Information, Role Models and Perceived Returns to Education: Experimental Evidence from Madagascar*

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Abstract

This paper shows that increasing perceived returns to education strengthens incentives for schooling when agents underestimate the actual returns. I conducted a field experiment in Madagascar to study alternative ways to provide additional information about the returns to education: simply providing statistics versus using a role model—an actual person sharing his/her success story. Some argue that role models may be more effective than providing statistics to a largely illiterate population. However, this proposition depends on how households update their beliefs based on the information the role model brings. Motivated by a model of belief formation, I randomly assigned schools to the role model intervention, the statistics intervention, or a combination of both. I find that providing statistics reduced the large gap between perceived returns and the statistics provided. As a result, it improved average test scores by 0.2 standard deviations. For those whose initial perceived returns were below the statistics, test scores improved by 0.37 standard deviations. Student attendance in statistics schools is also 3.5 percentage points higher than attendance in schools without statistics. Consistent with the theory, seeing a role model of poor background has a larger impact on poor children's test scores than seeing someone of rich background. Combining a role model with statistics leads to smaller treatment effects than statistics alone, also consistent with the theory. The key implication of my results is that households lack information, but are able to process new information and change their decisions in a sophisticated manner.

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1 Introduction

Universal primary enrollment is one of the Millennium Development Goals, and many countries, especially those in Africa, have devoted substantial efforts to attaining this objective. Nonetheless, low schooling persists even though market returns to education appear to be high and direct costs are low.[1] For example, in Madagascar, the estimated returns to one extra year in primary and secondary school are 5% and 12%, respectively. Primary education is free; yet, 40% of children entering first grade actually complete five years of primary school. Only half of those children who complete primary school continue on to secondary school. Even when children are enrolled, low learning, as reflected in the 63% pass rate at the primary-cycle examination, is an important concern (Tan 2005). In addition to low achievements, widespread student absenteeism during the school year suggests low effort on students' part.

While there can be several explanations for low schooling such as credit constraints, high discount rates, or low school quality,[2] I focus on another possibility: an information gap between perceived returns to schooling (what people consider to be the returns) and actual returns. Such a gap can exist due to costly gathering of information in isolated areas of developing countries. My paper documents this information gap in rural Madagascar. Households appear to have imperfect information about earnings associated with different levels of education, even in the presence of heterogenous returns. They will choose low education when they think the return is low (Foster and Rosenzweig (1996) and Bils and Klenow (2000)). Thus, we would expect that increasing perceived returns can strengthen incentives for schooling for those who may have initially underestimated the returns.

Once we know there is imperfect information about the returns to education, the next important step is to examine how to provide useful additional information. One straightforward way is to

[1] Psacharopoulos (1985) and Psacharopoulos (1994) estimate the returns to be high in many developing countries.

[2] For example, Oreopoulos (2003) explores the possible role of high discount rates in the decision of high-school dropouts. See Glewwe and Kremer (2005) for a more complete review.

provide statistics. The downside of this approach is that a largely illiterate population may not effectively process statistical numbers. An alternative way of informing households of the benefits of education is through a "role model," i.e. an actual person sharing his success story. This policy choice has been more popular than presenting numbers (for example, UNICEF has role model programs in various developing countries). Role models can be effective simply because stories are powerful, or because they contain information. Wilson (1987) proposes that role models bring back missing information about the upside distribution of returns to education. The impact of observing a role model will depend on how households update their beliefs based on the information the role model brings. Ray (2004) suggests that role models might be powerful only when they come from a similar background and, therefore, carry information relevant to the audience.[3]

My paper sheds further light on how to provide additional information about the returns to education. I ask the following three questions: (i) Are households' perceived returns to education different from the estimated average return, due to heterogeneity entirely or also imperfect information? (ii) How do households update beliefs when presented with statistics about the average return or with a specific role model? (iii) How do children adjust their efforts in response to the change in perceived returns? To address these questions, I first administered a survey in rural Madagascar to measure parents' perceived returns for their child and perceived returns for the average person in the population.[4] I then conducted a field experiment in 640 primary schools, in conjunction with the Madagascar Ministry of Education. The experimental design was motivated by a model of schooling decisions with heterogeneous returns and uncertainty about the return to education. When an agent is presented with the statistics, he updates his belief about the average

[3]Discussions on role models have featured both in the policy environment and in the academic literature. Most of the evidence to date focuses on a "mentoring" role model; for example, a teacher of the same race has a positive impact on a student's test scores (Dee 2004). My work studies a role model's informational effect, i.e. how people update beliefs based on the information the role model brings.

[4]This survey methodology follows the literature in the US on measuring perceived returns to education. Manski (1992) first brought this topic to attention by proposing that youths infer the returns from their sample of observations. Several papers have surveyed college students in the US for their perceptions of incomes associated with different educational levels: Betts (1996), Dominitz and Manski (1996), Avery and Kane (2004). Most find that American students estimate quite well the mean earnings for a cohort, and think they would earn slightly better than the mean.

return. When presented with a role model, he infers that heterogeneity in the returns to education is high, making the statistical estimate of the average return less relevant. Thus, role models will undermine the impact of the statistics intervention. The agent also infers from the role model's background that individuals from this background receive relatively high returns to education on average.

To test the theory's key predictions, I randomly assigned schools into three main treatment groups. In the "statistics" schools, teachers reported to parents and children the average earnings at each level of education, as well as the implied gain. The second intervention sent a role model to share with students and families his/her family background, educational experience, and current achievements. To investigate the proposition that a role model from the same background carries relevant information, I randomly assigned a role model of poor or rich background to different schools. The third treatment combines both the statistics and role model interventions together, investigating the possibility that role models may undermine statistics. I collected endline data on perceived returns, student attendance, and test scores to evaluate the impact of the interventions on beliefs and on effort at school roughly five months later.

I find that parents' median perceived return matches the average return estimated from household survey data. Nonetheless, there is a lot of dispersion in both perception of the average return and perception of the child's own return. There are two possible explanations for dispersion in perception of the child's own return: heterogeneity in the actual returns and imperfect information. I argue that while heterogeneity plays a role, some extent of imperfect information exists, as reflected in the larger dispersion in perception than in the real distribution of earnings.

The main results of the experiment match the model's predictions. Participants who received the statistics intervention updated their perceived returns. Providing statistics significantly decreases the gap between perceived returns and the estimated average return provided. This result holds for both perception of the average return and perception of one's own return. It suggests that part of the dispersion in perceived returns comes from imperfect information. Once households update their perceived returns, schooling decisions consequently respond. The statistics intervention improved average test scores by 0.2 standard deviations, only a few months later. For those whose initial perceived returns were below the statistics, test scores improved by 0.37 standard deviations. Student attendance in statistics schools is also 3.5 percentage points higher than attendance in schools without statistics.

The role model interventions offer very interesting results. By themselves, role models have small effects on average, but people seem to care about the information the role model brings. In particular, consistent with the theory, the role model's background matters. The role model from a poor background improved average test scores by 0.17 standard deviations, while the role model from a rich background had no impact. Moreover, this positive impact of poor-background role models on average test scores mainly reflects their influence on the poor (0.27 standard deviations). Again as the theory predicts, combining a role model with statistics undoes the effects of statistics. The role model may indicate high underlying heterogeneity in individual returns, implying that the statistics were imprecisely estimated. Thus, households do not update as much based on the statistics as they would otherwise.

These results have strong implications. First, households update their perception in a sophisticated way based on the information provided. Second, schooling investment seems responsive to changes in perceived returns. Third, in terms of policies to improve education in developing countries, providing statistical information can be a cost-effective instrument to enhance children's efforts at school, in contexts where individuals underestimate the returns. A quick back-of-the-envelope calculation using my results shows that the statistics intervention would cost 2.30 USD for an additional year of schooling and 0.04 USD for additional 0.10 standard deviations in test scores (cheaper than any prior programs evaluated with a randomized design). Lastly, when households do have correct perception of the returns on average, the results from this paper suggest that market interventions to improve the overall returns are an important way to increase school attendance and test scores.

Some existing evidence already shows that the provision of information may affect individual behaviors, such as Dupas (2006). In particular, Jensen (2007) demonstrates from a field experiment in the Dominican Republic that providing students with mean earnings by education led to a 4 percentage point increase in the probability of returning to school the following year. My work builds on this result along two fronts. First, I test whether statistics given to the parents affects the intensive margin of schooling–student attendance and test scores. Second, in terms of the research question, I study whether role models are effective in changing behaviors, either through their success story or through the relevance of their information. Addressing this research question would provide more depth to our understanding of how people update their belief.

The rest of this paper is organized as follows. Section 2 discusses a model of schooling decisions under Bayesian updating of perceived returns. In Section 3, I describe the field experiment: the statistics and role model programs, as well as the evaluation design. Section 4 discusses the data. Section 5 gives an overview of perceived returns to education at baseline, and then presents the estimation strategy and results. The final section concludes.

2 A Model of Schooling with Uncertainty about the Return to Education

To assess the conditions under which the statistics and role model programs may plausibly affect decisions, this paper integrates a simple framework of schooling with Bayesian updating about the return to education. This theory builds on the standard Card (1999) model of school choice with heterogeneity in individual returns to education. Here I formalize the possibility that agents measure their own return as well as the average return with errors. As a result, I explore two features of learning.

First, this section models learning about the average return to education. I show that agents update their estimate after observing the government's statistic on the average return. How much they update depends on their belief about the precision of the government's estimate. When there is high heterogeneity in individual returns in the population, the government's estimate of the average return is less precise. In that case, agents should put less weight on this statistic.

Second, an agent also learns about the relationship between his type and his return to education, above and beyond the population's average return. He infers this information from observing the government's choice of role model programs. School investment decisions are then made based on the posterior belief about the return to education.

2.1 Model Setup

Consider individual schooling choice under heterogeneous returns to education. An individual i has the following preferences[5]

$$EU = E_i \ln y_i(e_i) - c_i(e_i) \tag{1}$$

where log earnings is a linear function of education $\ln y_i(e_i) = a_i + b_i e_i$ and $c_i(e_i)$ denotes an increasing and convex cost function of education. In the standard model of investment in human capital, e_i represents years of schooling. Here I examine effort behaviors of children already enrolled in school. I refer to e_i as child effort in schooling, but the general intuition from the standard model remains. The optimal choice of effort solves the first-order condition

$$E_i[b_i] = c_i'(e_i) \tag{2}$$

Given that marginal cost is increasing in e_i, the optimal choice of effort will increase if the individual expects higher returns.

The individual's true return to education is determined by the actual average return in the

[5] I abstract from risk aversion here. Modeling log earnings as concave in the return to education b_i does not change the nature of updating perception.

population and by some heterogeneity factors (observable and unobservable characteristics)

$$b_i = \overline{b} + X_i\gamma + \varepsilon_i \tag{3}$$

where $\overline{b}$ denotes the actual average return in the population; for example, when the whole economy is doing better, everyone has higher returns. X_i is some observable characteristic that affects one's own return, such as parental wealth (rich or poor background). The last term ε_i captures any heterogeneity unobserved to others and only known by the individual, such as ability. Let ε_i be normally distributed $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$.

Uncertainty about one's own return comes from two sources: imperfect knowledge of the average return ($\overline{b}$) and that of the relationship between his characteristics and his own return (γ). First, assume as in the Bayesian approach that the individual's belief can be described as a prior distribution on the actual average return $\overline{b} \sim N(\overline{b_0}, \sigma_0^2)$. His perceived average return is $E_i[\overline{b}] \equiv \overline{b_0} = \overline{b} + \xi_i$. Second, he does not perfectly observe γ either: $E_i[\gamma] = \gamma + \eta_i$. What determines the effort decision is the individual's expected return

$$\underbrace{E_i[b_i]}_{Perceived\ Self} = \underbrace{E_i[\overline{b}]}_{Perceived\ Average} + E_i[X_i\gamma] + \varepsilon_i \tag{4}$$

$$= \underbrace{(\overline{b} + X_i\gamma + \varepsilon_i)}_{Actual\ return\ for\ Self} + \underbrace{(\xi_i + X_i\eta_i)}_{Errors} \tag{5}$$

With this framework in mind, the next subsection models how individuals update their perceived return after the statistics and role model interventions.

2.2 Updating Based on Statistics

Suppose the government receives a noisy signal about the average return $b_G = \overline{b} + \xi_G$. The government's noise is normally distributed $\xi_G \sim N(0, \sigma_G^2)$, i.e. the precision of its signal is $1/\sigma_G^2$. The government provides this statistic b_G to all agents. As the individual sees the government statistic about the average return, he will update his estimate of the average return toward that number. Bayesian updating leads to a normal posterior distribution (DeGroot 1970), with the following mean and variance

$$E_i[\bar{b}|b_G] = \frac{\sigma_G^2}{\sigma_0^2 + \sigma_G^2}\overline{b_0} + \frac{\sigma_0^2}{\sigma_0^2 + \sigma_G^2} b_G \tag{6}$$

$$Var_i[\bar{b}|b_G] = \frac{\sigma_0^2 \sigma_G^2}{\sigma_0^2 + \sigma_G^2} \tag{7}$$

The individual's posterior perceived average return is a weighted average of his prior and the government statistic. The weight depends on the precision of the government's signal: if σ_G^2 is small, the posterior becomes very close to the statistic. To elaborate, suppose the government's signal b_G comes from random sampling of n observations in the population. The variance of its estimate is $\sigma_G^2 = \frac{s^2}{n}$, where s^2 is an estimate of the population variance. That is, the government's signal is less precise when there is high underlying heterogeneity in the population. I will return to this point later when I discuss heterogeneity in more detail.

According to expression 4, agents will also update their own expected return toward the statistic. For people who had initially underestimated the average return ($\overline{b_0} < b_G$), their perceived return increases, resulting in higher effort e. However, one's relative position to the average $E_i[X_i\gamma] + \varepsilon_i$ is still unchanged.

2.3 Updating Based on Role Models

The next step is to examine how individuals update their belief after seeing a role model. The role model is simply one observation from the distribution and should not affect beliefs unless this person carries a signal about the return to education. I need to model explicitly what an individual thinks the role model is supposed to signal and why the government chooses to send information in this way. A useful framework in which role models might plausibly affect behaviors is a game between the government and an individual. I formalize individuals' beliefs about the programs and their behaviors in a Perfect Bayesian equilibrium. Recall that each agent is uncertain about the relationship between his characteristics and his own return (γ). Here a welfare-maximizing government receives a signal about this relationship. Through its role model programs, it conveys the information to people.

First, let me specify the observable characteristic X_i to be the individual's type. Suppose there is a continuum of agents of measure 1. There are 2 types H and L (born rich and poor). One's type is unknown to other individuals but observable to the government. Perceived return in expression 4 can now be written as

$$E_i[b_i] = E_i[\overline{b}] + \ E(\gamma_H) * H + E(\gamma_L) * L + \varepsilon_i \tag{8}$$

where H and L are dummies for each corresponding type. Without loss of generality, I look at an L-type individual throughout the rest of the model. He does not observe γ_L perfectly.

There are 3 states of nature with varying individual return. The "low heterogeneity" state occurs with probability $1-q$, in which case returns to education do not depend on one's type, i.e. $\gamma_H = \gamma_L = 0$. I call this state "low heterogeneity" since heterogeneity in individual returns in the population comes solely from unobservable (σ_ε^2) rather than from both observable and unobservable characteristics. Alternatively, when there is high heterogeneity (with probability q), this heterogeneity favors one type. In the good state ("good" from the L-type's point of view), being of type L affects the return positively $\gamma_L = \gamma_2 > 0$ while being of type H affects the return negatively $\gamma_H = \gamma_1 < 0$. Symmetrically, in the bad state, $\gamma_L = \gamma_1 < 0$ and $\gamma_H = \gamma_2 > 0$. There is uncertainty about the state. The probability of high heterogeneity is q , and the probability of the good state given high heterogeneity μ_0.

Definition 1 *After the payoff is realized, anyone with income above a threshold $\overline{y}$ is considered to be successful ("role model").*

Consider a static game between 2 players: a welfare-maximizing government and a low-type individual. The timing is as follows. Nature first decides on low or high heterogeneity. Under high heterogeneity, nature decides which type has the higher return (good or bad state for the L-type). The government knows exactly which state it is. The government decides whether to send a role model–example of success, and which type to send. The individual sees the government's action and infers information about the state. He then updates beliefs about the return using Bayes' rule, and chooses the optimal level of effort. The extensive form of the game is displayed in Appendix Figure 1.

2.3.1 Individual's Problem

Given the prior beliefs, a low-type individual's expected rate of return is

$$E_i[b_i] = E_i[\overline{b}] + q\mu_0\gamma_2 + q(1-\mu_0)\gamma_1 + \varepsilon_i \tag{9}$$

His choice of e solves

$$e_0 = \arg\max\{[E_i[\overline{b}] + q\mu_0\gamma_2 + q(1-\mu_0)\gamma_1 + \varepsilon_i]e - c_i(e)\} \tag{10}$$

The efficient choices of education for the low-type are as follows.

In the low heterogeneity state:

$$e^*_{lowhet} = \arg\max\{[E_i[\overline{b}] + \varepsilon_i]e - c_i(e)\} \tag{11}$$

In the good state:

$$e^*_{good} = \arg\max\{[E_i[\overline{b}] + \gamma_2 + \varepsilon_i]e - c_i(e)\} \tag{12}$$

In the bad state:

$$e^*_{bad} = \arg\max\{[E_i[\overline{b}] + \gamma_1 + \varepsilon_i]e - c_i(e)\} \tag{13}$$

2.3.2 Government

The welfare-maximizing government receives a fully informative signal of what the state is. It wants to choose an action to signal to the low-type agent about the state so that he can make the efficient choice of effort. The government wants the individual's choice to be as close as possible to the efficient choice. Consider the government's set of possible strategies $g \in \{Nobody, L, H\}$, which represents sending nobody, sending a low-type role model, or sending a high-type role model.

Given a signal status $s \in \{Lowhet, Good, Bad\}$, the government's objective function is

$$\min_{g(s)} |e(g) - e^*(s)| \tag{14}$$

where $e(g)$ is the response function of the low-type after observing the government's action g. $e^*(s)$ is the efficient effort level under each of the government's information sets

$$e^*(Lowhet) \equiv e^*_{lowhet} = \arg\max\{[E_i[\bar{b}] + \varepsilon_i]e - c_i(e)\} \tag{15}$$

$$e^*(Good) \equiv e^*_{good} = \arg\max\{[E_i[\bar{b}] + \gamma_2 + \varepsilon_i]e - c_i(e)\} \tag{16}$$

$$e^*(Bad) \equiv e^*_{bad} = \arg\max\{[E_i[\bar{b}] + \gamma_1 + \varepsilon_i]e - c_i(e)\} \tag{17}$$

2.3.3 Equilibrium Concept (Benchmark Model)

Proposition 2 *The following strategies and beliefs constitute a (pure-strategy) Perfect Bayesian equilibrium.*

Government's strategy g(s): $g(Lowhet) = Nobody, g(Good) = L, g(Bad) = H$

Low-type individual's strategy e(g): $e(Nobody) = e^*_{lowhet}, e(L) = e^*_{good}, e(H) = e^*_{bad}$

Individual beliefs at his decision node:

$probability[Lowhet|g = Nobody] = 1$

$probability[Good|g = L] = 1$

$probability[Bad|g = H] = 1$

Proof. We need to show that each strategy is the best response given the other party's strategy, and the beliefs are consistent with Bayes' rule.

At the final decision node, the low-type individual updates his belief on the state after observing the government's move. Given the government's strategy, seeing $g = Nobody$ means that the government signals the low heterogeneity state. Given the government's equilibrium strategy, the individual's posterior belief is $probability[Lowhet|g = Nobody] = 1$. The solution to his maximization problem is e^*_{lowhet} (see expression 11). Seeing $g = L$ implies that the state is good, so the individual updates

$$
\begin{aligned}
prob[good|g &= L] && (18)\\
&= \frac{p[L|good] * q\mu_0}{p[L|good]q\mu_0 + p[L|bad]q(1-\mu_0) + p[L|lowhet](1-q)} && (19)\\
&= \frac{1 * q\mu_0}{1 * q\mu_0 + 0 * q(1-\mu_0) + 0 * (1-q)} && (20)\\
&= 1 && (21)
\end{aligned}
$$

This is good news (also better news than seeing nobody) since he now thinks his return is $E_i[\bar{b}] + \gamma_2 + \varepsilon_i$, and the solution to his maximization problem is e^*_{good}. By similar logic, a high-type role model is bad news to the low-type individual, and leads to e^*_{bad}.

Given the individual's strategy, the government solves its minimization problem as in expression 14. It would not deviate from the equilibrium strategy since that would cause the individual to deviate from the efficient choice of effort. ■

2.4 Statistics and Role Models

This subsection summarizes the predictions of updating based on statistics and on role models from the previous two subsections, taking into consideration the effect of the combined interventions. Now in equilibrium, sending role models implies high underlying heterogeneity in the population.

Recall that the government's statistic b_G is less precise under high heterogeneity. As a consequence, the individual puts less weight on the government's statistic when the government also sends a role model.

The equilibrium strategies in the previous benchmark model can be extended to the following.

Government's strategy:

1. No signal about the average return, low heterogeneity state: do nothing
2. Noisy signal about the average return, low heterogeneity state: provide statistics alone
3. No signal about the average return, high heterogeneity state: send low-type role model if good state, send high-type role model if bad state
4. Noisy signal about the average return, high heterogeneity state: provide statistics, and a role model as in strategy 3.

Low-type individual's strategy:

1. Government does nothing: infer that it is the low heterogeneity state and choose effort accordingly
2. Statistics alone: update perceived returns $E_i[\bar{b}]$ and $E_i[b_i]$, infer that it is the low heterogeneity state, and change effort
3. Low-type role model: infer that it is the good state and increase effort
4. High-type role model: infer that it is the bad state and decrease effort
5. Statistics and low-type role model: update perceived returns, infer that it is the good state but put less weight on the statistics, and change effort
6. Statistics and high-type role model: update perceived returns, infer that it is the bad state and put less weight on the statistics, and change effort

These strategies give us a set of predictions for individual behaviors under the government's statistics and role model programs explored empirically in this paper.

2.5 Discussion

There are three important numbers here that will be relevant throughout the rest of the paper. The government has a signal b_G about the actual average return $\bar{b}$, and this is the statistic it provides. People initially do not know $\bar{b}$ and have a perceived return for the average $E_i[\bar{b}] \equiv \overline{b_0} = \bar{b} + \xi_i$. Each individual also has expected return for his own type, i.e. a perceived return to education for himself as in expression 4.

When mapped to the empirical setting, this model carries three main insights. First, it predicts that everyone updates toward the statistic about the average return. In particular, this statistic has the same effect for two individuals of different types who start with the same prior about the average return. Second, seeing a role model of the same type (initial background) is good news since this role model reveals to the agent that the heterogeneity is favorable to him. Meanwhile, seeing a role model from a different type is bad news. Third, combining statistics with a role model may signal high heterogeneity in the returns and undermine the impact of statistics.

The sections that follow will explore how people behave empirically when they receive the statistics and role model programs from the government.

3 Study Design

Imperfect knowledge of the return, as described in section 2's framework, is arguably common in many areas in developing countries. Most of rural Madagascar lies in secluded areas with limited access to outside information, and information on earnings is not covered by the media (radio). According to a pilot study by the Ministry of Education and UNICEF in November 2006, many local parents have difficulties estimating the income associated with various educational attainments.

From my survey data, 73% of the respondents report that it is difficult to learn about their peers and neighbors' income; 53% say there are frequent incidences of educated people out-migrating from the village. These observations suggest that rural households might have considerable uncertainty about the returns to education.

3.1 Description of the intervention

To learn about behavioral responses to role models and to returns to education statistics, I designed a field experiment to be carried out by the Ministry of Education (MENRS), with support from the French Development Agency (AFD), UNICEF, and the World Bank. This experiment was implemented as a government program, and households presumably responded in this context. The government programs evaluated here were launched at mid-school year, in February 2007 (the academic calendar in Madagascar runs from September to June).

One important feature of the design was that all participating schools organized a parent-teacher meeting. In the comparison group, parents and teachers discussed during this meeting any typical topics of the school.[6] In the other program schools, in addition to these discussions, Grade 4 students and their parents received either the "statistics" intervention, the "role model" intervention, or both during this meeting.

First, the "statistics" intervention sought to inform parents of the average returns to education, calculated from the nationwide population. In this treatment, school teachers first presented a few simple statistics based on the 2005 Madagascar Household Survey (Enquête auprès des Ménages) to all Grade 4 students and their parents at a school meeting. For each education level, the audience learned about the distribution of jobs by education, and the mean earnings of 25 year-old Malagasy females and males by levels of education. Then the teacher explained the magnitude of increased

[6]This placebo treatment allows me to avoid confounding the effects of meetings mandated by the government with the effects of statistics or role models. For example, I control for the potential impact coming from teachers suddenly becoming concerned that the government is paying attention to them, or any motivation to parents from being involved in the school.

income associated with higher educational levels, therefore implying percentage gains or returns to education. Discussion on these statistics lasted about 20 minutes. Parents also received a half-page information card featuring mean earnings by gender and by education, and a visual demonstration of the percentage gain (see sample card in the Appendix Figure 2). I refer to these statistics as the estimated average returns to education (b_G in the model). The numbers reported to families are predicted values from a Mincerian regression of log wage on education levels, age, age squared, and gender. These estimates are robust to adding region of birth fixed effects, but they may be biased due to potential endogeneity problems. Within the experiment, people should still respond to the new information provided that these estimates differ from their prior perception.

Second, the role model program mobilized three types of local role models to share their life story at treated schools. In this context, a "role model" is an educated individual with high income, who grew up in the local school district.[7] Motivated by the theoretical proposition that role models from different backgrounds carry different information, I randomly assigned a role model of poor or rich background to different schools. In practice, it was important to also have a role model of moderate income, possibly the relevant level of success for certain areas. The exact types are defined as follows:

- Role Model type LM (low to medium): a role model of *low-income background* similar to many students in the audience (the father and mother were farmers, the role model went to the village school, for example) who is now *moderately successful* (generating high productivity on farm, or owning a profitable shop)

- Role Model type LH (low to high): a role model of *low-income background* similar to many students in the audience, who is now *very successful* (government official or manager of a big enterprise, earning high income).

[7] Existing definitions of role models vary. A broader definition of a role model refers to any example of success that can inspire others to emulate him (Bala and Sorger 1998, Anderson and Ramsey 1990, Haveman and Wolfe 1995).

- Role Model type HH (high to high): a role model of *high-income background* (father works for government, mother is a school teacher, the role model went to a private preparatory school, for example) who is now *very successful.*

Through a local committee consisting of the school district head, a local NGO leader, and community leaders, MENRS identified and recruited 72 role models of different types between December 2006 and January 2007. This recruitment made no explicit distinction in terms of gender (and it turned out there were 15 female role models). UNICEF Communication Sector provided two days of training on communication skills to the chosen role models so that they could reflect on their personal experiences, write an abbreviated script and practice an oral presentation. This training only guided the stories to cover at least three bases of information: background, educational experiences, and current job and standard of living. These role models then visited selected schools (one visit per school) and shared their life stories with all 4th-graders and their parents at a school meeting. After the role model's speech (about 20 minutes), the meeting proceeded to questions and answers, and open discussions. According to field reports, the topics of discussions were mostly to clarify the role model's story, but the parents also expressed their doubts. They sometimes cited examples of teenagers in their village with a high school degree but without a permanent job. Most frequently, they justified the difficulties of sending children to schools during periods of food shortages.

Finally, in the combined treatment schools, both of the above interventions took place at the same school meeting. The school teacher first explained returns to education statistics, followed by the role model's exposition.[8] The school meetings were well-attended throughout my study sample.

[8] Discussion on the statistics took place first to help mitigate the possibility that it might be overshadowed by the role models.

3.2 Sample and evaluation design

The study sample consists of 640 public primary schools in 16 districts throughout rural Madagascar (see the map in Figure 1). To arrive at this study sample, I had excluded from the Ministry's roster a few schools that are too far away and extremely difficult to access. These 640 schools were divided into 8 groups of 80 each, to receive different combinations of the aforementioned "statistics" intervention, role model interventions and their combinations. Treatment assignment into the 8 groups was random, stratified by students' baseline test score and AGEMAD treatment status. AGEMAD is an on-going experiment aimed at improving management in the educational system, which also covered all the schools in my sample (Nguyen and Lassibille 2007).[9]

Table 1 describes the precise treatment design and distribution of program components. There are 8 treatment groups (TG0 to TG7). The columns represent the "role model" interventions by type (TG2, TG3, and TG4 received a role model only). The second row represents the "statistics" intervention (TG1 received statistics only). I define "Any Statistics" as the second-row groups of 320 schools, and "Any RM" as the 480 schools in the last three columns. TG5, TG6, and TG7 refer to the combined treatment schools, who received both the statistics and role model treatments. In all program schools, Grade 4 (aged 9-15) is the only treatment cohort. Other cohorts may have been indirectly affected since, for example, parents often have more than one child in the same primary school.

As mentioned earlier, the comparison group (TG0) still received the placebo meeting, but neither the statistics nor the role model interventions. Aside from the design table, 69 other schools were randomly chosen to be "pure control". Those schools did not come into contact with any announcement of the program, nor any baseline survey administered, nor any school meeting organized by the program. I will compare test scores in those schools (the only data available

[9] The AGEMAD packaged intervention provides (i) operational tools and training to administrators and teachers, (ii) report cards and accountability meetings with a purpose to improve the alignment of incentives. This cross-cutting design does not a priori restrict external validity since I do not expect any interactions between AGEMAD and the treatments explored in this paper. Indeed, when I test for this interaction, the treatment effects of statistics and role models on test scores do not vary significantly with AGEMAD status.

for this group) to those of the regular comparison group to detect any potential effect of simply participating in the experiment: answering survey questions and attending a meeting.

This evaluation design allows me to address the main questions in this paper concerning how individuals respond to information about the returns to education. First, TG1 versus TG0 tells us to what extent providing pure statistical information changes one's perceived returns and schooling decisions. Second, I can measure whether role models are overall effective in changing behaviors, or only someone of the same type has a positive impact on effort. Third, the combined treatment schools help us understand what happens to the impact of statistics when extra information such as a role model is also presented.

4 Data and Experimental Validity

4.1 Data

4.1.1 Background Data

Background information on the schools is available from administrative data collected by the Ministry of Education. In addition, I collected some information on household characteristics in a parent survey in all the schools of my sample. Table 2 presents descriptive statistics at baseline for the sample of schools and households in this study. The average primary school has around 215 students in total enrollment for Grades 1-5, and 30 students in Grade 4. From the baseline test scores, the average student can reach 60% of the competency level they are expected to master. Their families are mostly poor, but I will refer to the top half of income as the relative "rich" in this sample. Less than half of the parents finished primary school, despite their high level of self-reported literacy.

4.1.2 Perception of Returns to Education

Evaluation of the statistics and role model interventions rests on three main data sources collected during the experiment: parent surveys, school attendance data, and Grade 4 students' test scores. The first one is subjective data on beliefs, while the latter two give objective measures of schooling. All data, except attendance, were collected for my entire sample at baseline (mid-school year) and ex-post (at the end of the school year). The actual sample turned out to be slightly fewer than 640 schools since some did not have Grade 4 during the study period.

I designed a parent survey to measure the first outcome of interest–perceived returns to education. This data allows us to gain a better understanding of the potential information gap at the household. At the beginning and the end of this project, surveyors visited the homes of Grade 4 students and interviewed either parent of the child (55% of the respondents were mothers). My survey approach follows Jensen (2007) and previous literature to elicit each individual's perceptions of the returns to education, both for the average and for oneself. We want to measure these two numbers since dispersion in perceived returns for oneself reflects both heterogeneity in the actual returns and possible misperception. Dispersion in perceived average returns, on the other hand, would reflect misperception (unless parents do not fully understand the survey question).

The exact survey question on perceived average earnings is as follows:

> "Please estimate the average monthly earnings of current 25 year-old Malagasies without a primary school degree"

The same question repeats for other scenarios of educational attainment. There are four scenarios in total: no primary education, only primary education, only lower-secondary education, and only high school education. Respondents also gave an estimate of their own child's (the Grade 4 student) income in hypothetical cases of various educational attainments, in response to two consecutive questions:

> "Suppose, hypothetically, that your child were to leave primary school without obtaining the CEPE [primary school degree] and not complete any more schooling. What types of work do you think he/she might (be offered and) choose to engage in when he/she is 25 years old?"
>
> "How much do you think he/she will earn in a typical month at the age of 25?"

The answer to the first question is perceived job type by education. The answer to the second question is perceived earnings by education. From respondents' perceived earnings by education, I calculate the corresponding proportional gain in earnings due to education. I call this proportional gain "perceived returns to education." For each child, there are three levels of perceived returns: additional gain from primary education, lower-secondary education, and high school. For example, the perceived return to lower-secondary school is defined as

$$\frac{Perceived\ Earnings(Secondary) - Perceived\ Earnings(Primary)}{Perceived\ Earnings(Primary)}$$

In this paper, I refer to respondents' estimates of the average returns as "perceived returns for average," and those of the child as "perceived returns for self." I measure for each individual at baseline his perceived returns for self and for average. Endline perceived returns to education is individual-level data, and is name-matched to the baseline perceived returns at 75% match rate.

4.1.3 Schooling Outcomes

Attendance rate is measured by the ratio of students present to total enrollment, at the school-grade level. This attendance data was collected by surveyors during unannounced school visits (one visit per school). It is available for only a random subset of schools in the study sample. This variable indicates whether the role model and statistics interventions entice students to exert more effort to attend school.

Lastly, I examine students' achievement through individual test scores. The baseline and post-tests measure children's competency in three materials: mathematics, French, and Malagasy. The baseline test took place in February 2006, and the post-test was administered to the same children (in Grade 4) in June 2007, as part of the AGEMAD project. Due to administrative constraints, only a random sub-sample of 25 students maximum per school took the test. These tests were developed from existing PASEC exams.[10] They cover basic calculations and grammar questions in French and Malagasy, at the level that the students are supposed to master at this stage. These tests are achievement rather than ability tests, so performance can be improved by increasing effort. Test scores are calculated as the percentage of correct answers. Throughout the paper, I report test scores normalized by the control group mean and standard deviation for easier comparisons across different scales. Test score data is name-matched to the baseline perceived returns at 50% match rate.

4.2 Experimental Validity

First, as expected given the randomized design, Table 3 shows that baseline test scores, school size, and repetition rate are statistically indistinguishable across the treatment groups and the comparison group. Columns 4 to 6 reassure that pre-existing differences in household data are mostly insignificant as well, with low point estimates. Only baseline perceived returns for average seem to be different in the statistics and role model LM and LH groups.

Second, to minimize the potential bias caused by differential attrition, I tried to measure outcome variables for all the original participants of the program. Both the baseline and endline surveys were administered at the homes of the students just a few months apart. Any attrition is likely to be due to practical constraints of conducting the survey, such as unfavorable weather, rather than endogenous reasons related to the treatments themselves.

Column 1 of Table 4 presents mean attrition rates from the parent survey in all the treatment

[10] PASEC (Programme d'Analyse des Systèmes Educatifs de la CONFEMEN) is a program in 15 francophone countries that studies elements of learning for students.

groups. While the statistics treatment schools have quite high attrition, the differences in mean attrition are not statistically significant. Columns 2 to 6 examine whether the differences in baseline characteristics of schools with high and low attrition vary across treatment groups. These columns report coefficient estimates from regressing each baseline characteristic on attrition rate interacted with treatment group dummies. Only parental education appears different for schools of different attrition rates across some treatment groups.

The post-test was administered to as many of the baseline children as possible. The school director had asked children who no longer attended school to come at the day of the test; and test administrators tried to find the absent students at home. As shown in column 7 of Table 4, attrition rate in test score data is around 0.12 and similar across treatment groups. Column 8 shows that pretest score differences between attriters and stayers are also similar across treatment groups, implying that attrition is not likely to be selected in terms of the pretest.

Due to time and budget constraints, attendance data is available for only a random sub-sample of 176 schools. While the small sample size prevents very precise estimation, there should not be any attrition bias since this sub-sample was randomly chosen.

5 Estimation Strategy and Results

The objective of this paper is first to understand better the distribution of initial perceived returns to education, and how perceived returns for self and for average compare to the estimated average return. Then, I want to examine the effects of statistics and different kinds of role models on perceived returns to education and schooling outcomes. I present the findings below in that order.

5.1 Baseline Perceived Returns to Education

I exploit survey data on perceived jobs and perceived earnings as described in section 4.1.2. Figure 2A presents the fraction of the respondents who thought their children would work in a certain sector. If everyone has the correct perception, these fractions should match the empirical job distribution. Most parents associate higher education with jobs in the public sector. In reality, only 33% of high school graduates work for the government while 40% work in commerce and the private sector, a sharp contrast from the beliefs shown in this figure.

Answers to the survey question on perceived earnings reveal huge variations in parents' estimates of the returns at baseline. First, many parents do not report perceived earnings, answering "Don't Know" to the survey question (even though almost everyone could predict the job type and report his household income). Panel A of Table 5 presents the fraction of the sample not reporting perceived earnings for self and for average at baseline. Roughly one third of the respondents did not report perceived earnings for a particular level of education. More respondents claim to know earnings for higher education, perhaps since they can perceive standard salaries for the public sector but not the variable incomes in agriculture. The poor appear somewhat more likely not to report perceived earnings (also true for the less educated).

Second, conditional on knowing, perceived returns are dispersed; however, the median perception is close to the estimated average return (Mincer estimates from household survey data). Figure 2B plots the kernel densities of the empirical distribution of perceived returns. The wide dispersion in perceived returns for self may reflect both heterogeneity in returns and imperfect information. It is important to note that perception about the average returns also varies widely, revealing some extent of misperception. Differences between perceived return for self and that for average, i.e. an individual's relative position to the average, are mostly concentrated around zero.

Interestingly, in all cases, the median perceptions are well aligned with the estimated average returns. Despite large dispersion in perceived returns, the median of the distribution is quite close to the vertical line denoting the estimated average return in all the graphs of Figure 2B. Panels B and C of Table 5 report the median perceived returns and standard deviation. For example, the median person in the full sample thinks his marginal return to lower-secondary education is 0.67, i.e. 67% gain in income compared to completing just primary school. It is interesting to note that the poor have higher median perceived returns, though the standard deviation is also higher. These differences in perceived returns reflect underlying differences in perceived earnings. For all education levels, the poor's perceived earnings are consistently lower than those of the rich (see Panel D). Still, the poor expect to gain more from education. Poor people think they earn very little with lower education levels but can increase earnings substantially with higher education. The relatively rich people in my data think they can earn a fair amount even with little education.

Third, dispersion in perception appears larger than dispersion in the actual earnings recorded in household survey data. Panels D and E of Table 5 display the mean and standard deviation of perceived and observed earnings. The mean perceived earnings are higher, which might be reasonable if parents already take into account growth and inflation in estimating children's earnings in the future. The standard deviation in perception is always larger than that in the survey data, for all levels of education. This evidence again suggests some extent of imperfect information about the returns to education.

5.2 Estimation Strategy

I first ask whether the statistics program as a whole has an impact on perception and schooling by pooling the "statistics only" and "statistics with role model" schools to be the "any statistics" treatment. I ask the same question about the role model program as a whole. I also discuss the impact of statistics by itself, role model program by itself, and both interventions together. The main specifications are of the following form:

$$Y_{si} = \alpha + \gamma_0 * AnyStat_s + \delta X_{si} + \varepsilon_{si} \tag{22}$$

$$Y_{si} = \alpha + \gamma_1 * AnyRM_s + \delta X_{si} + \varepsilon_{si} \tag{23}$$

$$Y_{si} = \alpha + \gamma_2 * AnyStat_s + \gamma_3 * AnyRM_s + \gamma_4 * StatRM_s + \delta X_{si} + \varepsilon_{si} \tag{24}$$

where Y_{si} is an outcome variable for individual i in school s. AnyStat is a dummy equal to 1 if school s receives any statistics treatment, and similarly AnyRM for any role model treatment. $StatRM$ is an indicator for the schools that received the combined interventions, i.e. the intersection of AnyStat and AnyRM. γ's are the coefficients of interest, to be interpreted as the average treatment effect. For example, γ_2 in equation 24 is the difference between average Y in statistics (only) schools and that of the comparison schools. $\gamma_2 + \gamma_3 + \gamma_4$ is the effect of receiving both interventions relative to the comparison schools. Standard errors are clustered at the school level. Observations are weighted by the probability of selection, i.e. sampling weights, so that the coefficients of interest are estimated for the population. X_{si} refers to control variables in some specifications. In most cases, I control for the baseline value of the dependent variable, which is likely to have good explanatory power for the dependent variable and improve precision of the coefficient estimates.

For comparison and to evaluate the impact of role models by type, results from the complete specification of all treatment groups are also presented:

$$Y_{si} = \alpha + \sum_k \gamma^k * TG_s^k + \delta X_{si} + \varepsilon_{si} \tag{25}$$

where TG_s^k are indicators for whether school s belongs to treatment group k (k=1 to 7) as defined in the design Table 1. Since treatment assignment was random, the errors ε_{si} are orthogonal to treatment group dummies.

Motivated by the model's predictions, I also investigate the treatment effects by initial perception and by type (rich vs. poor). In particular, any schooling improvement due to the statistics treatment should come from individuals whose initial perceived returns were below the estimated average returns (I call this "underestimate"). I test this prediction by running the following regression:

$$
\begin{aligned}
(Posttest - Pretest)_{si} &= \alpha + \gamma_1 AnyStat_s + \gamma_2 AnyRM_s + \gamma_3 StatRM_s + \delta Pretest_{si} && (26)\\
&\quad + \lambda_1 AnyStat_s * 1(Under)_{si} + \lambda_2 AnyRM_s * 1(Under)_{si} && (27)\\
&\quad + \lambda_3 StatRM_s * 1(Under)_{si} + \theta * 1(Under) + \varepsilon_{si} && (28)
\end{aligned}
$$

where 1(under) is a dummy equal 1 if at baseline, the individual perceived the returns to be lower than the statistics provided. The coefficients of interest are $\lambda's$ on the interaction terms. A positive λ would imply stronger treatment effects on those who had underestimated the returns. Moreover, we expect role model LH to increase the poor's schooling investment, but not the rich's. I run a regression similar to equation 26, with all the seven treatment dummies interacted with an indicator for (relatively) rich households. I will present these results in addition to the average treatment effects.

5.3 Impact on Perceived Returns

5.3.1 Impact of Statistics on Perceived Returns

I first discuss the impact of the statistics intervention on endline perception, as summarized in Table 6. The fraction of respondents not reporting perceived earnings decreased substantially from the baseline to the endline survey. Only 15% of respondents in the comparison group failed to report their perception (answering "Don't Know"), perhaps since the perception questions were asked for the second time at the endline survey. The first column of Table 6 presents results for the probability of not reporting earnings as the dependent variable in equations 22, 23, 24, and 25. Since this "Don't Know" outcome is for each education level, these OLS regressions stack up 4 education levels[11] and include education dummies in the regressions. I cannot reject that the statistics treatment has zero impact on the likelihood of "Don't Know" perceived earnings. These

[11] No primary education, only primary education, only lower secondary education, and only high school education.

results are robust to controlling for baseline Don't Know status and robust to running probit. Results are similar for Don't Know perceived earnings for average (not shown). While this finding is surprising, it has the advantage that the results below are not biased by selective non-response.

The first-order question is whether people update perceived returns toward the statistics, as predicted by the model. I find that providing statistics reduces the gaps between baseline perceived returns and the estimated average returns that we saw in Figure 2B. Figure 3 and Figure 4 plot the kernel densities of endline perceived returns in statistics schools and comparison schools. Eyeballing these graphs, we see that the statistics schools' distribution tends to be more concentrated around the vertical line of estimated average return. In addition, dispersion in the empirical distribution of perceived returns also decreases. I reject the hypothesis that the variance of perceived returns is the same in the comparison schools and statistics schools (p-value from the variance ratio test is very close to zero). Table 6 confirms this conclusion by presenting estimates of equations 22, 23, 24, and 25. The outcome variable in columns 2 and 3 is now the absolute distance between endline perceived returns and the estimated average returns. Since the perceived return outcome is for three levels of education,[12] these OLS regressions include education dummies. Panel A shows that providing only statistics significantly decreases the gap by 0.149 from the control group average of 0.68. This reduction in the gap is similar for perceived returns for self and for average. Note that combining statistics with role models undoes this effect: the combined treatments have no impact on perceived returns. As a result, the average impact of any statistics on the gap is not significant (Panel B). I will return to this point later when I discuss role models.

Consistent with the theory, providing statistics leads individuals to update their perceived returns for average rather than their relative position to the average. Column 4 of Table 6 shows that the statistics treatment does not affect how far individuals think their returns are from their perceived average. The coefficient estimate on AnyStatistics is close to zero and insignificant. Given that people may have had imperfect information about the average returns, this evidence

[12] Primary education, lower secondary education, and high school.

suggests that they update their perceived returns for average toward the statistics and also update their perceived returns for self by the same amount.

The above estimations on endline perceived returns potentially face a sample selection concern since the "Don't Know" population is equivalent to missing data. However, the rate of "Don't Know" is similar in the statistics schools and the comparison schools. People who did not report perceived earnings have similar baseline characteristics across treatment groups, except for some cases of slight income differences. Thus, selection is not likely to severely bias the impact of statistics. In columns 5 and 6 of Table 6, I also restrict the sample to those who reported their perceptions in both survey rounds and find similar results. The impact of statistics on perception does not seem to be driven by the "Don't Know" population.

5.3.2 Impact of Role Models on Perceived Returns

Overall, the role model interventions have small effects on perception. The coefficients on role models in columns 2 and 3 of Table 6 are close to zero and statistically insignificant. On average, role models of any type decrease the gap between perceived return for self and the estimated average return by 0.013, but this estimate is not statistically distinguishable from zero (Panel A). Panel D reports the results for each type of role model. In the entire sample, none of the role model types has a statistically significant impact on the gap in perceived returns.

The only type that may affect perception is role model LH. Recall that type LH is a role model from the poor family background who has become very successful. When I control for baseline perceived returns in the restricted name-matched sample, I find that role model LH combined with statistics decreases the gap between perceived return for average and the estimated average return by 0.13. Column 8 presents the treatment effects for the sample of poor families. Role model LH, alone and when combined with statistics, decreases the gap for the poor. However, this effect is not statistically different from the effect of role model HH.

Consistent with the theory, role models undermine the impact of statistics in general. Throughout different samples of the regression in Panel A, the coefficient estimates on the combined treatment are of similar magnitude but of the opposite sign as the coefficient on statistics. In column 2, for example, statistics alone decreases the gap by 0.149 while statistics and role model changes the gap by -0.149 - 0.013 + 0.159 = -0.003, i.e. reverting the impact of statistics toward zero. This finding suggests that households give less weight to the statistics in their updating when it is accompanied by a role model since the role model signals high heterogeneity in the returns and, therefore, low precision of the statistics.

5.4 Impact on Education Investment

5.4.1 Impact of Statistics on Education Investment

Given that at least some people update their perceived returns toward the statistics, we would expect test scores and school attendance to also respond. In particular, providing statistics should increase test scores for children with low initial perceived returns.

The statistics program's impact on test scores is consistent with these theoretical predictions. Recall that these tests are achievement tests, and performance can be improved by exerting effort. Since test scores are persistent, I control for each child's pretest score and report results from equations 22, 23, 24, and 25 in column 2 of Table 7. The dependent variable is improvement in normalized test scores. As shown in Panel A, the statistics (only) program increases test score improvement by 0.20 standard deviations, conditional on what can be explained by the pretest. This coefficient estimate is both statistically and economically significant. When we pool all statistics schools together, test scores are on average 0.10 standard deviations higher than those in schools without the statistics intervention. As a robustness check, the simple difference regression that does not control for pretest score gives very similar coefficients, but less precisely estimated.

Individuals in our sample started with dispersed perceived returns, so we would expect the treatment effects on test scores to be heterogenous. The theory predicts that schooling improvement should come from individuals whose initial perceived returns were below the actual average returns. For the subsample of test score data that can be name-matched to the baseline perceived return data, column 6 presents the result from estimating equation 26. Consistent with the theoretical prediction, the coefficient estimate of the statistics interaction term is positive and statistically significant. In particular, providing statistics increased test scores for those who initially underestimated the returns by 0.365 standard deviations (column 4), while decreasing test scores for those who overestimated the returns by 0.223 standard deviations (column 5). Since the error terms are orthogonal to the treatment indicators, we can read these coefficients as the treatment effects for those initially overestimating or underestimating the returns. A concern in interpreting these results as Bayesian updating is that "underestimating" might be correlated with other factors affecting test scores. For example, everyone responded by increasing effort, but those who overestimated the returns are somehow also those with negative productivity of effort.

The results on school attendance are also indicative of the impact of statistics. Column 1 of Table 7 presents the results for school-level student attendance as the dependent variable in the main estimating equations. Since these attendance rates are class averages rather than individual-level data, observations are also weighted by class size. The regression outputs are for a random sub-sample of 176 schools for which attendance data post-treatment is available. I find that providing solely statistics increases average attendance by 7.846 percentage points, though imprecisely estimated due to the small sample size. Pooling all the statistics treatment together improves power. As reported in Panel B under column 1, schools that received any statistics treatment have on average 3.5 percentage points higher attendance rate in Grade 4, compared to the control group mean of 85.6%. The results are robust to controlling for baseline school characteristics and student attendance one school year before the treatment.

5.4.2 Impact of Role Models on Education Investment

Since role models have small effects on perception, their overall impact on schooling investment is also small, as expected. The average test score is practically the same in the schools that received any role model and those without role models (Panel C of Table 7). However, the role model's background seems to matter, as discussed in section 5.3.2. As shown in Panel D, column 2 of Table 7, role model type LH increased test score significantly by 0.17 standard deviations. Meanwhile, the estimated impact of role model HH is close to zero. I reject the null hypothesis that role model type LH and type HH have equal coefficients (F-test p-value of 0.06).

The theory predicts that role model LH should have a positive influence on test scores for students of poor family background. Column 9 reports estimation results from running a regression similar to equation 26, with all the seven treatment dummies interacted with an indicator for rich households. Role model LH increases average test score by 0.27 standard deviations for the poor, but has practically little impact (statistically insignificant) on children from richer families. In addition, I test for a difference-in-difference effect of role model LH vs. HH for the rich vs. poor. However, with the large standard errors around the coefficient estimate for RM HH, I cannot reject the difference between this coefficient and the coefficient on RM LH (the p-value is 0.34).

5.5 External Validity

Since all the comparison schools in my experiment organized a "placebo" school meeting, the treatment effects I have measured may be safely attributed to the statistics or role model treatments themselves. In addition, I have another group of "pure control" schools, which never came into contact with the program nor with the perceived returns survey. The average test score in those schools is very similar to that of the regular comparison schools. This evidence suggests that simply participating in the experiment, i.e. organizing a meeting and being surveyed, does not seem to have a significant impact on behaviors.

6 Conclusion

Information about the returns to education is essential to school decision making. In this paper, I document that households in rural Madagascar have imperfect information about the returns to education. I set up a field experiment to evaluate two approaches to alleviating imperfect information: providing statistics on the returns to education, and sending a role model to the school. Consistent with a model of belief formation, the results suggest that households update their perceived returns after receiving the statistics and change schooling decisions accordingly. The statistics intervention improved test scores by 0.37 standard deviations for those who had initially "underestimated" the returns, and reduced test scores for those who had "overestimated" the returns. As the theory predicts (and different from much of the policy discussion on role models), role models have an ambiguous effect. They signal heterogeneity in the return, reducing the impact of statistics toward zero. However, they increase schooling effort of those children whose family background matches theirs.

Overall, the statistics program is a very cost-effective way to entice children to attend school and improve test scores. Even though providing statistics decreased perceived returns to education for some children and increased perceived returns for others, it led to an increase in schooling on average. This program cost 0.08 USD per student but increased student attendance by 3.5 percentage points and improved test scores by 0.20 standard deviations after three months. This implies a program cost of 2.30 USD for an additional year of schooling and 0.04 USD for additional 0.10 standard deviations in test scores, more cost-effective than previous interventions evaluated in a randomized experiment (Jameel Poverty Action Lab 2005). Providing deworming drugs, to date the most cost-effective way to increase attendance, costs 3.50 USD for an additional year of schooling (Miguel and Kremer 2004). In terms of improving test scores, the extra-teacher balsakhi program in India costs 0.67 USD per improvement of 0.10 standard deviations (Banerjee, Duflo, Cole, and Linden 2007).

As a broader implication, my paper suggests that households respond to changes in perceived returns when making schooling decisions. Thus, they would probably respond if the actual market returns improved. As suggested in Foster and Rosenzweig (1996), market interventions to raise the market returns to education may be very effective in increasing education.

There are several caveats and as yet unexplored issues that I plan to address in continuing research. One main caveat is that the results presented here reveal only the short-run and direct impacts. It will be useful to follow the students in my sample to see if their enrollment in later school years increases because of the treatment, and if they will complete the primary cycle and go on to secondary school after Grade 5. Collecting outcome data for other children in the same school would also shed light on spillovers of information. Given the strong direct effects of statistics, it is important to investigate in future research whether and how strongly such information spreads to affect schooling decisions of other children in the same family, and of those in other families through teachers or parents' social networks.

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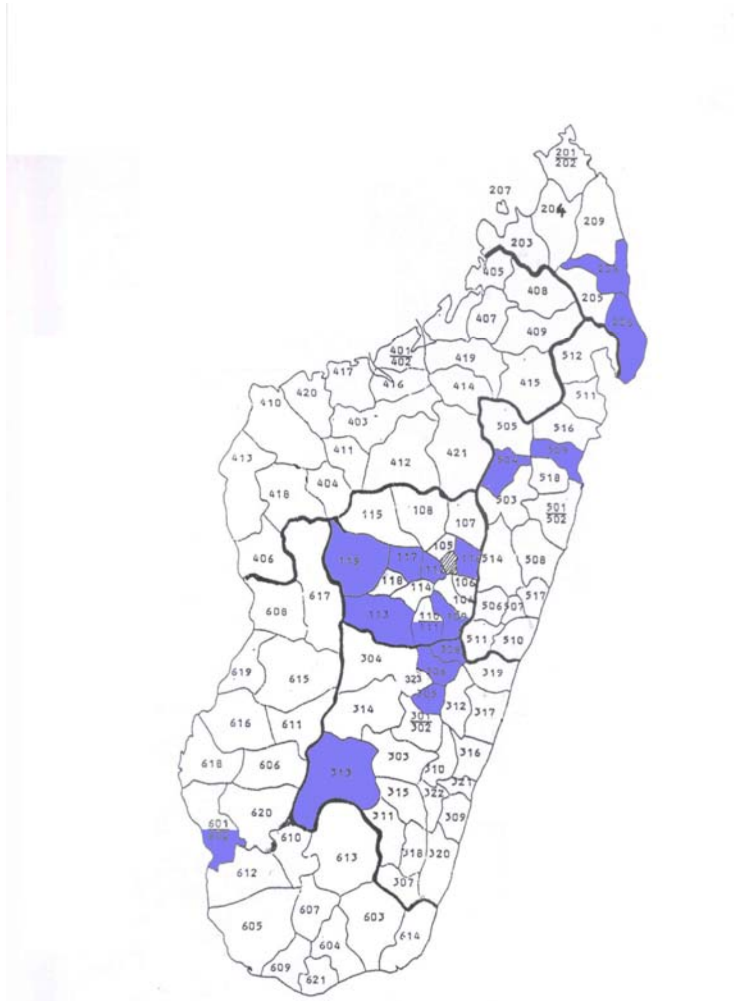
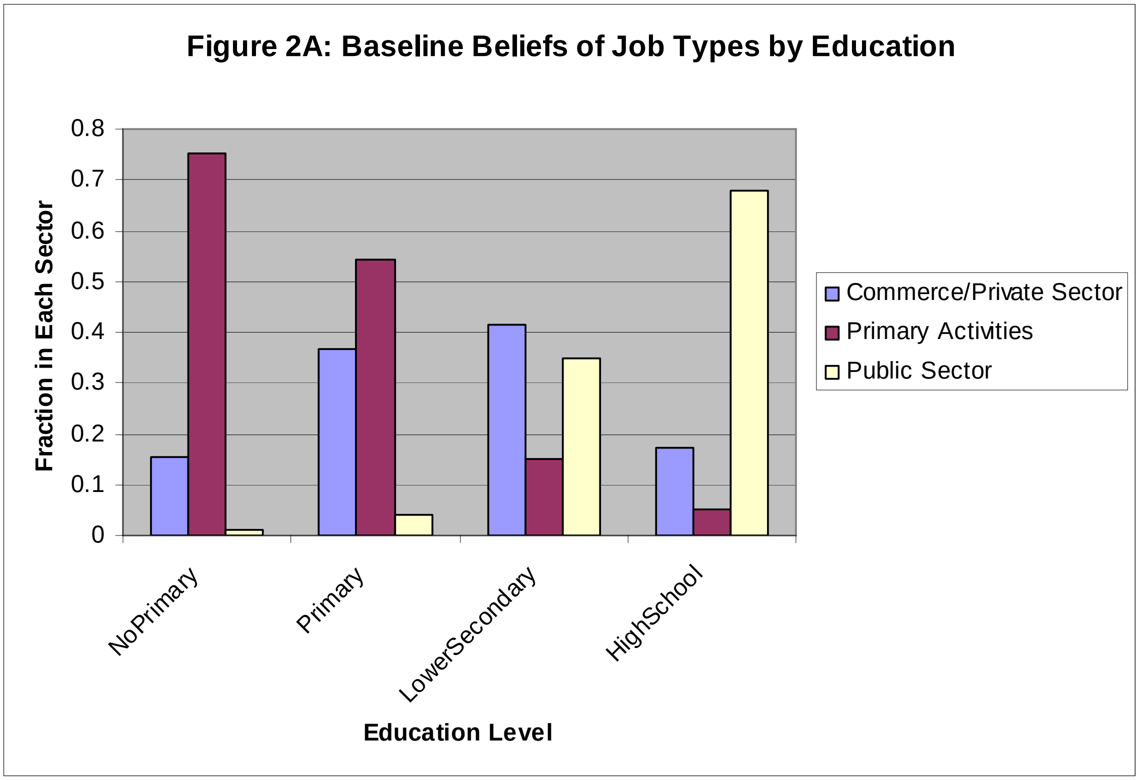
Figure 1: School District Map of Madagascar

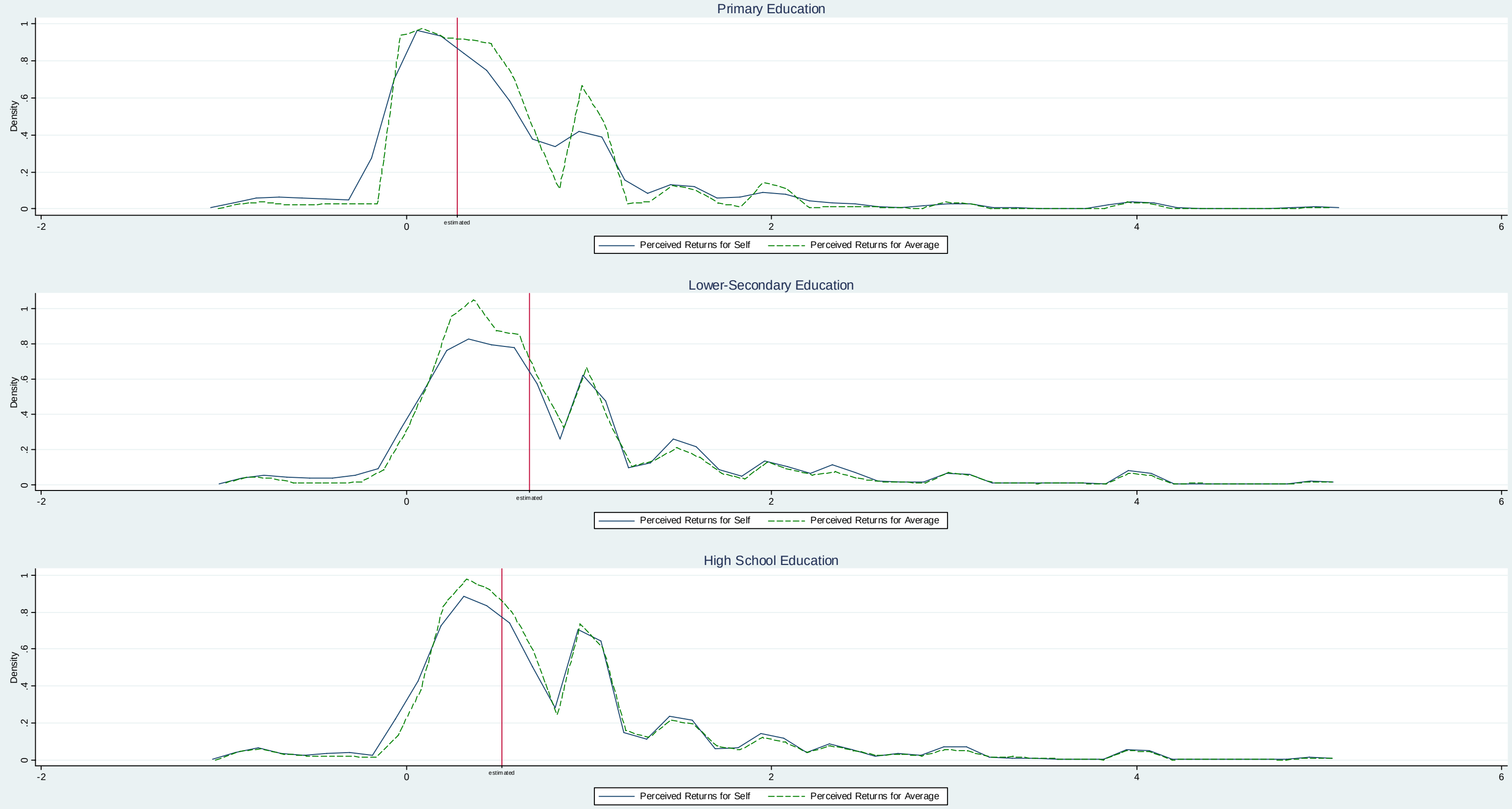


Notes: The shaded areas are the 16 school districts in my study sample



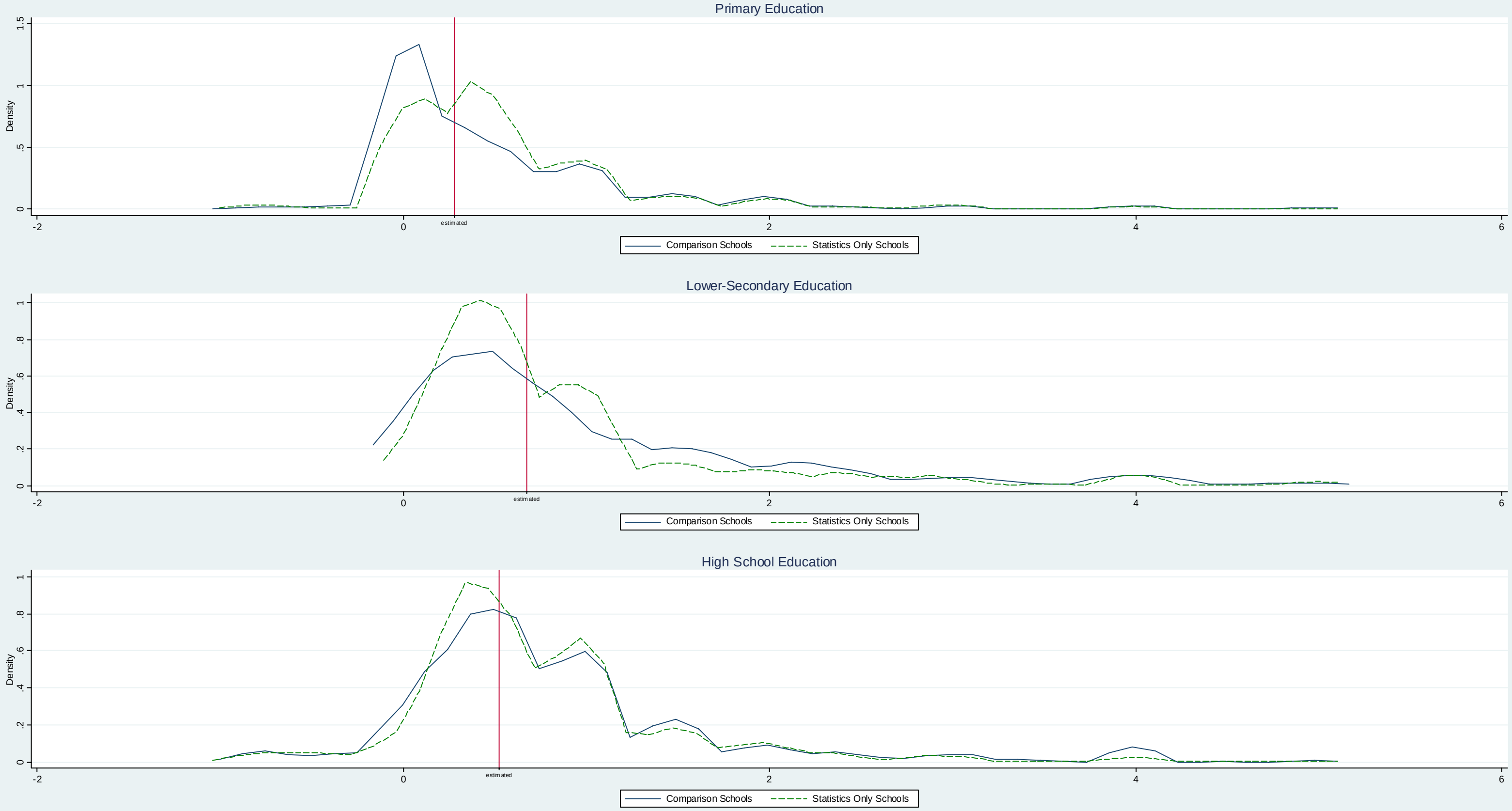
Notes: "Primary Activities" include agriculture, cattle-raising, fishing, and forestry activities. The survey questions on beliefs of job types ask respondents for the sector in which they think their child could work at the age of 25, under different hypothetical scenarios of educational attainment.

Figure 2B: Baseline Density of Perceived Returns for Self and for Average



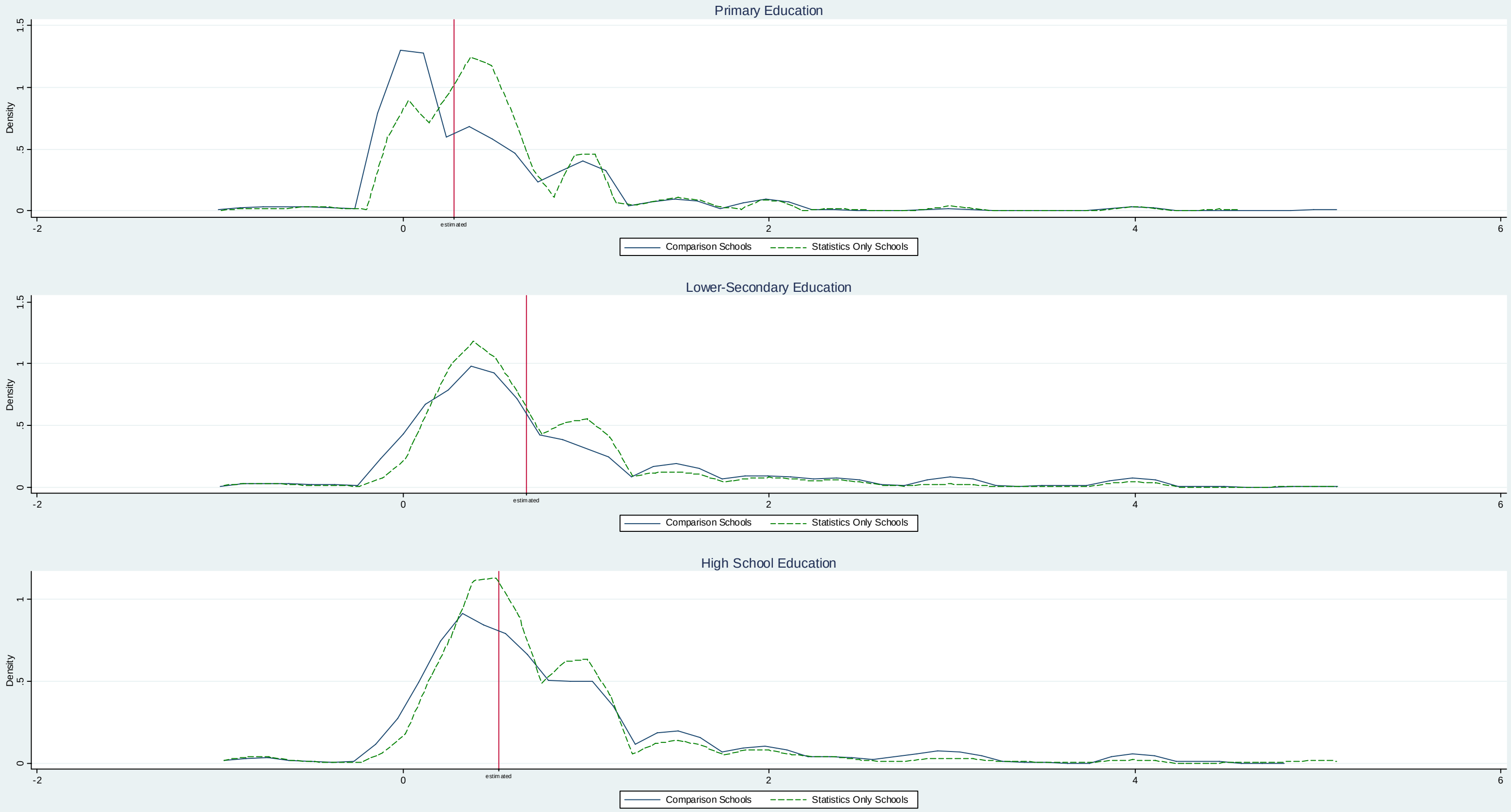
Note: Each panel graphs the kernel density of baseline perceived returns to each level of education.
The solid line represents perceived returns for self, and the dashed line represents those for average.
The vertical lines mark the estimated average returns. Observations are weighted by the sampling probability.
The few values above 5 are not shown.

Figure 3: Endline Density of Perceived Returns for Self Comparison Schools and Statistics Schools



Note: Each panel graphs the kernel density of endline perceived returns to each level of education.
The solid line represents the comparison schools, and the dashed line represents statistics schools.
The vertical lines mark the estimated average returns. Observations are weighted by the sampling probability.
The few values above 5 are not shown.

Figure 4: Endline Density of Perceived Returns for Average Comparison Schools and Statistics Schools



Note: Each panel graphs the kernel density of endline perceived returns to each level of education.
The solid line represents the comparison schools, and the dashed line represents statistics schools.
The vertical lines mark the estimated average returns. Observations are weighted by the sampling probability.
The few values above 5 are not shown.

Table 1: Experimental Design

	No RM	Role Model Treatment		
		Type LM	**Type LH**	**Type HH**
No Statistics	TG0: 80 schools	TG2: 80 schools	TG3: 80 schools	TG4: 80 schools
Statistics	TG1: 80 schools	TG5: 80 schools	TG6: 80 schools	TG7: 80 schools

Notes: "Any Statistics" Treatment refers to the second-row groups of schools. "Any RM" refers to the last three columns. The combined treatment refers to groups 5, 6, and 7 where both the statistics and role model interventions took place. TG0 denotes the regular control group.

Table 2: Descriptive Statistics

	Mean	Std. Dev.	Obs
	(1)	(2)	(3)
Panel A: School Variables			
Baseline Test Score	60.67	11.84	640
Enrollment	215.01	153.57	640
Repetition Rate	0.19	0.11	640
Number of Sections in School	5.51	2.03	640
Number of Classrooms in School	4.01	2.04	640
Panel B: Household Variables			
Respondent Age	42.48	9.46	17158
Female Respondent	0.55	0.50	17158
Household Size (in persons)	6.60	2.11	17158
Respondent Literacy: Read and Write	0.88	0.33	17158
Respondent Literacy: Calculations	0.85	0.35	17158
Mother Primary Education	0.41	0.49	17158
Mother Secondary or Higher Education	0.01	0.10	17158
Father Primary Education	0.44	0.50	17158
Father Secondary or Higher Education	0.03	0.16	17158
Household Monthly Income (in Ar)	49703.97	90615.65	16754

Notes: 2000 Ar~ 1 USD

Omitted Education category: No primary school

Table 3: Baseline Differences across Groups

	Dependent variables								
	Baseline Test Score	Enrollment	Repetition Rate	Mother Has Primary Education	Father Has Primary Education	Household Monthly Income (in Ar)	Fraction Not Reporting Perceived Own Earnings	Perceived Returns for Self	Perceived Returns for Average
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
TG1 = Statistics	-0.509	-9.437	-0.017	-0.038	-0.028	9557.45	-0.019	-0.079	-0.204
	(1.76)	(22.28)	(0.02)	(0.04)	(0.04)	(10047.76)	(0.08)	(0.09)	(0.065)**
TG2 = RM LM	0.03	44.375	0.012	-0.068	-0.063	855.201	0.075	-0.106	-0.155
	(1.83)	(24.40)	(0.02)	(0.032)*	(0.03)	(5122.38)	(0.08)	(0.09)	(0.074)*
TG3 = RM LH	0.163	8.663	0.006	0.014	-0.003	823.111	-0.144	-0.12	-0.143
	(1.78)	(20.32)	(0.02)	(0.03)	(0.03)	(4468.32)	(0.058)*	(0.08)	(0.069)*
TG4 = RM HH	0.268	13.613	0.02	-0.003	0.009	3967.85	0.068	0.073	0.029
	(2.01)	(28.50)	(0.02)	(0.03)	(0.03)	(4587.45)	(0.07)	(0.12)	(0.13)
TG5 = Statistics+RM LM	0.076	7.738	-0.019	-0.062	-0.066	-2095.79	-0.01	-0.084	-0.086
	(1.85)	(21.63)	(0.02)	(0.03)	(0.033)*	(4332.30)	(0.07)	(0.09)	(0.08)
TG6 = Statistics+RM LH	-0.254	26.888	0.012	-0.009	-0.017	10435.82	-0.045	-0.013	-0.037
	(1.95)	(21.60)	(0.02)	(0.04)	(0.03)	(8248.42)	(0.07)	(0.09)	(0.07)
TG7 = Statistics+RM HH	0.299	-9.687	0.02	-0.049	-0.051	295.55	-0.067	-0.1	-0.076
	(2.11)	(18.77)	(0.02)	(0.04)	(0.03)	(4736.78)	(0.07)	(0.09)	(0.08)
Constant	60.66	204.74	0.19	0.43	0.47	46591.49	0.41	0.78	1.11
	(1.365)**	(14.429)**	(0.014)**	(0.024)**	(0.023)**	(3,592.01)**	(0.054)**	(0.068)**	(0.061)**
Observations	640	640	640	17158	17158	16754	68632	31293	31306
F-stat (joint significance)	0.05	1.19	1.53	1.85	1.67	0.76	3.52	0.87	2.31

Notes: This table presents OLS results from regressing baseline school characteristics on different treatment group dummies.
Omitted category: control group.
Columns 1-3: school-level data, and robust standard errors in parentheses
Columns 4-6: individual-level data; Columns 7-9: individual data by education; standard errors in parentheses are clustered at the school level
Exchange rate: 2000 Ar~ 1 USD
Omitted education category: No primary school
* significant at 5%; ** significant at 1%

Table 4: Attrition in Endline Data

	Endline Perceived Returns						Post-test	
		Baseline Characteristics across Schools of Differential Attrition						*Diff (Attriters – Stayers)*
	Percent Attrition	Mother Has Primary Education	Father Has Primary Education	Household Monthly Income (in 10000 Ar)	Perceived Returns for Self	Perceived Returns for Average	Percent Attrition	Pretest Score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TG1 = Statistics	0.30	-0.097	-0.103	5.722	-0.338	-0.555	0.13	-0.182
	(0.11)	(0.15)	(0.13)	(4.35)	(0.42)	(0.277)*	(0.02)	(0.15)
TG2 = RM LM	0.19	-0.161	-0.182	3.364	-0.423	-0.387	0.14	0.037
	(0.07)	(0.12)	(0.110)+	(2.82)	(0.42)	(0.31)	(0.02)	(0.13)
TG3 = RM LH	0.15	-0.221	-0.179	1.033	-0.439	-0.391	0.11	0.047
	(0.07)	(0.108)*	(0.086)*	(2.32)	(0.35)	(0.28)	(0.01)	(0.16)
TG4 = RM HH	0.10	-0.195	-0.257	-0.2	0.058	-0.475	0.12	0.038
	(0.05)	(0.14)	(0.17)	(3.04)	(0.58)	(0.46)	(0.02)	(0.16)
TG5 = Statistics+RM LM	0.01	-0.205	-0.197	0.315	-0.31	0.125	0.12	-0.057
	(0.05)	(0.105)+	(0.083)*	(2.25)	(0.34)	(0.32)	(0.02)	(0.18)
TG6 = Statistics+RM LH	0.06	-0.014	-0.02	-5.272	-0.414	-0.624	0.10	-0.19
	(0.03)	(0.14)	(0.12)	(4.12)	(0.56)	(0.53)	(0.01)	(0.15)
TG7 = Statistics+RM HH	0.05	-0.442	-0.344	-2.663	0.004	-0.595	0.12	-0.13
	(0.02)	(0.204)*	(0.174)*	(2.66)	(0.46)	(0.42)	(0.01)	(0.17)
Control Group	0.09						0.13	
	(0.08)						(0.02)	
Observations	619	17029	17029	16627	31097	31125		13162

Notes:
Attrition rates in endline perceived returns data are at the school level.
Column 1: school attrition rates are weighted by class size in the baseline data and sampling probability. Robust standard errors in parentheses.
Columns 2-6 report the results from regressing each baseline characteristic on attrition rate interacted with treatment group dummies
Standard errors in parentheses are clustered at the school level. Omitted categories: Control group.
Attrition rates in posttest data are at the individual level. Column 8 reports the pretest score differences between attriters and stayers across groups
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 5: Perceived Earnings and Perceived Returns to Education at Baseline

	Full sample		Rich		Poor	
	Perceived (Self)	Perceived (Average)	Perceived (Self)	Perceived (Average)	Perceived (Self)	Perceived (Average)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fraction Not Reporting Perceived Earnings						
No Primary	0.37	0.38	0.35	0.33	0.38	0.41
Primary	0.35	0.37	0.32	0.32	0.35	0.39
Lower Secondary	0.30	0.34	0.27	0.29	0.31	0.37
High School	0.28	0.34	0.24	0.29	0.30	0.37
Panel B: Median Perceived Returns						
Primary	0.33	0.38	0.33	0.33	0.50	0.43
Lower Secondary	0.67	0.60	0.50	0.50	0.67	0.67
High School	0.67	0.67	0.63	0.65	0.67	0.67
Panel C: Standard Deviation of Perceived Returns						
Primary	1.52	1.14	1.40	1.05	1.60	1.21
Lower Secondary	1.85	1.66	1.50	1.38	2.10	1.89
High School	1.80	1.63	1.55	1.52	1.98	1.73
Panel D: Mean and Standard Deviation of Perceived Monthly Earnings (in Ar.)						
No Primary	46182	39117	53923	44325	38301	33509
	(56452)	(42582)	(59614)	(43248)	(51002)	(40611)
Primary	65352	55455	73311	62602	57506	47912
	(77133)	(62336)	(78101)	(65224)	(75178)	(57625)
Lower Secondary	109712	90920	117742	97972	101348	83185
	(120973)	(91504)	(124307)	(92108)	(115293)	(88921)
High School	197281	161548	207859	172628	185960	149695
	(219231)	(151763)	(225197)	(158897)	(210685)	(142717)
Panel E: Mean and Standard Deviation of Observed Monthly Earnings in Household Survey						
No Primary		20699				
		(30649)				
Primary		23812				
		(52465)				
Lower Secondary		54025				
		(77611)				
High School		100333				
		(157325)				

Notes: Earnings measured in Ariary (Ar). Exchange rate: 2000 Ar~ 1 USD

Table 6: Impact on Endline Perceived Returns to Education

	Dependent variables								
		Gap(#) (Entire sample)			Gap (Matched sample)				
	Not Report	Self	Average	Self – Average	Self	Average	Rich	Poor	Difference (Rich – Poor)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
AnyStatistics	0.054	-0.149	-0.158	-0.024	-0.23	-0.21	-0.123	-0.374	0.261
	(0.04)	(0.081)+	(0.085)+	(0.05)	(0.086)**	(0.086)*	(0.11)	(0.099)**	(0.126)*
AnyRM	0.089	-0.013	-0.062	0.009	-0.011	-0.068	0.069	-0.128	0.202
	(0.032)**	(0.07)	(0.07)	(0.04)	(0.08)	(0.06)	(0.09)	(0.09)	(0.104)+
Statistics+RM	-0.074	0.159	0.202	0.003	0.237	0.228	0.109	0.409	-0.313
	(0.05)	(0.096)+	(0.097)*	(0.06)	(0.106)*	(0.099)*	(0.14)	(0.118)**	(0.147)*
Panel B									
AnyStatistics	-0.003	-0.03	-0.007	-0.022	-0.053	-0.04	-0.051	-0.052	0.002
	(0.03)	(0.05)	(0.04)	(0.03)	(0.06)	(0.05)	(0.07)	(0.06)	(0.07)
Panel C									
AnyRM	0.053	0.061	0.033	0.01	0.106	0.043	0.128	0.065	0.061
	(0.025)*	(0.05)	(0.05)	(0.03)	(0.061)+	(0.06)	(0.075)+	(0.07)	(0.09)
Panel D									
TG1 = Statistics	0.054	-0.149	-0.158	-0.024	-0.23	-0.21	-0.123	-0.374	0.261
	(0.04)	(0.081)+	(0.085)+	(0.05)	(0.086)**	(0.086)*	(0.11)	(0.099)**	(0.126)*
TG2 = RM LM	0.15	0.052	-0.049	0.046	0.067	-0.06	0.188	-0.089	0.284
	(0.047)**	(0.09)	(0.08)	(0.05)	(0.10)	(0.08)	(0.13)	(0.12)	(0.138)*
TG3 = RM LH	0.04	-0.034	-0.054	-0.02	-0.07	-0.079	-0.015	-0.156	0.147
	(0.04)	(0.09)	(0.08)	(0.05)	(0.10)	(0.08)	(0.10)	(0.13)	(0.13)
TG4 = RM HH	0.059	-0.058	-0.081	-0.002	-0.037	-0.066	0.032	-0.144	0.177
	(0.04)	(0.09)	(0.09)	(0.05)	(0.10)	(0.08)	(0.14)	(0.10)	(0.13)
TG5 = Statistics+RM LM	0.041	0.057	0.052	-0.015	0.027	-0.043	0.043	-0.016	0.063
	(0.03)	(0.08)	(0.09)	(0.05)	(0.09)	(0.07)	(0.10)	(0.10)	(0.11)
TG6 = Statistics+RM LH	0.055	-0.089	-0.106	-0.023	-0.084	-0.13	-0.02	-0.179	0.159
	(0.04)	(0.08)	(0.08)	(0.05)	(0.08)	(0.072)+	(0.09)	(0.089)*	(0.10)
TG7 = Statistics+RM HH	0.124	0.054	0.029	0.009	0.077	0.051	0.196	-0.071	0.269
	(0.050)*	(0.08)	(0.08)	(0.05)	(0.09)	(0.08)	(0.12)	(0.10)	(0.141)+
Constant	0.15	0.68	0.60	85.59	0.68	0.61	0.63	0.78	0.82
	(0.026)**	(0.061)**	(0.063)**	(4.687)**	(0.060)**	(0.052)**	(0.068)**	(0.078)**	(0.074)**
Observations	61380	38262	39007	35990	18487	18774	9085	9261	18346
F-stat (TG3 + 6 = TG4 + 7)	1.58	0.92	0.94	0.49	1.80	2.53	1.80	0.65	0.53

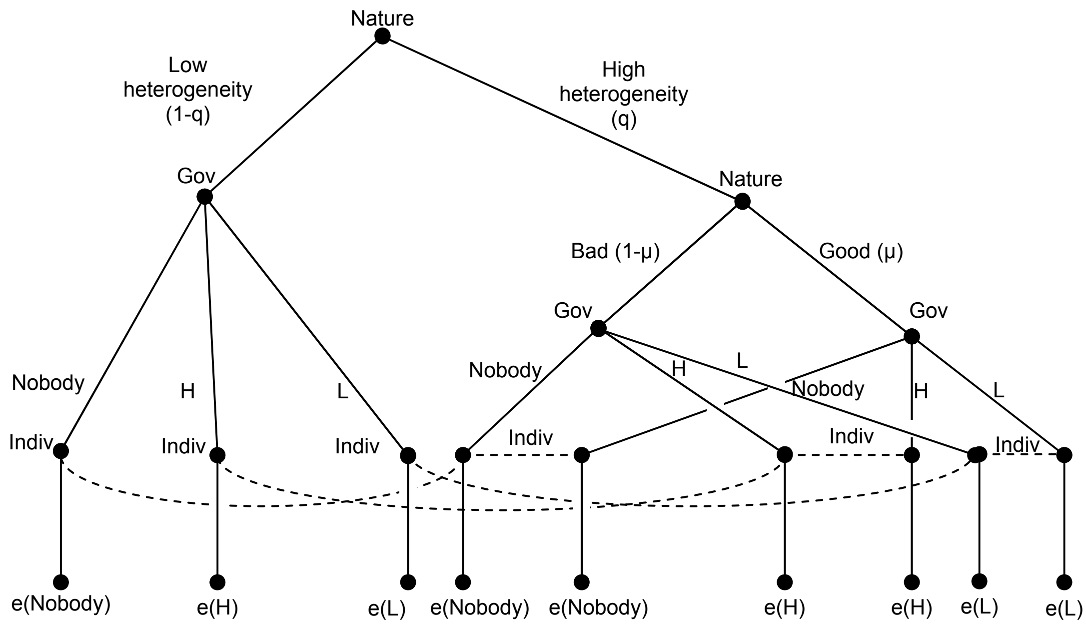
Notes: (#) Gap is the absolute distance |Perceived Returns – Estimated Average Returns|
Omitted categories: Control group. All regressions include dummies for education levels; coefficients not shown.
Standard errors clustered at the school level (621 schools); observations weighted by sampling probability
Columns 5-9: Sample matched to baseline perceived returns data; these regressions control for gap at baseline
Columns 7-9 present results for gap of perceived returns for self
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 7: Impact on Schooling Effort and Test Scores

	Dependent variables								
			(Normalized) Posttest - Pretest (Matched Sample)						
	Attendance	Test Scores	Test Scores	Under-estimated(#)	Over-estimated	Difference (Underestimated – Overestimated)	Rich	Poor	Difference (Rich – Poor)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A									
AnyStatistics	7.846	0.202	0.237	0.365	-0.223	0.576	0.249	0.264	-0.024
	(4.87)	(0.106)+	(0.111)*	(0.156)*	(0.17)	(0.193)**	(0.119)*	(0.137)+	(0.13)
AnyRM	4.947	0.074	0.079	0.112	-0.203	0.32	0.087	0.101	-0.016
	(5.00)	(0.08)	(0.08)	(0.10)	(0.12)	(0.131)*	(0.10)	(0.09)	(0.10)
Statistics+RM	-5.032	-0.132	-0.197	-0.384	0.273	-0.651	-0.217	-0.234	0.022
	(5.36)	(0.13)	(0.13)	(0.178)*	(0.20)	(0.229)**	(0.15)	(0.16)	(0.16)
Panel B									
AnyStatistics	3.517	0.105	0.091	0.079	-0.035	0.109	0.087	0.092	-0.01
	(2.021)+	(0.057)+	(0.06)	(0.08)	(0.11)	(0.12)	(0.08)	(0.07)	(0.09)
Panel C									
AnyRM	0.474	0.01	-0.014	-0.095	-0.105	0.016	-0.018	-0.01	-0.008
	(2.11)	(0.07)	(0.07)	(0.11)	(0.11)	(0.14)	(0.08)	(0.09)	(0.09)
Panel D									
TG1 = Statistics	7.796	0.202	0.237	0.365	-0.223	0.576	0.247	0.264	-0.025
	(4.93)	(0.106)+	(0.111)*	(0.157)*	(0.17)	(0.194)**	(0.119)*	(0.137)+	(0.13)
TG2 = RM LM	7.551	0.088	0.091	0.123	-0.231	0.353	0.164	0.055	0.105
	(5.44)	(0.10)	(0.11)	(0.12)	(0.17)	(0.158)*	(0.13)	(0.13)	(0.13)
TG3 = RM LH	-0.771	0.17	0.156	0.15	-0.123	0.28	0.086	0.271	-0.182
	(6.80)	(0.096)+	(0.090)+	(0.10)	(0.16)	(0.157)+	(0.09)	(0.112)*	(0.104)+
TG4 = RM HH	5.646	-0.022	-0.002	0.045	-0.271	0.326	0.01	0.019	-0.014
	(5.36)	(0.10)	(0.12)	(0.14)	(0.159)+	(0.176)+	(0.16)	(0.11)	(0.17)
TG5 = Statistics+RM LM	5.891	0.117	0.121	0.127	-0.106	0.226	0.009	0.233	-0.242
	(5.11)	(0.11)	(0.11)	(0.12)	(0.13)	(0.15)	(0.15)	(0.126)+	(0.17)
TG6 = Statistics+RM LH	7.098	0.139	0.113	0.077	-0.201	0.282	0.184	0.037	0.15
	(5.30)	(0.11)	(0.12)	(0.17)	(0.24)	(0.27)	(0.15)	(0.12)	(0.12)
TG7 = Statistics+RM HH	9.334	0.182	0.124	0.074	-0.139	0.218	0.138	0.129	0.004
	(4.779)+	(0.106)+	(0.10)	(0.11)	(0.17)	(0.17)	(0.11)	(0.13)	(0.11)
Constant	85.59	-1.24	-1.17	-1.16	-0.93	-0.93	-1.15	-1.20	-1.19
	(4.687)**	(0.066)**	(0.063)**	(0.079)**	(0.102)**	(0.101)**	(0.071)**	(0.074)**	(0.073)**
Observations	176	11659	6297	2877	492	3369	2911	3243	6154

Notes: (#) "Underestimated" denotes the subsample of individuals whose initial perceived returns were below the estimated average returns for some level of education
Omitted categories: Control group.
Column 1: school-level data, all attendance regressions control for school visit time.
Robust standard errors in parentheses; observations weighted by sampling probability and class size.
Columns 2-9: individual-level data. Standard errors clustered at the school level; observations weighted by sampling probability
Test score regressions all control for baseline pretest scores. Posttest scores are normalized by substracting the mean.
and divided by the standard deviation of the control group pretest.
Columns 3-9: Sample matched to baseline perceived returns data.
+ significant at 10%; * significant at 5%; ** significant at 1%

Appendix Figure 1: Extensive-Form Representation of the Game

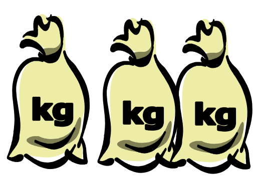
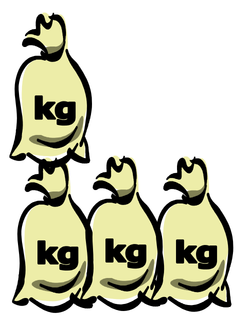
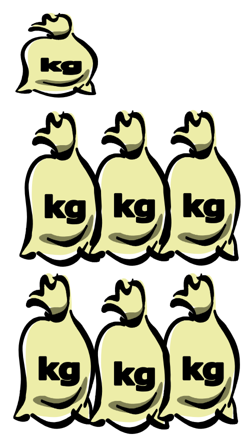
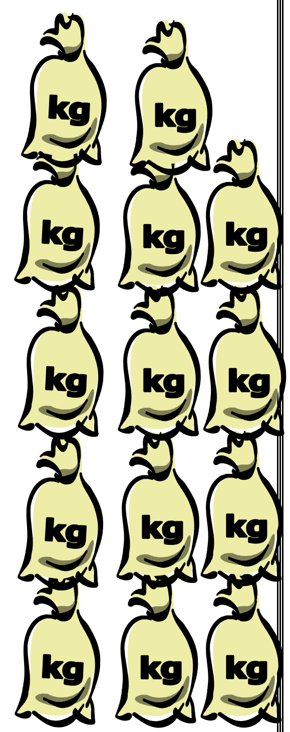


Appendix Figure 2: Information Card

Ministry of Education

RETURNS TO EDUCATION IN MADAGASCAR 2005

This table presents the average monthly income (in ARIARY) of 25 year-old Malagasies, by gender and by different educational levels.

.	**Without any degree**	**Primary school with CEPE**	**Lower secondary school with BEPC**	**At least high school with BAC**
Female	**34 524 Ar**	**44 119 Ar**	**73 771 Ar**	**163 344 Ar**
Male	**47 637 Ar**	**60 877 Ar**	**101 793 Ar**	**225 389 Ar**
Gain				

Source :Calculations from the 2005 Household Survey

Notes: The columns represent education levels (CEPE, BEPC, and BAC are the corresponding degrees); the rows give the mean earnings from household survey. 1 USD = 2000 Ar. The gain from education is illustrated by increased numbers of rice bags.