Learning about Comparative Advantage in Entrepreneurship: Evidence from Thailand PRELIMINARY DRAFT *

Anant Nyshadham†

October 12, 2011

Abstract

Entrepreneurial activity has been argued to be an important stimulus of growth, especially in less developed countries. However, consistent estimation of returns to entrepreneurship is made difficult due to potential selection into entrepreneurship on the basis of unobservable entrepreneurial ability. Furthermore, income maximizing agents have, possibly, limited information about their comparative advantage in entrepreneurial activities, rendering dynamic the decision to undertake entrepreneurial endeavors. This study develops a novel extension to projection-based panel data methods and employs this new technique to estimate a model of returns to entrepreneurship that allows for heterogeneity in entrepreneurial abilities and learning, while accounting for capital constraints. One advantage of this approach is its robustness to arbitrary relationships between latent heterogeneous abilities and sector and input choices. Another advantage is the ability to test between the full model and nested models which, alternately, restrict returns to be homogeneous and/or information to be perfect. I find strong evidence of selection into entrepreneurship on the basis of heterogeneous entrepreneurial abilities using data from household in Thailand. Specifically, the results show that the least productive non-entrepreneurial households have the highest returns to entrepreneurship. The learning results, though less precisely estimated, suggest that these households learn about their comparative advantage in entrepreneurship through low productivity shock realizations in the default sector and/or high realizations in the entrepreneurship sector. In contrast, the structural results do not suggest an important role for savings or credit constraints in the entrepreneurship decision process. Supplemental analysis using agricultural output prices and their interactions with the household's farm acreage as instruments for savings and self-reported credit constraints finds no significant effects of these on entrepreneurial entry.

*PLEASE DO NOT POST, DISTRIBUTE, OR CITE

†Yale University, Department of Economics. e-mail: anant.nyshadham@yale.edu. I would like to thank Ach Adhvaryu, Joe Altonji, Prashant Bharadwaj, A.V. Chari, Penny Goldberg, Fabian Lange, Chris Udry, and participants of the Yale Labor and Development Prospectus Workshops for their helpful comments. I would also like to especially thank Mike Boozer for his invaluable guidance and support. This is preliminary work. All errors are my own.

1 Introduction

The presence of a "poverty trap," particularly in developing societies is a classic notion in economics. The concept refers mostly to a set of empirical facts: the poor save less, are less likely to engage in entrepreneurship, invest less in productive technologies and human capital, and have low income growth. However, economists have debated the underlying causes of the persistence of poverty for decades. Some studies have suggested that the poor participate in low-growth sectors (unskilled wage labor and subsistence agriculture instead of entrepreneurship and skilled labor) and invest less in productivity enhancing technologies (physical and human capital) due to low actual or perceived net returns (Foster & Rosenzweig (2004)).

Specifically, under this hypothesis, "stayers" (agents that choose not to switch to higher productivity technologies or switch into higher growth sectors) fall into two general categories: low gross return and high cost. In particular, we might suspect that some agents have a comparative advantage in the technology or sector in question while others have a comparative advantage in the alternative. This heterogeneity in abilities will generate heterogeneous gross returns on which agents will base their decision of whether or not to adopt. The returns to schooling literature, for example, has emphasized the role of heterogeneous ability in schooling choice (e.g. Card (1995)).

However, a model which includes comparative advantage must also take a stance on whether agents have perfect information about their relative abilities in the technology or sector in question. The technology adoption literature has emphasized learning about returns as an important determinant of the rate of adoption (e.g. Foster & Rosenzweig (1995), Conley & Udry (2010)). Though the specific learning mechanism varies across these studies, they share the proposition that agents have imperfect information on the returns to adoption leading to a dynamic optimization problem.

Other studies have proposed financial constraints as an obstacle to switching sectors or technologies. In particular, the entrepreneurship literature has emphasized the role of credit constraints in the entry decision, proposing that these constraints preclude many households, perhaps even the highest return households, from starting businesses due to heterogeneous costs. Several theoretical studies in the macroeconomics literature have explored the entrepreneurship decision under financial constraints. Banerjee and Newman (1993, 1994) develop a model of occupational choice, financial constraints and long-term growth which proposes that entrepreneurial decisions under financial constraints can lead to a poverty trap, in that, given sufficient wealth inequality, the poor will choose wage work due to a lack of access to credit necessary for entrepreneurship.

Similarly, Buera (2009) develops a dynamic model of entrepreneurship under financial constraints. The model suggests that the relationship between wealth and entrepreneurship is non-monotonic in that it is positive for low levels of wealth, but negative for high levels of wealth. A calibration of the Buera (2009) model to US data suggests that credit constraints have much smaller effects on entry than on the intensive margin. Buera, Kaboski, and Shin (2011) develop a model which predicts that industries with higher capital intensities will suffer larger productivity losses due to capital misallocation than will industries with lower capital requirements.

Despite these theoretical results, empirical studies in developed contexts have found little evidence of a significant relationship between wealth and entrepreneurship. Hurst and Lusardi (2004) find empirical evidence in the US for a positive relationship at the highest levels of wealth and no significant relationship otherwise. Using data from the NLSY, Dunn and Holtz-Eakin (2000) find that wealth has little effect on entrepreneurship and parental wealth has, at most, weak effects, while parental entrepreneurial ability and experience have stronger effects. Midrigan and Xu (2011) provide a possible explanation for this apparently weak effect of credit constraints on entrepreneurship using data from developing contexts. They develop a dynamic model of firm entry under capital constraints and present a related calibration to plant-level data from the Korea and Columbia. They show that welfare losses due to credit constraints are quite small because high productivity firms can quickly save themselves out of these constraints.

Pauslon, Townsend, and Karaivanov (2006) amend a model of entrepreneurship under liquidity constraints first presented in Evans and Jovanovic (1989) to include, alternately, limited liability for borrowers and moral hazard. They then structurally estimate this model using the

Townsend Thai Project data which I also use in this paper. They find that wealth is strongly associated with entrepreneurship among lower income households, as predicted by the limited liability model, but moral hazard begins to matter more among wealthier households. Nevertheless, though the model that Paulson and Townsend present allows for heterogeneous entrepreneurial abilities, their estimation strategy is unable to test for the relative importance of ability and credit constraints in entrepreneurial choice. The results of previous studies, such as Dunn and Holtz-Eakin (2000) and Midrigan and Xu (2011) discussed above, might be explained by a model that allows heterogeneous abilities and related dynamics to play just as important a role in the entrepreneurship decision as credit constraints. The schooling literature has shown that a model of heterogeneous abilities can just as easily explain behavior once attributed to credit constraints (e.g. Carneiro and Heckman (2002)), while the entrepreneurship literature is lacking such a comparison.

Preliminary graphical analysis of the data employed in this study shows no change in the percentage of households engaged in entrepreneurship amidst a strong upward trend in savings and downward trend in self-reported financial constraints. I also find evidence that switching in and out of entrepreneurship declines over time. Additional preliminary analysis using agricultural output prices and their interactions with the household's farm acreage as instruments for savings and self-reported credit constraints finds no significant effects of these on entrepreneurial entry. This evidence leads me to question the importance of credit constraints in the entrepreneurial entry decision in this context and to look for alternate determinants of entrepreneurship that might explain the stable entrepreneurship percentage in the population and the high level of switching that declines over time.

In this paper, I present a model which includes comparative advantage in entrepreneurship, learning about comparative advantage, and credit constraints. I then develop an estimation strategy, building on projection-based panel data methods (e.g. Chamberlain (1982, 1984), Islam (1995), Suri (2011)), that recovers consistent estimates of the average return to entrepreneurship in the presence heterogeneity and learning. I can also estimate parameters that characterize the degree of heterogeneity and the relationship between entrepreneurial and non-entrepreneurial earnings, as well as the degree and direction of learning.

Using data from Thailand, I find strong evidence that households select into entrepreneurship on the basis of comparative advantage. Specifically, households with the highest non-entrepreneurial earnings have the lowest returns to entrepreneurship. The learning parameters, though imprecisely estimated, provide suggestive evidence that households do, in fact, learn about their comparative advantage in entrepreneurship over time. In particular, the results suggest that households learn from low productivity shock realizations in the default sector and/or high realizations in entrepreneurship that they have a comparative advantage in entrepreneurship and accordingly choose to switch into or stay in the entrepreneurial sector.

Nested models that restrict returns to be homogeneous, with or without perfect information, are rejected easily in this empirical context. Both static and dynamic models with heterogeneous returns cannot be rejected, or are weakly rejected; however, the estimate of the parameter measuring the degree of heterogeneity is only statistically significant in the full model with learning. I interpret these results as validating the additional complexity in the preferred model. In contrast, the structural results do not suggest an important role for savings or credit constraints in the entrepreneurship decision process.

This paper makes three main contributions to the literature. This is the first paper, to my knowledge, to explore the entrepreneurship decision in a model which allows for learning about comparative advantage, while still accounting for a general treatment of constraints on capital. Second, I make a methodological contribution with an extension to projection-based panel methods which allows for the estimation of a dynamic correlated random coefficients (DCRC) model. Finally, using this new estimation strategy, I can test between nested models of homogeneous returns and perfect information. The results verify that, even after accounting for capital constraints, the complexity in full model is necessary for explaining the behavior in the data. Additionally, I provide evidence that households on the margin are more likely constrained by low gross returns rather than high costs. This is particularly informative for policy-makers in developing contexts like the one investigated in this study. Specifically, encouraging entrepreneurial activity among non-entrepreneurial households might, in fact, not be the right policy, in that households that choose not to engage in entrepreneurial activity might have low returns to entrepreneurship.

The remainder of this paper is organized as follows: section 2 presents the model, section 3 develops the estimation strategy, section 5 discusses the data, section 6 reports and discusses the results, and section 7 concludes.

2 Model

2.1 Production Function

Let us consider a model of household production in which the household chooses amongst two production technologies in order to maximize income. Following Evans and Jovanovic (1989) and Paulson, Townsend, and Karaivanov (2006), one of the technologies or sectors will represent an entrepreneurial endeavor taking capital as an input, while the other will represent default production. In Thailand, the context in which the empirical analysis in this study is conducted, the default sector is subsistence agriculture in rural regions and/or wage labor in urban regions. Accordingly, unlike in previous versions of the model, default production will also take capital input.

Gross output of a household operating in the agricultural sector is given by the following production function:

$$Y_{it}^{F} = e^{\beta_t^F} K_{iFt}^{\rho^F} e^{\eta_i^F}, \tag{1}$$

where β_t^F is the average productivity on the farm (or in wage labor), K_{iFt} is capital input in farm production, and η_i^F is the heterogeneous component of farm-specific productivity. On the other hand, gross output of a household operating in the entrepreneurial sector is given by:

$$Y_{it}^{E} = e^{\beta_t^E} K_{iEt}^{\rho^E} e^{\eta_i^E}, \tag{2}$$

where β_t^E is the average productivity in entrepreneurial activities, K_{iEt} is capital input under entrepreneurship, and η_i^E is the heterogeneous component of productivity in entrepreneurial activities.

Since only the relative magnitude of η_i^F and η_i^E can be identified, I will define, following Lemieux (1993, 1998) and Suri (2011), a household's relative productivity in entrepreneurship over default farm activity using the following projections of η_i^F and η_i^E:

$$\eta_i^F = b_F(\eta_i^E - \eta_i^F) + \tau_i \tag{3}$$

$$\eta_i^E = b_E(\eta_i^E - \eta_i^F) + \tau_i \quad , \tag{4}$$

where $b_E = (\sigma_E^2 - \sigma_{EF})/(\sigma_E^2 + \sigma_F^2 - 2\sigma_{EF})$, $b_F = (\sigma_{EF} - \sigma_F^2)/(\sigma_E^2 + \sigma_F^2 - 2\sigma_{EF})$, with $\sigma_{EF} \equiv Cov(\eta_i^E, \eta_i^F)$, $\sigma_E^2 \equiv Var(\eta_i^E)$, and $\sigma_F^2 \equiv Var(\eta_i^F)$. The household's absolute advantage is represented by τ_i; that is, τ_i has the same effect on the household's productivity in both sectors and, accordingly, does not affect the sectoral choice.

The individual-specific output gain in entrepreneurship over default production can be redefined to be entrepreneurial comparative advantage, η_i, as

$$\eta_i \equiv b_F(\eta_i^E - \eta_i^F). \tag{5}$$

Defining $\phi \equiv b_E/b_F - 1$ and using equations (3) and (4), I can express the heterogeneous components of sector-specific productivities in terms of absolute advantage and entrepreneurial comparative advantage :

$$\eta_i^F = \eta_i + \tau_i \tag{6}$$

$$\eta_i^E = (1+\phi)\eta_i + \tau_i \quad . \tag{7}$$

Taking logs of production functions (1) and (2) and substituting in (6) and (7), I get

$$y_{it}^F = \beta_t^F + \rho^F k_{it}^F + \eta_i + \tau_i \tag{8}$$

$$y_{it}^E = \beta_t^E + \rho^E k_{it}^E + (1+\phi)\eta_i + \tau_i. \tag{9}$$

Defining D_{it} as a dummy for entrepreneurship which takes value $D_{it} = 1$ if household i owns a business in period t and $D_{it} = 0$ otherwise, I can write a generalized, log-linear gross output equation:

$$\begin{aligned} y_{it} &= D_{it}\Big[\beta_t^E + \rho^E k_{it}^E + (1+\phi)\eta_i + \tau_i\Big] + (1 - D_{it})\Big[\beta_t^F + \rho^F k_{it}^F + \eta_i + \tau_i\Big] \\ &= \beta_t^F + (\beta_t^E - \beta_t^F)D_{it} + \rho^F k_{it}^F + (\rho^E k_{it}^E - \rho^F k_{it}^F)D_{it} + \eta_i + \phi\eta_i D_{it} + \tau_i \end{aligned} \tag{10}$$

2.2 Learning

I assume that households know β_t^F, β_t^E, ρ^F, ρ^E, τ_i and ϕ, but have imperfect information about η_i. In particular, I will introduce an additive productivity shock, ε_{it}, and assume that $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2 = 1/h_\varepsilon)$. The generalized log-linear production function then becomes:

$$y_{it} = \beta_t^F + (\beta_t^E - \beta_t^F)D_{it} + \rho^F k_{it}^F + (\rho^E k_{it}^E - \rho^F k_{it}^F)D_{it} + (\eta_i + \varepsilon_{it})(1 + \phi D_{it}) + \tau_i \tag{11}$$

Households hold the initial belief that $\eta_i \sim N(m_{i0}, \sigma^2 = 1/h)$; and this belief is refined each period using productivity observations, l_{it}. That is, from y_{it}, households can compute

$$l_{it} = \frac{y_{it} - \beta_t^F - (\beta_t^E - \beta_t^F)D_{it} - \rho^F k_{it}^F + (\rho^E k_{it}^E - \rho^F k_{it}^F)D_{it} - \tau_i}{(1 + \phi D_{it})} = \eta_i + \varepsilon_{it}, \tag{12}$$

a noisy signal of their entrepreneurial comparative advantage, η_i, which is independent of the their period t sectoral choice.

Let $l_i^t = (l_{i1}, ..., l_{it})$ denote the history of household i's normalized entrepreneurial ability observations through period t. Then, the posterior distribution of η_i given history l_i^t is distributed

$N(m_t(l_i^t), 1/h_t)$, where

$$m_t(l_i^t) = \frac{hm_{i0} + h_\varepsilon(l_{i1} + ... + l_{it})}{h + th_\varepsilon}, \quad \text{and} \quad h_t = h + th_\varepsilon \tag{13}$$

2.3 Sector and Input Decisions

I will now discuss the household's period t sectoral choice and corresponding input decision. The timing is as follows:

1. household i chooses its production technology and the corresponding optimal level of capital input at the beginning of period t using its current expectation of its comparative advantage in entrepreneurship $m_{i,t-1} \equiv m_{t-1}(l_i^{t-1})$
2. household i produces y_{it} during period t and observes the productivity shock ε_{it}
3. at the end of period t, household i calculates l_{it} as in (12) and updates its expectation of η_i according to (13).

I will assume that the price of capital is r and that households face no cost of capital adjustment. I will first consider the case in which households are unconstrained with respect to capital. That is, households can acquire as much capital as desired at the given price r. Then, the household's input allocation decision in each sector can be represented as the solution to the following maximization problem:

$$\max_{K_{ijt}} E_t\Big[e^{\beta_t^j} K_{ijt}^{\rho^j} e^{\eta_i^j} - rK_{ijt}\Big] \quad j \in \{E, F\} \tag{14}$$

The household's optimal capital input level in entrepreneurship, as a function of of η_i, is

$$K_{iEt}^* = \left(\frac{\rho^E e^{\beta_t^E + (1+\phi)\eta_i + \tau_i}}{r}\right)^{\frac{1}{1-\rho^E}} \tag{15}$$

In the case of $D_{it} = 0$, the household's optimal capital level is

$$K^*_{iFt} = \left(\frac{\rho^F e^{\beta^F_t + \eta_i + \tau_i}}{r} \right)^{\frac{1}{1-\rho^F}} \tag{16}$$

Then, household i will choose to produce in the entrepreneurial sector in period t (i.e. $D_{it} = 1$) if $E_t[\ln(\pi^*_{iEt})] - E_t[\ln(\pi^*_{iFt})] = E_t[\ln(y^E_{it}(K^*_{iEt}) - rK^*_{iEt})] - E_t[\ln(y^F_{it}(K^*_{iFt}) - rK^*_{iFt})] > 0$, and in the default farm sector otherwise.[1] Using (8) and (9) and substituting in for optimal capital input using (15) and (16), I derive a cutoff rule for entrepreneurship. Household i will choose to produce in the entrepreneurial sector if

$$\begin{aligned} & E_t\left[\ln \left(e^{\beta^E_t + \eta_i(1+\phi) + \tau_i} \left(\frac{\rho^E e^{\beta^E_t + \eta_i(1+\phi) + \tau_i}}{r} \right)^{\frac{\rho^E}{1-\rho^E}} - r \left(\frac{\rho^E e^{\beta^E_t + \eta_i(1+\phi) + \tau_i}}{r} \right)^{\frac{1}{1-\rho^E}} \right) \right] \\ > \quad & E_t\left[\ln \left(e^{\beta^F_t + \eta_i + \tau_i} \left(\frac{\rho^F e^{\beta^F_t + (1+\phi)\eta_i + \tau_i}}{r} \right)^{\frac{\rho^F}{1-\rho^F}} - r \left(\frac{\rho^F e^{\beta^F_t + \eta_i + \tau_i}}{r} \right)^{\frac{1}{1-\rho^F}} \right) \right] \end{aligned} \tag{17}$$

where the expectation is with respect to the agent's information at the beginning of period t.

The estimation strategy developed below will not be able to separately identify the effects of m_{i0} and τ_i on sectoral choice. As τ_i only affects sectoral choice through its effects on optimal capital input decisions, I will make the simplifying assumption that $\rho^E \approx \rho^F \equiv \rho$ in order to remove the effect of τ_i on D_{it}. The added benefit of this assumption is that it greatly simplifies equation (17).[2] Applying this assumption, I get the following cutoff rule for $E_t[\eta_i]$:

$$\begin{aligned} E_t[\eta_i] &= m_{i,t-1} > -\frac{(\beta^E_t - \beta^F_t)}{\phi}, \quad \text{if} \quad \phi > 0 \\ E_t[\eta_i] &= m_{i,t-1} < -\frac{(\beta^E_t - \beta^F_t)}{\phi}, \quad \text{if} \quad \phi < 0 \end{aligned} \tag{18}$$

[1]Note I have assumed, for analytical simplicity, that households compare the expectation of log profits as opposed to profits in levels. This assumption has no substantive bearing on the predictions of the model, and most importantly, no effect on the estimation procedure discussed below.

[2]Relaxing this assumption will not affect the estimation strategy below, but will change slightly the interpretation of the recovered estimate of ϕ.

Note that sectoral choice depends on β_t^E, β_t^F, ϕ, and most importantly on $m_{i,t-1}$. Also, as shown in equation (18), the sign of ϕ will determine which direction of evolution in $m_{i,t-1}$ will drive switching in and out of entrepreneurship. In particular, if $\phi < 0$ I should expect that a *downward* evolution in $m_{i,t-1}$ will drive households to switch in or stay in the entrepreneurship sector, while an *upward* evolution will drive them to switch out or stay out.

2.4 Limited Liability and Capital Constraints

To address the emphasis placed on credit constraints in the existing entrepreneurship literature, I will now introduce one form of implied capital constraints through limited liability borrowing and discuss the implications for input and sector decisions. Of course, other forms of financial constraints (e.g. moral hazard, as in Paulson, Townsend, and Karaivanov (2006)) could be at play in this context. Nevertheless, the point of this section is mostly to illustrate the ability of the empirical strategy proposed below to deal with input restrictions more generally. I will reserve the discussion of robustness to alternate forms of financial constraints for the empirical strategy section below.

Following Paulson, Townsend, and Karaivanov (2006), suppose now that when a household borrows capital, it has the opportunity to default. That is, a household that has chosen to participate in sector j allocates $(A_{it} + K_{ijt})$ as capital input into the selected production technology, where A_{it} is the household's available savings and K_{ijt} is additional capital that is borrowed (or lent). If the household chooses to repay the loan, it receives

$$\begin{aligned} D_{it} &= 1: \qquad e^{\beta_t^E} K_{iEt}^{\rho} e^{(1+\phi)(\eta_i+\varepsilon_{it})} + r(A_{it} - K_{iEt}) \\ D_{it} &= 0: \qquad e^{\beta_t^F} K_{iFt}^{\rho} e^{\eta_i+\varepsilon_{it}} + r(A_{it} - K_{iFt}) \end{aligned} \tag{19}$$

If the household chooses to default, it receives

$$\begin{aligned} D_{it} &= 1: \qquad e^{\beta_t^E} K_{iEt}^{\rho} e^{(1+\phi)(\eta_i+\varepsilon_{it})} + \pi A_{it} \\ D_{it} &= 0: \qquad e^{\beta_t^F} K_{iFt}^{\rho} e^{\eta_i+\varepsilon_{it}} + \pi A_{it} \end{aligned} \tag{20}$$

where π is the fraction of assets A_{it} that the household must forfeit as collateral for the defaulted loan.[3]

Then, in equilibrium, a household can only borrow

$$K_{ijt} \leq \Big(1 + \frac{\pi}{r}\Big) A_{it}, \tag{21}$$

where $j \in \{E, F\}$. Then, we have that K^*_{ijt} is given by (15) or (16) (depending on sectoral choice) when the credit constraint is not binding. Note that K^*_{ijt} does not depend on assets, A_{it}, in (15) and (16). On the other hand, assuming that lenders learn about the household's comparative advantage at the same rate as the household and that lenders know the household's sectoral choice in period t, if

$$m_{i,t-1} \leq \left(\ln \Big[(\lambda A_{it})^{1-\rho} \frac{r}{\rho} \Big] - \beta^F_t - (\beta^E_t - \beta^F_t) D_{it} - \tau_i \right) \frac{1}{1 + \phi D_{it}} \tag{22}$$

where $\lambda \equiv \Big(1 + \frac{\pi}{r}\Big)$, then the constraint binds and $K^*_{ijt} = \lambda A_{it}$.

Now, with limited liability borrowing, the optimal capital choice will depend on assets A_{it}, the current expectation of comparative advantage, $m_{i,t-1}$, and whether or not the household's credit constraint binds, which itself depends on A_{it} and $m_{i,t-1}$.

3 Estimation

Redefining coefficients in equation (11), I arrive at the estimating equation:

$$y_{it} = \alpha_t + \beta_t D_{it} + \rho k_{it} + (\eta_i + \varepsilon_{it})(1 + \phi D_{it}) + \tau_i + \zeta_{it} \tag{23}$$

where $\alpha_t \equiv \beta^F_t$, $\beta_t \equiv (\beta^E_t - \beta^F_t)$, $k_{it} \equiv k^F_{it} + (k^E_{it} - k^F_{it}) D_{it}$, and measurement error ζ_{it} is assumed mean independent of sector and input decisions conditional on η_i and τ_i. That is, in particular, I will assume $E(D_{it}|\zeta_{it}, \eta_i, \tau_i) = E(D_{it}|\eta_i, \tau_i)$ and $E(k_{it}|\zeta_{it}, \eta_i, \tau_i) = E(k_{it}|\eta_i, \tau_i)$.

[3] Note that because the shock, ε_{it}, affects payoffs in both repayment and default states symmetrically, the default decision will not depend on this period's realization of ε_{it}. Therefore, there will be no default in equilibrium.

I will also assume $\beta_t = \beta \; \forall t$. Relaxing this assumption does not significantly change the empirical results. As discussed above, both D_{it} and k_{it} will depend on the mean of the household's prior distribution on η_i coming into period t, $m_{i,t-1}$, which I cannot observe. Accordingly, OLS estimates of β and ρ will be biased. I now develop a strategy, building on Chamberlain (1982, 1984), Islam (1995) and Suri (2011), which allows me to consistently estimate β and ρ, recover ϕ, and validate the importance of learning in this empirical context.

In particular, in order to recover consistent estimates of β and ρ, I must purge the composite unobserved term, $(\eta_i + \varepsilon_{it})(1 + \phi D_{it}) + \tau_i + \zeta_{it}$, of its correlation with D_{it} and k_{it}. For ease of exposition, I will ignore capital choices for the time being and deal only with the endogeneity in sectoral choice. I know from section 2.2 that the portion of $(\eta_i + \varepsilon_{it})$ which correlates with sectoral choices is $m_{i,t-1}$. I will begin by decomposing $m_{i,t-1}$ into two components which have distinct effects on the household's history of sectoral choices. Remember that

$$m_{i,t} = m_{i,t-1} + \xi_{it} \quad \Rightarrow \quad m_{i,t-1} = m_{i0} + \sum_{k=1}^{t-1} \xi_{ik}, \tag{24}$$

where ξ_{it} is a noise term orthogonal to $m_{i,t-1}$. Then, denoting $m_i^{t-1} \equiv \sum_{k=1}^{t-1} \xi_{ik}$ as the sum of the signals received up to period $t-1$, I have (ignoring capital)

$$y_{it} = \alpha_t + \beta_t D_{it} + (m_{i0} + m_i^{t-1} + \varphi_{it})(1 + \phi D_{it}) + v_{it}, \tag{25}$$

where $v_{it} \equiv \tau_i + \zeta_{it}$ and $\varphi_{it} \equiv \eta_i + \varepsilon_{it} - (m_{i0} + m_i^{t-1})$ are, by construction, orthogonal to sectoral choice in period t, D_{it}.

Following Chamberlain (1982, 1984), Islam (1995), and Suri (2011), we can overcome the endogeneity of D_{it} by projecting m_{i0} and m_i^{t-1} onto the history of sectoral choices. In particular, the law of motion of the prior, as expressed in equation (24), suggests that the initial belief, m_{i0}, will affect sectoral choices in all periods. On the other hand, the cumulative update, m_i^{t-1}, will only affect sectoral choices in period t onwards.

I will set $T = 2$ in the estimation below.[4] In the 2 period case, I have a projection of the initial belief which appears in the estimating equation for both periods and a belief update projection which appears only in the period 2 estimating equation: [5]

$$
\begin{aligned}
m_{i0} &= \lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_3 D_{i1} D_{i2} + \psi_{i0} && (26)\\
m_i^1 &= \theta_0 + \theta_2 D_{i2} + \psi_{i1} && (27)
\end{aligned}
$$

Note that the martingale structure of the prior on η_i implies that learning is *efficient*; that is, that all information the individual will use to make his decision at time t is fully summarized in the initial condition m_{i0} and the sum of the orthogonal updates to period $t-1$, m_i^{t-1}. In other words, the path by which the prior reaches $m_{i,t-1}$ will not, conditional on $m_{i,t-1}$ itself, affect sectoral choice in period t, D_{it}. Therefore, I need not include past sectoral choices in the update projection in equation (27) nor the interactions of future sectoral choices (though in a 2 period estimation, this is irrelevant).

Plugging projections (26) and (27) into equation (25), and grouping terms, I get the following log gross output equations:

$$
\begin{aligned}
y_{i1} &= \alpha_1 + \lambda_0 + D_{i1}\Big[\beta + (1+\phi)\lambda_1 + \phi\lambda_0\Big] + D_{i2}\Big[\lambda_2\Big] + D_{i1}D_{i2}\Big[(1+\phi)\lambda_3 + \phi\lambda_2\Big] \\
&\quad + (1+\phi D_{it})(\varphi_{it} + \psi_{i0}) + v_{i1} && (28)
\end{aligned}
$$

$$
\begin{aligned}
y_{i2} &= \alpha_2 + \lambda_0 + \theta_0 + D_{i1}\Big[\lambda_1\Big] + D_{i2}\Big[\beta + (1+\phi)(\lambda_2 + \theta_2) + \phi(\lambda_0 + \theta_0)\Big] \\
&\quad + D_{i1}D_{i2}\Big[(1+\phi)\lambda_3 + \phi\lambda_1\Big] + (1+\phi D_{it})(\varphi_{it} + \psi_{i0} + \psi_{i1}) + v_{i1} && (29)
\end{aligned}
$$

where ψ_{i0} and ψ_{i1} are the portions of m_{i0} and m_i^{t-1}, respectively, that are orthogonal to sectoral

[4] In the Appendix I explore an estimation in 3 periods because the learning structure is better defined than in the 2 period case.

[5] Note that beliefs at the start of period 1 consist only of the initial condition m_{i0} and, therefore, sectoral choice in period 1 will be made only on the basis of this initial belief

choices in all periods by construction.

Then, we have the following corresponding reduced form regressions:

$$\ln w_{i1} = \delta_1 + \gamma_1 D_{i1} + \gamma_2 D_{i2} + \gamma_3 D_{i1} D_{i2} + \nu_{i1} \tag{30}$$

$$\ln w_{i2} = \delta_2 + \gamma_4 D_{i1} + \gamma_5 D_{i2} + \gamma_6 D_{i1} D_{i2} + \nu_{i2} \tag{31}$$

Following Chamberlain (1982, 1984) and Suri (2011), my empirical strategy will be to first estimate the reduced form coefficients $\{\gamma_j : j \in [1, ..., 6]\}$ by seemingly unrelated regressions (SUR) and then to estimate from these coefficients the structural parameters of the model. There are 6 structural parameters of the model, $\{\lambda_1, \lambda_2, \lambda_3; \theta_2; \beta; \phi\}$, to be identified from the 6 reduced form coefficients using minimum distance estimation with the restrictions implied by the model. The minimum distance restrictions are

$$\begin{aligned}
\gamma_1 &= \beta + (1+\phi)\lambda_1 + \phi\lambda_0 \\
\gamma_2 &= \lambda_2 \\
\gamma_3 &= (1+\phi)\lambda_3 + \phi\lambda_2 \\
\gamma_4 &= \lambda_1 \\
\gamma_5 &= \beta + (1+\phi)(\lambda_2 + \theta_2) + \phi(\lambda_0 + \theta_0) \\
\gamma_6 &= (1+\phi)\lambda_3 + \phi\lambda_1
\end{aligned} \tag{32}$$

It appears from (32) that there are 8 structural parameters to be estimated. However, I will impose the following normalizations:

$$\lambda_0 = -\lambda_1 \overline{D_{i1}} - \lambda_2 \overline{D_{i2}} - \lambda_3 \overline{D_{i1} D_{i2}} \tag{33}$$

$$\theta_0 = -\theta_2 \overline{D_{i2}} \quad , \tag{34}$$

where $\overline{D_{i1}}$ is the average entrepreneurship decision in period j and $\overline{D_{i1} D_{i2}}$ is the average of the interaction between the entrepreneurship decisions in periods 1 and 2.

Because this model is just-identified, I cannot jointly test the restrictions imposed by this model using an over-identification test. However, in the extension discussed below, which incorporates endogenous capital choices along with the endogenous sectoral choices, the model is over-identified and can, accordingly, be tested.

Note that I have not included any exogenous covariates here. In theory, ν_{it} could include, along with v_{it}, any exogenous covariates from (25). Though the inclusion of exogenous covariates will affect the reduced form expressions (30) and (31), it will not affect the relationships between the coefficients on the D_{it}'s and their interactions in the reduced form regressions and the structural parameters. However, as this is an estimation of a log-linearized production function, I believe no additional covariates are appropriate with the exception of inputs, which are endogenous as shown above. I reserve the discussion of the treatment of endogenous inputs for section 3.2.

3.1 Structural Interpretation of Projection Coefficients

I observe in the data the conditional sample mean of log gross output for each entrepreneurship history in each of the three periods (i.e. $E(y_{it}|D_{i1}, D_{i2})$. I can express the interpretation of these conditional moments in two ways: 1) in terms of the estimated parameters $\{\lambda_1, \lambda_2, \lambda_3; \theta_2; \beta; \phi\}$, and 2) in terms of the structural components of the model $E(m_{i0}|D_{i1}, D_{i2})$, $E(m_i^1|D_{i1}, D_{i2})$, and, of course, β and ϕ. Comparing these two sets of expressions, I can derive structural interpretations for the estimated projection coefficients.

I have the following structural interpretations for the coefficients from the initial belief projection:

$$\lambda_1 = E[m_{i0}|D_{i1} = 1, D_{i2} = 0] - E[m_{i0}|D_{i1} = 0, D_{i2} = 0]; \tag{35}$$

$$\lambda_2 = E[m_{i0}|D_{i1} = 0, D_{i2} = 1] - E[m_{i0}|D_{i1} = 0, D_{i2} = 0]; \tag{36}$$

$$\lambda_3 = \Big\{E[m_{i0}|D_{i1} = 1, D_{i2} = 1] - E[m_{i0}|D_{i1} = 1, D_{i2} = 0]\Big\}$$

$$- \Big\{ E[m_{i0}|D_{i1} = 0, D_{i2} = 1] - E[m_{i0}|D_{i1} = 0, D_{i2} = 0] \Big\} \tag{37}$$

I have the following expressions for the coefficient from the belief update projection:

$$\begin{aligned} \theta_2 &= E[m_i^1|D_{i1} = 1, D_{i2} = 1] - E[m_i^1|D_{i1} = 1, D_{i2} = 0] \\ &= E[m_i^1|D_{i1} = 0, D_{i2} = 1] - E[m_i^1|D_{i1} = 0, D_{i2} = 0] \end{aligned} \tag{38}$$

These expressions suggest that if $\theta_2 < 0$, then households that switch into entrepreneurship, or do not switch out, experience relatively lower earnings in the non-entrepreneurial sector than those that do not switch. If I also have that $\phi < 0$, then those households that experience negative shocks in the non-entrepreneurial sector and, subsequently, switch into entrepreneurship have *larger* returns to entrepreneurship than those that do not receive these negative updates and, therefore, choose to stay in the non-entrepreneurial sector. That is, entrepreneurial households select into entrepreneurship on the basis of their comparative advantage in entrepreneurship, and households with the highest returns to entrepreneurship have the lowest non-entrepreneurial earnings.

3.2 Endogenous Inputs

As shown in section (2.4), a household's optimal capital allocation in the presence of credit constraints will depend on its level of savings, A_{it}, and its current expectation of its comparative advantage, m_{it}. Indeed, in the unconstrained case, optimal input choice still depends on m_{it}. While A_{it} has no effect on gross earnings except through its effect on inputs when the credit constraint binds, m_{it} has a direct effect on y_{it} by definition. Reintroducing capital into equation (25), I get

$$y_{it} = \alpha_t + \beta D_{it} + \rho k_{it} + (m_{i0} + m_i^{t-1})(1 + \phi D_{it}) + (\varphi_{it})(1 + \phi D_{it}) + v_{it}, \tag{39}$$

where v_{it} and φ_{it} are, by construction, orthogonal to input decision k_{it} in period t, along with D_{it}.

Therefore, I must only concern myself with the correlation between k_{it} (and, of course, D_{it} as well) and $m_{i0} + m_i^{t-1}$. Now, following the approach presented above, in order to purge the composite error of its correlation with D_{it} *and* k_{it}, I must include in the projections of m_{i0} and m_i^{t-1} not only the history of sectoral choices and, when appropriate, the interactions of sectoral choices across time, but also the history of input choices and its interaction with the history of sectoral choices. The new projections are

$$
\begin{aligned}
m_{i0} &= \lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_3 D_{i1} D_{i2} + \lambda_{k1} k_{i1} + \lambda_{k2} k_{i2} + \lambda_{k1-1} k_{i1} D_{i1} + \lambda_{k1-2} k_{i1} D_{i2} \\
&\quad + \lambda_{k1-12} k_{i1} D_{i1} D_{i2} + \lambda_{k2-1} k_{i2} D_{i1} + \lambda_{k2-2} k_{i2} D_{i2} + \lambda_{k2-12} k_{i2} D_{i1} D_{i2} + \psi_{i0} \qquad (40) \\
m_i^1 &= \theta_0 + \theta_2 D_{i2} + \theta_{k2} k_{i2} + \theta_{k2-2} k_{i2} D_{i2} + \psi_{i1} \qquad (41)
\end{aligned}
$$

I then proceed as above by substituting these new projections into equation (39) to get reduced form estimating equations similar to equations (30) and (31), but now including capital from each year and their interactions with the current sectoral choice. The corresponding reduced form regressions are

$$
\begin{aligned}
\ln w_{i1} &= \delta_1 + \gamma_1 D_{i1} + \gamma_2 D_{i2} + \gamma_3 D_{i1} D_{i2} + \gamma_4 k_{i1} + \gamma_5 k_{i2} + \gamma_6 k_{i1} D_{i1} + \gamma_7 k_{i1} D_{i2} \\
&\quad + \gamma_8 k_{i1} D_{i1} D_{i2} + \gamma_9 k_{i2} D_{i1} + \gamma_{10} k_{i2} D_{i2} + \gamma_{11} k_{i2} D_{i1} D_{i2} + \nu_{i1} \qquad (42) \\
\ln w_{i2} &= \delta_2 + \gamma_{12} D_{i1} + \gamma_{13} D_{i2} + \gamma_{14} D_{i1} D_{i2} + \gamma_{15} k_{i1} + \gamma_{16} k_{i2} + \gamma_{17} k_{i1} D_{i1} + \gamma_{18} k_{i1} D_{i2} \\
&\quad + \gamma_{19} k_{i1} D_{i1} D_{i2} + \gamma_{20} k_{i2} D_{i1} + \gamma_{21} k_{i2} D_{i2} + \gamma_{22} k_{i2} D_{i1} D_{i2} + \nu_{i2} \qquad (43)
\end{aligned}
$$

As above, I estimate the reduced form coefficients $\{\gamma_j : j \in [1, ..., 22]\}$ by seemingly unrelated regressions (SUR) and then estimate from these coefficients the structural parameters of the model. There are 17 structural parameters of the model,

$$\{\lambda_1, \lambda_2, \lambda_3, \lambda_{k1}, \lambda_{k2}, \lambda_{k1-1}, \lambda_{k1-2}, \lambda_{k1-12}, \lambda_{k2-1}, \lambda_{k2-2}, \lambda_{k2-12}; \theta_2, \theta_{k2}, \theta_{k2-2}; \rho, \beta; \phi\},$$

to be identified from the 22 reduced form coefficients using minimum distance estimation with the restrictions implied by the model. The minimum distance restrictions from this model are presented in the Appendix. This model is, therefore, well over-identified and the minimum distance restrictions implied by the model can be jointly tested. The over-identification test statistic under optimal minimum distance estimation equals the minimized value of the objective function and is distributed χ^2 with 5 degrees of freedom.

4 Nested Models

In this section, I show how the basic framework presented in section 3 above nests restricted models of heterogeneous returns to entrepreneurship with perfect information, homogeneous returns with imperfect information, and a simple fixed effects model with homogeneous returns and perfect information. For each of the nested models, I will start by amending the estimating equation (23) to reflect the particular set of restrictions imposed and, then, redefine the belief projections, estimating equations, and implied minimum distance restrictions, accordingly.

4.1 Heterogeneous Returns with Perfect Information: Correlated Random Coefficients

In the static correlated random coefficients (CRC) model, the estimating equation is nearly the same as in the full model:

$$y_{it} = \alpha_t + \beta D_{it} + \rho k_{it} + \eta_i(1 + \phi D_{it}) + \tau_i + \varepsilon_{it} \tag{44}$$

However, now the household is assumed to have perfect information about its entrepreneurial comparative advantage, η_i; hence, there is no longer an additive productivity shock, ε_{it}. Therefore, the relationship between η_i and the history of sectoral choices is static. That is, households will sort into a particular entrepreneurship history on the basis of η_i and their expectations of y_{it}^F and y_{it}^E; however, these expectations will not evolve over time as they do in the imperfect information case. Accordingly, I need only a single projection in which I project η_i onto the entrepreneurship decisions in both periods, their interaction, the capital choices in both periods, and the interaction of capital in both periods with entrepreneurship decisions and their interaction:

$$\begin{aligned}\eta_i \quad = \quad & \lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_3 D_{i1} D_{i2} + \lambda_{k1} k_{i1} + \lambda_{k2} k_{i2} + \lambda_{k1-1} k_{i1} D_{i1} + \lambda_{k1-2} k_{i1} D_{i2} \\ & + \lambda_{k1-12} k_{i1} D_{i1} D_{i2} + \lambda_{k2-1} k_{i2} D_{i1} + \lambda_{k2-2} k_{i2} D_{i2} + \lambda_{k2-12} k_{i2} D_{i1} D_{i2} + \psi_{i0} \end{aligned} \tag{45}$$

Substituting (45) into (44), I get equations for log gross output in terms of entrepreneurship in all periods and the interactions of these choices. Then, the corresponding reduced form equations are identical to those from the full model presented in equations (30) and (31); however, the minimum distance restrictions imposed by this model are different than those imposed by the full model. Under this model, I will estimate only 14 structural parameters

$$\{\lambda_1, \lambda_2, \lambda_3, \lambda_{k1}, \lambda_{k2}, \lambda_{k1-1}, \lambda_{k1-2}, \lambda_{k1-12}, \lambda_{k2-1}, \lambda_{k2-2}, \lambda_{k2-12}; \rho, \beta; \phi\}$$

from the 22 reduced form coefficients.

This nested model imposes 3 additional restrictions on the full model, namely

$$\theta_2 = \theta_{k2} = \theta_{k2-2} = 0 \tag{46}$$

The over-identification test statistic for this model corresponds to a joint test of the same restrictions imposed in the full model along with the additional restrictions in (46). That is, if I find that I can reject the full set of restrictions imposed by this static CRC model, but cannot reject a joint test of the restrictions imposed in the preferred dynamic CRC model, I can conclude that the additional restrictions in (46) are violated. As mentioned above, the test statistic is equal to the minimized value of the criterion function and is distributed χ^2 with 8 degrees of freedom.

4.2 Homogeneous Returns with Imperfect Information: Dynamic Correlated Random Effects

In a dynamic correlated random effects model (DCRE), the household is assumed, as in the preferred model, to have imperfect information about η_i; however, now η_i has the same effect on earnings in both sectors. In particular, the estimating equation becomes

$$y_{it} = \alpha_t + \beta D_{it} + \rho k_{it} + \eta_i + \varepsilon_{it}, \tag{47}$$

where η_i is now the household's fixed effect, which is known by the household (though still unobserved by the econometrician). Note that I have now omitted τ_i because, econometrically, I will be unable to distinguish between learning about η_i and learning about τ_i.

The household's current expectation of η_i can, once again, be split into two parts: the initial belief, m_{i0}, and the sum of the innovations to date, m_i^{t-1}. I can proceed, as above, by projecting m_{i0} onto entrepreneurship and input choices in all periods, and m_i^{t-1} onto choices in period t and all future choices:

$$m_{i0} = \lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_{k1} k_{i1} + \lambda_{k2} k_{i2} + \psi_{i0} \tag{48}$$

$$m_i^1 = \theta_0 + \theta_2 D_{i2} + \theta_{k2} k_{i2} + \psi_{i1} \tag{49}$$

Notice now that even in the initial belief projection (48), I have not included the interactions of entrepreneurship decisions across periods. This is because, once I assume that η_i has no effect on the return to entrepreneurship, the effect of the initial belief on earnings will no longer vary by the specific history of entrepreneurship choices across periods.

Therefore, the projections imply the following simplified reduced form equations:

$$y_{i1} = \delta_1 + \gamma_1 D_{i1} + \gamma_2 D_{i2} + \gamma_3 k_{i1} + \gamma_4 k_{i2} + \nu_{i1} \tag{50}$$

$$y_{i2} \;=\; \delta_2 + \gamma_5 D_{i1} + \gamma_6 D_{i2} + \gamma_7 k_{i1} + \gamma_8 k_{i2} + \nu_{i2} \tag{51}$$

However, in the spirit of econometrically testing between the nested models, I will use the full reduced form equations implied by the most general model and test the restrictions that the reduced form coefficients which appear in equations (42) and (43) from the full model, but not in equations (50) and (51) are zero. Therefore, from the 22 reduced form coefficients, I will estimate 8 structural parameters. That is, this model imposes 9 additional restrictions on the preferred model:

$$\lambda_{12} = \lambda_{k1-1} = \lambda_{k1-2} = \lambda_{k1-12} = \lambda_{k2-1} = \lambda_{k2-2} = \lambda_{k2-12} = \theta_{k2-2} = \phi = 0 \tag{52}$$

Accordingly, I need only estimate $\{\lambda_1, \lambda_2, \lambda_{k1}, \lambda_{k2}; \theta_2, \theta_{k2}; \rho, \beta\}$.

Once again, the over-identification test statistic for this model corresponds to a joint test of the same restrictions imposed in the full model along with the additional restrictions in (52). The test statistic for this model is distributed χ^2 with 14 degrees of freedom.

4.3 Homogeneous Returns with Perfect Information: Correlated Random Effects

The most restricted model imposes both that returns to entrepreneurship are homogeneous and that households have perfect information about their earnings in both sectors. That is, the only source of heterogeneity is additive and fixed over time. This amounts to assuming that the data generating process is a simple household fixed effects model. Under these assumptions, the estimating equation becomes

$$y_{it} = \alpha_t + \beta D_{it} + \rho k_{it} + \eta_i + \varepsilon_{it} \tag{53}$$

Notice that here also I have not included τ_i. This is because, once I assume that η_i does not affect returns to entrepreneurship and is known by households, it is fundamentally no different from the original interpretation of τ_i.

I now need only a single projection of η_i on the entrepreneurship decisions and input choices from all periods:

$$\eta_i \quad = \quad \lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_{k1} k_{i1} + \lambda_{k2} k_{i2} + \psi_{i0} \tag{54}$$

As in the DCRE case above, I need not include the interactions of these decisions across periods.

This model imposes 11 additional restrictions on my preferred model:

$$\lambda_{12} = \lambda_{k1-1} = \lambda_{k1-2} = \lambda_{k1-12} = \lambda_{k2-1} = \lambda_{k2-2} = \lambda_{k2-12} = \theta_2 = \theta_{k2} = \theta_{k2-2} = \phi = 0 \tag{55}$$

Notice that the set of additional restrictions in (55) includes the additional restrictions from both the static CRC model, (46), and the DCRE model, (52). I will estimate 6 structural parameters ($\{\lambda_1, \lambda_2, \lambda_{k1}, \lambda_{k2}; \rho, \beta\}$) from the 22 reduced form coefficients. The over-identification test from this estimation is distributed χ^2 with 16 degrees of freedom.

Using the over-identification tests on all of the nested models, I can explore the degree to which the added complexity in the preferred model (non-additive heterogeneity in returns and a relaxation of strict exogeneity to sequential exogeneity) is important in describing the relationship between income and entrepreneurship in the data. This is a major advantage to the theoretical and, particularly, the empirical approach I employ in this study.

5 Data

The data set used in the analysis is taken from the annual panel of the Townsend Thai Project. In 1997, the original survey was conducted on households from 4 provinces of Thailand. Two provinces were chosen from each of two distinct regions: the more developed Central Region and the more rural Northeast. Within each of the four provinces, 12 sub-regions (tambons) were randomly selected. Within each tambon, 4 villages were randomly selected for the sample.

From each of the 4 provinces, 4 of the original 12 tambons were randomly selected for annual resurvey. Consequently, of the original 48 tambons, 16 (4 from each province) are included in the 12 year annual household and business panel from which I will extract the data to be used in the empirical analysis. From 1999 onwards, questions regarding household businesses were added to the household survey instrument. I will construct a balanced panel using data from the 2005 and 2008 waves. In particular, I will use all households for which income and entrepreneurship information is available in both years. The sample I use consists of 1103 households.

The 3 year gap between survey waves ensures that households have sufficient time to adjust entrepreneurial activity, should they want to. Among the 1103 households in my sample, over 25% change their entrepreneurship decision. However, the proportion of households participating in the entrepreneurial sector is roughly stable across waves: 44% in 2005 and 47% in 2008.

The survey instrument includes questions regarding income over the 12 months prior to survey from farm and livestock activities, wage or salary work, household businesses, and other income such as rent and interest, as well as questions regarding input expenditure in farm and business enterprises. Information on savings, borrowing and lending, and participation in financial institutions was also collected. Finally, households were asked if they believed their farms and/or businesses would be more profitable if they were expanded, a measure of their being credit constrained.

5.1 Summary Statistics

In Tables Ia-c, I report means and standard deviations for variables of interest in the data. Table Ia presents summary statistics for the entire sample of log of gross income, entrepreneurship, input expenditure, household demographics, savings, self-reported credit constraints, and borrowing. I find that income grows only slightly in the sample from 2005 to 2008. However, the percentage of households with savings (a positive balance in an institutional savings account) grows considerably and the percentage of households that report being credit constrained drops to nearly 0. On the other hand, the probability that a household borrowed money in the past year and the probability that the household owns at least one business remain fairly stable.

In Tables Ib and Ic, I report summary statistics for the variables of interest by entrepreneurship history. Specifically, I split up the sample into households that engage in entrepreneurship in both years, in neither of the years, those that switch into entrepreneurship in 2008, and those that switch out in 2008. Note that these categories are strictly mutually exclusive. I will note first that, though it appears that the percentage of households that engage in entrepreneurship remains roughly the same each year, there is quite a bit of switching in and out of entrepreneurship. As mentioned above, roughly 25% of the sample switches their entrepreneurial status. In this sample, approximately 11% switch out and 14% switch in.

Table Ib also shows that households that run businesses tend to have similar gross incomes to those that don't; although households that never own a business have slightly lower incomes and households that own a business in both periods have slightly higher incomes. I also find that expenditure is higher among entrepreneurial households. Households that engage in entrepreneurship tend to be larger than those that do not; however, no perceivable differences exist between specific entrepreneurship histories. No significant difference exists in gender composition of households across entrepreneurship histories. Entrepreneurial households appear to be slightly younger on average and better educated than non-entrepreneurial households.

In Table Ic, I find that households that engage in entrepreneurship are more likely to have savings than those who do not. However, if we look over time at households that switch in, for example, it would appear that, if in fact there is a relationship, savings accrue contemporaneously with entrepreneurship, or even following it, rather than savings driving the entrepreneurship decision. Entrepreneurial households are actually more likely to report feeling financially constrained than non-entrepreneurial households in 2005, but the probability of reporting constraints goes to roughly 0 in 2008 for all entrepreneurship histories. Finally, entrepreneurial households are more likely to borrow than non-entrepreneurial households, but within entrepreneurship comparisons provide mixed evidence on the relationship.

5.2 Preliminary Analysis

As mentioned above in the discussion of Table Ia, the summary statistics for savings, self-reported financial constraints, and entrepreneurship show a pattern inconsistent with the notion that credit constraints are an important determinant of entrepreneurial entry. Using data from the waves in between the 2005 and 2008 surveys as well, I plot these variables to verify the trends suggested by the summary statistics. In particular, in Figure I, I plot the means for savings, self-reported credit constraints, and entrepreneurship in each of the 4 waves as well as a fitted line over time for each of the variables. I find that the trends suggested by the summary statistics in Table Ia are present in this higher frequency panel as well. In particular, savings increases and credit constraints decrease, but entrepreneurship stays fairly flat.

To explore this notion a bit further, I estimate the effects of variation in the global price of rice, the predominant agricultural output of Thailand, on savings, self-reported constraints, and entrepreneurship.[6] For this analysis, I use data from several more waves of the data (2000-2009) in order to allow for greater variation in the price of rice. These regressions are run using household fixed effects specifications and the results are reported in Table II. In columns 4-6 of Table II, I report results from the regression of savings, self-reported constraints, and the household business dummies, respectively, on the global price of rice and household fixed effects. In columns 1-3, I report results from specifications which also include the household's farm acreage (in Thai rai units [7]) and its interaction with the global price of rice. Across both sets of regressions, I find that output price shocks increase savings and decrease financial constraints, but do not significantly affect entrepreneurship.

Finally, I use the price shocks and their interaction with household farm rai to instrument for the savings and constrained dummies in a household fixed effects instrumental variables regression of entrepreneurship on savings, constraints, and both. The results from these regressions are reported in Table III. Once again, I find no evidence of an effect of savings and/or financial constraints on entrepreneurship. Taken together, Figure I and the results shown in Tables II and III suggests that perhaps access to credit is not an important determinant of entrepreneurship decisions, and provides motivation for the exploration of alternate drivers of entrepreneurial entry such as latent ability.

The model presented above proposes that evolution in the heterogeneous entrepreneurial

[6]Price data is taken from the IMF monthly agricultural commodity prices and averaged over the year.

[7]1 acre equals roughly 2.5 rai

comparative advantage of households drives households to switch in and out of entrepreneurship. Specifically, the model imposes that intertemporal correlations in choices are due to households learning about their static, but unknown comparative advantage. Nevertheless, a model with persistent, sector-specific i.i.d. shocks, but perfect information could also explain switching in the absence of any learning mechanism. In order, to motivate the imposition of a learning structure on the dynamic nature of latent heterogeneity, I explore trends in switching.

In particular, a learning mechanism would predict a downward trend in switching as the beliefs of a cohort of households converge to the true values of their comparative advantages, while persistent sector-specific shocks should generate a consistent level of switching in all periods, so long as the distribution from which these shocks are drawn is stationary. In Figure II, I plot the percentage of households that switch, either into or out of entrepreneurship, over time. I also reproduce the plot of entrepreneurship percentages over time for the sake of comparison. Indeed, the percentage of households who switch their entrepreneurial status from the last period is decreasing over time. Given the evidence from this preliminary analysis, I suspect that the model proposed above and estimated below is appropriate for this context.

6 Results

In this section, I present results from the empirical analysis discussed in section 3. However, for the sake of comparison, I begin by presenting ordinary least squares and household fixed effects estimates of the average return to entrepreneurship.

6.1 OLS and FE

In Table IV, I regress the log of total gross income of the household over the 12 months prior to survey on a binary for whether the household owned at least one business during that year. The results reported in column 3 of Table IV are from the specification with no additional covariates. The point estimate is quite large, positive, and significant at the 1 percent level. A unit change in the probability of a household owning a business is associated with a 64.6 percent increase in the household's income. In column 2, I include log input expenditure as a control and rerun the analysis. The inclusion of inputs significantly attenuates the estimate. The point estimate of the effect of entrepreneurship on log gross income is now 24.5 percent, but is still significant at the 1 percent level. In column 3, I also include village by time dummies to control for variations in input and output prices over time. That is, assuming that all households within a village face the same prices in each period, including these dummies accounts for the role of input and output prices in the household's sectoral choice. With these additional covariates, the point estimate rises slightly to 30.7 percentage points and is still significant at the 1 percent level.

In columns 4-6 of Table IV, I present results from specifications identical to those in columns 1-4, respectively, but with the addition of household fixed effects. The coefficients across all specifications are smaller in magnitude than the corresponding OLS estimates. In these FE specifications, I find that that village x time price controls have little effect on the coefficient of interest as compared to that from the specification including only inputs and the household fixed effects. However, as in the OLS specifications, the inclusion of log input expenditure decreases the magnitude of the effect of entrepreneurship on log gross income. In columns 4 and 5, I find that owning a household business is associated with a 17.8 and 19.4 percent increase in income, respectively, and these estimates are significant at the 5 percent level.

Of course, as discussed above, to the degree that households choose to engage in entrepreneurship on the basis of their perceived comparative advantage in it over farm production or wage work, the estimate of the coefficient of interest in OLS and FE specifications will be biased for the average return to entrepreneurship. The estimation strategy proposed and discussed above will allow me to recover a consistent estimate of the average return to entrepreneurship in the presence of both heterogeneous entrepreneurial abilities and learning as well as account for financial constraints, and will also allow me to quantify the degree of heterogeneity and learning in the data.

6.2 Reduced Form Coefficients

In Tables V and VI, I present the reduced form coefficients from which I will estimate the structural parameters of the econometric models set forth above using minimum distance. In the reduced form specifications reported in Table V, I regress the log of total gross income from each period on the entrepreneurship dummies for each period and their interactions. In Table VI, I report reduced form coefficients corresponding to the models with endogenous capital. As shown above, these specifications include, in addition to the history of entrepreneurship decisions, log input expenditure in both periods and their interactions with the history of entrepreneurship decisions. The reduced form coefficients are not particularly informative; accordingly, I will not provide a discussion of their interpretation here. Also, for the sake of brevity, I do not report reduced form coefficients corresponding to the specifications which include price controls[8].

6.3 Structural Minimum Distance Estimates

6.3.1 No Covariates

In Table VII, I present the optimal minimum distance estimates from the full CRC model with learning and the three nested, restricted models with no additional covariates. I present results from the CRE model in column 1. As mentioned above, the CRE model corresponds to a household fixed effects data generating process, that is, a model with homogeneous returns to entrepreneurship and perfect information. In particular, under this model latent ability has no effect on returns to entrepreneurship and the household's perception of this ability does not change over time.

Therefore, λ_j represents the dependance of the household's entrepreneurial choice in period j on latent ability; we need only one such parameter per period. The estimates of the λ's are both positive and precisely estimated. I will reserve, for the sake of brevity, the discussion of the interpretation of the projection coefficients in the context of the model for later, when I present results from the preferred model. The estimate of the average return to entrepreneurship, β, is

[8]Reduced form results for other specifications are available upon request

also positive and very precisely estimated. The point estimate is .3044, which is quite similar to the results from the FE regression reported in column 6 of Table IV. The restrictions implied by this model (namely, no heterogeneity in returns and no learning) cannot be rejected. However, this test has limited power due to the minimal degrees of freedom. Furthermore, the analogous test on the full model cannot be applied because that model is just-identified in the case of no covariates. Accordingly, I will not place much stock in these statistics, and will reserve the discussion of a comparison of the models for the case of endogenous capital below.

Column 2 of Table VII reports results from the dynamic CRE model which, once again, restricts returns to be homogeneous, but now allows for households to have imperfect information about this return. In the context of this model, the λ's characterize the heterogeneity in initial beliefs of households by entrepreneurship decisions, whereas the θ characterizes the degree and direction of learning (i.e. the heterogeneity in the update to beliefs between periods 1 and 2). The estimate of β is nearly identical to that in the static CRE model. The λ's are also nearly identical to those in the CRE model, while the θ is small and insignificant. The learning structure does not seem to improve the fit of the model, though this is likely due to the limited scope for learning in a 2 period model without endogenous capital.

In column 3 of Table VII, I present estimates from the static CRC model which allows for heterogeneous returns but again restricts information on entrepreneurial comparative advantage to be perfect. This model implies that latent heterogeneity will not only affect entrepreneurship decisions in each period, but also the specific history of choices across periods. Therefore, I have now 3 λ's corresponding to 4 possible entrepreneurship histories over the two periods, with the omitted history being never owning a business. Once again, I find that the λ's are precisely estimated. The estimate of β is once again positive and slightly larger in magnitude than in the homogeneous returns models, though less precisely estimated. The estimate of ϕ, which measures the degree to which households base their entrepreneurial decisions on their comparative advantage in entrepreneurship, is negative but insignificant. A negative estimate of ϕ implies that households with the lowest non-entrepreneurial earnings have the largest returns to entrepreneurship; however, the coefficient is not statistically significant from 0 so I will not dwell on its interpretation.

Finally, in column 4 of Table VII, I present estimates of the full model which allows for both selection on entrepreneurial comparative advantage and imperfect information. The estimates closely resemble those from the static CRC model, with the addition of a small and insignificant estimate of the θ_2. Of course, as shown in sections 2.3 and 2.4, the estimation should account for endogeneity in capital allocations as well as in sectoral choices.

6.3.2 Endogenous Capital

In Table VIII, I present results from all four models with the addition of endogenous capital as discussed in section 3.2. Once again, column displays results from the minimum distance estimation of the static CRE model. There are now 4 λ's (i.e. 1 additional for each of the input choices). The estimates of λ_1 and λ_{k2} are positive and significant at the 1 percent level, while the estimates of λ_2 and λ_{k1} are small and insignificant. The estimate of the average return to capital, ρ, is positive and significant at the 1 percent level with a point estimate of nearly .06. The estimate of β, though still positive and precisely estimated, drops in magnitude from the no covariates case to a point estimate .1858. The estimates of ρ and β are quite similar to the results from the household FE regressions presented in column 5 of Table IV, as expected. This model, unlike in the no covariates case, is well over-identified. The χ^2 test statistic corresponding to a joint test of the restrictions imposed by this simplest model is just over 85 with a p-value of less than 0.0001. I can easily reject this model in this empirical context.

In column 2, I present results from the dynamic CRE model with endogenous capital. Specifically, this model introduces two new parameters θ_2 and θ_{k2} to the entrepreneurial decision and capital choice in period 2, respectively. The estimates of these parameters are small and insignificant as in the case of no covariates. The estimates of the λ's are quite similar to those from the static CRE model. Though the estimates of ρ and β are qualitatively similar to those in column 1, the point estimate of ρ is slightly larger (0.0638) and that of β is smaller (0.1633). This model is also easily rejected with a χ^2 test statistic of roughly 84 and a corresponding p-value of less than 0.0001.

Column 3 displays results from the static CRC model. This model includes a total of 11 λ's corresponding to the history entrepreneurial choices, the history of capital allocations, and their interactions. The estimate of ρ is qualitatively similar to those from the homogeneous returns model, with a slightly larger point estimate (0.0671) that is still significant at the 1 percent level. The point estimate of β is larger in this model, with a point estimate of 0.2191, and is significant at the 1 percent level. The estimate of ϕ is, as in the analogous no covariates model, negative but insignificant at conventional levels. The χ^2 test statistic of this model is just under 15 with a corresponding p-value of 0.061. This model, though still rejected at conventional levels, appears to the explain the data much better than the homogeneous returns models presented in columns 1 and 2.

Finally, in column 4, I present results from the estimation of the most general model allowing for both heterogeneous returns and learning. The estimates of the λ's are qualitatively similar to those in column 3, as are the estimates of ρ and β; however, the magnitudes of the estimates of both ρ and β are larger than those from the static CRC model with point estimates of 0.0726 and 0.2408, respectively. Both estimates are still significant at the 1 percent level. The point estimate of ϕ in column is large negative and significant at the 5 percent level with a point estimate of -0.4614. As mentioned above a significant ϕ is evidence of selection into entrepreneurship on the basis of heterogeneous returns. In particular, a negative ϕ corresponds to selection on comparative advantage such that households with the lowest non-entrepreneurial earnings have the highest returns to entrepreneurship and accordingly are the households that choose to engage in entrepreneurship.

The estimate of the θ_2, though insignificant at conventional levels, is larger than in the no covariates case and still negative. The estimate of $\theta k2$ is also negative and insignificant. I cautiously interpret these negative θ's as suggestive evidence of learning about comparative advantage through negative productivity shock realizations in the default sector and/or positive shock realizations in the entrepreneurial sector, as discussed in section 3.1. Given that the estimate of the ϕ is only significant with inclusion of these learning parameters, I believe that the learning structure is, indeed, important for matching household behavior in the data. The imprecision in the estimates of the θ's is likely, at least in part, due to the limited scope afforded the learning structure in a two period estimation. Nevertheless, the full model is also rejected with a test statistic of 13 and a p-value of 0.022.

In the Appendix, I explore an extension of the estimation to a 3 period model. Due to the analytical intractability of fully endogenizing both entrepreneurship decisions and capital allocations in 3 periods, I must employ a more restrictive treatment of capital in order to estimate these models. The results from the 3 period estimation is qualitatively similar to the results from the 2 period estimation discussed here; however, the magnitudes of the estimates are generally much larger and the estimates of the learning parameters are negative, large and significant.

6.3.3 Endogenous Capital with Price Controls

Lastly, in Table IX, I present results from the estimation of all four models with endogenous capital, as in Table VIII, but now with the inclusion of village by time dummies as exogenous covariates. To the degree that input and output prices vary at the village level, the inclusion of village by time dummies in the first stage reduced form equations will purge the structural estimates of the effects of general non-linear trends in these prices. Across all four models, the results are quite similar to those in Table VIII. The removal of price variation has little effect on the results. However, one notable difference is that the static CRC model, presented in column 3, can no longer be rejected at conventional levels and the CRC model with learning is barely rejected at the 10 percent level. The homogeneous returns models, presented in columns 1 and 2, are still overwhelmingly rejected. Additionally, the estimates of the θ's from the full model in column 4 are larger in this specification, though still insignificant.

Figure III presents graphically the degree of heterogeneity and learning in the estimated perceived returns to entrepreneurship from the full model (i.e. the dynamic CRC model with learning from column 4 of Table IX) with both endogenous capital and price controls. That is, I can calculate from the estimated structural parameters the expected productivity gains from engaging in entrepreneurship that households uses in their entry decision in each period (i.e. $\beta + \phi(m_{i,t-1})$). Note that the estimates will recover the average perceived return for a given entrepreneurship history (i.e., they will only differentiate households by their entrepreneurship history); accordingly, there will be 4 different productivity gains in each time period. Figure III shows that households that switch into entrepreneurship and those that choose to stay in entrepreneurship, indeed, expect higher productivity gains in period two, whereas households that choose to stay out or switch out of entrepreneurship do not perceive such increases in the productivity gains. Additionally, the average perceived productivity gain over time varies across these different types of households, verifying that there is heterogeneity even in the initial beliefs.

Figure IV repeats this exercise for the static CRC model with both endogenous capital and price controls corresponding to column 3 in Table IX. Notice in this model perceived productivity gains will vary by entrepreneurship history, but not within entrepreneurship history over time. That is, the formula for perceived productivity gains is $\beta + \phi(\eta)$ in this model, which does not vary over time. Once again, I find that the perceived productivity gains vary by entrepreneurship history. The differences between productivity gains in Figures III and IV are not statistically significant, as mentioned above, but support a learning interpretation for the dynamics observed in the data.

6.4 Discussion of Alternate Explanations

Notice that, to the degree that latent heterogeneity reflects predominantly financial constraints rather than relative entrepreneurial abilities, the estimate of ϕ in both the static and dynamic CRC models should be positive. That is, if, as predicted by previous theoretical work, the highest ability households are most constrained, positive productivity shocks last period should drive these high ability households into entrepreneurship and lead to a positive relationship between earnings in the two sectors. Similarly, in the dynamic model, the estimates of the θ's ought to be positive as well. That is, if households are endogenously easing credit constraints through savings, such that the effect of the positive productivity shock in the default sector last period on earnings persists into the current period, perhaps through an investment of these savings into capital, the θ's will capture this dependence. The negative estimates of the θ's and the ϕ validate the interpretation of latent dynamic heterogeneity as learning about comparative advantage.

7 Conclusion

It has been proposed that entrepreneurship is an important stimulus of growth, especially in developing contexts where income risk in the subsistence agricultural sector can stifle investment. Despite the perceived importance of household enterprise, a minority of households in developing contexts engage in entrepreneurial activities. Previous studies have proposed that credit constraints preclude many households, perhaps even the highest return households, from starting businesses due to heterogeneous costs. On the other hand, heterogeneous abilities or, specifically, comparative advantage in entrepreneurship would also justify less entrepreneurship. However, heterogeneity in costs and/or returns are difficult to observe and account for in the estimation of returns to entrepreneurship.

Additionally, in the technology adoption literature, learning mechanisms have been proposed as determinants of the rate of adoption. A similar argument can be applied to entrepreneurship decisions. In fact, in the presence of heterogeneous returns, we might expect that households must learn about their entrepreneurial abilities over time. In this study, I present a model which includes both comparative advantage in entrepreneurship and learning. I then develop an econometric approach, following projection-based panel data methods proposed by Chamberlain (1982, 1984), Islam (1995), and Suri (2011), which can estimate this model of heterogeneous returns to entrepreneurship with imperfect information, while still accounting for credit constraints. Furthermore, I test between the full model and nested models which restrict returns to be homogenous and/or information to be perfect.

I estimate these models on data from an annual panel survey in Thailand. I find strong evidence of selection on comparative advantage in entrepreneurship. Specifically, the results suggest that households with the lowest earnings in non-entrepreneurial production have the highest returns to entrepreneurship, even after accounting for credit constraints. These results are informative for policy-makers in developing contexts like the one investigated in this study. The results suggest that encouraging entrepreneurial activity among non-entrepreneurial households might, in fact, not be the right policy, in that households that do not choose to engage in entrepreneurial activity might have low returns to entrepreneurship.

Additionally, the learning parameters, though imprecisely estimated, provide suggestive evidence that households learn about their high entrepreneurial comparative advantage through negative productivity shock realizations in the default sector and/or positive shock realizations in the entrepreneurship sector, and accordingly choose to switch into or stay in entrepreneurship. The imprecision in these estimates is likely due to the limited scope for learning in a 2 period estimation, which emphasizes the importance of an extension to a 3 period estimation.

References

[1] Banerjee, Abhijit V. and Andrew F. Newman. 1993. "Occupational Choice and the Process of Development." *Journal of Political Economy*, vol. 101, no. 2: 274-298.

[2] Banerjee, Abhijit V. and Andrew F. Newman. 1994. "Poverty, Incentives, and Development." *American Economic Review*, vol. 84, no. 2: 211-215.

[3] Buera, Francisco. "A dynamic model of entrepreneurship with borrowing constraints: theory and evidence." *Annals of Finance*, vol. 5, no. 3-4: 443-464.

[4] Buera, Francisco, Joseph Kaboski and Yongseok Shin. "Finance and Development: A Tale of Two Sectors." *American Economic Review*, vol. 101, no. 5: 1964-2002.

[5] Card, David. 1995. "Earnings, Schooling, and Ability Revisited." *Research in Labor Economics*, vol. 14.

[6] Carneiro, Pedro and James J. Heckman. 2002. "The Evidence on Credit Constraints in Post-Secondary Schooling." *The Economic Journal*, vol. 112, no. 482: 705-734.

[7] Chamberlain, Gary. 1982. "Multivariate Regression Models for Panel Data." *Journal of Econometrics*, vol. 18: 5-46.

[8] Chamberlain, Gary. 1984. "Panel Data." *Handbook of Econometrics*, ed. by Z. Griliches and M. Intriligator. Amsterdam: North-Holland.

[9] Conley, Timothy G. and Christopher R. Udry. 2010. "Learning about a new technology: pineapple in Ghana." *American Economic Review*, vol. 100, no.1: 35-69.

[10] DeGroot, Morris. 1970. *Optimal statistical decisions*. New York: McGraw Hill.

[11] Dunn, Thomas and Douglas Holtz-Eakin. "Financial Capital, Human Capital, and the Transition to Self-Employment: Evidence from Intergenerational Links." *Journal of Labor Economics*, vol. 18, no. 2: 282-305.

[12] Evans, David S. and Boyan Jovanovic. 1989. "An Estimated Model of Entrepreneurial Choice under Liquidity Constraints." *Journal of Political Economy,* vol. 97, no. 4: 808-827.

[13] Foster, Andrew and Mark Rosenzweig. 1995. "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture." *Journal of Political Economy,* vol. 103, no. 6: 1176-1209.

[14] Foster, Andrew and Mark Rosenzweig. 2004. "Agricultural Productivity Growth, Rural Economic Diversity, and Economic Reforms: India, 1970-2000." *Economic Development and Cultural Change,* vol. 52, no. 3: 509-542.

[15] Gibbons, Robert, Lawrence F. Katz, Thomas Lemieux, and Daniel Parent. 2005. "Comparative Advantage, Learning, and Sectoral Wage Determination." *Journal of Labor Economics,* vol. 23, no. 4: 681-723.

[16] Hurst, Erik and Annamaria Lusardi. "Liquidity Constraints, Household Wealth, and Entrepreneurship." *Journal of Political Economy,* vol. 112, no. 2: 319-347.

[17] Islam, Nazrul. 1995. "Growth Empirics: A Panel Data Approach." *The Quarterly Journal of Economics,* vol. 110, no. 4: 1127-1170.

[18] Lemieux, Thomas. 1993. "Estimating the Effects of Unions on Wage Inequality in a Two-Sector Model With Comparative Advantage and Non-Random Selection." Working Paper, CRDE and Departement de Sciences Economiques, Universite de Montreal.

[19] Lemieux, Thomas. 1998. "Estimating the Effects of Unions on Wage Inequality in a Two-Sector Model With Comparative Advantage and Non-Random Selection." *Journal of Labor Economics,* vol. 16, no. 2: 261-291.

[20] Midgrigan, Virgiliu and Daniel Xu. "Finance and Misallocation: Evidence from Plant-level Data." Working paper, New York University.

[21] Paulson, Anna L., Robert M. Townsend, and Alexander Karaivanov. 2006. "Distinguishing Limited Liability from Moral Hazard in a Model of Entrepreneurship." *Journal of Political Economy*

[22] Suri, Tavneet. 2011. "Selection and Comparative Advantage in Technology Adoption." *Econometrica,* vol. 79, no. 1: 159-209.

A Extension to 3 Periods

A.1 Heterogeneous Returns with Imperfect information (DCRC)

Remember the estimating equation from the full model (ignoring capital):

$$y_{it} = \alpha_t + \beta_t D_{it} + (m_{i0} + m_i^{t-1} + \varphi_{it})(1 + \phi D_{it}) + v_{it}, \tag{56}$$

where $v_{it} \equiv \tau_i + \zeta_{it}$ and $\varphi_{it} \equiv \eta_i + \varepsilon_{it} - (m_{i0} + m_i^{t-1})$ are, by construction, orthogonal to sectoral choice in period t, D_{it}. In 3 periods, I have the following projections:

$$m_{i0} = \lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_3 D_{i3} + \lambda_4 D_{i1} D_{i2} + \lambda_5 D_{i2} D_{i3} + \lambda_6 D_{i1} D_{i3} + \lambda_7 D_{i1} D_{i2} D_{i3} + \psi_{i0} \tag{57}$$

$$m_i^1 = \theta_{10} + \theta_{12} D_{i2} + \theta_{13} D_{i3} + \psi_{i1} \tag{58}$$

$$m_i^2 = \theta_{20} + \theta_{23} D_{i3} + \psi_{i2} \tag{59}$$

Plugging projections (57), (58) and (59) into equation (23), and grouping terms, I get the following log gross output equations for each of the three periods (ignoring covariates):

$$\begin{aligned} y_{i1} = {} & \alpha_1 + \lambda_0 + D_{i1}\Big[\beta + (1+\phi)\lambda_1 + \phi\lambda_0\Big] + D_{i2}\Big[\lambda_2\Big] + D_{i3}\Big[\lambda_3\Big] \\ & + D_{i1}D_{i2}\Big[(1+\phi)\lambda_4 + \phi\lambda_2\Big] + D_{i2}D_{i3}\Big[\lambda_5\Big] + D_{i1}D_{i3}\Big[(1+\phi)\lambda_6 + \phi\lambda_3\Big] \\ & + D_{i1}D_{i2}D_{i3}\Big[(1+\phi)\lambda_7 + \phi\lambda_5\Big] + (1+\phi)\psi_{i0} + v_{i1} \end{aligned} \tag{60}$$

$$\begin{aligned} y_{i2} = {} & \alpha_2 + \lambda_0 + \theta_{10} + D_{i1}\Big[\lambda_1\Big] + D_{i2}\Big[\beta + (1+\phi)(\lambda_2 + \theta_{12}) + \phi(\lambda_0 + \theta_{10})\Big] \\ & + D_{i3}\Big[\lambda_3 + \theta_{13}\Big] + D_{i1}D_{i2}\Big[(1+\phi)\lambda_4 + \phi\lambda_1\Big] + D_{i2}D_{i3}\Big[(1+\phi)\lambda_5 + \phi(\lambda_3 + \theta_{13})\Big] \end{aligned}$$

$$+ D_{i1}D_{i3}\left[\lambda_6\right] + D_{i1}D_{i2}D_{i3}\left[(1+\phi)\lambda_7 + \phi\lambda_6\right] + (1+\phi)\left[\psi_{i0} + \psi_{i1}\right] + v_{i2} \tag{61}$$

$$\begin{aligned}
y_{i3} &= \alpha_3 + \lambda_0 + \theta_{20} + D_{i1}\left[\lambda_1\right] + D_{i2}\left[\lambda_2\right] + D_{i3}\left[\beta + (1+\phi)(\lambda_3 + \theta_{23}) + \phi(\lambda_0 + \theta_{20})\right] \\
&\quad + D_{i1}D_{i2}\left[\lambda_4\right] + D_{i2}D_{i3}\left[(1+\phi)\lambda_5 + \phi\lambda_2\right] + D_{i1}D_{i3}\left[(1+\phi)\lambda_6 + \phi\lambda_1\right] \\
&\quad + D_{i1}D_{i2}D_{i3}\left[(1+\phi)\lambda_7 + \phi\lambda_4\right] + (1+\phi)\left[\psi_{i0} + \psi_{i2}\right] + v_{i3},
\end{aligned} \tag{62}$$

where ψ_{i0}, ψ_{i1}, and ψ_{i2} are the portions of η_i that are, by construction, orthogonal to sectoral choices in all periods.

Then, we have the following corresponding reduced form regressions:

$$\ln w_{i1} = \delta_1 + \gamma_1 D_{i1} + \gamma_2 D_{i2} + \gamma_3 D_{i3} + \gamma_4 D_{i1}D_{i2} + \gamma_5 D_{i2}D_{i3} + \gamma_6 D_{i1}D_{i3} + \gamma_7 D_{i1}D_{i2}D_{i3} + \nu_{i1} \tag{63}$$

$$\ln w_{i2} = \delta_2 + \gamma_8 D_{i1} + \gamma_9 D_{i2} + \gamma_{10} D_{i3} + \gamma_{11} D_{i1}D_{i2} + \gamma_{12} D_{i2}D_{i3} + \gamma_{13} D_{i1}D_{i3} + \gamma_{14} D_{i1}D_{i2}D_{i3} + \nu_{i2} \tag{64}$$

$$\ln w_{i3} = \delta_3 + \gamma_{15} D_{i1} + \gamma_{16} D_{i2} + \gamma_{17} D_{i3} + \gamma_{18} D_{i1}D_{i2} + \gamma_{19} D_{i2}D_{i3} + \gamma_{20} D_{i1}D_{i3} + \gamma_{21} D_{i1}D_{i2}D_{i3} + \nu_{i3} \tag{65}$$

There are 12 structural parameters of the model, $\{\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6, \lambda_7; \theta_{12}, \theta_{13}, \theta_{23}; \phi, \beta\}$, to be identified from the 21 reduced form coefficients using minimum distance estimation with the restrictions implied by the model. The minimum distance restrictions are

$$\begin{aligned}
\gamma_1 &= \beta + (1+\phi)\lambda_1 + \phi\lambda_0 \\
\gamma_2 &= \lambda_2 \\
\gamma_3 &= \lambda_3 \\
\gamma_4 &= (1+\phi)\lambda_4 + \phi\lambda_2 \\
\gamma_5 &= \lambda_5
\end{aligned}$$

$$
\begin{aligned}
\gamma_6 &= (1+\phi)\lambda_6 + \phi\lambda_3 \\
\gamma_7 &= (1+\phi)\lambda_7 + \phi\lambda_5 \\
\gamma_8 &= \lambda_1 \\
\gamma_9 &= \beta + (1+\phi)(\lambda_2 + \theta_{12}) + \phi(\lambda_0 + \theta_{10}) \\
\gamma_{10} &= \lambda_3 + \theta_{13} \\
\gamma_{11} &= (1+\phi)\lambda_4 + \phi\lambda_1 \\
\gamma_{12} &= (1+\phi)\lambda_5 + \phi(\lambda_3 + \theta_{13}) \\
\gamma_{13} &= \lambda_6 \\
\gamma_{14} &= (1+\phi)\lambda_7 + \phi\lambda_6 \\
\gamma_{15} &= \lambda_1 \\
\gamma_{16} &= \lambda_2 \\
\gamma_{17} &= \beta + (1+\phi)(\lambda_3 + \theta_{23}) + \phi(\lambda_0 + \theta_{20}) \\
\gamma_{18} &= \lambda_4 \\
\gamma_{19} &= (1+\phi)\lambda_5 + \phi\lambda_2 \\
\gamma_{20} &= (1+\phi)\lambda_6 + \phi\lambda_1 \\
\gamma_{21} &= (1+\phi)\lambda_7 + \phi\lambda_4 \qquad (66)
\end{aligned}
$$

It appears from (95) that there are 15 structural parameters to be estimated. However, I will normalize $\sum \lambda_j = 0$, $\sum \theta_{1k} = 0$, and $\sum \theta_{2m} = 0$. Accordingly,

$$
\begin{aligned}
\lambda_0 &= -\lambda_1\overline{D_{i1}} - \lambda_2\overline{D_{i2}} - \lambda_3\overline{D_{i3}} - \lambda_4\overline{D_{i1}D_{i2}} - \lambda_5\overline{D_{i2}D_{i3}} - \lambda_6\overline{D_{i1}D_{i3}} - \lambda_7\overline{D_{i1}D_{i2}D_{i3}} \qquad (67) \\
\theta_{10} &= -\theta_{12}\overline{D_{i2}} - \theta_{13}\overline{D_{i3}} \qquad (68) \\
\theta_{20} &= -\theta_{23}\overline{D_{i3}} \quad , \qquad (69)
\end{aligned}
$$

where $\overline{D_{ij}}$ is the average entrepreneurship decision in period j, $\overline{D_{ij}D_{ik}}$ is the average of the interaction between the entrepreneurship decisions in periods j and k, and $\overline{D_{i1}D_{i2}D_{i3}}$ is the average of the interaction of entrepreneurship decisions in all three periods.

Under optimally-weighted minimum distance estimation, the over-identification test statistic is equal to the minimized value of the criterion function and is distributed χ^2 with 9 degrees of freedom (21 reduced form coefficients - 12 structural parameters = 9).

A.2 Structural Interpretation of Projection Coefficients

I observe in the data the conditional sample mean of log gross output for each entrepreneurship history in each of the three periods (i.e. $E(y_{it}|D_{i1}, D_{i2}, D_{i3})$). I can express the interpretation of these conditional moments in two ways: 1) in terms of the estimated parameters $\{\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6, \lambda_7; \theta_{12}, \theta_{13}, \theta_{23}; \phi, \beta\}$, and 2) in terms of the structural components of the model $E(m_{i0}|D_{i1}, D_{i2}, D_{i3})$, $E(m_i^1|D_{i1}, D_{i2}, D_{i3})$, $E(m_i^2|D_{i1}, D_{i2}, D_{i3})$, and, of course, ϕ and β. Comparing these two sets of expressions, I can derive structural interpretations for the estimated projection coefficients.

I have the following structural interpretations for the coefficients from the initial belief projection:

$$
\begin{aligned}
\lambda_1 &= E[m_{i0}|D_{i1}=1, D_{i2}=0, D_{i3}=0] - E[m_{i0}|D_{i1}=0, D_{i2}=0, D_{i3}=0]; && (70)\\
\lambda_2 &= E[m_{i0}|D_{i1}=0, D_{i2}=1, D_{i3}=0] - E[m_{i0}|D_{i1}=0, D_{i2}=0, D_{i3}=0]; && (71)\\
\lambda_3 &= E[m_{i0}|D_{i1}=0, D_{i2}=0, D_{i3}=1] - E[m_{i0}|D_{i1}=0, D_{i2}=0, D_{i3}=0]; && (72)\\
\lambda_4 &= \Big\{E[m_{i0}|D_{i1}=1, D_{i2}=1, D_{i3}=0] - E[m_{i0}|D_{i1}=1, D_{i2}=0, D_{i3}=0]\Big\} \\
&\quad -\Big\{E[m_{i0}|D_{i1}=0, D_{i2}=1, D_{i3}=0] - E[m_{i0}|D_{i1}=0, D_{i2}=0, D_{i3}=0]\Big\} && (73)\\
\lambda_5 &= \Big\{E[m_{i0}|D_{i1}=0, D_{i2}=1, D_{i3}=1] - E[m_{i0}|D_{i1}=0, D_{i2}=1, D_{i3}=0]\Big\} \\
&\quad -\Big\{E[m_{i0}|D_{i1}=0, D_{i2}=0, D_{i3}=1] - E[m_{i0}|D_{i1}=0, D_{i2}=0, D_{i3}=0]\Big\} && (74)\\
\lambda_6 &= \Big\{E[m_{i0}|D_{i1}=1, D_{i2}=0, D_{i3}=1] - E[m_{i0}|D_{i1}=1, D_{i2}=0, D_{i3}=0]\Big\} \\
&\quad -\Big\{E[m_{i0}|D_{i1}=0, D_{i2}=0, D_{i3}=1] - E[m_{i0}|D_{i1}=0, D_{i2}=0, D_{i3}=0]\Big\} && (75)\\
\lambda_7 &= \Big\{E[m_{i0}|D_{i1}=1, D_{i2}=1, D_{i3}=1] - E[m_{i0}|D_{i1}=1, D_{i2}=1, D_{i3}=0]\Big\}
\end{aligned}
$$

$$
\begin{aligned}
&-\Big\{E[m_{i0}|D_{i1}=1,D_{i2}=0,D_{i3}=1]-E[m_{i0}|D_{i1}=1,D_{i2}=0,D_{i3}=0]\Big\}\\
&-\Big\{E[m_{i0}|D_{i1}=0,D_{i2}=1,D_{i3}=1]-E[m_{i0}|D_{i1}=0,D_{i2}=1,D_{i3}=0]\Big\}\\
&+\Big\{E[m_{i0}|D_{i1}=0,D_{i2}=0,D_{i3}=1]-E[m_{i0}|D_{i1}=0,D_{i2}=0,D_{i3}=0]\Big\} \qquad (76)
\end{aligned}
$$

I have the following expressions for the coefficients from the two belief update projections:

$$
\begin{aligned}
\theta_{12} &= E[m_i^1|D_{i1}=0,D_{i2}=1,D_{i3}=0]-E[m_i^1|D_{i1}=0,D_{i2}=0,D_{i3}=0]\\
&= E[m_i^1|D_{i1}=1,D_{i2}=1,D_{i3}=0]-E[m_i^1|D_{i1}=1,D_{i2}=0,D_{i3}=0]\\
&= E[m_i^1|D_{i1}=0,D_{i2}=1,D_{i3}=1]-E[m_i^1|D_{i1}=0,D_{i2}=0,D_{i3}=1]\\
&= E[m_i^1|D_{i1}=1,D_{i2}=1,D_{i3}=1]-E[m_i^1|D_{i1}=1,D_{i2}=0,D_{i3}=1]; \qquad (77)\\
\theta_{13} &= E[m_i^1|D_{i1}=0,D_{i2}=0,D_{i3}=1]-E[m_i^1|D_{i1}=0,D_{i2}=0,D_{i3}=0]\\
&= E[m_i^1|D_{i1}=0,D_{i2}=1,D_{i3}=1]-E[m_i^1|D_{i1}=0,D_{i2}=1,D_{i3}=0]\\
&= E[m_i^1|D_{i1}=1,D_{i2}=0,D_{i3}=1]-E[m_i^1|D_{i1}=1,D_{i2}=0,D_{i3}=0]\\
&= E[m_i^1|D_{i1}=1,D_{i2}=1,D_{i3}=1]-E[m_i^1|D_{i1}=1,D_{i2}=1,D_{i3}=0]; \qquad (78)\\
\theta_{23} &= E[m_i^2|D_{i1}=0,D_{i2}=0,D_{i3}=1]-E[m_i^2|D_{i1}=0,D_{i2}=0,D_{i3}=0]\\
&= E[m_i^2|D_{i1}=0,D_{i2}=1,D_{i3}=1]-E[m_i^2|D_{i1}=0,D_{i2}=1,D_{i3}=0]\\
&= E[m_i^2|D_{i1}=1,D_{i2}=0,D_{i3}=1]-E[m_i^2|D_{i1}=1,D_{i2}=0,D_{i3}=0]\\
&= E[m_i^2|D_{i1}=1,D_{i2}=1,D_{i3}=1]-E[m_i^2|D_{i1}=1,D_{i2}=1,D_{i3}=0]; \qquad (79)
\end{aligned}
$$

These expressions suggest that if θ_{12}, θ_{13}, $\theta_{23} < 0$, then households that switch into entrepreneurship, or do not switch out, experience relatively lower earnings in the non-entrepreneurial sector than those that do not switch. If I also have that $\phi < 0$, then those households that experience negative shocks in the non-entrepreneurial sector and, subsequently, switch into entrepreneurship have *larger* returns to entrepreneurship than those that do not receive these negative updates and, therefore, choose to stay in the non-entrepreneurial sector. That is, entrepreneurial households select into entrepreneurship on the basis of their comparative advantage in entrepreneurship, and households with the highest returns to entrepreneurship have the lowest non-entrepreneurial earnings.

A.3 Nested Models

A.3.1 Heterogeneous Returns with Perfect Information: Correlated Random Coefficients

In the static correlated random coefficients (CRC) model, the estimating equation is the same as in the full model:

$$y_{it} = \alpha_t + \beta D_{it} + \rho^F k_{it}^F + (\rho^E k_{it}^E - \rho^F k_{it}^F) D_{it} + \eta_i + \phi \eta_i D_{it} + \tau_i + \varepsilon_{it} \tag{80}$$

I need only a single projection in which I project η_i onto the entrepreneurship decisions in all periods and their interactions:

$$\eta_i = \lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_3 D_{i3} + \lambda_4 D_{i1} D_{i2} + \lambda_5 D_{i2} D_{i3} + \lambda_6 D_{i1} D_{i3} + \lambda_7 D_{i1} D_{i2} D_{i3} + \psi_{i0} \tag{81}$$

Then, the corresponding reduced form equations are identical to those from the full model presented in equations (63), (64), and (65); however, the minimum distance restrictions imposed by this model are different than those imposed by the full model. Under this model, I will estimate only 9 structural parameters $\{\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6, \lambda_7; \phi, \beta\}$ from the 21 reduced form coefficients.

This nested model imposes 3 additional restrictions on the full model, namely

$$\theta_{12} = \theta_{13} = \theta_{23} = 0 \tag{82}$$

The test statistic is distributed χ^2 with 12 degrees of freedom.

A.3.2 Homogeneous Returns with Imperfect Information: Dynamic Correlated Random Effects

In a dynamic correlated random effects model (DCRE), the estimating equation becomes

$$y_{it} = \alpha_t + \beta D_{it} + \rho^F k_{it}^F + (\rho^E k_{it}^E - \rho^F k_{it}^F) D_{it} + \eta_i + \tau_i + \varepsilon_{it}, \tag{83}$$

where η_i is the household's fixed effect that the household does not know.

The corresponding projections are:

$$m_{i0} = \lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_3 D_{i3} + \psi_{i0} \tag{84}$$

$$m_i^1 = \theta_{10} + \theta_{12} D_{i2} + \theta_{13} D_{i3} + \psi_{i1} \tag{85}$$

$$m_i^2 = \theta_{20} + \theta_{23} D_{i3} + \psi_{i2} \tag{86}$$

Then, from the the usual 21 reduced form coefficients, I will estimate only 7 structural parameters. That is, this model imposes 5 additional restrictions on the preferred model, specifically

$$\lambda_4 = \lambda_5 = \lambda_6 = \lambda_7 = \phi = 0 \tag{87}$$

Accordingly, I need only estimate $\{\lambda_1, \lambda_2, \lambda_3; \theta_{12}, \theta_{13}, \theta_{23}; \beta\}$.

Under optimal minimum distance estimation, the test statistic is, once again, equal to the minimized value of the criterion function and is distributed χ^2 with 14 degrees of freedom.

A.3.3 Homogeneous Returns with Perfect Information: Correlated Random Effects

In the most restricted model, the estimating equation becomes

$$y_{it} = \alpha_t + \beta D_{it} + \rho^F k_{it}^F + (\rho^E k_{it}^E - \rho^F k_{it}^F) D_{it} + \eta_i + \varepsilon_{it} \tag{88}$$

I now need only a single projection of η_i on the entrepreneurship decisions from all periods:

$$\eta_i \quad = \quad \lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_3 D_{i3} \psi_{i0} \tag{89}$$

This model imposes 8 additional restrictions on my preferred model:

$$\lambda_4 = \lambda_5 = \lambda_6 = \lambda_7 = \theta_{12} = \theta_{13} = \theta_{23} = \phi = 0 \tag{90}$$

The over-identification test from this estimation is distributed χ^2 with 17 degrees of freedom.

A.4 Data

The most recent available wave of data is from the 2009 resurvey. For the 3 period estimation, I will construct a balanced panel using data from the 2001, 2005, and 2009 waves. In particular, I will use all households for which income and entrepreneurship information is available in all 3 years. The sample I use consists of 794 households.

The 4 year gaps between survey waves ensure that households have sufficient time to adjust entrepreneurial activity, should they want to. Among the 794 households in my sample, nearly 49% change their entrepreneurship decisions at least once from 2001 to 2009. However, the proportion of households participating in the entrepreneurial sector is roughly stable across waves: 44.7% in 2001, 48.5% in 2005, and 46.6%.

A.4.1 Summary Statistics

In Tables A.1a-c, I report means and standard deviations for variables of interest in the data. Table Ia presents summary statistics for the entire sample of log of gross income, entrepreneurship, input expenditure, savings, household demographics, expected income, financial perceptions, and credit participation. I find that income grows only slightly in the sample from 2001 to 2009, entrepreneurship remains stable on average, and input expenditure declines slightly. The percentage of households with savings grows considerably, expected income nearly doubles, and the percentage of households that report being credit constrained drops to nearly 0, although borrowing remains fairly stable over the years.

In Tables A.1b and A.1c, I report summary statistics for these same variables of interest by entrepreneurship history. Specifically, I split up the sample into households that engage in entrepreneurship in all three years, in none of the years, those that switch into entrepreneurship in 2005 or out in 2005, and those that switch in and those that switch out in 2009. Note that these categories are not strictly mutually exclusive. That is, a household can, for example, switch into entrepreneurship in 2005 and out again in 2009.

Table A.1b shows that households that run businesses tend to have higher gross incomes than those that don't and that the income of households that switch into entrepreneurship grows more steeply than that of households that switch out. I also find that expenditure is higher among entrepreneurial households. Assets seem to grow considerably among households of all entrepreneurship histories, but slightly more amongst households who switch out of entrepreneurship and those that never engage in entrepreneurship.

Households that engage in entrepreneurship tend to be larger than those that do not; however, no perceivable differences exist between specific entrepreneurship histories. No significant differences exist in age and gender composition of households across entrepreneurship histories. Entrepreneurial households appear to be better educated than non-entrepreneurial households, but once again no systematic pattern appears among entrepreneurial households.

In Table A.1c, I find that households that engage in entrepreneurship in all years have steeper expected income growth than switchers and those that never engage in entrepreneurship. The incidence of negative shocks in year prior to survey decreases over time across all entrepreneurship histories as does the percentage of households reporting credit constraints. Households that always engage in entrepreneurship or switch into entrepreneurship tend to borrow more than those that switch out or never engage in entrepreneurship. Borrowing remains stable over time across all entrepreneurship histories.

A.5 Results

In this section, I present results from the empirical analysis discussed above. I begin by presenting ordinary least squares and household fixed effects estimates of the effect of entrepreneurship on log of total gross income.

A.5.1 OLS and FE

In Table A.2, I regress the log of total gross income of the household over the 12 months prior to survey on a binary for whether the household owned at least one business during that year. The results reported in column 4 of Table A.2 are from the specification with no additional covariates. The point estimate is quite large, positive, and significant at the 1 percent level. A unit change in the probability of a household owning a business is associated with a 76 percent increase in the household's income.

In column 3, I include village by time dummies to control for variations in input and output prices over time. That is, assuming that all households within a village face the same prices in each period, including these dummies accounts for the role of input and output prices in the household's sectoral choice. I find that these additional controls have little effect on the coefficient of interest. The point estimate rises slightly to 79 percentage points and is still significant at the 1 percent level.

In columns 1 and 2, I include additional controls for input expenditure and savings. In column 2, I report results from a specification which includes the log of total expenditure on inputs by the household. The necessity of including inputs is implied by the model and significantly affects the coefficient of interest. I find in column 2, that owning a household business is now associated with a 35 percent increase in household income. The coefficient is still significant at the 1 percent level.

In column 1, I report results from a specification which includes a binary for whether the household has any savings and its interaction with input expenditure, along with the village x time dummies and input expenditure alone. This specification corresponds to the predictions of the model once I include limited liability and the implied credit constraints. In particular, there will be a differential optimal input allocation when the household is credit constrained, and the household will be most credit constrained when it has no savings. I find in column 1 that the inclusion of these additional controls for credit constraints have little effect on the coefficient of interest. The results are nearly identical to those in column 2.

In columns 5-8 of Table A.2, I present results from specifications identical to those in columns 1-4, respectively, but with the addition of household fixed effects. The coefficients across all specifications are smaller in magnitude than the corresponding OLS estimates. Once again, we see that village x time price controls have little effect on the coefficient of interest as compared to that from the specification including no covariates beyond the household fixed effects. Similarly, the inclusion of the savings dummy and its interaction with input expenditure has little effect on the coefficient of interest over the inclusion of log input expenditure alone. In columns 5 and 6, I find that owning a household business is associated with roughly a 22 percent increase in income.

Of course, as discussed above, to the degree that households choose to engage in entrepreneurship on the basis of their perceived comparative advantage in it over farm production or wage work, the estimate of the coefficient of interest in OLS and FE specifications will be biased for the average return to entrepreneurship. The estimation strategy proposed and discussed above will allow me to recover a consistent estimate of the average return to entrepreneurship in the presence of both heterogeneous entrepreneurial abilities and learning, and will also allow me to quantify the degree of heterogeneity and learning in the data.

A.5.2 Reduced Form Coefficients

In Table A.3, I present the reduced form coefficients from which I will estimate the structural parameters of the econometric model set forth above using minimum distance. In the reduced form specifications, I regress the log of total gross income from each period on the entrepreneurship dummies for each period, their interactions when appropriate, and any covariates in a seemingly unrelated regressions framework. In Table A.3, I report reduced form coefficients in the case of no covariates. The reduced form coefficients are not particularly informative; accordingly, I do not report reduced form coefficients for all sets of covariates[9].

A.5.3 Structural Minimum Distance Estimates (No Covariates)

In Table A.4, I present the optimal minimum distance estimates from the full CRC model with learning and the three nested, restricted models with no additional covariates. I present results from the CRE model in column 1. As mentioned above, the CRE model corresponds to a household fixed effects data generating process, that is, a model with homogeneous returns to entrepreneurship and perfect information. In particular, under this model latent ability has no effect on returns to entrepreneurship and the household's perception of this ability does not change over time.

Therefore, λ_j represents the dependance of the household's entrepreneurial choice in period j on latent ability; we need only one such parameter per period. The estimates of the λ's are all positive and precisely estimated. I will reserve, for the sake of brevity, the discussion of the interpretation of the projection coefficients in the context of the model for later, when I present results from the preferred model. The estimate of the average return to entrepreneurship, β, is also positive and very precisely estimated. The point estimate is .32, which is nearly identical to that from the FE regression results reported in Table A.2. Nevertheless, the restrictions implied by this model (namely, no heterogeneity in returns and no learning) can be rejected. The χ^2 test statistic is over 18 with a p-value of .0026

In column 2 of Table A.4, I present estimates from the static CRC model which allows for heterogeneous returns but still restricts information on entrepreneurial comparative advantage to be perfect. This model implies that latent heterogeneity will not only affect entrepreneurship decisions in each period, but also the specific history of choices across periods. Therefore, I have now 7 λ's corresponding to 8 possible entrepreneurship histories over the three periods, with the omitted history being never owning a business.

Once again, I find that the λ's are precisely estimated. The estimate of β is once again posi-

[9]Reduced form results for other specifications are available upon request

tive and precisely estimated, though slightly smaller in magnitude than that in the CRE model. The estimate of ϕ, which measures the degree to which households base their entrepreneurial decisions on their comparative advantage in entrepreneurship, is positive and large but insignificant. A positive estimate of ϕ implies that households with the highest non-entrepreneurial earnings also have the largest returns to entrepreneurship; however, the coefficient is not statistically significant from 0 so I will not dwell on its interpretation. Once again, I will refrain from discussing the interpretation of the projection coefficients, as the interpretation depends on the restrictions imposed by the model and this particular model is rejected as well. The χ^2 test statistic is nearly 37 with a p-value of .0002.

Column 3 of Table A.4 reports results from the dynamic CRE model which, once again, restricts returns to be homogeneous, but now allows for households to have imperfect information about this return. In the context of this model, the λ's characterize the initial beliefs of households with different entrepreneurship histories, whereas the θ's characterize the degree and direction of learning. The estimate of β is nearly identical to that in the static CRE model and in the FE specification reported in Table A.2. I cannot reject the restrictions imposed by this model. In particular, the learning structure seems to improve the fit of the model.

Finally, in column 4 of Table A.4, I present estimates of the preferred model which allows for both selection on entrepreneurial comparative advantage and imperfect information. The β is once again well-estimated with a point estimate of .35. The ϕ is precisely estimated as well and negative. Despite the fact that I cannot reject the dynamic CRE model, the significant estimate of ϕ suggests that there is, in fact, heterogeneity in returns to entrepreneurship. The negative ϕ implies that households with the largest non-entrepreneurial income have the lowest returns to entrepreneurship.

A.5.4 Structural Minimum Distance Estimates (Price Controls)

In Table A.5, I present results from all four models with additional village by time dummies as price controls. The results are slightly changed, but the overall pattern of results is the same as those presented in Table A.4. The point estimates of β from both CRE models (presented in columns 1 and 3) are roughly unchanged, but the β's in the CRC models (reported in columns 2 and 4) are both larger than the corresponding estimates without controls. The estimates of β in the static and dynamic CRC models, reported in columns 2 and 4 of Table A.5, are roughly 50 and 100 percent larger, respectively, with price controls than without. The estimate of ϕ in the static CRC model is now negative, but still not statistically significantly different from 0. In the dynamic CRC model, the estimate of ϕ is nearly identical with and without price controls. With the inclusion of village by time dummies, I cannot reject the restrictions implied by any of the models. However, the p-values suggest that the preferred dynamic CRC model still fits best, followed once again by the dynamic CRE model.

A.5.5 Structural Minimum Distance Estimates (Price and Input Controls)

The model suggests the inclusion of the log of inputs in the reduced form regressions. Accordingly, I repeat the analysis with log of total input expenditure in all periods and their interaction with current entrepreneurship as controls, along with the village by time dummies. The second stage minimum distance estimates from this model with both price and input controls are reported in Table A.6. I find that, once again, the pattern of results is quite similar to that presented in Table A.5.

The estimates of β in the static CRE and CRC models, presented in columns 1 and 2 respectively, resemble those from Table A.5, though they are slightly larger and now insignificant. The estimate of ϕ in the static CRC model is still negative, but is now larger in magnitude and significant. Both these static models are rejected with p-values less than .0001. The dynamic CRE model, reported in column 3, is now rejected with a χ^2 of 6.68 and a p-value of .0354. The estimate of β is still positive and precisely estimated, but is now much larger with a magnitude of 1.278.

The full model, again, cannot be rejected. The estimate of β in the CRC model with learning, presented in column 4, is slightly larger than that from the dynamic CRE model, presented in column 3, with a magnitude of 1.3721. The estimate of ϕ in column 4 of Table A.6 is negative, significant and 60 percent larger than that reported in Table A.5. The specifications reported in

Table A.6 best correspond to the model discussed in section 2 above, and accordingly, I place the most emphasis on these results. Taken together, the results suggest that, indeed, both selection on comparative advantage and learning about comparative advantage play a large role in the household's entrepreneurship decision.

The θ's, which measure the updates to the household's perception of its comparative advantage in entrepreneurial activities (or more accurately, the portion of this updated information which affects the household's entrepreneurship decisions in future periods), are also precisely estimated and negative. These results suggest that households receive negative shocks in the non-entrepreneurial sector and learn from these shocks that they have a comparative advantage in entrepreneurship. Accordingly, these households switch into entrepreneurship and achieve large returns to entrepreneurship; indeed, they achieve larger returns than would the households that chose to stay in the non-entrepreneurial sector.

Figures A.1a and A.1b presents graphically the degree of heterogeneity and learning in the estimated perceived returns to entrepreneurship from the full model (i.e. the dynamic CRC model with learning from column 4 of Table A.6) with both endogenous capital and price controls. In 3 periods, there will be 8 different productivity gains in each time period corresponding to 8 possible entrepreneurship histories. I find that households that switch into entrepreneurship and those that choose to stay in entrepreneurship, indeed, expect increases in productivity gains in the current period, whereas households that choose to stay out or switch out of entrepreneurship do not perceive such increases in the productivity gains. Additionally, the average perceived productivity gain over time varies across these different types of households, verifying that there is heterogeneity even in the initial beliefs.

Figures A.2a and A.2b repeats this exercise for the static CRC model with both endogenous capital and price controls corresponding to column 3 in Table A.6. Once again, I find that the perceived productivity gains vary by entrepreneurship history. The differences between productivity gains in Figures A.1a-b and A.2a-b are statistically significant, as mentioned above, and support a learning interpretation for the dynamics observed in the data.

B Omitted Equations

The minimum distance restrictions implied by the 2 period dynamic CRC model with endogenous capital are:

$$
\begin{aligned}
\gamma_1 &= \beta + (1+\phi)\lambda_1 + \phi\lambda_0 \\
\gamma_2 &= \lambda_2 \\
\gamma_3 &= (1+\phi)\lambda_{12} + \phi\lambda_2 \\
\gamma_4 &= \rho + \lambda_{k1} \\
\gamma_5 &= \lambda_{k2} \\
\gamma_6 &= (1+\phi)\lambda_{k1-1} + \phi\lambda_{k1} \\
\gamma_7 &= \lambda_{k1-2} \\
\gamma_8 &= (1+\phi)\lambda_{k1-12} + \phi\lambda_{k1-2} \\
\gamma_9 &= (1+\phi)\lambda_{k2-1} + \phi\lambda_{k2} \\
\gamma_{10} &= \lambda_{k2-2} \\
\gamma_{11} &= (1+\phi)\lambda_{k2-12} + \phi\lambda_{k2-2} \\
\gamma_{12} &= \lambda_1 \\
\gamma_{13} &= \beta + (1+\phi)(\lambda_2 + \theta_2) + \phi(\lambda_0 + \theta_0) \\
\gamma_{14} &= (1+\phi)\lambda_{12} + \phi\lambda_1 \\
\gamma_{15} &= \lambda_{k1} \\
\gamma_{16} &= \rho + \lambda_{k2} + \theta_{k2} \\
\gamma_{17} &= \lambda_{k1-1} \\
\gamma_{18} &= (1+\phi)\lambda_{k1-2} + \phi\lambda_{k1} \\
\gamma_{19} &= (1+\phi)\lambda_{k1-12} + \phi\lambda_{k1-1} \\
\gamma_{20} &= \lambda_{k2-1} \\
\gamma_{21} &= (1+\phi)(\lambda_{k2-2} + \theta k2 - 2) + \phi(\lambda_{k2} + \theta k2)
\end{aligned}
$$

$$\gamma_{22} = (1+\phi)\lambda_{k2-12} + \phi\lambda_{k2-1} \tag{91}$$

The corresponding normalizations of λ_0 and θ_0 are

$$\begin{aligned}
\lambda_0 &= -\lambda_1\overline{D_{i1}} - \lambda_2\overline{D_{i2}} - \lambda_3\overline{D_{i1}D_{i2}} - \lambda_{k1}\overline{k_{i1}} - \lambda_{k2}\overline{k_{i2}} - \lambda_{k1-1}\overline{k_{i1}D_{i1}} - \lambda_{k1-2}\overline{k_{i1}D_{i2}} \\
&\quad + \lambda_{k1-12}\overline{k_{i1}D_{i1}D_{i2}} + \lambda_{k2-1}\overline{k_{i2}D_{i1}} + \lambda_{k2-2}\overline{k_{i2}D_{i2}} + \lambda_{k2-12}\overline{k_{i2}D_{i1}D_{i2}} + \psi_{i0} \qquad (92) \\
m_i^1 &= \theta_0 + \theta_2\overline{D_{i2}} + \theta_{k2}\overline{k_{i2}} + \theta_{k2-2}\overline{k_{i2}D_{i2}} + \psi_{i1}
\end{aligned}$$

The minimum distance restrictions implied by the 2 period static CRC model with endogenous capital are:

$$\begin{aligned}
\gamma_1 &= \beta + (1+\phi)\lambda_1 + \phi\lambda_0 \\
\gamma_2 &= \lambda_2 \\
\gamma_3 &= (1+\phi)\lambda_{12} + \phi\lambda_2 \\
\gamma_4 &= \rho + \lambda_{k1} \\
\gamma_5 &= \lambda_{k2} \\
\gamma_6 &= (1+\phi)\lambda_{k1-1} + \phi\lambda_{k1} \\
\gamma_7 &= \lambda_{k1-2} \\
\gamma_8 &= (1+\phi)\lambda_{k1-12} + \phi\lambda_{k1-2} \\
\gamma_9 &= (1+\phi)\lambda_{k2-1} + \phi\lambda_{k2} \\
\gamma_{10} &= \lambda_{k2-2} \\
\gamma_{11} &= (1+\phi)\lambda_{k2-12} + \phi\lambda_{k2-2} \\
\gamma_{12} &= \lambda_1 \\
\gamma_{13} &= \beta + (1+\phi)\lambda_2 + \phi\lambda_0 \\
\gamma_{14} &= (1+\phi)\lambda_{12} + \phi\lambda_1 \\
\gamma_{15} &= \lambda_{k1}
\end{aligned}$$

$$
\begin{aligned}
\gamma_{16} &= \rho + \lambda_{k2} \\
\gamma_{17} &= \lambda_{k1-1} \\
\gamma_{18} &= (1+\phi)\lambda_{k1-2} + \phi\lambda_{k1} \\
\gamma_{19} &= (1+\phi)\lambda_{k1-12} + \phi\lambda_{k1-1} \\
\gamma_{20} &= \lambda_{k2-1} \\
\gamma_{21} &= (1+\phi)\lambda_{k2-2} + \phi\lambda_{k2} \\
\gamma_{22} &= (1+\phi)\lambda_{k2-12} + \phi\lambda_{k2-1}
\end{aligned} \tag{93}
$$

The normalization of λ_0 is identical to that from the DCRC model above.

The minimum distance restrictions implied by the 2 period dynamic CRE model with endogenous capital are:

$$
\begin{aligned}
\gamma_1 &= \beta + \lambda_1 \\
\gamma_2 &= \lambda_2 \\
\gamma_4 &= \rho + \lambda_{k1} \\
\gamma_5 &= \lambda_{k2} \\
\gamma_{12} &= \lambda_1 \\
\gamma_{13} &= \beta + \lambda_2 + \theta_2 \\
\gamma_{15} &= \lambda_{k1} \\
\gamma_{16} &= \rho + \lambda_{k2} + \theta_{k2} \\
\gamma_3 &= \gamma_6 = \gamma_7 = \gamma_8 = \gamma_9 = \gamma_{10} = \gamma_{11} = \gamma_{14} = \gamma_{17} = \gamma_{18} = \gamma_{19} = \gamma_{20} = \gamma_{21} = \gamma_{22} = 0
\end{aligned} \tag{94}
$$

Finally, the minimum distance restrictions implied by the 2 period static CRE model with endogenous capital are:

$$
\begin{aligned}
\gamma_1 &= \beta + \lambda_1 \\
\gamma_2 &= \lambda_2
\end{aligned}
$$

$$
\begin{aligned}
\gamma_4 &= \rho + \lambda_{k1} \\
\gamma_5 &= \lambda_{k2} \\
\gamma_{12} &= \lambda_1 \\
\gamma_{13} &= \beta + \lambda_2 \\
\gamma_{15} &= \lambda_{k1} \\
\gamma_{16} &= \rho + \lambda_{k2} \\
\gamma_3 &= \gamma_6 = \gamma_7 = \gamma_8 = \gamma_9 = \gamma_{10} = \gamma_{11} = \gamma_{14} = \gamma_{17} = \gamma_{18} = \gamma_{19} = \gamma_{20} = \gamma_{21} = \gamma_{22} = 0 \quad (95)
\end{aligned}
$$

Figure I

Trends in Savings, Self-reported Constraints, and Entrepreneurship

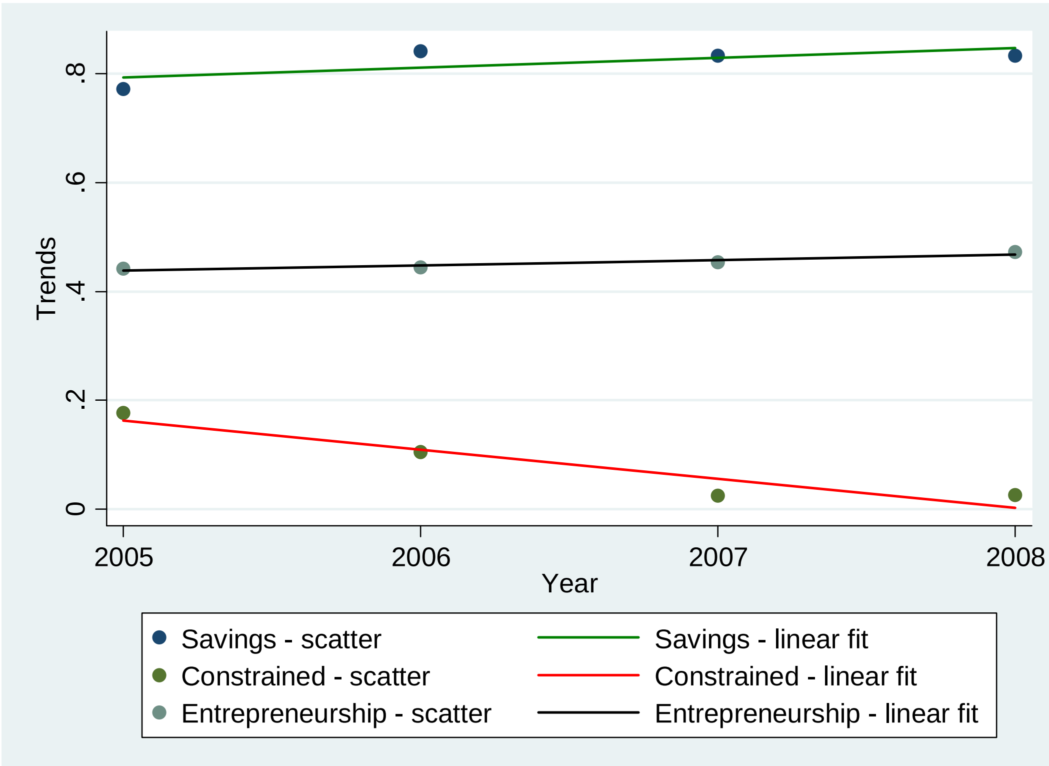

Figure II

Trends in Entrepreneurship and Switching

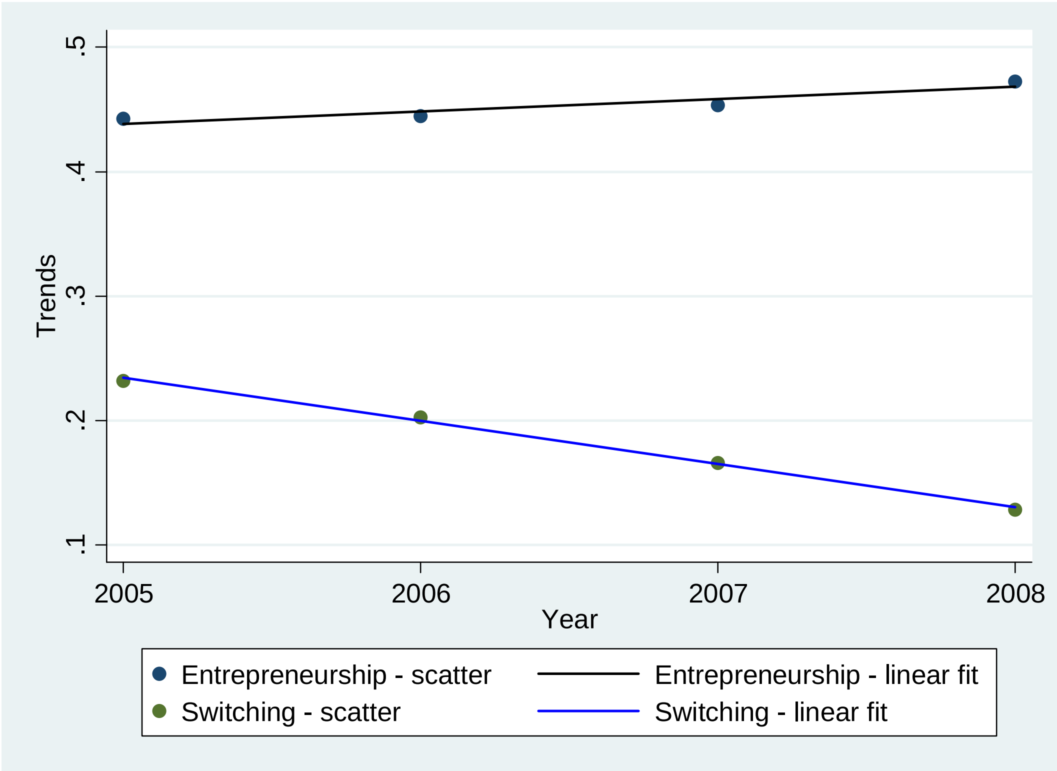

Figure III

Dynamic CRC: Perceived Productivity Gains ($\beta + \phi\ m_{i,t-1}$)

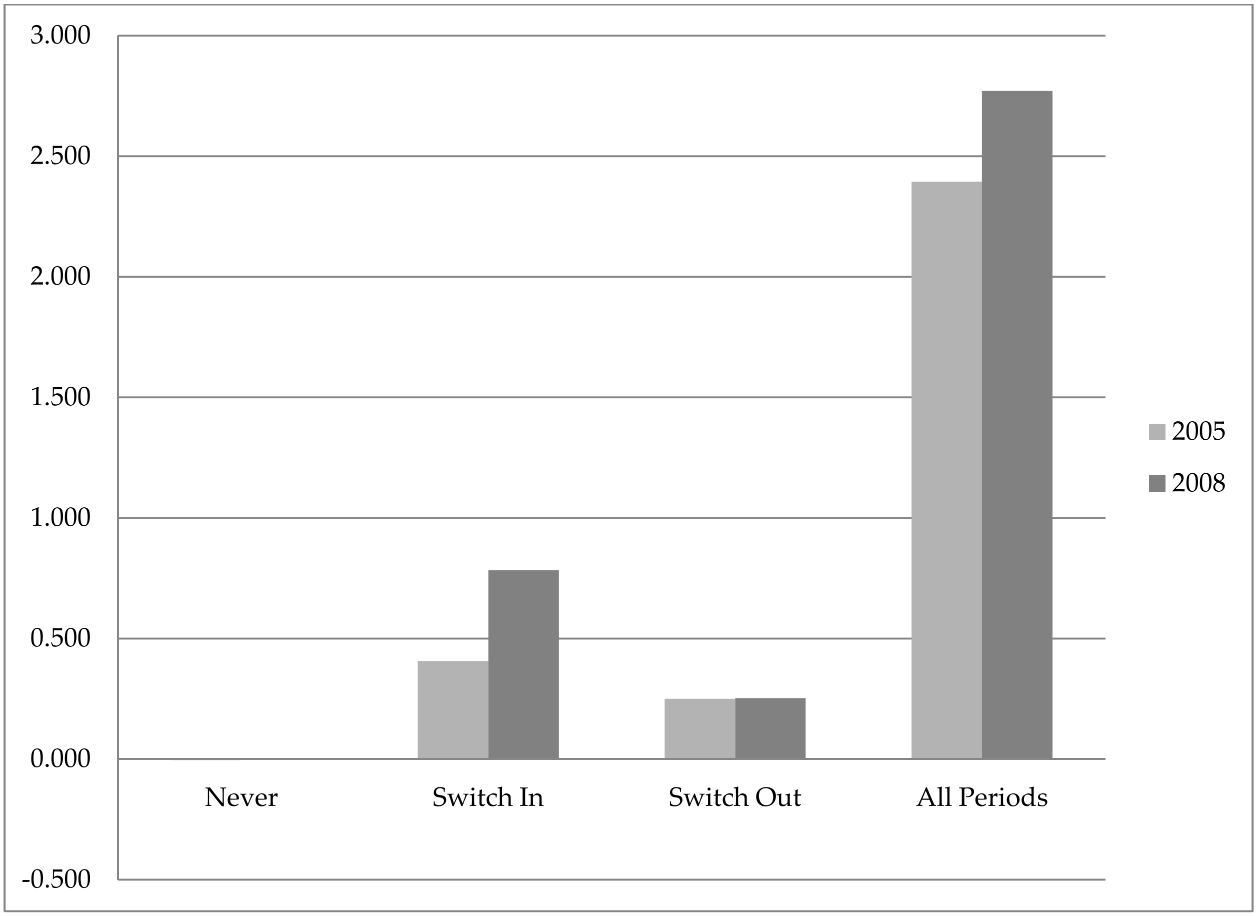

Figure IV

Static CRC: Perceived Productivity Gains ($\beta + \phi\ \eta$)

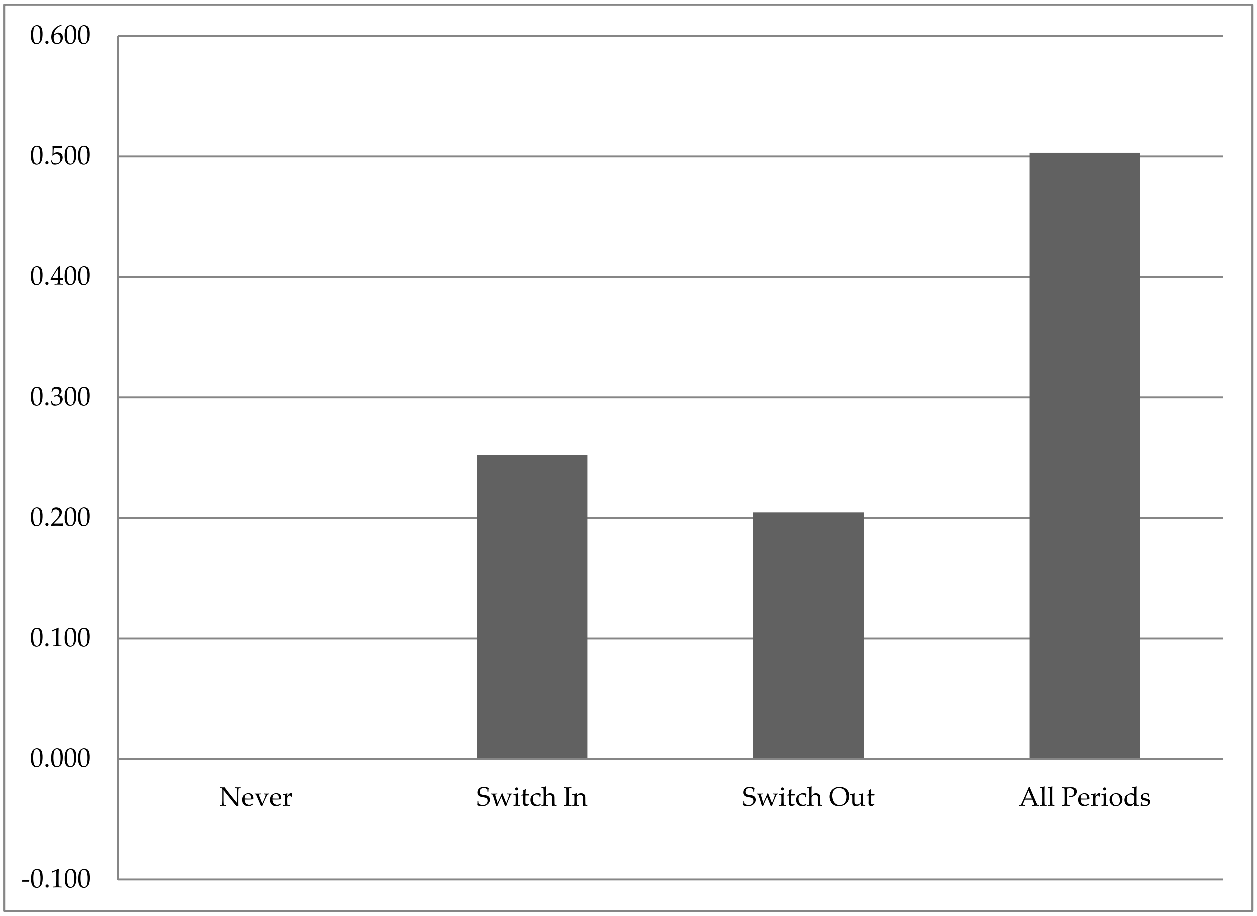

Table Ia: Summary Statistics

	Mean	SD
Count	1103	
Income		
ln(gross income), 2005	11.58	1.04
ln(gross income), 2008	11.84	1.03
Entrepreneurship		
Household Business, 2005	0.44	0.50
Household Business, 2008	0.47	0.50
Inputs		
ln(Total Expenditure), 2005	8.23	4.09
ln(Total Expenditure), 2008	8.16	4.50
Household Demographics, 2005		
Household Size	4.23	1.74
Average Age	37.64	13.20
Proportion Male	0.47	0.20
Proportion Completed Primary School	0.27	0.26
Savings		
Household Has Savings, 2005	0.77	0.42
Household Has Savings, 2008	0.83	0.37
Credit Constrained		
Expansion would be profitable, 2005	0.18	0.38
Expansion would be profitable, 2008	0.03	0.16
Borrowing		
Any Loans, 2005	0.80	0.40
Any Loans, 2008	0.77	0.42

Notes: Please see data appendix for details on the construction of variables.

Table Ib: Summary Statistics by Entrepreneurship History (Income, Expenditure, and Demographics)

	Business in Both Years		Switch In		Switch Out		Never Own Business	
Count	364		156		123		460	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Income								
ln(gross income), 2005	11.99	1.08	11.42	0.90	11.85	0.91	11.23	0.96
ln(gross income), 2008	12.24	1.18	11.99	0.79	11.82	0.90	11.49	0.89
Inputs								
ln(Total Expenditure), 2005	10.44	2.19	8.09	3.74	9.97	2.38	6.07	4.57
ln(Total Expenditure), 2008	10.59	2.64	9.59	2.98	7.01	4.90	6.07	4.86
Household Demographics, 2005								
Household Size	4.36	1.60	4.49	1.70	4.30	1.72	4.02	1.85
Average Age	35.89	11.35	35.25	11.61	38.35	13.05	39.64	14.73
Proportion Male	0.48	0.18	0.49	0.18	0.47	0.20	0.46	0.23
Proportion Completed Primary School	0.32	0.26	0.28	0.25	0.27	0.25	0.23	0.25

Notes: Please see data appendix for details on the construction of variables.

Table Ic: Summary Statistics by Entrepreneurship History (Financial Constraints)

	Business in Both Years		Switch In		Switch Out		Never Own Business	
Count	364		156		123		460	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Savings								
Household Has Savings, 2005	0.87	0.34	0.74	0.44	0.86	0.35	0.68	0.47
Household Has Savings, 2008	0.90	0.30	0.86	0.35	0.88	0.33	0.76	0.43
Credit Constrained								
Expansion would be profitable, 2005	0.26	0.44	0.10	0.30	0.28	0.45	0.10	0.31
Expansion would be profitable, 2008	0.03	0.18	0.05	0.22	0.01	0.09	0.02	0.13
Borrowing								
Any Loans, 2005	0.90	0.31	0.82	0.38	0.83	0.38	0.71	0.45
Any Loans, 2008	0.87	0.34	0.83	0.37	0.78	0.42	0.67	0.47

Notes: Please see data appendix for details on the construction of variables.

Table II: Agricultural Price and Savings

Household FE Estimates of Effects Global Price of Rice on Savings, Constraints, and Entrepreneurship

	Price x Farm Intensity			Price		
	Savings Account	Self-reported Constraints	Household Business	Savings Account	Self-reported Constraints	Household Business
Price x Farm Rai	0.000532	-0.0418***	0.000582			
	(0.00782)	(0.00855)	(0.00910)			
Price	0.0169***	-0.0586***	0.00155	0.0165***	-0.0674***	0.000744
	(0.00259)	(0.00283)	(0.00301)	(0.00209)	(0.00225)	(0.00244)
Farm Rai	0.0484	0.213***	0.0813**			
	(0.0315)	(0.0344)	(0.0366)			
Observations	11,039	11,039	11,039	11,040	11,323	11,040
R-squared	0.007	0.088	0.001	0.007	0.084	0.000

Notes: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table III: Entrepreneurship Decision

Household FE IV Estimates of Effects Savings and Constraints on Entrepreneurship

	Household Owns a Business		
Saving	0.0450	0.0973	
	(0.911)	(0.144)	
Constrained	-0.0134		-0.0246
	(0.230)		(0.0365)
Farm Rai	0.0820	0.0780***	0.0854***
	(0.0742)	(0.0280)	(0.0287)
First Stage - F Stat: Saving	22.09	22.09	
First Stage - p-value: Saving	< 0.0001	< 0.0001	
First Stage - F Stat: Constrained	305.71		305.71
First Stage - p-value: Constrained	< 0.0001		< 0.0001
Observations	11,039	11,039	11,039
R-squared	0.0257	0.0221	0.0056

Notes: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). 4 yr mean price is the average price over of survey and the 3

Table IV: OLS and FE Estimates of Returns to Entrepreneurship

OLS and FE Estimates of Effects of Entrepreneurship on ln(Gross Earnings)

	OLS			FE		
	Prices & Inputs	Inputs	No Covariates	Prices & Inputs	Inputs	No Covariates
Household Business	0.307***	0.245***	0.646***	0.178**	0.194**	0.332***
	(0.0452)	(0.0467)	(0.0516)	(0.0797)	(0.0812)	(0.0804)
ln(Input Expenditure)	0.106***	0.103***		0.0675***	0.0646***	
	(0.00640)	(0.00653)		(0.0130)	(0.0130)	
Observations	2,206	2,206	2,206	2,206	2,206	2,206
R-squared	0.432	0.239	0.095	0.860	0.828	0.815

Notes: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Price controls consist of village x time dummies.

Table V: Reduced Forms (No Covariates)

3 Period Reduced Form Estimates

CA-CRC	ln(gross income), 2005	ln(gross income), 2008
Household Business 2005	0.622125***	0.330006***
	(0.093139)	(0.090673)
Household Business 2008	0.189557**	0.499113***
	(0.084756)	(0.075249)
Household Business 2005 x 2008	-0.05661	-0.08094
	(0.130628)	(0.126392)
Observations	1103	1103

Notes: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table VI: Reduced Forms (Endogenous Capital)

3 Period Reduced Form Estimates

CA-CRC	ln(gross income), 2005	ln(gross income), 2008
Household Business 2005	-0.41665	-0.0900717
	(0.556897)	(0.3444885)
Household Business 2008	-0.51667*	-0.1824934
	(0.26424)	(0.2472835)
Household Business 2005 x 2008	-1.52826**	-2.143647***
	(0.744836)	(0.5956344)
ln(Total Input Expenditure) 2005	0.054438***	0.0017576
	(0.012373)	(0.0108551)
ln(Total Input Expenditure) 2008	0.018068	0.0683273***
	(0.011494)	(0.0099818)
ln(Total Input Expenditure) 2005 x Household Business 2005	0.095389*	0.0375822
	(0.056787)	(0.0343597)
ln(Total Input Expenditure) 2005 x Household Business 2008	-0.03761	-0.033545*
	(0.023784)	(0.0181576)
ln(Total Input Expenditure) 2005 x [Household Business 2005 x 2008]	0.127256*	0.061872
	(0.076373)	(0.0538664)
ln(Total Input Expenditure) 2008 x Household Business 2005	-0.02025	-0.0036433
	(0.020782)	(0.0195239)
ln(Total Input Expenditure) 2008 x Household Business 2008	0.087205***	0.0738686***
	(0.025812)	(0.0245127)
ln(Total Input Expenditure) 2008 x [Household Business 2005 x 2008]	0.024283	0.1338589***
	(0.044773)	(0.0497242)
Observations	1103	1103

Notes: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table VII: OMD Structural Estimates (No Covariates)

3 Period Minimum Distance Estimates

	CRE	CRE with learning	CA-CRC	CA-CRC with learning
λ_1	0.2889***	0.2888***	0.3313***	0.3300***
	(0.0608)	(0.0630)	(0.0900)	(0.0907)
λ_2	0.1668***	0.1677***	0.1877**	0.1896**
	(0.0628)	(0.0644)	(0.0833)	(0.0848)
λ_{12}			-0.0301	-0.0288
			(0.2606)	(0.2685)
θ_2		-0.0038		-0.0083
		(0.0590)		(0.0729)
β	0.3044***	0.3064***	0.3436	0.3493
	(0.0546)	(0.0624)	(0.2050)	(0.2146)
ϕ			-0.1647	-0.1732
			(0.8056)	(0.8235)
χ^2	0.428	0.4238	0.0135	
df	3	2	1	0
observations	1103	1103	1103	1103
p-value	0.9344	0.809	0.9075	

Notes: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table VIII: OMD Structural Estimates (Endogenous Capital)

3 Period Minimum Distance Estimates

	CRE	CRE with learning	CA-CRC	CA-CRC with learning
λ_1	0.2830***	0.2915***	-0.0057	0.0179
	(0.0541)	(0.0562)	(0.3378)	(0.3295)
λ_2	0.0393	0.0310	-0.5282**	-0.4863*
	(0.0560)	(0.0580)	(0.2569)	(0.2639)
λ_{12}			-2.7344**	-3.6703**
			(1.2236)	(1.8511)
λ_{k1}	-0.0063	-0.0074	-0.0042	-0.0062
	(0.0078)	(0.0079)	(0.0102)	(0.0105)
λ_{k2}	0.0299***	0.0310***	0.0079	0.0098
	(0.0081)	(0.0082)	(0.0105)	(0.0109)
$\lambda_{k1\text{-}1}$			0.0361	0.0358
			(0.0323)	(0.0322)
$\lambda_{k1\text{-}2}$			-0.0446**	-0.0505**
			(0.0211)	(0.0228)
$\lambda_{k1\text{-}12}$			0.1518*	0.1841*
			(0.0793)	(0.1004)
$\lambda_{k2\text{-}1}$			-0.0095	-0.0104
			(0.0179)	(0.0187)
$\lambda_{k2\text{-}2}$			0.0970***	0.0962***
			(0.0246)	(0.0250)
$\lambda_{k2\text{-}12}$			0.1144	0.1755
			(0.0749)	(0.1205)
θ_2		0.0392		-0.3772
		(0.0620)		(0.4516)
θ_{k2}		-0.0067		-0.0082
		(0.0071)		(0.0082)
$\theta_{k2\text{-}2}$				0.0342
				(0.0376)
ρ	0.0595***	0.0638***	0.0671***	0.0726***
	(0.0087)	(0.0098)	(0.0102)	(0.0119)
β	0.1858***	0.1633***	0.2191***	0.2408***
	(0.0510)	(0.0607)	(0.0647)	(0.0878)
ϕ			-0.3052	-0.4614**
			(0.2113)	(0.2149)
χ^2	85.1951	84.2665	14.9055	13.149
df	16	14	8	5
observations	1103	1103	1103	1103
p-value	<0.0001	<0.0001	0.061	0.022

Notes: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table IX: OMD Structural Estimates (Endogenous Capital and Price Controls)

3 Period Minimum Distance Estimates

	CRE	CRE with learning	CA-CRC	CA-CRC with learning
λ_1	0.2099***	0.2133***	0.1465	0.1627
	(0.0484)	(0.0510)	(0.2425)	(0.2464)
λ_2	0.1396	0.1356**	-0.2109	-0.1345
	(0.0518)	(0.0545)	(.2433)	(0.2606)
λ_{12}			-2.1101**	-4.1961
			(1.0329)	(2.9516)
λ_{k1}	0.0056	0.0055	0.0068	0.0050
	(0.0071)	(0.0072)	(0.0091)	(0.0096)
λ_{k2}	0.0231***	0.0231***	0.0133	0.0139
	(0.0077)	(0.0079)	(0.0096)	(0.0105)
$\lambda_{k1\text{-}1}$			0.0143	0.0137
			(0.0235)	(0.0247)
$\lambda_{k1\text{-}2}$			-0.0346**	-0.0453**
			(0.0168)	(0.0204)
$\lambda_{k1\text{-}12}$			0.1512**	0.2543
			(0.0739)	(0.1627)
$\lambda_{k2\text{-}1}$			-0.0130	-0.0123
			(0.0153)	(0.0171)
$\lambda_{k2\text{-}2}$			0.0603**	0.0601**
			(0.0253)	(0.0259)
$\lambda_{k2\text{-}12}$			0.0603	0.1715
			(0.0508)	(0.1585)
θ_2		0.0149		-0.7488
		(0.0683)		(0.7710)
θ_{k2}		-0.0002		-0.0050
		(0.0079)		(0.0090)
$\theta_{k2\text{-}2}$				0.0709
				(0.0677)
ρ	0.0608***	0.0610***	0.0641***	0.0686***
	(0.0084)	(0.0095)	(0.0095)	(0.0119)
β	0.1764***	0.1688***	0.2287**	0.3512***
	(0.0519)	(0.0631)	(0.1138)	(0.1166)
ϕ			-0.1432	-0.5512*
			(0.3476)	(0.2947)
χ^2	67.2846	67.2263	12.8105	9.2845
df	16	14	8	5
observations	1103	1103	1103	1103
p-value	<0.0001	<0.0001	0.1185	0.0982

Notes: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Price controls are village x time dummies.

Table A.1a: Summary Statistics

Count	794	
	Mean	**SD**
Income		
ln(gross income), 2001	11.365	1.080
ln(gross income), 2005	11.563	1.073
ln(gross income), 2009	11.951	1.037
Entrepreneurship		
Household Business, 2001	0.447	0.498
Household Business, 2005	0.485	0.500
Household Business, 2009	0.466	0.499
Inputs		
ln(Total Expenditure), 2001	8.710	3.671
ln(Total Expenditure), 2005	8.558	3.836
ln(Total Expenditure), 2009	8.119	4.692
Household Demographics, 2001		
Household Size	4.630	1.803
Average Age	35.076	11.515
Proportion Male	0.490	0.196
Proportion Completed Primary School	0.241	0.244
Savings		
Household Has Savings, 2001	0.722	0.448
Household Has Savings, 2005	0.787	0.410
Household Has Savings, 2009	0.849	0.358
Credit Constrained		
Expansion would be profitable, 2001	0.283	0.451
Expansion would be profitable, 2005	0.180	0.385
Expansion would be profitable, 2009	0.006	0.079
Borrowing		
Any Loans, 2001	0.732	0.443
Any Loans, 2005	0.827	0.378
Any Loans, 2009	0.775	0.418

Notes: Please see data appendix for details on the construction of variables.

Table A.1b: Summary Statistics by Entrepreneurship History (Income, Expenditure, and Demographics)

	Household Business, All Years		Switch In, 2005		Switch In, 2009		Switch Out, 2005		Switch Out, 2009		No Household Business, All Years	
Count	177		144		98		114		113		229	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Income												
ln(gross income), 2001	12.007	1.044	11.058	0.855	11.485	0.877	11.705	0.908	11.464	1.060	10.840	1.058
ln(gross income), 2005	12.145	1.119	11.554	1.007	11.311	0.875	11.506	0.836	11.841	0.966	11.150	1.038
ln(gross income), 2009	12.553	1.071	11.851	1.097	12.100	0.860	11.895	0.967	11.938	0.943	11.556	0.871
Inputs												
ln(Total Expenditure), 2001	10.728	1.879	8.816	2.798	9.433	2.726	9.602	3.164	9.026	3.278	6.337	4.488
ln(Total Expenditure), 2005	10.698	2.140	9.878	1.910	8.379	3.513	7.721	4.293	10.162	2.088	6.218	4.463
ln(Total Expenditure), 2009	11.028	2.542	8.628	4.150	9.789	3.095	7.925	4.895	7.281	5.024	5.578	4.962
Household Demographics, 2001												
Household Size	4.802	1.682	4.750	1.740	4.867	1.983	4.825	2.032	4.841	1.869	4.223	1.675
Average Age	33.403	9.883	34.770	11.306	33.342	10.080	36.001	10.513	35.563	12.490	36.429	12.973
Proportion Male	0.508	0.174	0.481	0.190	0.499	0.177	0.485	0.191	0.489	0.200	0.484	0.222
Proportion Completed Primary School	0.291	0.242	0.251	0.234	0.224	0.248	0.241	0.234	0.264	0.252	0.194	0.245

Notes: Please see data appendix for details on the construction of variables.

Table A.1c: Summary Statistics by Entrepreneurship History (Expectations and Financial Constraints)

	Household Business, All Years		Switch In, 2005		Switch In, 2009		Switch Out, 2005		Switch Out, 2009		No Household Business, All Years	
Count	177		144		98		114		113		229	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Savings												
Household Has Savings, 2001	0.785	0.412	0.806	0.397	0.796	0.405	0.728	0.447	0.752	0.434	0.590	0.493
Household Has Savings, 2005	0.864	0.343	0.882	0.324	0.745	0.438	0.789	0.409	0.876	0.331	0.677	0.469
Household Has Savings, 2009	0.898	0.303	0.882	0.324	0.878	0.329	0.860	0.349	0.894	0.309	0.769	0.423
Credit Constrained												
Expansion would be profitable, 2001	0.429	0.496	0.111	0.315	0.378	0.487	0.465	0.501	0.310	0.464	0.153	0.361
Expansion would be profitable, 2005	0.254	0.437	0.306	0.462	0.082	0.275	0.088	0.284	0.265	0.444	0.100	0.301
Expansion would be profitable, 2009	0.006	0.075	0.007	0.083	0.000	0.000	0.009	0.094	0.027	0.161	0.000	0.000
Borrowing												
Any Loans, 2001	0.780	0.416	0.799	0.402	0.755	0.432	0.693	0.463	0.770	0.423	0.659	0.475
Any Loans, 2005	0.904	0.295	0.868	0.340	0.827	0.381	0.772	0.421	0.858	0.350	0.760	0.428
Any Loans, 2009	0.881	0.324	0.833	0.374	0.806	0.397	0.719	0.451	0.805	0.398	0.668	0.472

Notes: Please see data appendix for details on the construction of variables.

Table A.2: OLS and FE Estimates of Returns to Entrepreneurship

OLS and FE Estimates of Effects of Entrepreneurship on ln(Gross Earnings)

	OLS			FE		
	Prices & Inputs	Village x Year Dummies (Prices)	No Covariates	Prices & Inputs	Village x Year Dummies (Prices)	No Covariates
Household Business	0.323***	0.730***	0.703***	0.207***	0.344***	0.335***
	(0.0462)	(0.0533)	(0.0527)	(0.0528)	(0.0561)	(0.0539)
ln(Input Expenditure)	0.122***			0.0837***		
	(0.00682)			(0.00930)		
Saving						
ln(Input Expenditure) x Saving						
Observations	2382	2382	2382	2382	2382	2382
R-squared	0.494	0.348	0.103	0.808	0.784	0.714

Notes: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table A.3: Reduced Forms (No Covariates)

3 Period Reduced Form Estimates

CA-CRC			
	ln(gross income), 2001	ln(gross income), 2005	ln(gross income), 2009
Household Business 2001	0.7512355***	0.292082**	0.1536777
	(0.1201872)	(0.1179832)	(0.116516)
Household Business 2005	0.3414445**	0.4957916***	0.2872718**
	(0.1555664)	(0.1631501)	(0.1446528)
Household Business 2009	0.3959503***	-0.0119661	0.412997***
	(0.1156851)	(0.1293239)**	(0.1134258)
Household Business 2001 x 2005	-0.2520913	0.0529046**	0.0125243
	(0.2270075)	(0.2184674)	(0.2121847)
Household Business 2005 x 2009	-0.5825456***	-0.1281288	-0.4018229*
	(0.1975787)	(0.220998)	(0.2118423)
Household Business 2005 x 2009	0.0099898	0.2383108	0.2456194
	(0.2179544)	(0.2033951)	(0.2217376)
Household Business 2001 x 2005 x 2009	0.5029016	0.0560268	0.2864134
	(0.3115253)	(0.3039726)	(0.3185183)
Observations	794	794	794

CRE			
	ln(gross income), 2001	ln(gross income), 2005	ln(gross income), 2009
Household Business 2001	0.80438***	0.455691***	0.3821854***
	(0.070678)	(0.0730799)	(0.0769318)
Household Business 2005	0.0549523	0.4699694***	0.1602469**
	(0.0779932)	(0.0774549)	(0.0794876)
Household Business 2009	0.2539151***	0.0486012	0.4065949***
	(0.075768)	(0.0751018)	(0.0750582)
Observations	794	794	794

Notes: Standard errors in parentheses.

Table A.4: OMD Structural Estimates (No Covariates)

3 Period Minimum Distance Estimates				
	CRE	CA-CRC	CRE with learning	CA-CRC with learning
λ_1	0.4377***	0.3474***	0.4381***	0.2151**
	(0.0636)	(0.0816)	(0.0656)	(0.0873)
λ_2	0.1397**	0.2212**	0.0945	0.3589***
	(0.0653)	(0.0917)	(0.0685)	(0.1084)
λ_3	0.1351**	0.2327***	0.2195***	0.3792***
	(0.0635)	(0.0777)	(0.0738)	(0.1138)
λ_4		-0.2063*		-0.0913
		(0.1115)		(0.1933)
λ_5		-0.2667***		-0.5695***
		(0.0944)		(0.1482)
λ_6		-0.1682		0.2811
		(0.1222)		(0.1853)
λ_7		0.2913**		0.6316*
		(0.1216)		(0.3426)
θ_{12}			0.0257	0.0384
			(0.0813)	(0.124)
θ_{13}			-0.1799**	-0.3732***
			(0.0698)	(0.112)
θ_{23}			-0.172**	-0.365***
			(0.0866)	(0.1269)
β	0.3214***	0.2533**	0.3661***	0.3508***
	(0.0396)	(0.1179)	(0.0582)	(0.076)
ϕ		1.7414		-0.4361***
		(1.5006)		(0.1653)
χ^2	18.264	36.8296	2.8813	10.5018
df	5	12	2	9
observations	794	794	794	794
p-value	0.0026	0.0002	0.2368	0.3114

Notes: Standard errors in parentheses.

Table A.5: OMD Structural Estimates (Village x Time Price Controls)

	3 Period Minimum Distance Estimates			
	CRE	CA-CRC	CRE with learning	CA-CRC with learning
λ_1	0.394***	0.8014**	0.3916**	0.6756**
	(0.1595)	(0.3247)	(0.1629)	(0.2695)
λ_2	0.3517**	1.3912***	0.3574**	1.2873***
	(0.1729)	(0.4641)	(0.1729)	(0.2964)
λ_3	0.3002**	0.9208***	0.3473***	1.0025***
	(0.1273)	(0.2719)	(0.131)	(0.2476)
λ_4		-1.4343***		-1.2883***
		(0.5356)		(0.4402)
λ_5		-1.6357***		-1.5924***
		(0.5111)		(0.3514)
λ_6		-0.7754**		-0.5841
		(0.3901)		(0.3682)
λ_7		1.977***		2.0015***
		(0.5662)		(0.4776)
θ_{12}			0.0659	0.1109
			(0.0865)	(0.1644)
θ_{13}			-0.1126	-0.2425**
			(0.0751)	(0.1096)
θ_{23}			-0.0634	-0.1434
			(0.0899)	(0.1621)
β	0.3503***	0.489***	0.3341***	0.6653***
	(0.0439)	(0.1745)	(0.0681)	(0.1528)
ϕ		-0.1481		-0.4012**
		(0.206)		(0.1838)
χ^2	6.1566	9.2078	3.447	2.7871
df	5	12	2	9
observations	794	794	794	794
p-value	0.2913	0.6851	0.1784	0.9721

Notes: Standard errors in parentheses.

Table A.6: OMD Structural Estimates (Price and Input Controls)

	3 Period Minimum Distance Estimates			
	CRE	CA-CRC	CRE with learning	CA-CRC with learning
λ_1	0.6533**	1.228**	0.1465	0.4713*
	(0.3183)	(0.5284)	(0.1486)	(0.2415)
λ_2	-0.217	0.6752*	-0.0923	0.3408
	(0.1544)	(0.3639)	(0.131)	(0.2662)
λ_3	-0.1712	0.2506	-0.004	0.2058
	(0.1561)	(0.224)	(0.1195)	(0.2095)
λ_4		-1.7015***		-0.9611**
		(0.5833)		(0.4343)
λ_5		-1.4007***		-0.8544**
		(0.4486)		(0.3331)
λ_6		-0.6961		-0.4582
		(0.4291)		(0.3283)
λ_7		2.1388***		1.596***
		(0.6173)		(0.5791)
θ_{12}			-1.4107**	-4.3341*
			(0.6418)	(2.5437)
θ_{13}			-0.0709	-0.2038
			(0.0793)	(0.1241)
θ_{23}			-0.9726*	-3.4065*
			(0.5315)	(1.986)
β	0.4664	0.5428	1.278**	1.3721**
	(0.4882)	(0.4745)	(0.6285)	(0.6202)
ϕ		-0.3388***		-0.6509***
		(0.0927)		(0.1634)
χ^2	378.5737	465.467	6.68	12.1924
df	5	12	2	9
observations	794	794	794	794
p-value	0.0001	0.0001	0.0354	0.2027

Notes: Standard errors in parentheses.

Figure A.1a

Dynamic CRC: Perceived Productivity Gains ($\beta + \phi\ m_{i,t-1}$)

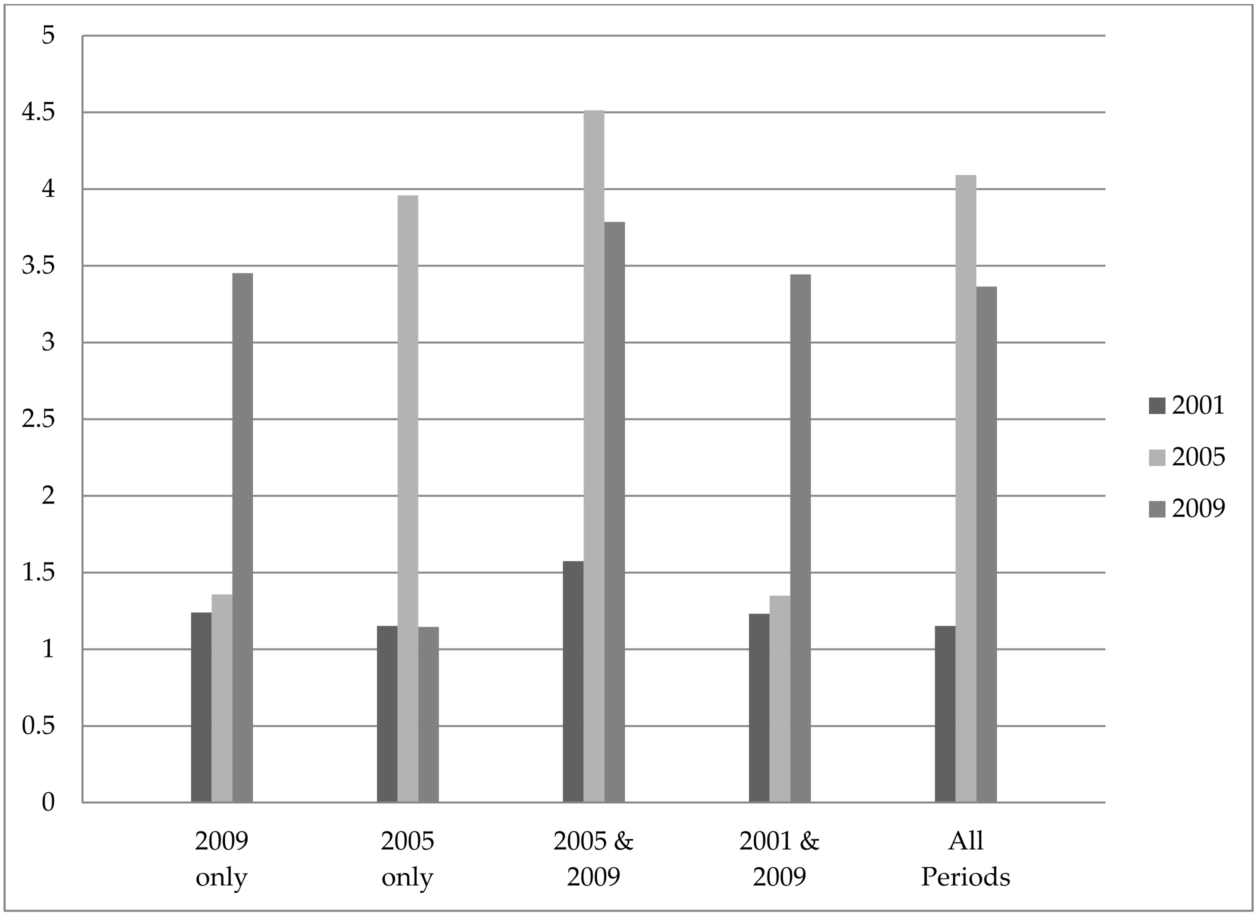

Figure A.1b

Dynamic CRC: Perceived Productivity Gains ($\beta + \phi\, m_{i,t-1}$)

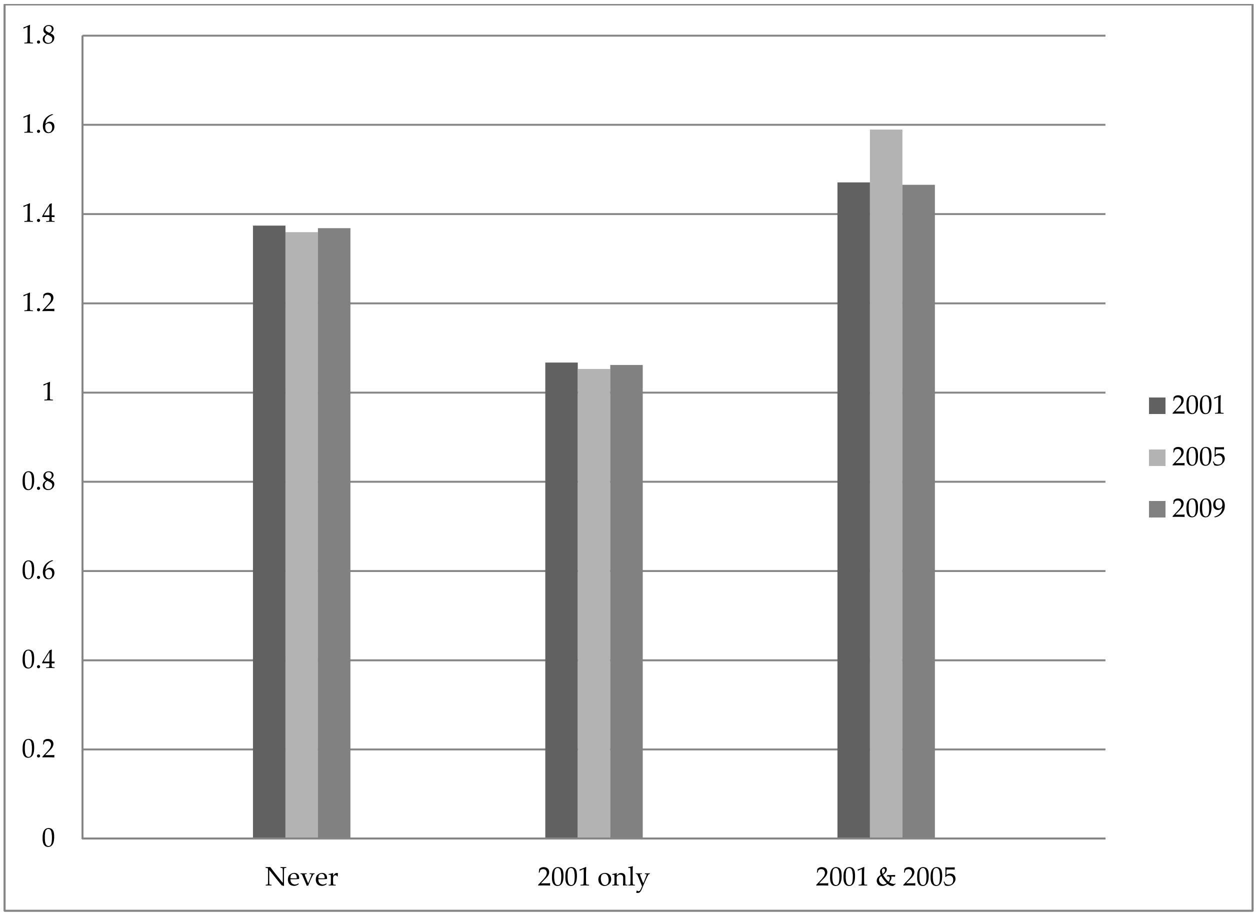

Figure A.2a

Static CRC: Perceived Productivity Gains ($\beta + \phi\ \eta$)

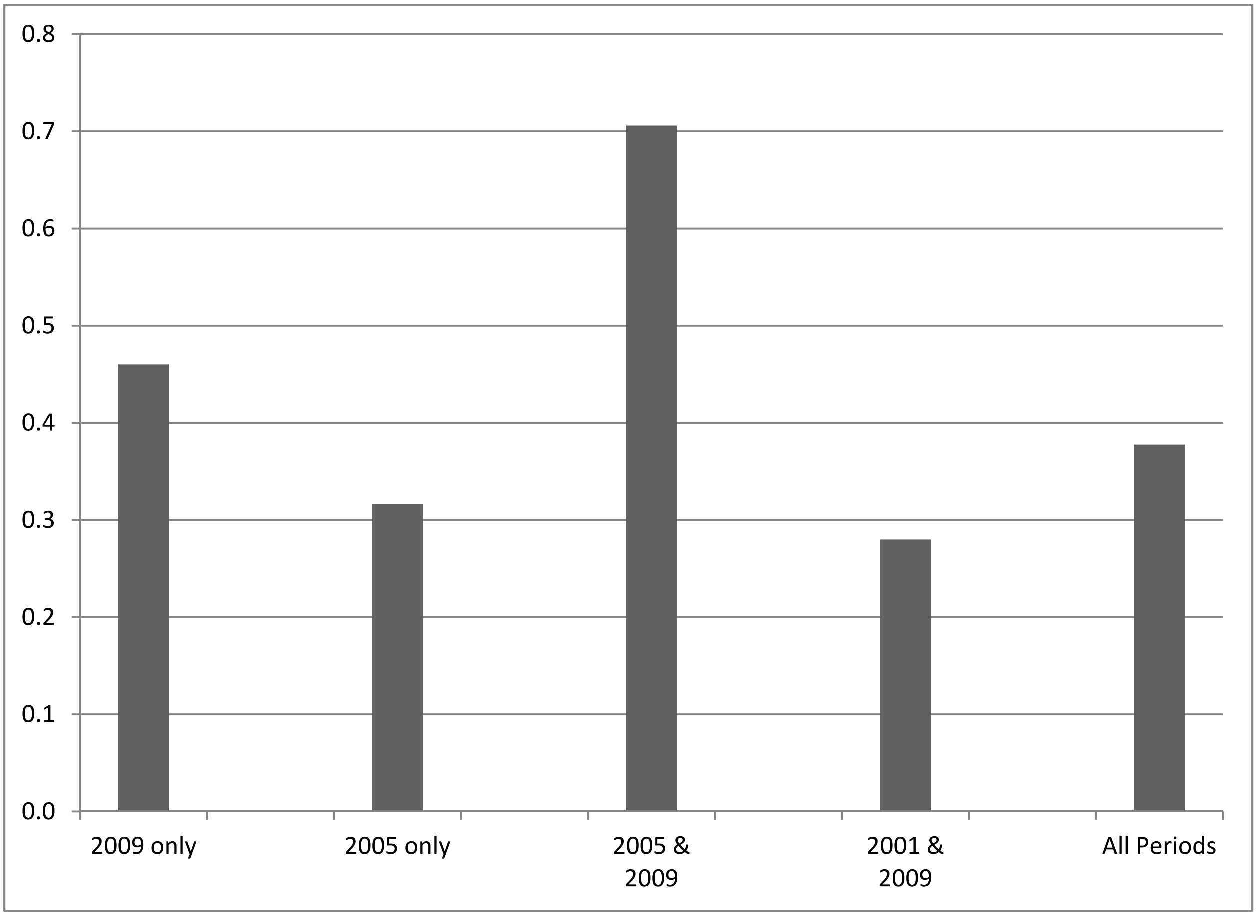

Figure A.2b

Static CRC: Perceived Productivity Gains ($\beta + \phi\ \eta$)