Learning about Comparative Advantage in Entrepreneurship: Evidence from Thailand
SUPPLEMENT

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A Extension to 3 Periods

A.1 Heterogeneous Returns with Imperfect information (DCRC)

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

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

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:

$$m_{i0} = \lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_3 D_{i3} + \lambda_4 D_{i1} D_{i2} + \lambda_5 D_{i2} D_{i3} + \lambda_6 D_{i1} D_{i3} + \lambda_7 D_{i1} D_{i2} D_{i3} + \psi_{i0} \tag{2}$$

$$m_i^1 = \theta_{10} + \theta_{12} D_{i2} + \theta_{13} D_{i3} + \psi_{i1} \tag{3}$$

$$m_i^2 = \theta_{20} + \theta_{23} D_{i3} + \psi_{i2} \tag{4}$$

Plugging projections (2), (3) and (4) into equation (1), and grouping terms, I get the following log gross output equations for each of the three periods (ignoring covariates):

$$\begin{aligned} y_{i1} = {} & \alpha_1 + \lambda_0 + D_{i1}\Big[\beta + (1+\phi)\lambda_1 + \phi\lambda_0\Big] + D_{i2}\Big[\lambda_2\Big] + D_{i3}\Big[\lambda_3\Big] \\ & + D_{i1}D_{i2}\Big[(1+\phi)\lambda_4 + \phi\lambda_2\Big] + D_{i2}D_{i3}\Big[\lambda_5\Big] + D_{i1}D_{i3}\Big[(1+\phi)\lambda_6 + \phi\lambda_3\Big] \\ & + D_{i1}D_{i2}D_{i3}\Big[(1+\phi)\lambda_7 + \phi\lambda_5\Big] + (1+\phi)\psi_{i0} + v_{i1} \end{aligned} \tag{5}$$

$$\begin{aligned} y_{i2} = {} & \alpha_2 + \lambda_0 + \theta_{10} + D_{i1}\Big[\lambda_1\Big] + D_{i2}\Big[\beta + (1+\phi)(\lambda_2 + \theta_{12}) + \phi(\lambda_0 + \theta_{10})\Big] \\ & + D_{i3}\Big[\lambda_3 + \theta_{13}\Big] + D_{i1}D_{i2}\Big[(1+\phi)\lambda_4 + \phi\lambda_1\Big] + D_{i2}D_{i3}\Big[(1+\phi)\lambda_5 + \phi(\lambda_3 + \theta_{13})\Big] \\ & + D_{i1}D_{i3}\Big[\lambda_6\Big] + D_{i1}D_{i2}D_{i3}\Big[(1+\phi)\lambda_7 + \phi\lambda_6\Big] + (1+\phi)\Big[\psi_{i0} + \psi_{i1}\Big] + v_{i2} \end{aligned} \tag{6}$$

$$y_{i3} = \alpha_3 + \lambda_0 + \theta_{20} + D_{i1}\Big[\lambda_1\Big] + D_{i2}\Big[\lambda_2\Big] + D_{i3}\Big[\beta + (1+\phi)(\lambda_3 + \theta_{23}) + \phi(\lambda_0 + \theta_{20})\Big]$$

$$+ D_{i1}D_{i2}\bigg[\lambda_4\bigg] + D_{i2}D_{i3}\bigg[(1+\phi)\lambda_5 + \phi\lambda_2\bigg] + D_{i1}D_{i3}\bigg[(1+\phi)\lambda_6 + \phi\lambda_1\bigg]$$

$$+ D_{i1}D_{i2}D_{i3}\bigg[(1+\phi)\lambda_7 + \phi\lambda_4\bigg] + (1+\phi)\bigg[\psi_{i0} + \psi_{i2}\bigg] + v_{i3}, \tag{7}$$

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:

$$\begin{aligned}
\ln w_{i1} &= \delta_1 + \gamma_1 D_{i1} + \gamma_2 D_{i2} + \gamma_3 D_{i3} + \gamma_4 D_{i1}D_{i2} + \gamma_5 D_{i2}D_{i3} + \gamma_6 D_{i1}D_{i3} + \gamma_7 D_{i1}D_{i2}D_{i3} + \nu_{i1} && (8)\\
\ln w_{i2} &= \delta_2 + \gamma_8 D_{i1} + \gamma_9 D_{i2} + \gamma_{10} D_{i3} + \gamma_{11} D_{i1}D_{i2} + \gamma_{12} D_{i2}D_{i3} + \gamma_{13} D_{i1}D_{i3} + \gamma_{14} D_{i1}D_{i2}D_{i3} + \nu_{i2} && (9)\\
\ln w_{i3} &= \delta_3 + \gamma_{15} D_{i1} + \gamma_{16} D_{i2} + \gamma_{17} D_{i3} + \gamma_{18} D_{i1}D_{i2} + \gamma_{19} D_{i2}D_{i3} + \gamma_{20} D_{i1}D_{i3} + \gamma_{21} D_{i1}D_{i2}D_{i3} + \nu_{i3} && (10)
\end{aligned}$$

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

$$\begin{aligned}
\gamma_1 &= \beta + (1+\phi)\lambda_1 + \phi\lambda_0\\
\gamma_2 &= \lambda_2\\
\gamma_3 &= \lambda_3\\
\gamma_4 &= (1+\phi)\lambda_4 + \phi\lambda_2\\
\gamma_5 &= \lambda_5\\
\gamma_6 &= (1+\phi)\lambda_6 + \phi\lambda_3\\
\gamma_7 &= (1+\phi)\lambda_7 + \phi\lambda_5\\
\gamma_8 &= \lambda_1\\
\gamma_9 &= \beta + (1+\phi)(\lambda_2 + \theta_{12}) + \phi(\lambda_0 + \theta_{10})\\
\gamma_{10} &= \lambda_3 + \theta_{13}\\
\gamma_{11} &= (1+\phi)\lambda_4 + \phi\lambda_1\\
\gamma_{12} &= (1+\phi)\lambda_5 + \phi(\lambda_3 + \theta_{13})\\
\gamma_{13} &= \lambda_6\\
\gamma_{14} &= (1+\phi)\lambda_7 + \phi\lambda_6\\
\gamma_{15} &= \lambda_1\\
\gamma_{16} &= \lambda_2
\end{aligned}$$

$$
\begin{aligned}
\gamma_{17} &= \beta + (1+\phi)(\lambda_3 + \theta_{23}) + \phi(\lambda_0 + \theta_{20}) \\
\gamma_{18} &= \lambda_4 \\
\gamma_{19} &= (1+\phi)\lambda_5 + \phi\lambda_2 \\
\gamma_{20} &= (1+\phi)\lambda_6 + \phi\lambda_1 \\
\gamma_{21} &= (1+\phi)\lambda_7 + \phi\lambda_4 \qquad (11)
\end{aligned}
$$

It appears from (11) 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,

$$
\begin{aligned}
\lambda_0 &= -\lambda_1\overline{D_{i1}} - \lambda_2\overline{D_{i2}} - \lambda_3\overline{D_{i3}} - \lambda_4\overline{D_{i1}D_{i2}} - \lambda_5\overline{D_{i2}D_{i3}} - \lambda_6\overline{D_{i1}D_{i3}} - \lambda_7\overline{D_{i1}D_{i2}D_{i3}} \qquad (12) \\
\theta_{10} &= -\theta_{12}\overline{D_{i2}} - \theta_{13}\overline{D_{i3}} \qquad (13) \\
\theta_{20} &= -\theta_{23}\overline{D_{i3}} \quad , \qquad (14)
\end{aligned}
$$

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:

$$
\begin{aligned}
\lambda_1 &= E[m_{i0}|D_{i1}=1, D_{i2}=0, D_{i3}=0] - E[m_{i0}|D_{i1}=0, D_{i2}=0, D_{i3}=0]; \qquad (15) \\
\lambda_2 &= E[m_{i0}|D_{i1}=0, D_{i2}=1, D_{i3}=0] - E[m_{i0}|D_{i1}=0, D_{i2}=0, D_{i3}=0]; \qquad (16) \\
\lambda_3 &= E[m_{i0}|D_{i1}=0, D_{i2}=0, D_{i3}=1] - E[m_{i0}|D_{i1}=0, D_{i2}=0, D_{i3}=0]; \qquad (17) \\
\lambda_4 &= \Big\{E[m_{i0}|D_{i1}=1, D_{i2}=1, D_{i3}=0] - E[m_{i0}|D_{i1}=1, D_{i2}=0, D_{i3}=0]\Big\}
\end{aligned}
$$

$$
\begin{aligned}
& -\Big\{E[m_{i0}|D_{i1}=0,D_{i2}=1,D_{i3}=0]-E[m_{i0}|D_{i1}=0,D_{i2}=0,D_{i3}=0]\Big\} && (18)\\
\lambda_5 \;=\; & \Big\{E[m_{i0}|D_{i1}=0,D_{i2}=1,D_{i3}=1]-E[m_{i0}|D_{i1}=0,D_{i2}=1,D_{i3}=0]\Big\} \\
& -\Big\{E[m_{i0}|D_{i1}=0,D_{i2}=0,D_{i3}=1]-E[m_{i0}|D_{i1}=0,D_{i2}=0,D_{i3}=0]\Big\} && (19)\\
\lambda_6 \;=\; & \Big\{E[m_{i0}|D_{i1}=1,D_{i2}=0,D_{i3}=1]-E[m_{i0}|D_{i1}=1,D_{i2}=0,D_{i3}=0]\Big\} \\
& -\Big\{E[m_{i0}|D_{i1}=0,D_{i2}=0,D_{i3}=1]-E[m_{i0}|D_{i1}=0,D_{i2}=0,D_{i3}=0]\Big\} && (20)\\
\lambda_7 \;=\; & \Big\{E[m_{i0}|D_{i1}=1,D_{i2}=1,D_{i3}=1]-E[m_{i0}|D_{i1}=1,D_{i2}=1,D_{i3}=0]\Big\} \\
& -\Big\{E[m_{i0}|D_{i1}=1,D_{i2}=0,D_{i3}=1]-E[m_{i0}|D_{i1}=1,D_{i2}=0,D_{i3}=0]\Big\} \\
& -\Big\{E[m_{i0}|D_{i1}=0,D_{i2}=1,D_{i3}=1]-E[m_{i0}|D_{i1}=0,D_{i2}=1,D_{i3}=0]\Big\} \\
& +\Big\{E[m_{i0}|D_{i1}=0,D_{i2}=0,D_{i3}=1]-E[m_{i0}|D_{i1}=0,D_{i2}=0,D_{i3}=0]\Big\} && (21)
\end{aligned}
$$

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

$$
\begin{aligned}
\theta_{12} &= E[m_i^1|D_{i1}=0,D_{i2}=1,D_{i3}=0]-E[m_i^1|D_{i1}=0,D_{i2}=0,D_{i3}=0]\\
&= E[m_i^1|D_{i1}=1,D_{i2}=1,D_{i3}=0]-E[m_i^1|D_{i1}=1,D_{i2}=0,D_{i3}=0]\\
&= E[m_i^1|D_{i1}=0,D_{i2}=1,D_{i3}=1]-E[m_i^1|D_{i1}=0,D_{i2}=0,D_{i3}=1]\\
&= E[m_i^1|D_{i1}=1,D_{i2}=1,D_{i3}=1]-E[m_i^1|D_{i1}=1,D_{i2}=0,D_{i3}=1]; && (22)\\
\theta_{13} &= E[m_i^1|D_{i1}=0,D_{i2}=0,D_{i3}=1]-E[m_i^1|D_{i1}=0,D_{i2}=0,D_{i3}=0]\\
&= E[m_i^1|D_{i1}=0,D_{i2}=1,D_{i3}=1]-E[m_i^1|D_{i1}=0,D_{i2}=1,D_{i3}=0]\\
&= E[m_i^1|D_{i1}=1,D_{i2}=0,D_{i3}=1]-E[m_i^1|D_{i1}=1,D_{i2}=0,D_{i3}=0]\\
&= E[m_i^1|D_{i1}=1,D_{i2}=1,D_{i3}=1]-E[m_i^1|D_{i1}=1,D_{i2}=1,D_{i3}=0]; && (23)\\
\theta_{23} &= E[m_i^2|D_{i1}=0,D_{i2}=0,D_{i3}=1]-E[m_i^2|D_{i1}=0,D_{i2}=0,D_{i3}=0]\\
&= E[m_i^2|D_{i1}=0,D_{i2}=1,D_{i3}=1]-E[m_i^2|D_{i1}=0,D_{i2}=1,D_{i3}=0]\\
&= E[m_i^2|D_{i1}=1,D_{i2}=0,D_{i3}=1]-E[m_i^2|D_{i1}=1,D_{i2}=0,D_{i3}=0]\\
&= E[m_i^2|D_{i1}=1,D_{i2}=1,D_{i3}=1]-E[m_i^2|D_{i1}=1,D_{i2}=1,D_{i3}=0]; && (24)
\end{aligned}
$$

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 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 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[1].

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

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 positive 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 3 of the paper, 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.