (MTE), and local average treatment effects (LATE) under nonrandom assignment (see Björklund and Moffitt (1987) and Heckman, Tobias, and Vytlacil (2001)).[46] These approaches do not fully address the issues at hand and do not exploit the panel nature of the data, but they provide useful benchmarks.

With assumptions of normality, it is straightforward to estimate the selection corrected treatment effects using a two-step control function procedure. The first stage is a probit describing the hybrid adoption decision, from which selection correction terms are computed and used as controls in second stage sector-specific yield functions. The ATE uses estimates from this second step. The TT adjusts the estimated ATE for the sample of those who actually plant hybrid. The slope of the MTE describes whether people who are more likely to use hybrid for unobservable reasons (i.e., have a higher error in the selection equation) have higher or lower returns from planting hybrid.

The exclusion restriction I use is the distance to the closest fertilizer store (not to where fertilizer is actually purchased), which proxies for the availability of the technologies. The treatment effects are shown in Table IV separately for 1997 and 2004. The ATE's are all large and positive, ranging from 1.3 to 2.4, with smaller TT estimates. The MTE slope is consistently negative and significant: −0.99 in 2004 and −2.51 in 1997. A nonzero MTE slope implies heterogeneity in returns and the sign of the MTE slope provides information on the underlying selection process. The negative MTE slopes imply that the farmers who are more likely to use hybrid are those who have the lower relative returns to using hybrid, that is, there is negative selection on returns in hybrid.

I also estimate the IV (LATE) specification. An issue with IV estimates is that the results are often different if different instruments are used. This is attributed to underlying heterogeneity in the population where the separate instruments affect a different subset of the population, resulting in the different LATE estimates (i.e., an average of heterogeneous returns that is instrument dependent). However, the instrument itself does not always highlight which subset of the population it affects (Heckman (1997)). The lower panel of Table IV reports two versions of IV. The first data column reports an estimate of over 200%, which uses the distance to the closest stock of fertilizer as the excluded instrument. The second data column uses the interactions of this distance measure with dummies for the household's asset quintile as excluded instruments (the distance and asset quintile main effects are included in both

[46]The treatment effects are defined as follows. The ATE is given by $E((y^H - y^N)|X = x) = x(\gamma^H - \gamma^N)$, the TT is given by $\mathrm{TT}(x, z, h(Z) = 1) = x(\gamma^H - \gamma^N) + (\rho_H\sigma_H - \rho_N\sigma_N)\phi(z\pi)/\Phi(z\pi)$, and the MTE is given by $\mathrm{MTE}(x, u_i^s) = x(\gamma^H - \gamma^N) + (\rho_H\sigma_H - \rho_N\sigma_N)u_i^s$, where $y^H - y^N$ is the yield gain from hybrid, u_i^H and u_i^N are as defined earlier, $\sigma_H^2 = \mathrm{Var}(u_i^H)$, $\sigma_N^2 = \mathrm{Var}(u_i^N)$, u_i^s is the error in the selection equation, $\rho_H = \mathrm{Corr}(u_i^H, u_i^s)$ and $\rho_N = \mathrm{Corr}(u_i^N, u_i^s)$; $\phi(\cdot)$ and $\Phi(\cdot)$ represent the normal probability and cumulative distribution functions, respectively, and $\mathrm{Var}(u_i^s) = 1$.

TABLE IV

HECKIT AND TREATMENT EFFECT ESTIMATES UNDER NONRANDOM ASSIGNMENT (ATE, TT, MTE, LATE)[a]

	Heckman Two-Step Estimates: Selection Correction λ		Implied Treatment Effects		
Year	Hybrid Sector	Nonhybrid Sector	ATE	TT	MTE Slope
1997	−0.854 (0.170)	1.659 (0.864)	2.391	0.917	−2.512 (0.880)
2004	−0.957 (0.181)	0.028 (0.152)	1.279	0.921	−0.985 (0.237)

IV (LATE) Estimates (Conditional on Covariates)		
First stage: Effect of distance	−0.288 (0.108)	—
First stage: Effect of distance interacted with wealth quintile ($\times$ 100)		
Second wealth quintile (coefficient on interaction)	—	−0.221 (0.302)
Third wealth quintile (coefficient on interaction)	—	−0.057 (0.032)
Fourth wealth quintile (coefficient on interaction)	—	0.329 (0.288)
Fifth wealth quintile (coefficient on interaction)	—	0.507 (0.273)
F test p-value on excluded instruments	0.008	0.108
Second stage: Effect of predicted hybrid on yields	2.768 (1.123)	1.536 (0.816)

[a]Standard errors are given in parentheses. All regressions control for covariates. The first two upper panel data columns show (for each year) the two-step selection corrected estimates of coefficients on the inverse Mills ratio for hybrid and nonhybrid sectors from $h_i = Z_i'\pi + u_i^s$, $y_i^H = X_i'\gamma^H + \lambda^H[\phi(Z_i'\hat{\pi})/\Phi(Z_i'\hat{\pi})]$, and $y_i^N = X_i'\gamma^N + \lambda^N[\phi(Z_i'\hat{\pi})/(1-\Phi(Z_i'\hat{\pi}))]$. The third data column reports the average treatment effect accounting for selection and the fourth data column reports the treatment on the treated. Finally, the MTE slope is just the difference in the λ coefficients for the hybrid and nonhybrid selection terms (the difference between coefficients reported in the first two data columns). ATE, TT, and MTE are all evaluated at the mean X_i's. The lower panel reports two set of IV estimates. The first data column uses the distance to *closest* fertilizer supplier (not where fertilizer is purchased) as the excluded instrument. The second data column uses the distance interacted with wealth quintiles as excluded instruments (controlling for the asset quintile dummies and the distance main effect in both stages). All regressions control for the full set of covariates as per earlier tables (including household size and controls for the age–sex composition of the household as above).

stages). This strategy allows distance to be more of a constraint for poorer households. These estimates are on the order of 150%, still very large when compared with the earlier OLS and household fixed effects estimates, and indicate high returns to hybrid for the supply (of seed and fertilizer) constrained farmers.

Overall, the preliminary evidence from these approaches indicates large positive returns for at least some subpopulations of farmers, but also evidence of substantial heterogeneity in returns with negative selection into the use of hybrid.

5.3. *Motivation for Heterogeneity in Returns*

This section presents some preliminary regressions that further motivate heterogeneity in returns. Previous research has developed tests for heterogeneity in returns for experimental data (see Heckman, Smith, and Clements (1997)). Since the data here are not experimental, the results are not reported, but using such tests I do reject the null of no heterogeneity.[47]

Table V presents some evidence of selection on the part of farmers in their adoption decisions. The adoption history of a farmer is split into a set of dummy variables to analyze whether farmers with different histories have different returns (see Jakubson (1991) and Card and Sullivan (1988)). A "joiner" is a farmer who does not plant hybrid the first period, but does the next, and a "leaver" is a farmer who plants hybrid the first period, but not the next. Similarly, "hybrid stayers" always use hybrid and "nonhybrid stayers" always use nonhybrid. Table V compares the yields for each of these groups in 1997 and 2004 separately. If there was no selection at all, we would expect the leavers in 1997 to be no different from the hybrid stayers in 1997, and no different from the joiners in 2004. Similarly, the joiners in 1997 and the leavers in 2004 should be no different from the omitted group (the nonhybrid stayers). I can reject most of these restrictions, implying that there is selection, and leavers and joiners are distinct (unlike in a fixed effects model).

Finally, in Table VI, I look for heterogeneity in the returns to hybrid along observables, estimating OLS and fixed effects yield functions separately for hybrid and nonhybrid farmers. In the OLS case, the returns to some of the covariates are different, although not family or hired labor. In the case of the fixed effects specifications, it is only the return to fertilizer that is different across hybrid and nonhybrid sectors. The last row reports estimates of the return to hybrid (evaluated at the mean inputs), still showing a significant return to hybrid.

[47]These tests include looking at the Frechet–Hoeffding bounds, bounding the variance in the percentiles of the returns distribution, and testing whether this bound is different from zero (see Suri (2006)).

TABLE V

SELECTION RETURNS BY HYBRID HISTORY (JOINERS, LEAVERS, AND STAYERS): DEPENDENT VARIABLE IS YIELDS (LOG MAIZE HARVEST PER ACRE)[a]

	Without Covariates		With Covariates	
Variable	1997 Yield	2004 Yield	1997 Yield	2004 Yield
Hybrid stayers	1.505 (0.066)	1.280 (0.056)	0.869 (0.073)	0.683 (0.063)
Leavers	0.809 (0.094)	0.648 (0.079)	0.537 (0.084)	0.370 (0.069)
Joiners	1.007 (0.114)	0.883 (0.096)	0.469 (0.101)	0.498 (0.084)
Acres ($\times$ 100)	—	—	0.561 (0.782)	−0.744 (0.802)
Seed kg per acre ($\times$ 10)	—	—	0.218 (0.035)	0.197 (0.032)
Land preparation costs per acre ($\times$ 1000)	—	—	0.066 (0.023)	0.058 (0.021)
Fertilizer per acre ($\times$ 1000)	—	—	0.063 (0.012)	0.061 (0.012)
Hired labor per acre ($\times$ 1000)	—	—	0.028 (0.008)	0.057 (0.010)
Family labor per acre ($\times$ 1000)	—	—	0.415 (0.075)	0.318 (0.064)

[a]Standard errors are in parentheses. In each year, the regression $y_i = \delta + \mu_1 h_{i11} + \mu_2 h_{i10} + \mu_3 h_{i01} + X_i'\pi + u_i$ is run both with and without the covariates, where h_{i11} is the dummy indicating that farmer i is a hybrid stayer (plants hybrid in both periods), h_{i10} indicates he is a leaver (plants hybrid the first year, not the second), and h_{i01} indicates he is a joiner (plants hybrid the second year, not the first). The coefficients reported are μ_1, μ_2, and μ_3. Covariates included that are not reported above are province dummies, household size, variables for the age–sex composition of the household (includes variables for the number of boys (aged <16 years), the number of girls, the number of men (aged 17–39), the number of women, and the number of older men (aged >40 years)), the main season rainfall, and the average long term main season rainfall. Note that hired labor is measured in KShs per acre and family labor is measured in hours per acre.

6. CRC ESTIMATES

This section describes the results for the CRC model. I report estimates for the pure hybrid model described in detail above (with and without covariates). In addition, I report results for the endogenous covariates and joint hybrid–fertilizer technology sector models.

Tables VII, VIIIA, VIIIB, and VIIIC present the CRC model reduced form and structural estimates. These tables report only the optimal minimum distance (OMD) estimates where the weight matrix used in the minimum distance problem is the inverse of the variance–covariance matrix of the reduced form coefficients. If the minimum distance problem is overidentified, the χ^2 test statistic on the overidentification test is the value of the minimand in the OMD problem.[48]

[48]Equally weighted minimum distance (EWMD) estimates use the identity matrix as the weight matrix and diagonally weighted minimum distance (DWMD) estimates use the OMD matrix with the off-diagonal elements set to zero (see Pischke (1995)). The OMD estimates are efficient, but may be biased in small samples and can, therefore, be outperformed by EWMD (see Altonji and Segal (1996)). For all the results in the paper, the EWMD and DWMD estimates are extremely similar to OMD, but the OMD estimates are asymptotically efficient, so only they are reported. See Suri (2006) for the EWMD and DWMD estimates.

TABLE VI

HETEROGENEITY BY OBSERVABLE RETURNS IN THE HYBRID/NONHYBRID SECTOR: DEPENDENT VARIABLE IS YIELDS (LOG MAIZE HARVEST PER ACRE)[a]

	OLS With Covariates		FE With Covariates	
Variable	Hybrid	Nonhybrid	Hybrid	Nonhybrid
Acres ($\times$ 10)	0.144 (0.056)	−0.053 (0.149)	−0.381 (0.153)	−0.941 (0.379)
Seed kg per acre ($\times$ 10)	0.281 (0.035)	0.129 (0.036)	0.219 (0.047)	0.147 (0.063)
Land preparation costs per acre ($\times$ 1000)	0.056 (0.018)	0.135 (0.031)	0.033 (0.024)	0.097 (0.060)
Fertilizer per acre ($\times$ 1000)	0.064 (0.008)	0.143 (0.032)	0.040 (0.011)	0.081 (0.086)
Hired labor per acre ($\times$ 1000)	0.047 (0.007)	0.026 (0.010)	0.054 (0.011)	0.035 (0.029)
Family labor per acre ($\times$ 1000)	0.297 (0.064)	0.435 (0.081)	0.497 (0.094)	0.581 (0.177)
Year = 2004	0.568 (0.050)	0.595 (0.068)	0.467 (0.058)	0.689 (0.096)
Average return (β) when returns vary by observables (evaluated at mean X's)	0.480 (0.048)		0.091 (0.076)	
Number of observations	1517	887	1517	887

[a]Standard errors are given in parentheses. The specification $y'_{it} = \delta^j + X_{ti}\gamma^j + \varepsilon^j_{it}$, $j \in H, N$, is estimated separately for the sample of farmers who use hybrid and nonhybrid maize. The covariates included that are not reported are province dummies, household size, age–sex composition of the household (includes variables for the number of boys (aged <16 years), the number of girls, the number of men (aged 17–39), the number of women, and the number of older men (aged >40 years)), the main season rainfall, and the average long term main season rainfall. The results are similar for the three period sample without family labor as a covariate. Note that hired labor is measured in KShs per acre and family labor is measured in hours per acre.

Throughout, the results show that the selection into hybrid is negative, with the farmers having the lowest yields in nonhybrid having the highest returns to planting hybrid. The estimated ϕ is consistently negative, which illustrates that the households that do better on average, do relatively worse at hybrid as the sign of ϕ describes the sorting process. The CRC model results are, therefore, consistent with the earlier MTE results.

Table VII presents the two period reduced forms for the CRC model. The first data column shows the reduced form estimates without covariates as a benchmark. The second data column controls for all the inputs and the third for all the inputs interacted with hybrid. The reduced forms are estimated via seemingly unrelated regressions with the most general variance–covariance estimation. The estimates in Table VII are for the basic specification described above, where hybrid is the only endogenous variable and the projection used is given by equation (29). Table VIIIA reports the structural OMD results and the χ^2 statistics for all three specifications. The estimates of ϕ are consistently negative. I also report the structural estimates for the case where the sample excludes two districts with very high adult mortality between 1997 and 2004,[49]

[49]Thanks to an anonymous referee for pointing this out. Jayne and Yamano (2004) documented how this mortality affects the value of high value crops produced, but not the value or productivity of maize.

TABLE VII

TWO PERIOD BASIC COMPARATIVE ADVANTAGE CRC MODEL REDUCED FORM ESTIMATES: DEPENDENT VARIABLE IS YIELDS (LOG MAIZE HARVEST PER ACRE)[a]

	Without Covariates		With Endogenous Covariates		With Interactions With Hybrid	
	Yields, 1997	Yields, 2004	Yields, 1997	Yields, 2004	Yields, 1997	Yields, 2004
Hybrid, 1997	0.833 (0.121)	0.471 (0.099)	0.719 (0.103)	0.316 (0.088)	0.926 (0.252)	0.139 (0.092)
Hybrid, 2004	1.139 (0.122)	0.766 (0.103)	0.702 (0.110)	0.508 (0.092)	0.474 (0.122)	0.520 (0.222)
Hybrid 1997 × hybrid 2004	−0.458 (0.156)	−0.194 (0.132)	−0.358 (0.132)	−0.098 (0.110)	−0.084 (0.147)	−0.115 (0.117)
Acres (× 10)	—	—	0.106 (0.067)	−0.006 (0.098)	−0.220 (0.302)	−0.799 (0.300)
Seed kg per acre (× 10)	—	—	0.230 (0.052)	0.433 (0.060)	0.211 (0.062)	0.200 (0.086)
Land preparation cost per acre (× 1000)	—	—	0.124 (0.025)	0.133 (0.039)	0.033 (0.051)	0.353 (0.077)
Fertilizer per acre (× 1000)	—	—	0.079 (0.018)	0.042 (0.014)	0.281 (0.073)	0.106 (0.035)
Hired labor per acre (× 1000)	—	—	0.025 (0.014)	0.053 (0.010)	0.008 (0.014)	0.049 (0.019)
Family labor per acre (× 1000)	—	—	0.399 (0.115)	0.186 (0.071)	0.676 (0.187)	0.198 (0.128)
R-squared	0.285	0.232	0.454	0.441	0.486	0.489

[a]Standard errors are given in parentheses. Reduced forms are estimated with standard covariates and then with interactions of all the covariates with hybrid. Covariates not reported include main season rainfall, household size, and age–sex composition of the household (includes variables for the number of boys (aged <16 years), the number of girls, the number of men (aged 17–39), the number of women, and the number of older men (aged >40 years)). Note that hired labor is measured in KShs per acre and family labor is measured in hours per acre. Where the covariates are interacted with hybrid, only main effects of the covariates are reported. Reduced forms are for the case where all covariates are exogenous: only hybrid is correlated with the comparative advantage, θ_i. See Table VIII for the projection and structural estimates. The reduced form equations run are $y_{i1} = \delta_1 + \gamma_1 h_{i1} + \gamma_2 h_{i2} + \gamma_3 h_{i1} h_{i2} + \xi_{i1}$ and $y_{i2} = \delta_2 + \gamma_4 h_{i1} + \gamma_5 h_{i2} + \gamma_6 h_{i1} h_{i2} + \xi_{i2}$ for 1997 and 2004, respectively.

TABLE VIIIA

TWO PERIOD BASIC COMPARATIVE ADVANTAGE CRC MODEL OMD STRUCTURAL ESTIMATES[a]

	With Only Hybrid Endogenous					
	Full Sample			Without HIV Districts		
	Without Covariates	With Covariates	With Interactions With Hybrid	Without Covariates	With Covariates	With Interactions With Hybrid
λ_1	0.648 (0.093)	0.565 (0.087)	0.456 (0.090)	0.471 (0.099)	0.305 (0.089)	0.139 (0.092)
λ_2	1.007 (0.112)	0.665 (0.104)	0.473 (0.116)	1.139 (0.122)	0.710 (0.112)	0.466 (0.123)
λ_3	1.636 (4.854)	−1.690 (4.316)	−0.485 (0.199)	−4.800 (9.173)	−0.936 (0.308)	−0.497 (0.257)
β	−0.543 (1.874)	1.023 (1.480)	3.534 (24.05)	2.287 (4.222)	0.623 (0.100)	0.790 (0.169)
ϕ	−0.794 (0.411)	−1.317 (1.262)	−17.82 (137.4)	−1.010 (0.228)	−1.518 (0.310)	−2.196 (1.142)
χ_1^2	40.089	11.25	139.5	175.5	114.1	305.2

[a]Standard errors are given in parentheses. The reduced forms for these estimates are reported in Table VII (for the case where only the hybrid decision is endogenous, i.e., correlated with the θ_i's). The projection used in this model is $\theta_i = \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i1} h_{i2} + v_i$. The structural coefficients reported are the average return to hybrid (β), the comparative advantage coefficient (ϕ), and the projection coefficients (λ's). OMD is optimal weighted (the weight matrix is the inverted reduced form variance–covariance matrix) minimum distance. Results from diagonally weighted (the weight matrix is the OMD weight matrix with the off-diagonal elements set to zero) and equally weighted minimum distance are similar. The χ^2 statistic on the overidentification test is the value of the OMD minimand. Results are reported for two samples: the full sample and the sample without two districts where HIV is prevalent. In addition, minimum distance results for three different specifications are reported: without covariates, with covariates, and with covariates and interactions of the covariates with the hybrid decision (reported in Table VII). All the specifications with covariates assume that all covariates are exogenous: only hybrid is correlated with the comparative advantage, θ_i. Covariates include acreage, land preparation costs, fertilizer, hired labor, family labor, main season rainfall, household size and age–sex composition of the household (includes variables for the number of boys (aged <16 years), the number of girls, the number of men (aged 17–39), the number of women, and the number of older men (aged >40 years)).

TABLE VIIIB

JOINT SECTOR COMPARATIVE ADVANTAGE CRC MODEL OMD STRUCTURAL ESTIMATES[a]

	With Joint Sector Fertilizer-Hybrid Decision			
	Full Sample		Without HIV Districts	
	With Covariates	With Interactions With Hybrid	With Covariates	With Interactions With Hybrid
β	0.639 (0.095)	1.148 (0.813)	0.420 (0.051)	0.901 (0.175)
ϕ	−1.602 (1.684)	−3.133 (4.003)	−1.687 (0.554)	−2.051 (1.282)

[a]Standard errors are given in parentheses. OMD is optimal weighted (the weight matrix is the inverted reduced form variance–covariance matrix) minimum distance. Results from diagonally weighted (the weight matrix is the OMD weight matrix with the off-diagonal elements set to zero) and equally weighted minimum distance are similar. The structural coefficients reported are average return to hybrid (β) and the comparative advantage coefficient (ϕ). Results are reported for two samples: the full sample and the sample without two HIV districts and are for two periods of data. In addition, minimum distance results for two different specifications are reported: with covariates and with covariates and interactions of the covariates with the hybrid decision. All the specifications with covariates assume that all covariates other than hybrid and/or fertilizer are exogenous. Covariates include acreage, land preparation costs, fertilizer, hired labor, family labor, main season rainfall, household size, and age–sex composition of the household (includes variables for the number of boys (aged <16 years), the number of girls, the number of men (aged 17–39), the number of women, and the number of older men (aged >40 years)).

what I call the non-HIV sample. The results are much more precise and stable across specifications for this sample.

Tables VIIIB and VIIIC present structural estimates of ϕ for the case where fertilizer endogenously enters the farmer's decisions. In Table VIIIB, I report results for the case where there is a joint hybrid–fertilizer decision on the part of the farmer so that he is in the technology sector if he uses both hybrid and fertilizer;[50] otherwise, he is not. Results for ϕ are again consistently negative, and significant mostly in the specifications that exclude the two high mortal-

TABLE VIIIC

COMPARATIVE ADVANTAGE CRC MODEL OMD ESTIMATES: BOTH HYBRID AND FERTILIZER ENDOGENOUS[a]

	With Both Fertilizer and Hybrid as Endogenous Projection: $\theta_i = \lambda_0 + \lambda_1 h_{i1} + \lambda_2 h_{i2} + \lambda_3 h_{i1} h_{i2} + \lambda_4 h_{i1} f_{i1} + \lambda_5 h_{i2} f_{i1} + \lambda_6 h_{i1} h_{i2} f_{i1} + \lambda_7 h_{i1} f_{i2} + \lambda_8 h_{i2} f_{i2} + \lambda_9 h_{i1} h_{i2} f_{i2} + \lambda_{10} f_{i1} + \lambda_{11} f_{i2} + v_i$			
	Full Sample		Without HIV Districts	
	With Covariates	With Interactions With Hybrid	With Covariates	With Interactions With Hybrid
β	0.088 (0.096)	0.915 (0.417)	0.603 (0.060)	0.686 (0.174)
ϕ	−0.449 (0.176)	−3.772 (2.707)	−1.788 (0.277)	−2.118 (0.641)

[a]The notes for Table VIIIB apply here also.

[50]The fertilizer decision I use involves chemical fertilizers. The results are similar if I include the use of manure as part of the fertilizer decision.

ity districts. Finally, in Table VIIIC, I allow for fertilizer to be endogenous and correlated with the θ_i's, using the projection in equation (35). Again, the estimates of ϕ in Table VIIIC are consistently negative across all OMD specifications, again more so for the sample without the two high mortality districts.

Overall, to summarize these results, the null hypothesis that ϕ is equal to zero is often rejected and estimates of ϕ are consistently negative.[51] These results hold predominantly for the non-HIV districts in the sample, that is, after leaving out 2 of the overall 22 districts in the sample. For these households, the selection into hybrid is negative, with the farmers having the lowest yields in nonhybrid having the highest returns to planting hybrid.

6.1. *Recovering the Distribution of* $\widehat{\theta_i}$

Given the CRC structural estimates of the λ's and the form of the projection given by either equations (29) or (35), the θ_i's can be predicted for a given history of hybrid (and fertilizer) use. However, to do so, 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 (35). For equation (29), since h_{it} is binary and each history is accounted for, the projection is essentially saturated (for example, polynomials in adoption would be redundant since adoption is a dummy variable). Using the predicted distribution of θ_i, the predicted τ_i's can be derived via the yield function. Intuitively, the process of recovering the distribution of θ_i is building a counterfactual set of returns for the nonadopters using a weighted average of the experience of every type of farmer, where "type" refers to the farmer's hybrid history.

For the simple two period model (Table VIIIA), since the predicted θ_i's are obtained from the projection in equation (29), the distribution of the predicted θ_i's has just four mass points. There are only four possible hybrid histories: nonhybrid stayers, hybrid stayers, leavers, and joiners. The results indicate that the nonhybrid stayers have the most negative $\widehat{\theta_i}$, followed by the hybrid stayers, then the leavers and joiners. While the nonhybrid stayers have the lowest predicted θ_i's, they have the highest returns to hybrid as $\phi < 0$.[52]

Using the projection in equation (35), I can similarly estimate the distribution of θ_i using the estimates in Table VIIIC. 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 (35), which includes the amount of fertilizer used. To plot the distribution of the $\widehat{\theta_i}$'s and the overall return to hybrid, I use the estimates from

[51]The results without covariates and across all EWMD and DWMD specifications are similar. In addition, the following robustness checks give similar results: dropping the Coast province, allowing for depreciation of assets used in land preparation (for example, a tractor, which only 2% of households own), valuing yields and all the inputs using prices where possible, and using estimated profits instead of yields.

[52]I do not report these estimates as they do not account for the endogeneity of fertilizer (see Suri (2006)).

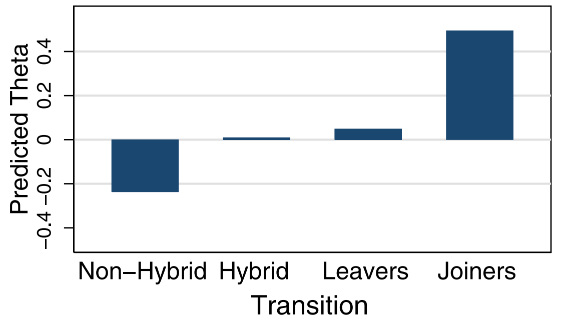

FIGURE 5A.—Distribution of comparative advantage.

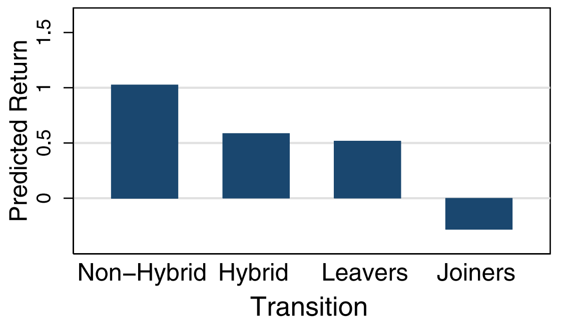

FIGURE 5B.—Distribution of returns.

the third data column of Table VIIIC, which excludes the two HIV districts and controls only for covariates. This is a simpler model to compute the overall return to hybrid, since hybrid is not interacted with all the covariates. The results are not different across the last two columns in Table VIIIC, so I opt to use this simpler model for the purposes of plotting the distribution of the comparative advantage and the returns.

Figure 5A shows the means of the $\widehat{\theta}_i$ by transition: again, the nonhybrid stayers have the most negative $\widehat{\theta}_i$, followed by the hybrid stayers, then the leavers and joiners. Figure 5B shows the distribution of returns across the sample by transition. The distribution of returns is given by $\beta + \phi\theta_i$, where β is the structural coefficient on h_{it} in equation (20), that is, the average return to hybrid. Since $\phi < 0$, the ordering of returns is the reverse of the ordering of θ_i's, that is, the nonhybrid stayers have the most negative θ_i's, but the highest positive returns. The joiners and leavers have close to zero returns (they are the marginal farmers) and the hybrid stayers have lower positive returns. Note that the sign of ϕ determines the ordering of the magnitude of the returns across transitions; this ordering is by no means mechanical. Figure 5C shows the distribution of the predicted $\widehat{\theta}_i$'s by transition. Finally, as a check, Figure 5D shows

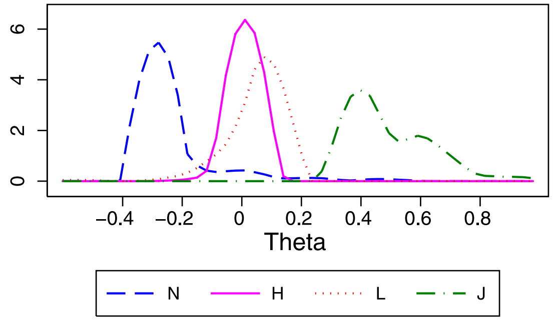

FIGURE 5C.—Endogenous hybrid and fertilizer use.

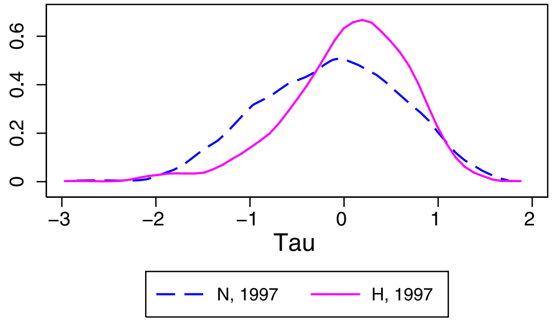

FIGURE 5D.—Distribution of tau, by adoption decision in 1997.

the corresponding distribution of the predicted τ_i's, which were constructed to be orthogonal to the hybrid choice.

7. DISCUSSION

Figure 5B resolves one puzzle about low adoption rates: the hybrid joiners and leavers are marginal farmers in the sense of having very low returns as compared to the average return. However, while the empirical results resolve this one puzzle of why some farmers move in and out of hybrid despite high returns for the average farmer, the results indicate a further puzzle: the very large counterfactual returns to growing hybrid for the nonhybrid stayers. To examine this latter puzzle, I return to the decision rule in equation (25) and relate the estimated gross returns to observable supply and demographic characteristics of the farmers (just for the sample excluding the two HIV districts). Table IX illustrates that the households with the lower predicted $\widehat{\theta}_i$'s have much higher cost determinants. Recall that throughout the sample period, the price of hybrid seed was fixed across the country. This meant that seed suppliers had no incentives to locate far away from markets or roads as there was no compensating price increase.

The regressions in Table IX therefore correlate the predicted $\widehat{\theta}_i$'s with observable cost measures in the data.[53] The observables considered are the distance from the household to the closest fertilizer seller, distance to the closest matatu (public transport) stop, distance to the closest motorable road, distance to the closest extension services, a set of dummies for education of the household head, a dummy for whether the household tried to get credit, a dummy for whether the household tried to get credit but did not receive any, a dummy for whether the household received any credit, and province dummies. Villages are large and heterogeneous, and these measures of costs and infrastructure vary even within a village. The infrastructure and education variables correlate strongly with the predicted $\widehat{\theta}_i$'s, but the credit variables do not. The last column shows similar results without province dummies.[54]

These results indicate that while there are high potential returns to the farmers who never grow hybrid during the sample period, they face higher costs and supply constraints. The IV/LATE estimates in Table IV also suggested that distance and infrastructure are constraining factors. From Table IV, the IV estimates are about 150%, which implies that those affected by the infrastructure instrument are the nonhybrid stayers, since these IV estimates are of the same magnitude as the estimated returns for the nonhybrid stayers.

Thus, given existing seed supply locations and infrastructure constraints, the adoption decisions appear to be quite rational. Liberalizing the seed market and seed prices may have large benefits. In addition, while I do not have the data for a social return calculation to expanding supply, encouraging greater seed supply to the more remote areas of Kenya could have large benefits, but will also have large costs of expanding infrastructure.

7.1. *Competing Explanations*

Finally, I discuss some alternative explanations of adoption behavior that are popular in the literature. The first is a model of learning, where households are uninformed about the benefits of a technology and they experiment to learn what the returns are. Learning models give rise to the familiar S-shaped curves of adoption rates over time (see Griliches (1957)). In my data, adoption rates show no such dynamics. Aggregate adoption remains constant over the span

[53]As pointed out by an anonymous referee, given how the $\widehat{\theta}_i$'s are estimated, it could induce a mechanical positive correlation between the estimated $\widehat{\theta}_i$'s and the costs even if no such correlation exists. Simulating the model for a range of true values of ϕ showed that the bias is small and in the opposite direction to the sign of the correlations reported in Table IX. Whenever $\phi < 0$ (as is the case for my estimates), for example, the bias would always mean a positive coefficient between costs and the estimated $\widehat{\theta}_i$'s, whereas the correlations in Table IX are all negative.

[54]These results are all for the model with endogenous hybrid and fertilizer (estimates from Table VIIIC).

TABLE IX

CORRELATES OF ESTIMATED θ_i'S: DEPENDENT VARIABLE IS THE ESTIMATED θ_i'S[a]

	(1)	(2)	(3)	(4)	(5)
Distance to closest fertilizer seller ($\times$ 100)	−0.301 (0.122)	−0.289 (0.121)	−0.285 (0.121)	−0.285 (0.121)	−0.315 (0.063)
Distance to motorable road ($\times$ 100)	−0.904 (0.503)	−0.887 (0.501)	−0.901 (0.502)	−0.898 (0.501)	−0.978 (0.285)
Distance to matatu stop ($\times$ 100)	0.032 (0.298)	−0.034 (0.298)	−0.016 (0.298)	−0.028 (0.299)	−0.021 (0.165)
Distance to extension services ($\times$ 100)	−0.130 (0.155)	−0.063 (0.155)	−0.063 (0.155)	−0.061 (0.155)	0.002 (0.091)
Tried to get credit ($\times$ 10)	—	−0.138 (0.153)	—	—	—
Tried but did not receive credit ($\times$ 10)	—	—	0.027 (0.347)	—	—
Received credit ($\times$ 10)	—	—	—	−0.047 (0.154)	−0.164 (0.144)
Dummies for household head education	No	Yes	Yes	Yes	Yes
(p-value on joint significance)		(0.002)	(0.002)	(0.000)	(0.000)
Province dummies	Yes	Yes	Yes	Yes	No

[a]Standard errors are given in parentheses. This table reports the correlations of the predicted θ_i's with various observables. The predicted θ_i's used are from the two period case with endogenous hybrid and fertilizer use (Table VIIIC). The observables are the average of the 1997 and 2004 values. Columns (1)–(4) show the results while controlling for province dummies. Since a lot of the variation in infrastructure may be aggregate, column (5) also shows the results without province dummies, but just for the "Received credit" variable on the credit side (the results are no different for the other credit variables).

of almost 10 years. In fact, there are no dynamics in any of the inputs, even after a large rainfall shock due to El Nino in 1998. Any conventional model of learning does not appear to be borne out by these aggregates, although there may have been learning effects closer to the introduction of hybrid in Kenya: Gerhart (1975) showed S-shaped curves in the 1970's, curves that flattened out at low aggregate adoption rates prior to 1997.

The switching between hybrid and nonhybrid from period to period may look like experimentation, but recall that hybrid and fertilizer have been available for a few decades now. In addition, 90% and 83% of households have used hybrid and fertilizer before, respectively. Table IID does not show any systematic persistence in adoption; the cycling behavior is about as prevalent as the noncycling. In the qualitative parts of the survey, farmers who were using traditional varieties were asked why they were not using hybrid and only about 0.3% cited experimenting or on trial. In addition, Duflo, Kremer, and Robinson (2008a) found little evidence of learning in western Kenya. Learning therefore seems to be unimportant in this setting.[55]

There are different varieties of hybrid, so it may be possible that households are learning about these types and are switching to newer varieties over time. In this case, there should still be aggregate increases in adoption over time. For two periods of the survey (2002 and 2004), the data include exactly what type of hybrid variety was used. In 2002, 61.5% of maize plots were planted with hybrid 614, 6% each of 625 and 627, and 4% of 511. The release dates of these varieties were 1986, 1981, 1996, and the 1960's, respectively. In 2004, 69.5% of plots were planted with 614, 5% with 627, and 4% each with 625 and 511. It seems that most households use rather old varieties of hybrid seed. As a further check, I categorize the type of hybrid used in 2004 as new or not, where anything released after 1990 is defined as new. I cannot look at leavers as I do not know what hybrid type they used in 1997, and in 2004 they do not use hybrid. Of the hybrid stayers, about 11.5% use new hybrids and 12.9% of the joiners use new hybrids. These two means are not statistically significantly different from each other (the p-value is 0.702).

A second set of alternative explanations deals with the role of credit constraints. Credit constraints do not seem to be of first order importance for several reasons. First, a strikingly large number of households are able to get access to credit, especially for agricultural purposes, and of those that try to get credit, most get it. In 2004, 41% of all households tried to get credit and 83% of them got it. In 1997, these figures were collected for agricultural credit, where 33.7% of households tried to get agricultural credit and 90% got it. There

[55]On the methodological side, a learning model with heterogeneity in returns would imply a random coefficient model with feedback. Chamberlain (1993) showed that such models suffer from identification problems. Gibbons, Katz, Lemieux, and Parent (2002) estimated a random coefficient model with learning, but they relied on the structure of the learning process and an extremely long panel (the National Longitudinal Survey of Youth) to identify the model.

are no significant differences between the hybrid stayers, nonhybrid stayers, leavers, and joiners in the three credit variables (whether the farmer tried to get credit, whether he received it, and whether he tried to get credit but did not receive it). The p-values on these F-tests are all above 0.20. Also, none of these credit variables correlates strongly with comparative advantage in Table IX. A caveat here is that these variables are not necessarily good measures of credit constraints, since households that may be constrained may not even try to get credit.

The patterns in Table V also do not fit a *pure* liquidity constraints story. Say the variation in adoption is completely explained by liquidity constraints. In this case, if a nonhybrid farmer does better than average in terms of yields, it will lead him to use hybrid in the next period, but in that second period, he should have the average hybrid yield, such that nonhybrid households that have higher yields than average in the first period should have no different than average hybrid yields in the second period. So, for 1997–2004, the coefficient on joiners would be greater than zero in 1997 and equal to the coefficient on the hybrid stayers in 2004. Similarly, the leavers should do worse than the hybrid stayers in 1997 and no different than the nonhybrid stayers in 2004. These joint restrictions are rejected in Table V. Liquidity constraints alone do not, therefore, seem to explain the patterns in the data.

The final alternative hypothesis is differences in tastes between hybrid and nonhybrid (as in Latin America). In Kenya, hybrid and nonhybrid output are indistinguishable and sold at the same price. The survey asked farmers why they chose the variety they plant, and an equal fraction of hybrid and nonhybrid farmers said it was because they preferred the taste. The differential tastes hypothesis does not seem to fit the Kenyan case.

8. CONCLUSION

This paper examines the adoption decisions and benefits of hybrid maize in the context of Kenya, where adoption trends have been relatively constant for the past decade, yet vary considerably across space. To examine this setting, in contrast to much of the literature on technology adoption, I use a framework that abandons learning about a homogeneous technology, and that instead considers a model and empirical approach that allows for heterogeneous returns to hybrid that correlate with the hybrid adoption decision. My framework emphasizes the large disparities in farming and input supply characteristics across the maize growing areas of Kenya. Within this framework, I find that for the non-HIV districts in the sample, returns to hybrid maize vary greatly. Furthermore, in these districts, farmers who are on the margin of adopting and disadopting (and who do so during my sample period) experience little change in yields.

The experimental evidence for Kenya, along with simple OLS and IV estimates, has indicated average high, positive returns to these agricultural technologies. This has indicated a puzzle as to why adoption rates had flattened out well below 100% despite the seemingly large gains that could be had by adopting hybrid. The experimental and IV evidence appeared to indicate that maize growers in Kenya were leaving "money on the table" by not adopting hybrid seed. However, the experiments and IV results reveal little else about the returns. The framework of heterogeneous returns in this paper allows the estimation of not just average returns, but also the distribution of returns across the sample of farmers. I find strong evidence of heterogeneity in returns to hybrid maize, with comparative advantage playing an important role in the determination of yields and adoption decisions.

My findings regarding the heterogeneity in returns have important implications for policy. Looking at a distribution of returns across the sample of farmers allows me to separate out farmers with low returns from those with high returns into a group that could be targeted by policy interventions. For a small group of farmers in the sample (only 20% of the sample), returns to growing hybrid (as opposed to their observed choice of nonhybrid) would be extremely high, yet they do not adopt hybrid maize. I show that these farmers have high fixed costs that prevent them from adopting hybrid, as they have poor access to seed and fertilizer distributors. In terms of policy, alleviating these constraints would increase yields for these farmers although this may not be a socially optimal intervention. Furthermore, liberalization of the seed supply market and of hybrid seed prices might encourage seed suppliers to locate in the more distant areas. For a large fraction of my sample, the returns to hybrid maize are smaller and these farmers choose to adopt. While I do not build risk into the choice framework used in this paper, farmers may use hybrid maize, even when the mean returns to hybrid are low, as it helps insure them against bad outcomes. For these farmers, since they do not seem to be constrained, they would benefit from improved research and development efforts in developing new hybrid strains and a biotechnology effort similar to that of, say, India, where releases of newer hybrids occur often and lead to continual yield improvements. Finally, the heterogeneity in returns to the hybrid technology, on the whole, suggests quite rational and relatively unconstrained adoption of existing hybrid strains, in contrast to the evidence from the experimental and IV literatures.

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