Income Shocks, Child Fostering and Education in Senegal

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Abstract

This paper examines the practice of child fostering in Senegal. Specifically, it looks at the treatment that fostered children are subject to in their host families relative to their host siblings. It compares the effect of exogenous income shocks on biological and fostered children in the same family. This comparison reveals whether there is a differential in educational investment between the two groups while accounting for any gap in treatment that might exist at baseline. Fluctuations in household economic conditions significantly change three variables for fostered children: their ability to read and write, their school enrollment, and their primary school completion rate. On the other hand, for biological children, these same metrics are mostly unchanged whether the shock is positive or negative. This leads to positive shocks shrinking the differences in educational ability, school enrollment and future earnings between the two groups by 0.21 points, 16 p.p. and 35 basis points respectively; negative shocks worsen the gap between them in the same magnitude. These results indicate that fostered children are less insured than their host siblings, although there is no difference in educational outcomes between the two groups absent any shock.

Keywords: Senegal, Children, Fostering, Education, Income Shock.

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1 Introduction

Child fostering is the practice of sending children to host households with whom the family has biological or social ties. This institution, unlike foster care in developed countries, uses more informal fostering processes and is less concerned with legal protections (Abebe 2011, Blackie 2014). The phenomenon is prevalent in many West African countries[1]. In our representative sample, as of 2011, 34.4 per cent of the households in Senegal had at least one fostered child living with them and 17.9 per cent of families had at least one of their biological children living elsewhere, for a total of 45.8 per cent of household participating in fostering. In addition, 12 per cent of all adults were once fostered children before they turned 15 years old. Children are mainly sent away for the following four reasons: to give them a chance to have better opportunities to attend school and further their education, to correct for gender imbalances within a household, to deal with negative aggregate shocks, and to assist other households in their household chores (Akresh 2009). Similarly, when households experience positive aggregate shocks, they are in a position to take in fostered children for the purpose of strengthening ties with other members of the same network.

The integration of non-biological children into a household is a complex process. The non-biological children are far away from their biological mothers and will miss out on the mother-child relationship that some deem crucial to their personal growth. Moreover, the evolutionary science's kin selection theory implies that parents are generally predisposed to care more about their biological children and invest more in them. This would incentivize them to follow discriminatory practices, such as giving relatively more house duties to the fostered children and/or investing less in their education (Pilon 1992). These are some of the reasons numerous international organizations, as well as many economists[2], are against

[1] As of 2006, 12.5 per cent of Senegalese children aged less than 18 years were fostered children, 32 per cent of households either sent or received fostered children, and 14 per cent of adults had been fostered in their childhood. Additionally, in the West African region, the percentage of households hosting a foster child varied between 15 to 26 according to the latest Demographic and Health Surveys (See Marazyan et al. 2011).

[2] See Bledsoe and Brandon 1989, Haddad and Hoddinott 1994, UNICEF 1999, Lin and McCanahan 2000, Kielland and Sanogo 2002, Bisha et al. 2003.

this phenomenon. Proponents of fostering[3] emphasize the social returns to the practice and claim that fostered children are no worse off than their host siblings in their host families.

Analyzing the treatment that fostered children receive and the potential discrimination they might be subject to can be challenging. This is because comparing the treatment of biological and non-biological children at any one point in time does not provide information about the human capital investment that the two groups received at baseline. A more accurate analysis would look at resource allocation at the margin, which reveals the investment that these children would receive had they started with the same initial endowment. Indeed, income shocks, which are common in developing countries, help assess the determinants that matter the most in the grand scheme of deciding whether and how much to invest in a child's education when there are children of different statuses living in the same household.

The aim of the paper is therefore twofold. Firstly, it focuses on exogenous income shocks that households' experience to study the marginal investment that both biological and non-biological children receive. In doing so, it answers the following questions: Is there a differential in treatment in the way parents allocate resources between biological and non-biological children when income shocks hit? Does this treatment differential translate into a discrepancy between the educational enrollment and attainment of biological children and those of fostered children? Does the gap in educational outcomes lead to earnings differential in the future? Secondly, the paper analyzes fostering as an insurance mechanism for households and looks at how household composition changes as a result of shocks: Do households foster in children in good times and out in bad times?

To study these questions on fostering decisions and on the discrimination that it potentially creates, I write a model for utility-maximizing parents who wrestle with the decision to invest in the education of their children, both biological and non-biological, when income shocks hit. The first hypothesis of the model is that changes in household income correlate positively with changes in investment in education, but that the effect is smaller for non-

[3] More details about the basis of this view are given in the literature review section.

biological children. The second prediction of the model is that households foster in when they experience good shocks and foster out in bad times. This second hypothesis would mean that fostering acts as an insurance tool and send children to live with other households that are in better economic conditions. To test these predictions, I rely on a rich panel data on households in Senegal, a Sub-Saharan African country where 77.5 per cent of the labor force are in the agricultural sector[4].

The rest of the paper is organized as follows. Section II reviews the existing literature on child fostering and on differences in investment in the education of biological and fostered children. Section III discusses the model at length, and Section IV discusses the data used for the study. Section V analyzes the methodology of the paper, and Section VI presents and discusses the results. Concluding remarks are offered in Section VII.

2 Literature Review

There exists a strong literature on the rationale behind parents' decisions to participate in child fostering in Sub-Saharan Africa. Isiugo-Abanihe (1985), Zimmerman (2003) and Serra (2009) find evidence that enhancing a child's human capital investment is a motive for parents sending their children to environments where they have access to better healthcare and more learning opportunities. As Zimmerman says, "They tend to move from homes that have difficulty enrolling them in school to homes that are more apt to do so" (Zimmerman 2003, p.557). Anthropologists, demographers and sociologists have also looked at the labor aspect of fostering. Goody (1982), Oppong and Bleck (1982) and Ainsworth (1996) support the narrative that child fostering persists to correct for gender imbalances to have about an equal number of both genders and maximize household production in terms of chores given to girls (cooking, cleaning, getting water, etc.) and those associated with boys (farming, getting firewood, taking care of the livestock, etc.). By the same token, Akresh (2009) uses data he collected in Burkina Faso to posit that households send their children to other members of

[4]See CIA Factbook on Senegal: https://www.cia.gov/library/publications/the-world-factbook/

their biological or social network as a way to deal with negative aggregate shocks.

Fostering can act as an insurance tool where most models of insurance generally fail. Firstly, it allows households to insure against aggregate shocks when they are not in the same location and face different types of aggregate shocks than other m members of the same biological or social networks. Secondly, it does not suffer from adverse selection – households not being able to tell which family, among their network, is a good risk and which is not – and moral hazard – households not working hard to maximize outcome as a result of getting insured though fostering . Similar to insurance through inter-village marriages, enforcement is not an issue in the context of fostering because fostered-out parents can always rely on their biological children to get information about the risk and effort level of individuals in the receiving families.

It might also seem counterintuitive that parents would ever want to foster in, given that they could allocate the extra resources to their other biological children, invest in assets or buy durable goods instead. However, these households live in collectivist societies where social conventions give a high importance to social ties and social networks. They also live in an environment where earnings tend to be volatile, meaning that a household can experience a positive shock one year only to find itself with a negative shock the following year. In the data used for this study, comparing 2006 and 2011, 60 per cent of the adoptive households in 2006 were no longer involved in the practice of fostering by 2011 whereas 20 percent of the non-participating families in 2006 were fostering in or fostering out children five years later. As such, it is crucial for these households to maintain their social ties with the other members of their network by taking in their children whenever needed.

These papers analyze why fostering is still prevalent in Sub-Saharan Africa; many other studies address the effectiveness of fostering. These studies focus on the treatment that fostered children receive in their host families, but the findings are mixed. Vandermeersch (2002), Marcoux (1994), Lloyd and Gage-Brandon (1993) all find that fostered children fare worse than their host siblings in terms of household chores, school enrollment and school performance. But, it was not until recently when more extensive data was collected and made available that a different narrative started emerging from the studies on fostering. For example, Beck, De Vreyer, Marazyan et al. (2014) focus on the schooling and household chores of children in Senegal and posit that fostered children are treated as well as their host siblings. Hamilton, Cheng and Powell (2007) rationalize this positive absence of discrimination with the idea that fostered-in parents enrich the lives of their non-biological children to make up for the lack of biological ties, the absence of the mother-child relationship and the psychological cost of being sent away that these children might suffer. Much like Becker, Murphy and Tamara (1990), they draw upon the Becker and Lewis (1978) quantity-quality model in which parental human capital investment in children is purely motivated by parental altruism.

At the same time, these studies are all one-time studies of cross-sectional data. They draw conclusions about the existence, or lack thereof, of a discrimination only in absolute terms since it is impossible to know the level of investment for the two groups if there is no information about them at baseline. The studies do not tell how the biological children were doing before the arrival of the fostered children, or how the fostered children were being treated in their native households. The fact that these studies do not account for the reference point of the two groups of children in terms of investment received for education means the conclusion drawn from them could be misleading. They do not provide information on how much better or worse off the two groups of children are in relation to their starting points.

For the non-biological children, Akresh (2009) deals with this issue of different reference points by comparing the wellbeing of fostered children and that of their biological siblings left behind. He uses school attainment, school performance and amount of household chores as proxies and states that, while fostered children in Burkina Faso might be doing worse than their host brothers and sisters, they would be worse off had they stayed in their native households. As for the biological children, an application of the quantity-quality trade-off model of Becker (1973) to fostering suggests that bringing fostered children in the household would leave the biological children worse off. In other words, households face a scarcity of resources which means that whenever they choose to take in more children, the existing children see a decrease in the investment they receive because they now have to share the fixed amount of resources with more people. On the other hand, this quantity-quality trade-off has been missing in many empirical settings (see Angrist et al 2005, Shultz and Joshi 2007, Qian 2009). Since a one-time snapshot analysis does not provide evidence for or against this quantity-quality tradeoff, any conclusion draw from these studies on the effect of fostering on biological children would seem incomplete.

The main contribution of this paper is that it gives a more representative picture of the effect of fostering on adopted children and their host siblings. Here, the issue of reference point is moot because I use panel data that allows me to know the investment that the children are getting at baseline and track said investment as household income changes. The investment that both fostered and biological children receive in the future can then be compared to their reference point at baseline. In this way, finding that there is a gap between the investment that the two groups of children receive in the second period is not necessarily a bad outcome if this gap is less than what it was at baseline. Using a panel data also allows to control for household and individual fixed effects. Indeed, households' and individuals' specific traits could be sources of biases in the matching process between fostered-out children and fostered-in parents[5].

Another addition of this paper is that it compares the differential in treatment between biological and non-biological children to that between biological boys and girls. The discrimination that girls are subject to is well documented in the literature. Indeed, scholars have extensively studied whether changes in household economic conditions leads to a different treatment of boys versus girls. For example, Foster (1995) finds that girls' well-being is more responsive to changes in prices of goods and to variations in household income than that of boys. Rose (1999) finds a positive correlation between positive rainfall shocks in childhood

[5]The Methodology section of this paper presents more details on this fixed effect analysis.

and the likeliness that girls survive relative to boys.[6] One natural question to follow up with is to ask whether the narrative for non-biological children is similar to that of girls in terms of the discrimination to which they might be subject.

3 Model

The model seeks to answer three questions: How does the investment that non-biological children receive compare to that of biological children? How does this investment in education change as household income fluctuates? How do fostering decisions change as income shocks hit?

Before laying out the basics of the model, it is worth mentioning that it ignores the possibility of parents being purely altruistic in their decision to invest in human capital, as Becker, Murphy and Tamara (1990) suggest. Rather, it describes the intra-family transfer behavior as an exchange-based quid-pro-quo, meaning that parents looks at it as if they are making loans to liquidity-constrained children at early ages expecting to be paid back in the form of money transfers and services at old age (Cox 1987, Cox 1990, Cox and Ranks 1992, Lillard and Willis 1996).

3.1 The Set Up

The model is a two-period model in which the overall utility of the parents, presented as follows, depends on their utility today and tomorrow:

$$u = u(c_t) + \beta u(c_{t+1}) \tag{1}$$

This household utility depends on consumption in the current period and on consumption tomorrow.

[6] As for the differential in health investment, the narrative is also similar: Behrman (1988) finds that the gap between the standardized nutritional level of girls and boys widens as the agricultural season goes from peak to lean.

The utility today is:

$$u(c_t) = \log c_t \tag{2}$$

The consumption function need be a concave function. This is because a linear function would mean that the parents will put all their resources into consumption if the marginal utility from investing in children's human capital is lower than that from consumption. Likewise, they would invest in children's education only if it provides them with higher utility. This would lead to corner solutions and would defeat the purpose of the model. I choose the logarithm function for the consumption function but the conclusions from the model would be unchanged had I chose another type of concave function.

Let N be the total number of children, both biological and non-biological, in the household at time t and y^k_{t+1} be the future income of child k in period $t+1$. y^k_{t+1} depends on h^k_t, the child k's human capital (schooling level) in period t, and is given by the function $y^k_{t+1} = \sqrt{h^k_t}$[7]. This income function displays decreasing returns to schooling, which should be reflective of the fact that parents prefer allocating evenly among children and give them reasonable schooling level with decent returns rather than put all the investment in one child and let her get a high schooling level with marginally minimal returns. I do not include the child's natural ability to excel at school in the model.

The utility in period $t+1$ depends on transfers from children. Let θ_k be the fraction of child k's income that parents will receive in the future. θ_k depends on the probability of receiving transfers from kid k in the future, as well as on the frequency of the transfers[8]. The parental utility in the future is as follows:

[7] Note that this function does not need to take this specific form. I could raise the function any power between 0 and 1 or I could use a logarithm function instead. This would not change the results of the model.

[8] In period t, the value of θ_k is based on perception since the transfers occur only in period $t+1$.

$$u(c_{t+1}) = \log\Big(\sum_{k=1}^{N} \theta_k y_{t+1}^k\Big)$$
$$= \log\Big(\sum_{k=1}^{N} \theta_k (h_t^k)^{1/2}\Big) \tag{3}$$

The overall utility of the parents can now be expressed as:

$$u = \log(c_t) + \beta \log\Big(\sum_{k=1}^{N} \theta_k (h_t^k)^{1/2}\Big) \tag{4}$$

The constraint that the household faces is:

$$rN + \sum_{k=1}^{N} h_t^k + c_t \le y_t \tag{5}$$

$$n_f \ge 0 \tag{6}$$

$$n_b \ge 0 \tag{7}$$

$$h_t^k \ge 0 \tag{8}$$

$$c_t \ge 0 \tag{9}$$

r is a fixed cost that the parents incur for raising a kid and is the same for all children in the household. n_b is the total number of biological children in the family and n_f is the number of non-biological children the parents fostered in. y_t is the income of the parents in period t and it is taken as exogenous in the model. Since I expect to get interior solutions for the investment in children's education, the number of children fostered in and out, and the household consumption level, the last four constraints (equations ((6), (7), (8) and (9)) are not binding because nobody will be up against the constraint of receiving zero investment and consuming nothing. As such, these constraints are ignored when the model is solved.

3.2 Optimal Investment Allocation with N=2

I now aim to find the optimal investment that each child should receive for their investment. Let us assume that the family only has two children, one biological and one fostered. This means that $n_b = 1$, $n_f = 1$ and $N = 2$. Parents seek to find, for their children, the schooling level that maximizes their own utility over the feasible set defined in equation (5). Therefore, the maximization problem that the parents solve is as follows:

$$\begin{aligned} \underset{h_t^b, h_t^f, c_t}{\text{Max}} \quad & u = \log c_t + \beta \log \left(\theta_b (h_t^b)^{1/2} + \theta_f (h_t^f)^{1/2} \right) \\ \text{s.t.} \quad & 2r + h_t^b + h_t^f + c_t \leq y_t \end{aligned}$$

The Lagrangian is given by:

$$\mathcal{L} = \log c_t + \beta \left(\theta_b (h_t^b)^{1/2} + \theta_f (h_t^f)^{1/2} \right) + \lambda [y_t - 2r - h_t^b - h_t^f - c_t] \tag{10}$$

Solving this Lagrangian yields:

$$\frac{\partial \mathcal{L}}{\partial h_t^b} = \frac{1}{2} \frac{\beta \theta_b (h_t^b)^{-1/2}}{\theta_b (h_t^b)^{1/2} + \theta_f (h_t^f)^{1/2}} - \lambda = 0 \tag{11}$$

$$\frac{\partial \mathcal{L}}{\partial h_t^f} = \frac{1}{2} \frac{\beta \theta_f (h_t^f)^{-1/2}}{\theta_b (h_t^b)^{1/2} + \theta_f (h_t^f)^{1/2}} - \lambda = 0 \tag{12}$$

$$\frac{\partial \mathcal{L}}{\partial c_t} = \frac{1}{c_t} - \lambda = 0 \tag{13}$$

$$y_t - 2r - h_t^b - h_t^f - c_t = 0 \tag{14}$$

I use equations (11) and (12) to have:

$$\frac{\theta_b}{(h_t^b)^{1/2}} = \frac{\theta_f}{(h_t^f)^{1/2}} \tag{15}$$

$$(h_t^b)^{1/2} = \frac{\theta_b (h_t^f)^{1/2}}{\theta_f} \Rightarrow h_t^b = \left(\frac{\theta_b}{\theta_f}\right)^2 h_t^f \tag{16}$$

I use equation (16) to rewrite equation (11) as:

$$\frac{\partial \mathcal{L}}{\partial h_t^b} = \frac{\beta}{2}\left(\frac{\theta_b}{\theta_b h_t^b + \frac{\theta_f^2}{\theta_b} h_t^b}\right) = \lambda \tag{17}$$

With this value of λ, I get:

$$c_t = \frac{1}{\lambda} = \frac{2}{\beta} h_t^b + \frac{2}{\beta}\left(\frac{\theta_b}{\theta_f}\right)^2 h_t^b \tag{18}$$

I plug the identity from equations (16) and (18) into equation (14) to get:

$$\Rightarrow y_t - 2r - \left(\frac{\theta_f}{\theta_b}\right)^2 h_t^b - h_t^b - \frac{2}{\beta} h_t^b - \frac{2}{\beta}\left(\frac{\theta_f}{\theta_b}\right)^2 h_t^b = 0 \tag{19}$$

$$\Rightarrow y_t - 2r - \left(\frac{(2+\beta)(\theta_b^2 + \theta_f^2)}{\beta \theta_b^2}\right) h_t^b = 0 \tag{20}$$

$$\Rightarrow (h_t^b)^\star = \left(\frac{\beta}{2+\beta}\right)\left(\frac{\theta_b^2}{\theta_f^2 + \theta_b^2}\right)(y_t - 2r) \tag{21}$$

Let I_k be the investment in the education of child k. I_k corresponds to the child's optimal schooling level $(h_t^k)^\star$. (21) implies:

$$I_b^\star = \left(\frac{\beta}{2+\beta}\right)\left(\frac{\theta_b^2}{\theta_f^2 + \theta_b^2}\right)(y_t - 2r) \tag{22}$$

Using (15) and (21), I then get gives:

$$I_f^\star = \left(\frac{\beta}{2+\beta}\right)\left(\frac{\theta_f^2}{\theta_f^2 + \theta_b^2}\right)(y_t - 2r) \tag{23}$$

(22) and (23) show that the investment that each child receives depends on the parental

income, the total cost of raising the children but is determined by the rate of transfers of the child.

Let $\xi_f = \frac{\theta_f^2}{\theta_f^2+\theta_b^2}$ and $\xi_b = \frac{\theta_b^2}{\theta_f^2+\theta_b^2}$. This implies:

$$I_k^{\star} = \xi_k \Big(\frac{\beta}{2+\beta}\Big)(y_t - 2r) \tag{24}$$

Since I cannot derive the specific value of θ for the two children in the model, I rely on the existing literature and on the data used for this study[9] to make an assumption about which one of the two individuals should have a higher transfer rate. As noted in the introduction, there seems to be a frequent movement of children between host parents and biological parents. This means that fostered children do not necessarily stay with their host parents for an extended period of time. As such, a host parent might invest in their non-biological children only to see them leave and go back to their native households before recouping the returns to their investment. This would mostly likely reduce or completely cut the tie between the fostered child and the fostered-in parents, making it more unlikely that transfers will happen in period $t+1$.

On the other hand, there is also the argument that a biological child might very well leave the family to join another household in future periods in the case when the family experiences negative shocks. The relationship between the biological child and her parents might then weaken in the process of distancing herself from her native home. However, the temporary nature of fostering implies that biological children, even when fostered out, are not away from their parents for too long and will eventually return back home, making it unlikely that they will not transfer any money to their biological parents will occur in the future.

Moreover, one could argue that biological children naturally have a stronger affinity towards their biological parents than fostered children have towards their host parents because

[9] Section II and Section IV cover, in more details, the content of the data used for this paper and findings from the existing literature on fostering.

the biological children naturally love more and care more about their parents. Therefore, regardless of the income level of the two groups in the future and their location in period $t+1$, non-biological children might be less likely to transfer money and take care of their host parents than their host siblings.

With this assumption that θ_b is higher than θ_f, $\xi_b > \xi_f$ and this means that $I_b^\star > I_f^\star$. I therefore arrive at the first statement of the model:

Statement 1: *For a given level of income, parents invest more in biological children than in fostered children.*

So, for a given income, the model predicts that biological children receive a higher investment for their education, which means that there is a level difference, in favor of biological children, in the resource allocated to the two groups of children.

In addition, ξ_k is positive since all the terms it depends on are positive. It therefore follows that $\frac{\partial I_k^\star}{\partial y_t} = \xi_k\left(\frac{\beta}{2+\beta}\right) \geq 0$, which leads to the following statement:

Statement 2: *Investment in education is increasing in household income for both biological and fostered children.*

The assumption that that θ_b is higher than θ_f also means that $\xi_f\left(\frac{\beta}{2+\beta}\right) < \xi_b\left(\frac{\beta}{2+\beta}\right) \Rightarrow \frac{\partial I_f^\star}{\partial y_t} < \frac{\partial I_b^\star}{\partial y_t}$. This leads to the following statement:

Statement 3: *The effect of income shocks on investment in education is smaller for fostered children relative to their host siblings.*

This subsection could easily be modified into a general proof by considering the fact that the model is set up such that all children have the same traits except for their biological vs fostered status. This means that all children in the same category (biological or fostered) have the same rate of transfer and would bring in the same return for the parents in period $t + 1$. Moreover, these children with the same status receive the same human capital investment given that the human capital function has decreasing returns. Thus, all children of the same status would be indistinguishable from one another and the general maximization problem would be as follows:

$$\begin{aligned} \underset{h_t^b, h_t^f, c_t}{\text{Max}} \quad & u = \log c_t + \beta \log \left(\theta_b n_b \sqrt{h_t^b} + \theta_f n_f \sqrt{h_t^f} \right) \\ \text{s.t.} \quad & Nr + n_b h_t^b + n_f h_t^f + c_t \leq y_t \end{aligned}$$

The statements from this general model would be the same as in the model with $N = 2$.

3.3 Household Fostering Decisions

I now aim to answer the following questions: How does the number of fostered children in the family change as household economic conditions fluctuate? How does the number of biological children send away vary depending on the nature of the income shock?

3.3.1 Decision to Foster in

Finding the optimal number of fostered children is akin to dealing with the quantity-quality tradeoff detailed in the literature review. This is because the household has to choose between quantity and quality of investment. They could either invest all the resources into the education of the biological child, give her a chance to have a high quality of education and reap benefits from her subsequent high earnings in the future. They could alternatively let in non-biological children, spread out the entire investment across the different children to maximize the number of children from whom they will be getting transfers in the future, although the transfer per child might be lower because of the relatively low investment these children would each receive.

I am specifically interested in the correlation between income shocks and households' decision to receive in children from elsewhere. I therefore look at the interaction between income and the number of fostered children from the optimal utility function, which is derived using the optimal children's human capital investment and the optimal household consumption level from the general maximization problem.

The household has n_f fostered children and n_b biological children living with them, which means that $N = n_b + n_f$. n_b is exogenous in period t The budget constraint expressed in (5) becomes:

$$r(n_b + n_f) + \sum_{k=1}^{N} h_t^k + c_t \leq y_t \tag{25}$$

Let us assume that all children within the same group k have homogenous characteristics and have the same optimal schooling level h_t^k. This means that $\sum_{k=1}^{n_f} (h_t^k)^{1/2} = n_f (h_t^f)^{1/2}$ and $\sum_{k=1}^{n_b} (h_t^k)^{1/2} = n_b (h_t^b)^{1/2}$. Equation (25) now becomes:

$$r(n_b + n_f) + n_b h_t^b + n_f h_t^f + c_t \leq y_t \tag{26}$$

The maximization problem of the household then becomes:

$$\begin{aligned} \underset{h_t^b, h_t^f, c_t}{\text{Max}} \quad & u = \log(c_t) + \beta \log\left(\theta_b n_b (h_t^b)^{1/2} + \theta_f n_f (h_t^f)^{1/2}\right) \\ \text{s.t.} \quad & r(n_b + n_f) + n_b h_t^b + n_f h_t^f + c_t \leq y_t \end{aligned}$$

The Lagrangian is given as:

$$\mathcal{L} = \log c_t + \beta \log\left(\theta_b n_b (h_t^b)^{1/2} + \theta_f n_f (h_t^f)^{1/2}\right) + \lambda[y_t - c_t - r(n_b + n_f) - n_b h_t^b - n_f h_t^f] \tag{27}$$

The optimal investment that each group of children k should receive and the optimal household consumption level are as follows:

$$I_k^{\star} = n_k h_t^k = \Big(\frac{\beta}{\beta+2}\Big)\Big(\frac{n_k\theta_k^2}{n_f\theta_f^2 + n_b\theta_b^2}\Big)(y_t - r(n_b + n_f)) \tag{28}$$

$$c_t^{\star} = \Big(\frac{2}{\beta+2}\Big)(y_t - r(n_b + n_f)) \tag{29}$$

The overall utility of the household under this scenario is as follows:

$$u = \log\Big(\frac{2}{2+\beta}(y_t - r(n_b+n_f))\Big) + \beta\log\Big(\Big(\frac{\beta}{2+\beta}\Big)(n_f\theta_f^2 + n_b\theta_b^2)^{1/2}(y_t - r(n_b+n_f))^{1/2}\Big) \tag{30}$$

The partial derivative of this utility function with respect to income gives:

$$u_y = \Big(\frac{6+\beta}{4+2\beta}\Big)\frac{1}{y_t - r(n_b + n_f)} \tag{31}$$

The cross partial derivative of utility with respect to income and number of fostered children is:

$$u_{yn_f} = \Big(\frac{6+\beta}{4+2\beta}\Big)\frac{r}{(y_t - r(n_b + n_f))^2} \tag{32}$$

$\frac{6+\beta}{4+2\beta}$, r and $(y_t - r(n_b + n_f))^2$ are all positive parameters $\Rightarrow u_{yn_f} > 0 \Rightarrow \frac{\partial n_f}{\partial y_t} > 0$

That the last inequality stems directly from the cross partial derivative is a mathematical theorem from calculus. Intuitively, a positive cross partial derivative means that the marginal utility of fostered children increases when income increases. This implies that parents should foster in more children when y increases if they want to maximize their utility. This positive correlation between income and the number of fostered children leads to the next statement of the model:

Statement 4: *The number of fostered children is increasing in household income.*

3.3.2 Decision to Foster Out Biological Children

I now aim to determine how households' decision to send away biological children changes as income fluctuates. Specifically, I seek to assess the correlation between income and the number of biological children fostered out. Let N_b be the total number of biological children that the parents have given birth to and let n_{out} be the number of biological children fostered out to other members of the household's social and biological networks. The number of biological children that the parents raise and have to allocate resources for is $N_b - n_{out}$. I set $n_f = 0$ for the simple reason that parents would get rid of non-biological children before thinking about sending away biological ones. The total number of children that the parents are directly in charge of becomes: $N = (N_b - n_{out})$. The budget constraint expressed in (5) becomes:

$$r(N_b - n_{out}) + \sum_{k=1}^{N} h_t^k + c_t \leq y_t \tag{33}$$

The assumption that all children within the same subgroup show homogenous characteristics and that their investment is interchangeable still holds. This means that $\sum_{k=1}^{N_b - n_{out}} (h_t^k)^{1/2} = (N_b - n_{out})(h_t^b)^{1/2}$. Equation (33) can then be expressed as:

$$r(N_b - n_{out}) + (N_b - n_{out})h_t^b + c_t \leq y_t \tag{34}$$

The maximization problem of the fostered-out family then becomes:

$$\begin{aligned} \underset{h_t^b, c_t}{\text{Max}} \quad & u = log(c_t) + \beta \log \Big(\theta_b (N_b - n_{out})(h_t^b)^{1/2}\Big) \\ \text{s.t.} \quad & r(N_b - n_{out}) + (N_b - n_{out})h_t^b + c_t \leq y_t \end{aligned}$$

Solving the Lagrangian gives the following optimal investment that each biological child receives and the optimal household consumption level:

$$I_k^\star = h_t^k = \left(\frac{\beta}{\beta+2}\right)\left(\frac{1}{N_b - n_{out}}\right)(y_t - r(N_b - n_{out})) \tag{35}$$

$$c_t^\star = \left(\frac{2}{\beta+2}\right)(y_t - r(N_b - n_{out})) \tag{36}$$

The overall utility of the household then becomes:

$$u = \log\left(\frac{2}{2+\beta}(y_t - r(N_b - n_{out}))\right) + \beta \log\left(\left(\frac{\beta}{2+\beta}\right)\left(\theta_b(N_b - n_{out})^{1/2}(y_t - r(N_b - n_{out}))^{1/2}\right)\right) \tag{37}$$

The cross partial derivative of the utility with respect to income and the number of biological children fostered out is:

$$u_{yn_{out}} = \left(\frac{6+\beta}{4+2\beta}\right)\frac{-r}{(y_t - r(N_b - n_{out}))^2} < 0 \tag{38}$$

Similar to the reasoning given in the previous subsection, the negative cross partial derivative of (38) implies that $\frac{\partial n_{out}}{\partial y_t} < 0$, which leads to the last statement of the model:

Statement 5: *Parents foster out biological children when a negative shock happens.*

This statement means that parents send away biological children to other members of their network in bad times but bring them back into the household when they are hit by a positive income shock.

3.4 Summary of Predictions

In summary, the model gives me the following predictions to test:

- Parents foster in children during good times and send away children in bad times.
- Fostered children receive less investment for their education than their host siblings.

- Investment is increasing in household income.
- Positive shocks accentuate differences in investment between biological and fostered children while negative shocks close the gap between the two groups.

4 Data

To test out the model, I rely on the 2006 and 2010-2011 Enquetes sur la Pauvrete et la Structure Familiale (EPSF 2006 and EPSF 2010/2011), two datasets which are the fruits of a cooperation between the National Statistical Agency of Senegal and a team of French researchers (Centre de Recherches pour le Developpement International). The first round of the project is a comprehensive dataset that contains information on 14379 Senegalese individuals in 1774 households drawn randomly from the census data and clustered in 150 Enumerations Areas. 30 of these Enumerations Areas are in Dakar, the capital city, 56 in other cities and 64 in rural areas. In each EA, twelve households chosen randomly are interviewed. Of the people interviewed in the sample, 53.4 per cent are from a rural area and 52.5 per cent are 20 years old or less. 55 per cent of the individuals in the sample are singles (including children) and 8.6 per cent are polygamous. The second round of the dataset follows the same households as in the first round and the survey asks questions similar to those of the first round. It contains 28209 households in 3042 households, a result of the newly formed families out of those previously interviewed in 2006.

The primary goal of the dataset is to study the composition of Senegalese families, which are often fairly large and complexly structured. Studying the seemingly ambiguous and complex relationships and dynamics between the different members of households will allow for a thorough understanding of how the household deals with both idiosyncratic and aggregate shocks and why these events would affect different household members differently. As such, the study characterizes households as primary if they are chosen in the sample to be interviewed. A 'secondary household' is then a household in which lives a spouse or a co-wife of a head of household surveyed in the primary sample. Similarly, each household is divided into many clusters. A cluster is defined as a subgroup of individuals within the household whose decisions in some areas may be independent of household members outside of the subgroup. As such, a cluster is always comprised of an adult (often the head of the household or one of the wives) and other household members (wife's own children, parents of the head of the cluster, etc) who rely directly on the head of the cluster for all their expenditures. I should note that the household head has a cluster separate from that of his wife or wives.

The dataset has two main components. The first part focuses on the composition of the household, its socio-economic situation and history, the status of its children, its members who have left the family, and the health status and the employment status of its members. The second component focuses on the household's expenditures and provides information on the budgetary organization of the household, as well as on the transfers, loans, borrowings and savings of its members.

The dataset categorizes the children as biological, fostered or other non-biological. It also gives information on the parents of non-biological children in terms of their occupation, education level, idiosyncratic shocks and health level. Moreover, the dataset provides information on the fostering status, place of residence, current educational level and occupation of all the households' children living elsewhere, as well as on the host households of these children fostered out. Of these fostered out children, 66 per cent are women, 52 per cent are between 5 and 14 years old, 46.9 per cent are sent to a person of their maternal lineage and 26.9 to maternal grandmothers. The two rounds of interviews are therefore useful because they allow for a comparison between fostered and host children.

In terms of combining the two rounds together, I was able to match 12618 individuals in 1548 households, for a household attrition rate of only 12.7 per cent. 1761 individuals in 681 households in the first round were not found again in 2011 and no information was found on 15499 persons in 1374 households from the second round of the interviews.

To instrument income shock with rainfall, I use, in addition to these two EPSFs, a rainfall data from the Physical Sciences Division of the Earth System Research Laboratory of the University of Delaware in collaboration with the National Oceanic and Atmospheric Administration. It provides, from 1980 to 2010, monthly average of precipitation levels in centimeters for grids delimited by 0.5 degrees latitude by 0.5 degrees longitude from 1980 to 2010. I extract the monthly data needed for all the grids that correspond to the different districts in Senegal from 2000 to 2010.

5 Methodology

5.1 Descriptive Statistics

Before analyzing how fluctuations in economic conditions interact with the phenomenon of child fostering, I present key summary statistics that help in understanding the narrative and the rationale behind these questions of this study. These summary statistics focus on comparing families engaged in fostering-out, those involved in fostering-in and those that do not take part in this type of exchange. I then present key educational and health metrics for fostered and host children as well as for children in non-participating families. I present these numbers for both 2006 and 2011 to highlight any trend to which the phenomenon of child fostering is subject.

5.2 Methodological Issues

The independent variable of interest is household income, denoted with I_h. Since the dataset do not provide information on wages of employed household members and profits/revenues of self-working ones, I follow the methodology of Brewster et al. (2012) to get an income proxy from the ownership of physical assets by aggregating the value of the equipment, livestock, land and money deposited in banks that the household has at its disposal.

I normalize this income proxy to have a mean of zero for the sample.[10]

5.2.1 Biases with the Income Variable

The income variable is subject to many possible biases. It could be endogenous in the model because it can potentially suffer both omitted variable bias and reverse causality. The issue of omitted variable bias arises from the fact that income is most likely to be related with other unobservable characteristics that could affect the decision to foster in and out. For example, it could be that families with higher income have a stronger affinity towards children and intrinsically have a higher desire to raise children from elsewhere. Or it could be that other members of their biological or social network would want to send them their own children since their higher income puts them in a position to take better care of children. In an extreme case, it could be that the powerful position they have in their network allows them to be in charge of the entire matching process between children and households and might bias this matching process in a specific way. These situations would lead to this household with higher income getting a biased number of children or receiving the healthiest and the smartest children. As for the issue of reverse causality, It is hard to know the direction of causality for the correlation between income and number of non-biological children. A scarcity of resources could lead parents to foster out because they want to freeze out resources and smoothen household consumption, allowing them to experience little to no fluctuations in their economic conditions. On the other hand, they could foster in and out as a way to deal with good or bad fluctuations.

5.2.2 Household Fixed Effect

The panel data allow me to reframe the model to be a household fixed effect model in order to deal with the issue of omitted variable bias. While this consideration does not get rid of the issue of not being able to identify unobservable characteristics that are specific

[10] Although I could have used income per capita in the study, I stick to household income because all the variables used for the income proxy are given at the household level.

to the household, it fixes the possible bias that might arise from it. This is because the fixed effect analysis fixes household specific traits over time. Any change in the number of non-biological children would therefore be the result of factors other than these intrinsic characteristics. Note that this addition is only effective if these household characteristics are time-invariant, i.e. that they do not change over time.

5.2.3 Rainfall as an Instrument

To address the issue of reverse causality, I focus on exogenous change in income and use rainfall as an instrument for exogenous variation in household income level (See Paxson 1992). I statistically test whether rainfall is a valid identification strategy by focusing on two aspects: the existence of a first-stage, which answers the question of whether rainfall correlates with income, as well as the exclusion restriction, which checks whether rainfall is uncorrelated with any other independent variable. While an analysis of the validity of these two criteria is given in the next section, it is helpful to elaborate on why rainfall is chosen as an instrument and how it should intuitively constitute a strong candidate for specification.

For the first criterion, farmers in Senegal, much like in many other developing countries in Sub Saharan Africa, practice intensive farming and rely heavily on manual labor using little technological inputs that would enhance production. As such, the production level of these farmers, which is often their sole source of income, is mostly decided by the amount of rain that their crops receive. As for the second criterion, rainfall is an exogenous random phenomenon. The amount of rain that a land gets should be independent of any characteristics – observable and unobservable, reported and unreported – related to the landowner and her land. Therefore, rainfall should not be correlated with any of the control variables.

Of course, this lack of correlation holds with the assumption that the effort level of land tenants and the availability of technology to them are held constant across the time period of the study. A farmer A who has a good output level in 2006 with bad rainfall thanks to a good level of technology presumably keeps that high level of technology in 2011.

Likewise, a farmer B who, due to a lack of effort, obtains a low output level in 2006, even with enough rainfall, keeps the same effort level throughout. Note that the consistency in the heterogeneity of farmers in terms of their personal characteristics and environments is in line with the fixed effect component of the analysis. In addition to using rainfall as an instrument variable, I account for the relevance of agriculture and rainfall to a household's income level by interacting the IV with the binary variable of whether the family is in rural zones. Indeed, I assume that the income of those living in urban areas is not affected as much by rainfall.

I therefore define income in accordance to rainfall by normalizing, for household h in district g, the rainfall received in a given year t as follows:

$$R_{hgt} = Norm(R_{gt}) = \frac{R_{gt} - \frac{1}{N}\sum_{i=N}^{N+10} R_{gt}}{\sigma_{R_{gt}}} \tag{39}$$

The annual rainfall R_{gt} is defined as the total amount of rain between May and October of that year, which is the rainy season when agricultural activities peak in Senegal. The long-term average is defined as the mean annual rainfall between year N and year $N+10$. In our study, $N = 2000$. A normalized annual rainfall $Norm(R_t)$ lower than the long-term average is considered a bad year while a good year occurs when the difference is positive. Using district-specific long-term mean guarantees that income shocks are defined at the district level and accounts for the natural variation in rainfall level across different districts. Here, households are grouped and categorized based on their latitude and longitude, instead of the enumeration area they are part of in the survey. Households in the same square of latitude and longitude will be in the same district, even though they might be in different EAs.

5.3 Investment in Education and Educational Outcomes

I first aim to compare the investment that fostered-in parents put into the education of their biological offspring and their non-biological children and the consequences of said investment on educational ability and educational attainment of the children.

For the investment in education, the first proxy I consider is the private tutoring that children receive. I look at whether the children get extra tutoring outside of normal school classes. This information addresses the question of investment in education directly since providing tutoring to a children corresponds to investing more in her education: it shows that parents want to enhance and strengthen the child's knowledge by providing her with resources outside of her regular schooling classes. Moreover, it deals directly with resource allocation since parents have to divert resources away from other sources of consumption to meet the expenditure associated with tutoring.[11]

The second proxy I use to measure investment in children's education is the ability of the child to read, write, and perform simple calculations. This variable take on four values from 0 to 3, with 0 being assigned to the children who cannot perform any of the 3 tasks and 3 to those who can do them all. While this variable is static (once a child can read or write, the value of the variable for her should not change over time), it could capture accurately how much attention the child receives from her parents. Indeed, I can safely assume that two children of the same household attending the same type of school receive the same quality of education. Any difference in the change in their ability to write and read from 2006 to 2011 could be attributable to the relative attention they get from their parents. This could be manifested, for example, in parents speaking the official schooling language to only a subset of the children, buying books for them, watching television with them or reading stories together with them; while the other subset spends more time on household chores and other labor activities. In this case, looking at educational ability would effectively capture this difference in investment between the two groups.[12]

[11] The differential in treatment might stem from a totally rational and utility-maximizing decision. Parents might want to invest more in children who are more likely to be successful later in life to ensure that everything goes as smoothly for them as possible and to maximize their own returns. As Akresh et al. (2010) posit, it could be the case that parents only give extra resources to the smartest of their offspring to ensure their resources go to the children whom they can get the maximum returns from. On the other hand, altruistic parents might give more resources only to the children who are struggling at school to make sure they do not fall behind at school. In either case, there would be a differential in treatment not because of children's fostering status itself but because of differences in traits between fostered and biological children.

[12] Nonetheless, the difference in the educational ability could stem from a difference in the quality of education received. For example, it could be that students in private school advance faster in their educational ability than their counterparts who go to public school. But this is not an issue in this study since most of the children (97 per cent) in the dataset attend public

As for the measurement of how well children are doing at school, I choose two proxies: school enrollment (whether the child is enrolled at school), primary school completion rate (whether the child had finished primary school)[13], and the number of classes that the child has repeated[14].

For these five dependent variables, I restrict the data to children in fostered-in families and use a two stage least square model with a household fixed effect as follows:

$$Y_{iht} = \beta_1 + \beta_2 I_{ht} + \beta_3 Age_i + \beta_4 Male_i + \beta_5 F_i + \beta_6 I_{ht} * F_i + \nu_h + \nu_t \tag{40}$$

$$I_{iht} = \alpha_1 + \alpha_2 R_{ht} + \varepsilon_h \tag{41}$$

$$Y_{iht} = \beta_1 + \beta_2 \widehat{I_{ht}} + \beta_3 Age_i + \beta_4 Male_i + \beta_5 F_i + \beta_6 \widehat{I_{ht}} * F_i + \nu_h + \nu_t \tag{42}$$

(41) and (42) are the equations for the two stage least square regression, which instrumentalize income with rainfall. The dependent variable Y in equation (42) represents the five variables mentioned above on her school enrollment and educational ability and attainment. I represents the income level of individual i's household, and F is a dummy variable indicating whether the child wis fostered. Controlling for age, birth order and gender, β_2 gives the effect of shocks on the educational metrics of non-biological children while β_5 reveals whether, for a given income, there is a difference in the outcome variable between biological and fostered children, absent any shock. β_6 gives the difference in the effect of economic fluctuations on the dependent variable between biological and non-biological children. It reveals how worse off the fostered children are in comparison with their host siblings when income

schools.

[13] A caveat of using school enrollment and attainment is that the findings can suffer from bias if either of the two groups is naturally more gifted and has a higher ability than the other. For example, if the non-biological children are generally smarter and are not as challenged at school than their host siblings, then comparing their grade completion to that of their host siblings would favor them since they would tend to repeat less classes. This would lead to a downward bias in the differential in educational outcomes. Likewise if parents send only the least smart of their offspring, then the bias would be positive. An effective way to take care of these possible unobserved heterogeneity between fostered and non-fostered children is to introduce individual fixed effect. However, this would hinder the statistical power and the significance of the ensuing results.

[14] It could be that by the time a child is sent to her non-biological children, she had had many interruptions. Indeed, one of the main reasons why children are fostered for educational purposes is the existence of repeated interruptions throughout their curriculum progress in their native environment. This could be because the child has no secondary school to go to in the native area after finishing primary school or simply because the biological parents do not have the financial means to send the kid to secondary school.

shocks hit. I then run conditional regressions for (42) first considering only households in urban areas, then only those living far away from the cities.

Finally, I run conditional regressions for (40), (41) and (42), considering only biological boys and girls in fostered-in families. This is to see how the investment fostered children receive relative to biological children compares with that of biological girls relative to biological boys in the same household. This comparison would allow me to infer reasons for the potential difference in resource allocation among the different groups of children.

5.4 Fostering as an Insurance Mechanism

Finally, I aim to test the hypothesis of the model that households foster out in bad times and foster in during good times. If this hypothesis holds, then the social returns to fostering are significant because it would mean that fostering allows household to alleviate income shocks by freezing out resources during bad times and helping other households in need when positive shocks occur. In addition, it would mean that children are sent from households that have trouble taking good care of them to those in better position.

For the household fixed effect equation, I have the following reduced form equation:

$$Y_{ht} = \alpha_i + \beta R_{ht} + \mu_{ht} \tag{43}$$

Two variables are considered for the dependent variable Y. Firstly, I consider the household fostering status, a categorical variable that takes three values: -1 if the number of biological children fostered out exceeds that of non-biological fostered in, 0 if they are the same and 1 if the household fosters in more children than out. Secondly, to use a less static measure of fostering decisions, I also consider the total number of fostered children living in the household as the dependent variable Y.

Instead of household fixed effect, I also run regressions using a vector of controls $\mathbf{X_h}$ made up of household specific characteristics (such as household size, number of clusters, sex of household head, employment status and education level of household members, language spoken at home, whether the household head is polygamous and whether any household adult had been fostered when she was young, etc.). The first-stage and second-stage regressions of the 2SLS are as follows:

$$I_{ht} = \beta_1 + \beta_2 R_{ht} + \varepsilon_h \tag{44}$$

$$Y_{ht} = \alpha_i + \beta \widehat{I_{ht}} + \delta \mathbf{X_{ht}} + \eta_h \tag{45}$$

I then run conditional regressions for (43), (44) and (45) , first considering only households in urban zones, then only those living far away from the cities.

6 Results

6.1 Statistics on Households

Tables 1A and 1B provide descriptive statistics on the different types of households present in our simple. They only include the households for which at least one member is present in both waves of interviews and drop those that were not merged successfully. This leaves the number of households at 1577 out of the 1800 interviewed. The first column is on fostered-out families, which are families with at least one biological child being raised elsewhere. A biological child has the status of a fostered out kid if she is sent to an environment where her education and the investment she receives behoove the head of the receiving entity. As such, the fostered out demographics comprises children sent to Koranic school and other households but excludes those that moved away after getting married or after finding a job in a relatively far away place. This is because the latter group is more self-dependent and does not rely on any adult for a source of income and investment. In the sample, there are 96 households that are part of the fostered-out category. The second column of the two tables focuses on the 292 households that have at least one non-biological child living under their roof while the last column is reserved to the 1189 uninvolved households, which are those that do not take part in the practice of fostering at all.

Table 1A: Characteristics of Different Types of Households at Baseline

	Fostered Out	Fostered In	Not Involved
DEMOGRAPHICS			
Household Size	10.0	10.3	8.0
Number of Clusters	2.8	2.8	2.5
Number of Fostered Children	0.5	1.8	0.0
Number of Biological Children	5.9	5.0	4.7
HM Fostered Before 15 Yrs Old	0.6	0.9	0.4
HH is Male	0.8	0.7	0.8
Urban	0.5	0.6	0.5
EDUCATION AND EMPLOYMENT			
HH Completed Primary School	0.2	0.2	0.2
HM Completed Primary School	0.4	0.5	0.4
HM Are Employed	0.4	0.3	0.4
HH is Employed	0.7	0.7	0.7
HM Are Self Employed	0.1	0.1	0.1
SOCIOECONOMIC STATUS			
Net Good Shocks	-0.7	-0.3	-0.5
Consumption Risk	1.9	2.1	2.1
Relative Conditions	-0.1	0.0	0.0
HOUSEHOLD CONDITIONS			
House Ownership	0.6	0.8	0.6
Primary School ¡ 30mn away	0.9	0.9	0.8
Hospital ¡ 30mn away	0.7	0.7	0.7
WEALTH AND HEALTH			
Wealth	-0.0	0.0	0.0
Change in Wealth	5.2	4.8	9.6
Current Health	2.5	2.6	2.5
Observations	96	292	1189

Table 1A reports information from the 2006 round of the EPSF and provides information on the three types of households at baseline. It reveals any noticeable difference between the characteristics of the households that should be taken into consideration in analyzing data and interpreting results later on. Fostered-in households, with an average of 10.3 household members and 2.8 clusters, tend to have a larger family size and a higher number of clusters than the uninvolved and the fostered-out ones. The fact that they welcome non-biological children in their households causes a systematic exogenous increase in the number of people living with them. Unsurprisingly, they also have more fostered children than the two other groups, with the uninvolved having zero fostered children as expected and the fostered-out having 0.5 on average. That fostered-out families also have fostered-in children can seem counterintuitive but the nature of the exchange does not exclude families both receiving and sending away children at the same time. Secondly, households are more likely to foster in when they have at least one adult who was fostered before the age of 15, forging the idea that families sustain their strong, long-lasting and somewhat permanent social and biological ties by keeping the exchange one generation after another. Lastly, there does not seem to be any noticeable difference between the urbanization level and the likelihood of the household head being male across the three different groups at baseline.

As for the human capital of household members, the numbers seem to be homogenous across the three different groups. There is little to no difference in the employment rate of household members and in the likelihood that the head of the household completed primary school, as well as in the probability that household members are self-employed. Similarly, the household wealth level[15] and the level of health self-reported by household members do not differ much across the three categories.

On the other hand, the information on socioeconomic status and the physical conditions of the households seems to suggest that fostered-in families are doing relatively better in years prior to 2006. While there is no significant difference in risk associated with consumption[16] and the distance to the nearest school or hospital, fostered out families report having a relatively lower standard of living in their community[17], as well as a smaller number of positive shocks in the past five years[18]. Similarly, fostered-in families are more likely to own

[15]The wealth variable is normalized to have a mean of 0 in the sample.

[16]This measures the likelihood that the family will not have the financial means to meet its expected expenditures next year. A higher value means the household is facing more risk.

[17]This number is from a question that asks households how they think they are doing relative to other members of their community in terms of living conditions.

[18]This number is from a question that asks households to list any good or bad year they have experienced between 2000 and 2005, based on their own judgment, benchmark and standard. The fact that the average is negative from all the three

the house in which they currently live in.

Table 1B: Changes in Characteristics of the Different Types of Households from 2006 to 2011

	Fostered Out	Fostered In	Not Involved
DEMOGRAPHICS			
Household Size	1.1	0.7	2.1
Level of Urbanization	-0.0	0.0	0.0
Share Fostered Out	0.2	0.0	0.0
Share Fostered In	0.1	0.4	0.1
Share Not Involved	0.7	0.6	0.8
HH is Male	-0.0	-0.0	-0.0
HUMAN CAPITAL			
HH Completed PS	0.2	0.2	0.2
HM Completed PS	0.1	0.1	0.1
HM Employment Status	0.0	0.0	0.0
HH Employment Status	0.1	0.0	0.0
Self-Employment	0.1	0.1	0.1
SOCIOECONOMIC STATUS			
Net Good Shocks	0.0	-0.3	-0.2
Consumption Risk	0.2	0.1	0.1
Relative Conditions	-0.0	-0.1	-0.0
HOUSEHOLD CONDITIONS			
House Ownership	0.1	-0.0	0.0
Primary School ¡ 30mn away	0.1	0.0	0.1
Hospital ¡ 30mn away	0.1	0.1	0.1
WEALTH			
Wealth	0.0	0.0	0.0
Net Wealth	-7.0	-6.0	-7.8
Observations	96	292	1189

The idea that fostering decisions are contextual is reflected in the complementary Table 1B above, which provide information on the changes in the variables discussed above from 2006 to 2011. The table shows that, of the families that have non-biological children at baseline, 60 per cent are no longer involved in the practice. The change in status from fostered-in to uninvolved comes from the fact that the fostered-in group has relatively more negative shocks between 2006 and 2011. Similarly, 70 per cent of fostered-out families are

groups might stem from the tendency of individuals to self-report a year when it is bad opposed to when it is good.

no longer involved in the phenomenon. These changes in status across the three groups do not come from changes in the human capital of the household members[19], which are not substantial in both absolute and relative terms. Rather, the change in status seems to align with changes in wealth and in shocks experienced between 2006 and 2011.

Therefore, the main takeaway from these statistics is that while there seems to be homogeneity in the individual characteristics of household members, children seem to be moving from worse-off families to the ones which are relatively better in terms in living standard, consumption level and history of shocks. This is consistent with the prediction of the model, namely that fostering sends children from worse off families to relatively well-off ones. It is worth noting that the exchanges that take place seem to be based on short-term socioeconomic conditions more so than on the somewhat static characteristics of the households. This rationale is valid to have in an environment where the wellbeing of individuals might change substantially from one time period to another regardless of what their initial endowment and their individual strengths and traits are.

6.2 Statistics on Children

Tables 2A and 2B focus on the different types of children in the sample. Similar to the categorization at the household level, I present three groups of children: those living outside their native households (fostered children), those living with their biological parents and with non-biological siblings (biological children in families with fostered-in children) and children in non-participating households. Table 2A reports only information at baseline while Table 2B tracks changes in the variables of interest between 2006 and 2011 and allows for a difference-in-difference analysis.

Table 2A shows that fostered-in children are older and are more likely to be the first born in their native households in comparison to the two other children demographics, suggesting that sending parents tend to choose the oldest of their offspring to send away. When the

[19]These variables tend to be more static by definition. For example, the fact that the household head has finished primary school does not change from 2006 to 2011.

Table 2A: Characteristics of Children of Different Status at Baseline

	Fostered	Biological	Not Involved
DEMOGRAPHICS			
Age	11.5	10.4	9.7
Male	0.5	0.5	0.5
First Born	0.4	0.2	0.2
SCHOOL METRICS			
School Attendence	0.8	0.8	0.7
Is in Primary School	0.5	0.5	0.6
Finished Primary School	0.6	0.6	0.5
Is in Secondary School	0.1	0.1	0.1
Koranic School	0.2	0.1	0.1
Age at First Grade	7.2	6.7	6.9
Number of Classes Repeated	0.6	0.5	0.6
Can Read	0.4	0.3	0.3
Can Write	0.4	0.4	0.3
Simple Calcul	0.4	0.4	0.3
HEALTH METRICS			
Current Health	1.5	2.2	2.0
Observations	334	942	3726

motive for fostering out is to assist in household chores, it makes sense to choose, among the offspring, the one who is more ready to take on manual work. Similarly when fostering serves for educational purposes, sending parents might choose their child who is the most advanced in grade completion. These criteria are generally satisfied by the oldest of the children. On the same subject of demographics, the likelihood of the child being male, which is about 0.5 for all three groups, indicates that the gender composition of children seems balanced. This is in line with fostering being practiced to correct for gender imbalances and to have both gender be equally represented in the household.

As for school enrollment, fostered-in children are as likely to be in school as their host siblings. The metrics on school attainment are also similar: there is no substantial difference in the likelihood of being in primary or secondary school and in the probability of completing primary school. However, non-biological children tend to start school, on average, 6 months later than their host siblings while there is no substantial difference in the number of times they repeated classes. This suggests that the age at which fostered children start school, more so than the interruptions they have had, explains why they are in the same current level as their host siblings even though they are older than them.

In terms of educational ability, non-biological children are not worse off than their host siblings in their ability to read a simple paragraph, write simple sentences and perform simple math. This evidence would indicate that fostered and biological children are not far away from each other on the natural ability curve. This is contrary to the hypothesis that non-biological children could be selected such that they will be on a different spot of the ability curve than their host siblings. For example, parents sending the smartest of their offspring for educational purposes could mean that these fostered children have substantially higher intrinsic ability to do well at school and are also naturally healthier than their host siblings. The data does not seem to support such hypothesis.

The picture on natural ability is however different when the self-reported health level is considered. Biological children are half a unit healthier than their non-biological siblings. Whether this discrepancy is intrinsic in nature or a result of a differential in treatment between the two groups is up to speculation but this narrative seems to contradict the hypothesis that parents send away the healthiest and strongest of their offspring, especially when the motive of fostering is to assist in household chores.

Table 2B shows that 60 per cent of the non-biological children in 2006 have moved to another status by 2011. Some have moved back to their biological parents while others have gone on to live more independent lives, be they to be married and/or to start working. The gender composition across the three groups did not change in the five years span.

As for changes in school metrics, they are generally identical across the two groups. The changes in school enrollment status, the number of repeated classes and the ability to read, write and simple calculations are consistent across the three groups. Private school enrollment is almost non-existent across the three groups and this might be due to the availability and the relative decency of public school as well as the financial burden associated

Table 2B: Change in Characteristics of Children from 2006 to 2011

	Fostered	Biological	Not Involved
DEMOGRAPHICS			
Age	3.3	2.7	3.4
Male	-0.0	-0.0	-0.0
Share Fostered In	0.4	0.0	0.0
SCHOOL METRICS			
School Attendence	-0.2	-0.3	-0.3
Is in Primary School	0.0	0.1	0.0
Finished Primary School	0.2	0.1	0.1
Is in Secondary School	0.1	0.2	0.2
Koranic School	-0.1	-0.1	-0.1
Number of Classes Repeated	0.1	0.2	0.2
Can Read	-0.2	-0.2	-0.1
Can Write	-0.2	-0.2	-0.1
Simple Calcul	0.1	0.0	0.1
Private School	0.0	0.0	0.0
HEALTH METRICS			
Current Health	0.2	-0.1	0.1
Observations	334	942	3726

with going to private schools. It might be intriguing that a child would regress in her ability to read, write and perform calculations as these should be static skills that never go away once they are learnt. However, given that parents are usually filling the survey questionnaire for their children, they might be judging their educational ability relative to the level they expect these skills to be at. As such, one could see how a child could regress in her reading and writing skills relative to her benchmark.

The main takeaway from these two tables is that, if anything, non-biological children, albeit older, are no worse off than their host siblings in terms of education and health level. The static nature of some of the school metrics makes it hard to get a clear picture of how the human capital of the children changes from 2006 to 2011. A more thorough analysis is required to examine the possible disparities in investment received and in educational outcomes.

6.3 Strength of Instrument

Table 3 displays the correlation between income, the independent variable of interest, and rainfall, the instrument. It shows a one-centimeter increase in rain leads to a 2 p.p. increase in income, with the correlation being significant at the 1 per cent level for all households in the sample. Additionally, the coefficient of the interactive binary variable shows that the effect of rainfall is stronger for household in rural areas. This should be of no surprise since rainfall is more relevant to a person when the activity from which she generates income depends more heavily on it. As such, people in rural areas, whose sources of income are mostly farming and animal husbandry, find their fates mostly decided by the level of rain they receive. On the other hand, people in cities tend to engage more in activities in the secondary and tertiary sector and their income level has little to do with how much rain they receive. That is why the correlation appears to be stronger for families far away from cities.

Table 3: Correlation Between Rainfall and Wealth

	(1) All
Rain	0.02***
	(0.00)
Rain x Rural	0.01**
	(0.00)
Mean	−0.12
Standard Deviation	0.03
Observations	3162.00
R-Squared	0.27

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table 4 shows that, in addition to the strong correlation between rainfall and income, the exclusion restriction criterion is satisfied. Indeed, rainfall does not correlate with any of the household characteristics that will be used as controls later on. This means that whether a family experiences rainfall shocks is independent of the individual characteristics of its members, as well as its human capital, composition and structure. I therefore proceed with rainfall in the following analyses.

Table 4: Determinants of Rainfall Shocks

	(1) Rural
Household Size	0.00
	(0.00)
Number of Clusters	0.01
	(0.01)
HH is Male	-0.02
	(0.02)
HH is Polygamous	-0.03
	(0.02)
HH Completed Primary School	-0.01
	(0.03)
HM Are Employed	-0.03
	(0.03)
HM Have Bank Acct	-0.00
	(0.00)
House Ownership	-0.02
	(0.02)
Mean	0.27
Standard Deviation	0.22
Observations	738.00
R-Squared	0.01

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

6.4 Investment in Education

Tables 5A and 5B display how children's educational ability changes as a result of changes in economic conditions. 5A is restricted to fostered children and their host siblings while 5B applies to only biological boys and girls.

Consistent with the prediction of the model, 5A shows a positive effect of rainfall shocks on children's ability to read, write and perform simple calculations. As families experience a one-centimeter positive change in the amount of rain they receive, they see an increase of 0.23 units, significant at the 10 per cent level, in their children's ability to read, write and perform calculations. Since one unit of educational ability represents going from having zero skills to having one of the three skills (for example going from being an illiterate to being able to read a full paragraph or going from not being able to count numbers to performing simple calculations), these 0.23 units increase in educational ability as a result of receiving more rain are considerate. Moreover, consistent with the most recent vague of papers of fostering, there is no level difference in educational ability between the two groups of children since

Table 5A: Effect of Rainfall on Ability to Read and Write (HH FE)

	(1) All	(2) Urban	(3) Rural
Rainfall	0.23*	0.14	0.23
	(0.13)	(0.19)	(0.21)
Biological	-0.01	0.10	-0.12**
	(0.04)	(0.06)	(0.05)
Rainfall x Biological	-0.22**	-0.20*	-0.07
	(0.08)	(0.12)	(0.13)
Age	0.07***	0.07***	0.07***
	(0.00)	(0.00)	(0.00)
Male	0.12***	0.09*	0.15***
	(0.03)	(0.05)	(0.04)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	-0.83***	-0.80***	-0.88***
	(0.09)	(0.12)	(0.15)
Mean	1.18	1.47	0.86
Standard Deviation	1.17	1.16	1.09
Observations	3866.00	2043.00	1823.00
R-Squared	0.54	0.52	0.50

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

the coefficient of the dummy representing whether the child is biological is not significant at any reasonable level. This implies that for a given level of income, absent any shock, the educational ability of fostered children is not distinguishable from that of their host siblings.

Moreover, the coefficient of the interactive term, being significant and negative, suggests that biological children are barely affected by fluctuations in their household economic conditions: they only see an increase of 0.01 units in their educational ability. This means that rainfall leads to considerable changes in the educational ability of fostered children but has little effect for biological children. when there is more rain. The coefficient of the interactive term also implies that the difference in educational ability between fostered children and their host siblings shrinks by 0.22 units when the shock is positive. In other words, a negative change in rainfall exacerbates the difference in educational ability between the two groups. In addition, the age of the child, as well as her gender, seem to dictate heavily how much improvement she will see in her reading and writing skills when household income exogenously increases. Indeed, being a year older and being a male leads to an increase in ability to read and write by 19 units.

Table 5B: Effect of Rainfall on Ability to Read and Write (HH FE)

	(1) All	(2) Urban	(3) Rural
Rainfall	0.22***	0.04	0.28***
	(0.07)	(0.12)	(0.10)
Male	0.22***	0.15***	0.25***
	(0.03)	(0.04)	(0.03)
Rainfall x Male	-0.15***	-0.23***	-0.07
	(0.05)	(0.09)	(0.07)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	-0.69***	-0.60***	-0.71***
	(0.05)	(0.08)	(0.09)
Mean	1.02	1.36	0.66
Standard Deviation	1.14	1.17	1.00
Observations	7387.00	3758.00	3629.00
R-Squared	0.47	0.45	0.44

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table 5B is restricted to biological boys and girls. The table shows that rainfall correlates positively with their educational ability but the negative coefficient of the interactive term shows that the effect is much stronger on girls. Girls see an increase in educational ability of 0.22 units whereas boys only experience an increase of 0.07 units when there is a one-centimeter increase in rainfall. The story here seems to be that the nature of shock affects the investment that biological girls receive more than that of biological boys. In addition, the significance of the dummy representing whether the child is male is significant, which means that for a given level of income, boys receive more investment than girls.

Results from table 5B and 6B suggest that biological girls and non-biological children, relative to their comparison group, are significantly more affected by the shocks their households experience. A valid hypothesis to explain why non-biological children and biological girls are treated similarly relative to their comparison group is that the rate of transfer expected from kids, rather than the love/care the parents have for the children, matters more in parents's decision making process. If love/care factor was a more determinant factor in parents' decision to allocate resources between children, then biological girls should have been treated in the same way as biological boys[20]. Similarly, if the expected rate of transfer

[20]This would be be under the condition that the love that parents have for their children and the importance they give to their success in life are the same for all the children in the family and that parents do not base the love they have for their

did not matter much to parents, then they would give a similar treatment to biological and non-biological children.

I could elaborate on hypotheses explaining why the investment of biological children is unaffected by changes in economic conditions whereas that of fostered is heavily dependent on it. But the scope of the study is to recognize this difference in the effect of shocks on the fates of the two groups and examine its consequences on their lives. I therefore move to the question of whether the differential in investment between biological boys and girls translates to a difference in their school enrollment and their schooling level.

6.5 Educational Enrollment and Attainment

This section compares the educational enrollment and attainment of biological and non-biological children.

Table 7A: Effect of Rainfall on School Enrollment (HH FE)

	(1) All	(2) Urban	(3) Rural
Rainfall	0.22***	0.14*	0.20**
	(0.06)	(0.08)	(0.10)
Biological	-0.05***	-0.02	-0.06**
	(0.02)	(0.03)	(0.03)
Rainfall x Biological	-0.16***	-0.10*	-0.23***
	(0.04)	(0.05)	(0.06)
Age	-0.02***	-0.02***	-0.01***
	(0.00)	(0.00)	(0.00)
Male	0.02*	0.03*	0.01
	(0.01)	(0.02)	(0.02)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	-0.37***	-0.38***	-0.28***
	(0.04)	(0.05)	(0.07)
Mean	0.66	0.73	0.59
Standard Deviation	0.47	0.44	0.49
Observations	3866.00	2043.00	1823.00
R-Squared	0.46	0.43	0.49

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table 7A gives the effect of rainfall shocks on educational enrollment. The first coefficient reveals that, for fostered children, rainfall correlates positively and strongly with being

children on the success level they anticipate for them in the future. There would be a preference among children if love is a factor of how well parents think their children will do in the future.

enrolled at school. A one-centimeter increase in the rainfall level increases the likelihood of fostered children going to school by 22 percentage points and the effect is stronger for children in rural areas than for those in urban zones. As expected, the gender of the child, as well as her age, strongly correlates with school enrollment. The significance of the coefficient of the gender variable suggests that being a male enhances enrollment status by 2 p.p. The coefficient on the dummy on whether the child is biological is significant at the 1 per cent level and suggests that fostered children, for a given level of income, are more likely to be enrolled at school than their host siblings. However, this coefficient of 5 percentage points is little compared to the two other coefficients of interests (0.22 and 0.16).

The interactive term between rainfall level and being a biological child, which is minus 16 percentage points, implies that positive shocks lead to a significant difference in outcome between biological and non-biological children. Whereas fostered children, as a result of a positive shock, enjoy an increase in their enrollment level by 22 p.p., their host siblings only see a increase of 6 p.p., significant at the 1 per cent level, in their likelihood to enroll. Essentially, the enrollment status of biological children remains more or less steady regardless of the changes in household resources. But the enrollment rate of fostered children increases in household income. In terms of the differential in school enrollment, this finding is certainly good news when the rain shock is positive: the difference in enrollment rate between the two groups shrinks by 16 p.p. as a result for a one-unit positive fluctuation in economic resources. But a negative shock would instead accentuate the gap in enrollment status between the two groups.

The narrative is similar when the primary school completion rate of the two groups is considered. Table 8A shows that the school enrollment, the age and the gender of the child strongly and positively correlate with her probability of finishing primary school. A child will, on average, have a 0.01 lower completion rate less classes than a child who is a year younger. This means that children are less likely to have interruptions and advance to the next grade the higher their schooling level. Moreover, there does not seem to be a difference between the primary school completion rate of fostered children and that of their host siblings for a given level of income, as the insignificant coefficient on the biological dummy suggests. As for the differential in the effect of rainfall shocks between the two groups, 8A shows that fostered children see an increase of 16 p.p. in their likelihood of finishing primary school when households experience positive shocks while that of their host siblings has a smaller change of 9 p.p. This means that the gap in primary school completion rate lessens by 7 p.p. whenever the shock is positive.

Table 8A: Effect of Rainfall on Probability of Finishing Primary School (HH FE)

	(1) All	(2) Urban	(3) Rural
Rainfall	0.16***	0.15*	0.10
	(0.06)	(0.08)	(0.09)
Biological	0.01	0.05*	-0.04*
	(0.02)	(0.03)	(0.02)
Rainfall x Biological	-0.07**	-0.03	-0.06
	(0.04)	(0.05)	(0.06)
Age	-0.01***	-0.01***	-0.00**
	(0.00)	(0.00)	(0.00)
Male	0.01	0.03*	-0.01
	(0.01)	(0.02)	(0.02)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	0.07**	0.10**	0.09
	(0.04)	(0.05)	(0.07)
Mean	0.68	0.76	0.58
Standard Deviation	0.47	0.43	0.49
Observations	3749.00	1989.00	1760.00
R-Squared	0.49	0.42	0.54

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

The pattern from these results on educational outcomes seems to be uniform. First, the investment that fostered children receive, unlike that of their host siblings, depends on the fluctuations in household resources. The educational outcomes of these non-biological children are not insulated against the volatility that comes with fluctuations in household resources. On the other hand, biological children are insured against changes in economic conditions and the resources they receive stay constant regardless of the nature of the shock. Consequently, the difference in investment and educational outcomes shrinks in good times but worsens in bad times. That positive shocks lower the differential in treatment between the two groups is not in line with the prediction of the model. Rather, these findings suggest that parents do not jeopardize the resources allocated to their biological children and invest in non-biological children only if they have extra resources for them.

How much does the difference in the effect of exogenous shocks on the educational outcomes of the two groups matter in the long run? I examine this question in the next subsection.

6.6 How Much Earnings Do Children Lose due to Fostering?

I first estimate the private rate of returns to education in Senegal and use it to determine the earnings that fostered children gain relative to biological children by having a higher enrollment rate and a higher primary school completion rate whenever positive shocks happen.

I start with the specifications given by Mincer (1962) and control for the variables that Weiss (1995) deems relevant:

$$\ln Y_i = \alpha + \beta_1 S_i + \beta_2 X_i + \beta_3 X_i^2 + \beta_4 Male_i + \beta_5 E_i + \beta_5 F_i + \beta_6 S * F_i + \varepsilon_i \qquad (46)$$

Y represents the earnings of individual i, S her schooling level, X her experience level[21]. E is a dummy indicating whether the person is currently employed, F a dummy variable indicating whether the person was fostered when she was young and $S * F$ is a dummy that interacts schooling level with the fostering status of the person.

There are two main issues with using this approach to calculate the rate of returns to education. Firstly, making any causal interpretation of coefficients from a simple OLS would be overly ambitious[22]. Secondly, the observations for which we have information about earnings might be representative of a subset of the dataset with specific characteristics and

[21] I use age as a proxy for experience due to lack of information about individuals' experience level. This is consistent with the existing literature (see Arsena and Suela 2011).

[22] As Humphreys describes, this OLS model could be incomplete because of the presence of ability endogeneity and omitted variable bias, the possibility of the relationship between wages and education being non-linear and the potential for different experience premiums for people with different levels of education.

skew the results to a given direction accordingly (See Asadullah 2006). For example, it is reasonable to expect information on wage to be missing for people working in the agricultural sector, those who are self-employed or those who have lower reading/writing abilities. This would mean that only the individuals who are relatively well off report their earnings.

Despite these glaring limitations of this simple model, I stick to it for the sake of simplicity and also due to lack of data on key metrics that I could use to expand the vector of controls and make the coefficients more trustworthy. In addition, I use wealth as my dependent variable since the dataset I use does not provide information on income or profits. I restrict the analysis to the individuals no younger than 25 years old.

It is worth mentioning that the relevance and validity of this earning estimate to children in the dataset rely on the idea that the relation between educational attainment and earnings has not changed over time. While it could be easy to refute this strong assumption[23], I assume that skill prices as well as cohort quality are not vastly changing over time.

Table 10 gives the coefficients of equation (46). The private RORE are estimated at 5 per cent for both biological and non-biological children. This means that those who finish primary school, compared to those who did not, enjoy at least a 5 per cent differential in income because of the completion. In the context of our findings above, this means that a unit-positive income shock, by reducing the gap in primary school completion rate between fostered and biological children by 7 p.p., close out the gap in future earnings by at least 35 basis points. Similarly, a negative shock would increase the differential in future earnings by the same magnitude. While these 0.35 p.p. are not substantial by any means, it is good to mention that it is a lower bound of the earnings differential that I have to rely on for lack of a better measurement of educational attainment. Had there been a more explicit measure of the last class completed by the children, the earnings would be estimated more accurately. The coefficient of the fostered variable in table 10 indicates that being send away

[23]For example, one hypothesis would be that technological advancements and structural changes in job markets in Senegal has made education nowadays more rewarding than it used to be in the past. This would could a downward bias in the estimates of this model. In addition, the intrinsic abilities of the younger cohorts could vastly differ from those of older cohorts and this could lead to a bias in the current private rate of returns to education if I equate it with older RORE.

Table 10: Earnings and School Attainment

	(1) All	(2) House	(3) Urban	(4) Rural
Schooling Level	0.05***	0.05***	0.05***	-0.00
	(0.00)	(0.00)	(0.00)	(0.01)
Experience	-0.00**	-0.00**	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Experience Squared	0.00***	0.00***	0.00**	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Male	-0.16***	-0.15***	-0.24***	0.25**
	(0.05)	(0.06)	(0.06)	(0.12)
Employed	-0.02	0.04	0.01	-0.38***
	(0.05)	(0.06)	(0.06)	(0.14)
Fostered	-0.15	-0.19	-0.04	-0.55*
	(0.13)	(0.16)	(0.15)	(0.28)
Schooling Level x Fostering	0.01	0.02*	-0.00	0.05**
	(0.01)	(0.01)	(0.01)	(0.02)
Year=2006	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)
Year=2011	0.15***	-0.00	0.10*	0.43***
	(0.05)	(0.06)	(0.06)	(0.13)
Mean	1.50	1.69	1.49	1.55
Standard Deviation	1.81	1.71	1.81	1.78
Observations	5643.00	3656.00	4559.00	1084.00
R-Squared	0.03	0.04	0.05	0.02

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

to another household should not affect future earnings in any significant way. This suggests that being fostered does not manifest itself in any monetary ways in the long term. Had fostered children stayed at home, they would earn no more once they enter the labor force. Additionally, the coefficient of the gender variable suggests, perhaps rather surprisingly, than female adults earn more than male adults. But this could be due to the fact that female adults who are in the labor force might be in the upper echelon of the earnings curve.

6.7 Household Fostering Decisions

This subsection presents results on the household fostering decisions as their economic conditions fluctuates.

The results from adding household fixed-effects appear inconclusive. Table 11A shows that, when time-invariant household characteristics are controlled for, the effect of fluctuations in economic conditions on fostering status is negative for both rural and urban families. This would mean that as economic conditions improve, families are more likely to foster out

Table 11A: Wealth and Total Number of Fostered Children (HH FE)

	(1) All	(2) Urban	(3) Rural
Rain	-0.03	-0.08*	0.03
	(0.03)	(0.04)	(0.04)
Mean	0.30	0.29	0.29
Standard Deviation	0.78	0.78	0.83
Observations	3363.00	1729.00	1321.00
R-Squared	0.00	0.00	0.00

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table 11B: Wealth and Net Number of Fostered Children (HH FE)

	(1) All	(2) Urban	(3) Rural
Rain	-0.03	-0.07**	0.01
	(0.02)	(0.03)	(0.02)
Mean	0.11	0.11	0.11
Standard Deviation	0.42	0.43	0.43
Observations	3363.00	1729.00	1321.00
R-Squared	0.00	0.01	0.00

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

and have the status of fostered-out households than to foster in and be a household with non-biological children. But the correlation is insignificant at any reasonable level when the whole sample is considered. Similarly, Table 11B displays a negative but insignificant correlation between the number of non-biological children of the family and the rainfall shock they experience. This would indicate that changes in number of fostered-in children are not related to the nature of the shocks the household experiences.

The findings from the data are not consistent with the prediction of the model, which is that the more positive the shock experienced, the more non-biological children the household takes in. Firstly, the counterintuitive results seem to imply that households, all else equal, might be more inclined to foster out than foster in. This might be due to the fact that fostering out seems less altruistic than fostering in. Indeed, there is no major cost associated with sending away a child and the household benefits greatly by freeing up resources previously allocated to the child. On the other hand, the immediate costs associated with fostering in might reduce the attractiveness of and the benefits from nurturing social and biological ties, which is the main reason for fostering in. Secondly, that no definitive statement can be made out of these results might stem from the fact that more than half of the households in the data are not involved in fostering at all and this inertia makes it challenging to detect changes in fostering decisions and in the number of fostered children. In addition, 40 per cent of households in the second round of the dataset have the status of a fostered out family, which means that, between 2006 and 2011, many families have sent children away. As a result, the fostering status is more skewed to the left for the 2011 survey causing the change in fostering status to be negative.

Thirdly, it is worth to remember that some households live in remote areas and face a resource scarcity that does not allow for household members to migrate for better economic opportunities often. As such, these households would exploit the extra resources from exogenous positive shocks to send their children away for better educational opportunities and to enhance their human capital accumulation. This could explain the negative sign of the coefficient of interest in Table 11A and 11B. Lastly, network formation, which is not the scope of this study, could be such that members of the same network have the same shock patterns and experience the same types of aggregate shocks. If this is the case, then it would not be too beneficial for these households to participate in fostering given that it would not help them alleviate the risk they face against aggregate shocks.

The ineffectiveness of fostering to mitigate risk and its inability to put children in better environment severely hinder the returns to the practice. The weak correlation between the total number of fostered children and the nature of the income shock suggests that households, even when they experience an exogenous increase in their economic resources, do not foster in children from other members of their network. If anything, it seems that households send away children in good times. This means that children are not necessarily moving from families with negative shocks to those with positive shocks, implying that their host environment is no more conducive to the blossoming of their human capital than their native homes. In addition, fostering, which theoretically is a great risk mitigating tool, does not seem to be an effective way for households to alleviate shocks. This is not so much because households cannot send away children in bad times, but it is because there seems to be little willingness from them to take in children from elsewhere.

7 Discussion

7.1 Implications of Results

The paper first attempts to examine the effect of fostering on children's wellbeing by comparing the educational investment, educational attainment and earnings of biological and non-biological children. Consistent with the existing literature, it finds that, for a given level of income, there does not seem to be a difference in educational outcomes between fostered children and their host siblings.

The main finding from the paper is that fostered children appear to be less insured than their host siblings, even though there is no level difference in the ability to read and write, the school enrollment, the primary school completion rate and the future earnings between them and their host siblings. When a positive fluctuation in income occurs and freezes out resources, fostered children get to benefit more from this change. When bad times hit, these same fostered children are unfortunately more likely to be sacrificed than their host siblings. Interpreting the findings at the cross-sectional level implies that fostered children receive better treatment relative to their host siblings the higher the income of their host households.

It is therefore unsurprising that studies on this topic have yielded different results. Indeed, studies done in the context of negative shocks could come out with the finding that fostered children are treated worse than their host counterparts while these same studies would find no discrimination had they been done under positive shocks.

Finally, the paper attempts to examine the effectiveness of fostering as a risk-mitigating tool by looking at whether it helps households insure against risk by having them send away children in bad times and receive in children in good times. The inconclusive effect of shocks on household fostering status and on number of fostered children suggests that it is unclear how positive fluctuations in economic conditions affect the fostering status and the number of fostered children in the family. These results are in line with the findings in the existing literature and challenges those who advocate for the practice of fostering on the basis of its social returns.

7.2 Limitations of Study

Although the data used in the study is comprehensive in terms of the information provided, it presents a few caveats that limit the strengths of the findings. Firstly, it does not give explicit information on the wages of employed household members and the profit level of those who are self-employed. As a result of individuals' income level being unavailable, I had to rely on their sources of wealth and create a income proxy to substitute for income. The results from this paper could have yielded different and stronger results if individuals' income had been used instead. Secondly, the analyses could improve greatly if the data presented information about the school performance of children, such as their grades and their examination scores, as this would allow for the use of less coarse and static measures of the investment that children receive for their education.

Although the data used is longitudinal, it will be beneficial for future studies to have more rounds of interviews to rely upon to perform their analyses. In particular, it would be useful to track fostered children until adulthood and be able to get information on their wages, experience level and employment status. Estimates on earnings from such comprehensive data should yield better earnings estimate than the crude Mincerian approach I had to rely on in this paper.

It is also worth mentioning that the results of this paper could be biased due to the non-consideration of three important points. The first factor is the social returns to both education and fostering that could play an important role in shaping the treatment that fostered children are subject to. The second factor is the psychological costs associated with being fostered. Indeed, one could argue that, regardless of whether or not fostered children are mistreated in their host families, their level of well being is overestimated since they could suffer from homesickness (being away from their roots), missing out on the mother-child relationship or having to adapt to a new environment. This would indicate that my results underestimate the differential in well-being between fostered and host children. Thirdly, it is not rare to have parents send their children elsewhere because they have encountered issues raising them. For example, the child could be troublesome and could present behavioral issues to the parents, forcing them to send her to a more strict and rigid environment. This would imply that the discrimination that non-biological children are subject to is overestimated since the children fostered for correctional purposes could be severely mistreated.

7.3 Would Fostered Children Be Better Off Staying at Home?

A natural question to ask after looking at the differential in treatment between fostered and non-fostered children is: How would fostered children fare off had they not been sent away from their biological family in the first place. I restrict the analysis to the subset of the sample consisting only of children who are not fostered in 2006. I define as treated those who become fostered by 2011 and leave the rest as part of the control group. I use a difference-in-difference estimation to test how the gap in treatment between the two groups changes from 2006 to 2011. The difference-in-difference equation is as follows:

$$Y_{it} = \beta_1 + \beta_2 F_i + \beta_3 T_t + \rho F_i * T_t + \beta_4 Age_i + \beta_5 Male_i + \delta \varepsilon_{it} \tag{47}$$

The dependent variable Y represents two educational metrics: the last class completed by the child and the number of repeated classes. F is the treatment dummy and takes the value of 1 if the child is not fostered in 2006 and is fostered in 2011. The coefficient ρ is the coefficient of interest. It is the difference-in-differences estimate since it reveals how the gap in schooling metrics between the control and the treated group change as the treatment is applied.

Table 12: Difference-in-Difference Estimates of Educational Metrics

	(1) Educational Attainment	(2) Repeated Classes
Fostered	-0.89	0.06
	(1.28)	(0.10)
Year is 2011	0.56**	0.02
	(0.25)	(0.02)
Fostered x 2011	-1.16	-0.11
	(1.53)	(0.12)
Age	0.29***	0.04***
	(0.02)	(0.00)
Male	0.24	0.05**
	(0.23)	(0.02)
Mean	7.97	0.63
Standard Deviation	5.35	0.87
Observations	1885.00	6294.00
R-Squared	0.16	0.12

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table 12 shows the results of the difference-in-differences regressions with the dependent variables being educational attainment and number of repeated classes. Looking at the coefficient of the interactive dummy shows that the difference-in-differences estimate for both dependent variables is not statistically significant, suggesting that the difference in educational outcomes between the two groups at baseline is not statistically different from that in 2011. The two groups see similar changes in their educational attainment and number of repeated classes: 0.56 classes, significant at the 5 per cent level, in grade completion, and no significant change in the number of repeated classes. This means that fostered children would not be worse off had they stayed home. This result is not in line with the findings of Akresh (2009) who posits that fostered children would fare worse off had they stayed at home.

The reason why this very important question is relegated to the discussion section is that the fostering dummy is endogenous in the model. Indeed, it is very likely that fostering out biological children freezes out resources for the children left behind and leads to their better treatment. This would bias the difference-in-differences estimate upwards. Moreover, the stable unit treatment value assumption would not be satisfied since being part of the treatment improves the value of the dependent variable for the individuals in the control group. A more rigorous analysis would require instrumentalizing for the fostering status of the children. The data used here does not allow for such thorough study because fostered-out children cannot be matched to their biological families. The hope, however, is that this basic framework will spark future research on this specific question.

7.4 Policy Implications

Fostering acts as a good savings mechanism because it presents an opportunity for the fostered-in parents to have an additional stream of income from their non-biological children later in life. Senegal, like many other developing countries, lacks the public provision of a strong social security platform, unlike in developed countries where governments provide for people to live comfortably after retirement. Fostering therefore seems to be a natural process to go through but the governments in these developing countries, seeking to provide and formalize savings provisions, might decide to revise this informal mechanism.

In reviewing the practice of fostering, the focus should be on how to improve the outcomes of all the parties involved rather than take a side on whether to ban it or not. The fact that the practice has sustained generation after generation indicates that the individuals and families involved in it must be gaining positive returns, regardless of whether these returns can be fully captured by any rigorous model. Indeed, as the results of this paper suggest, dealing with the issue of fostering is more complex than just analyzing the level difference in treatment between fostered children and their host siblings.

The main finding of this paper is that fostered children receive a better treatment from their host parents when income increases and that this improvement in their conditions does not cause any prejudice to their host siblings. This result implies that, as economic growth strengthens and real terms GDP per capita increases in Senegal and other Sub-Saharan African countries, there should be a Pareto improvement leaving no party engaged in fostering worse off than before. It is for this reason that it makes sense to advocate for the continuing practice of fostering.

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Appendices

A Summary Statistics on Fostered-Out Children in 2006

Table A1: Characteristics of Fostered-Out Children at Baseline

	Fostered Out
BIOLOGICAL MOTHER	
Attended School	0.4
Is Employed	0.4
Is Not Working in Agriculture	0.5
BIOLOGICAL FATHER	
Attended School	0.7
Is Employed	0.8
Is Not Working in Agriculture	0.7
RECEIVING ADULT	
Attended School	0.8
Is Employed	0.6
Is Not Working in Agriculture	0.6
Is Male	0.1
CHILD STATISTICS	
Is Male	0.3
Age	14.4
Goes to School	0.4
Completed Primary School	0.7
Inactive/Unemployed	0.1
Observations	2178

Table A2: Characteristics of Fostered-Out Children in 2011

	Fostered Out
BIOLOGICAL MOTHER	
Attended School	0.4
Is Employed	0.5
Is Not Working in Agriculture	0.6
BIOLOGICAL FATHER	
Attended School	0.6
Is Employed	0.9
Is Not Working in Agriculture	0.7
RECEIVING ADULT	
Attended School	0.8
Is Employed	0.7
Is Not Working in Agriculture	0.5
Is Male	0.1
CHILD STATISTICS	
Is Male	0.5
Age	14.4
Goes to School	0.4
Completed Primary School	0.7
Inactive/Unemployed	0.2
Observations	3849

B Educational Outcomes

Table B1: Effect of Income on Tutoring Received by Biological and Non-Biological Children

	(1) All	(2) Urban	(3) Rural
Wealth	-0.02	-0.02	-0.02
	(0.01)	(0.02)	(0.02)
Biological	-0.02	-0.01	-0.03**
	(0.02)	(0.03)	(0.02)
R2_wealth_proxy_biological	0.00	0.00	0.00
	(0.02)	(0.03)	(0.02)
Age	-0.00	-0.01**	-0.00
	(0.00)	(0.00)	(0.00)
R2_male	-0.02	-0.04*	0.01
	(0.01)	(0.02)	(0.01)
Mean	0.11	0.17	0.06
Standard Deviation	0.32	0.38	0.24
Observations	2153.00	1008.00	1145.00
R-Squared	0.00	0.01	0.01

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table B2: Effect of Income on Tutoring Received by Biological Boys and Girls

	(1) All	(2) Urban	(3) Rural
Wealth	-0.00	-0.01	-0.00
	(0.00)	(0.01)	(0.00)
Male	-0.00	-0.02**	0.01
	(0.01)	(0.01)	(0.01)
R2_wealth_proxy_male	-0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)
Mean	0.08	0.13	0.04
Standard Deviation	0.27	0.33	0.19
Observations	9936.00	4550.00	5386.00
R-Squared	0.00	0.00	0.00

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table B2: Effect of Income on Ability to Read and Write

	(1) All	(2) Urban	(3) Rural
Wealth	0.05	0.04	0.16*
	(0.04)	(0.05)	(0.09)
Biological	0.02	0.16***	-0.13**
	(0.04)	(0.05)	(0.05)
Income x Biological	-0.09**	-0.11**	-0.02
	(0.04)	(0.05)	(0.08)
Age	0.07***	0.07***	0.07***
	(0.00)	(0.00)	(0.00)
Male	0.12***	0.09**	0.15***
	(0.03)	(0.05)	(0.04)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	-0.78***	-0.81***	-0.76***
	(0.04)	(0.07)	(0.06)
Mean	1.18	1.47	0.86
Standard Deviation	1.17	1.16	1.09
Observations	3866.00	2043.00	1823.00
R-Squared	0.54	0.53	0.50

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table B4: Effect of Income on Ability to Read and Write of Biological Boys and Girls

	(1) All	(2) Urban	(3) Rural
Wealth	0.00	0.02	-0.02
	(0.02)	(0.03)	(0.04)
Male	0.24***	0.19***	0.24***
	(0.03)	(0.04)	(0.03)
Income x Male	0.01	0.00	0.02
	(0.03)	(0.04)	(0.07)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	-0.57***	-0.64***	-0.51***
	(0.03)	(0.04)	(0.04)
Mean	1.02	1.36	0.66
Standard Deviation	1.14	1.17	1.00
Observations	7387.00	3758.00	3629.00
R-Squared	0.47	0.45	0.44

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table B5: Effect of Income on School Enrollment of Biological and Non-Biological Children

	(1) All	(2) Urban	(3) Rural
Wealth	0.02	0.05**	-0.05
	(0.02)	(0.02)	(0.04)
Biological	-0.03	0.00	-0.06**
	(0.02)	(0.02)	(0.03)
Income x Biological	-0.01	-0.03	0.01
	(0.02)	(0.02)	(0.04)
Age	-0.02***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)
Male	0.02	0.03*	0.01
	(0.01)	(0.02)	(0.02)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	-0.29***	-0.34***	-0.24***
	(0.02)	(0.03)	(0.03)
Mean	0.66	0.73	0.59
Standard Deviation	0.47	0.44	0.49
Observations	3866.00	2043.00	1823.00
R-Squared	0.46	0.43	0.49

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table B6: Effect of Income on School Enrollment of Biological Boys and Girls

	(1) All	(2) Urban	(3) Rural
Wealth	-0.00	-0.01	0.01
	(0.01)	(0.01)	(0.02)
Male	0.11***	0.10***	0.11***
	(0.01)	(0.02)	(0.02)
Income x Male	0.01	0.01	0.01
	(0.01)	(0.02)	(0.03)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	-0.38***	-0.41***	-0.34***
	(0.01)	(0.02)	(0.02)
Mean	0.51	0.60	0.41
Standard Deviation	0.50	0.49	0.49
Observations	7387.00	3758.00	3629.00
R-Squared	0.46	0.47	0.49

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table B7: Effect of Income on Educational Attainment of Biological and Non-Biological Children

	(1) All	(2) Urban	(3) Rural
Wealth	0.35	0.50	0.74
	(0.93)	(1.02)	(2.73)
Biological	0.57	0.68	0.16
	(0.53)	(0.64)	(0.88)
Income x Biological	-0.39	-0.51	0.03
	(0.91)	(1.01)	(2.68)
Age	0.30***	0.34***	0.13
	(0.05)	(0.06)	(0.08)
Male	-0.16	-0.38	0.34
	(0.40)	(0.48)	(0.66)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	0.19	0.56	-1.86*
	(0.52)	(0.61)	(1.07)
Mean	6.98	7.36	5.90
Standard Deviation	4.34	4.63	3.17
Observations	670.00	495.00	175.00
R-Squared	0.64	0.63	0.76

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table B8: Effect of Income on Educational Attainment of Biological Boys and Girls

	(1) All	(2) Urban	(3) Rural
Wealth	-0.06	-0.05	3.03
	(0.20)	(0.20)	(7.46)
Male	0.09	0.08	-0.16
	(0.31)	(0.37)	(0.97)
Income x Male	-0.14	-0.13	-4.59
	(0.29)	(0.30)	(7.61)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	0.79**	0.78**	1.21*
	(0.32)	(0.39)	(0.66)
Mean	7.63	8.07	6.58
Standard Deviation	4.69	4.98	3.72
Observations	1562.00	1102.00	460.00
R-Squared	0.61	0.65	0.62

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table B9: Effect of Rainfall on Number of Repeated Classes of Biological and Non-Biological Children

	(1) All	(2) Urban	(3) Rural
Rainfall	0.05	-0.23	0.23
	(0.15)	(0.20)	(0.27)
Biological	-0.01	0.06	-0.03
	(0.04)	(0.06)	(0.06)
Rainfall x Biological	0.11	0.30**	-0.11
	(0.10)	(0.13)	(0.16)
Age	0.07***	0.06***	0.07***
	(0.00)	(0.00)	(0.01)
Male	0.05	0.07	0.02
	(0.04)	(0.05)	(0.05)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	-0.09	-0.00	-0.09
	(0.10)	(0.12)	(0.19)
Mean	0.63	0.68	0.56
Standard Deviation	0.88	0.89	0.86
Observations	2538.00	1521.00	1017.00
R-Squared	0.42	0.42	0.44

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table B10: Effect of Rainfall on Number of Repeated Classes of Biological Boys and Girls

	(1) All	(2) Urban	(3) Rural
Rainfall	0.22**	0.27**	0.06
	(0.10)	(0.13)	(0.19)
Male	0.06*	0.10**	0.01
	(0.03)	(0.05)	(0.05)
Rainfall x Male	0.04	0.07	0.01
	(0.07)	(0.10)	(0.12)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	-0.11*	-0.15*	0.02
	(0.07)	(0.09)	(0.13)
Mean	0.72	0.78	0.61
Standard Deviation	0.90	0.92	0.85
Observations	4036.00	2562.00	1474.00
R-Squared	0.32	0.33	0.40

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table B11: Effect of Income on Repeated Number of Classes of Biological and Non-Biological Children

	(1) All	(2) Urban	(3) Rural
Wealth	-0.11**	-0.12**	0.10
	(0.05)	(0.05)	(0.21)
Biological	-0.03	-0.01	-0.02
	(0.04)	(0.06)	(0.07)
Income x Biological	0.04	0.04	0.06
	(0.05)	(0.05)	(0.25)
Age	0.07***	0.06***	0.07***
	(0.00)	(0.00)	(0.01)
Male	0.05	0.08	0.02
	(0.04)	(0.05)	(0.05)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	-0.02	0.00	0.02
	(0.05)	(0.07)	(0.08)
Mean	0.63	0.68	0.56
Standard Deviation	0.88	0.89	0.86
Observations	2538.00	1521.00	1017.00
R-Squared	0.42	0.42	0.44

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table B12: Effect of Income on Repeated Number of Classes

	(1) All	(2) Urban	(3) Rural
Wealth	0.02	0.03	-0.38*
	(0.03)	(0.03)	(0.22)
Male	0.06*	0.09**	0.04
	(0.03)	(0.04)	(0.05)
Income x Male	0.02	0.01	0.35
	(0.04)	(0.04)	(0.24)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	0.03	0.04	0.07
	(0.04)	(0.05)	(0.06)
Mean	0.72	0.78	0.61
Standard Deviation	0.90	0.92	0.85
Observations	4036.00	2562.00	1474.00
R-Squared	0.32	0.33	0.40

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table B13: Effect of Rainfall on Enrollment in Koranic School of Biological and Non-Biological Children

	(1) All	(2) Urban	(3) Rural
Rainfall	0.01	-0.03	0.10**
	(0.03)	(0.04)	(0.05)
Biological	-0.00	-0.01	0.02
	(0.01)	(0.01)	(0.01)
Rainfall x Biological	0.04**	0.08***	-0.05*
	(0.02)	(0.03)	(0.03)
Age	0.00***	0.00***	0.00
	(0.00)	(0.00)	(0.00)
Male	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	-0.18***	-0.14***	-0.24***
	(0.02)	(0.03)	(0.04)
Mean	0.06	0.06	0.06
Standard Deviation	0.23	0.23	0.23
Observations	3749.00	1989.00	1760.00
R-Squared	0.40	0.42	0.43

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table B14: Effect of Rainfall on Enrollment in Koranic School of Biological and Non-Biological Children

	(1) All	(2) Urban	(3) Rural
Wealth	-0.00	-0.01	0.02
	(0.01)	(0.01)	(0.02)
Biological	-0.01	-0.03***	0.02
	(0.01)	(0.01)	(0.01)
Income x Biological	0.01	0.01	0.02
	(0.01)	(0.01)	(0.02)
Age	0.00***	0.00***	0.00
	(0.00)	(0.00)	(0.00)
Male	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
Year=2006	0.00	0.00	0.00
	(.)	(.)	(.)
Year=2011	-0.16***	-0.12***	-0.19***
	(0.01)	(0.01)	(0.01)
Mean	0.06	0.06	0.06
Standard Deviation	0.23	0.23	0.23
Observations	3749.00	1989.00	1760.00
R-Squared	0.40	0.41	0.43

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

C Household Fostering Decisions

Table C1: Effect of Rainfall on Net Number of Fostered Children (2SLS with controls)

	(1) All	(2) All	(3) All	(4) Urban	(5) Rural
Wealth	0.00	0.00	0.49	-0.73	0.32
	(0.01)	(0.01)	(0.42)	(1.64)	(0.26)
Number of Clusters		-0.00	-0.01	0.04	-0.02
		(0.01)	(0.01)	(0.05)	(0.01)
HH is Male		-0.06***	-0.07**	-0.02	-0.04
		(0.02)	(0.03)	(0.13)	(0.04)
HH is Polygamous		-0.01	-0.02	-0.05	-0.01
		(0.02)	(0.03)	(0.08)	(0.04)
HH Completed Primary School		0.00	-0.08	0.13	-0.10*
		(0.02)	(0.07)	(0.23)	(0.06)
HM Are Employed		-0.10***	-0.18**	-0.05	-0.24**
		(0.03)	(0.09)	(0.10)	(0.12)
HM Speak Wolof at Home		-0.05***	-0.05*	-0.11**	0.02
		(0.02)	(0.03)	(0.05)	(0.05)
One HM has a Bank Acct		0.00*	0.00	-0.00	-0.00
		(0.00)	(0.00)	(0.00)	(0.00)
House Ownership		0.05***	0.06**	-0.07	0.06
		(0.02)	(0.03)	(0.24)	(0.04)
HM Fostered Before 15 Yrs Old		0.25***	0.27***	0.17	0.27***
		(0.02)	(0.03)	(0.16)	(0.03)
Observations	3112	3112	3112	1276	1526

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table C2: Effect of Rainfall on Total Number of Fostered Children (2SLS with controls)

	(1) All	(2) All	(3) All	(4) Urban	(5) Rural
Wealth	0.00	0.01	0.98	-0.65	0.68
	(0.01)	(0.01)	(0.82)	(2.05)	(0.51)
Number of Clusters		0.01	-0.01	0.05	-0.01
		(0.01)	(0.02)	(0.07)	(0.02)
HH is Male		-0.12***	-0.12**	-0.09	-0.08
		(0.04)	(0.06)	(0.16)	(0.07)
HH is Polygamous		0.09**	0.08	0.00	0.12
		(0.04)	(0.06)	(0.10)	(0.08)
HH Completed Primary School		-0.02	-0.17	0.08	-0.20*
		(0.03)	(0.14)	(0.29)	(0.11)
HM Are Employed		-0.19***	-0.35**	-0.13	-0.46**
		(0.06)	(0.17)	(0.12)	(0.23)
HM Speak Wolof at Home		-0.12***	-0.10*	-0.18***	-0.01
		(0.03)	(0.05)	(0.07)	(0.09)
One HM has a Bank Acct		0.00	-0.00	-0.00	-0.00
		(0.00)	(0.00)	(0.00)	(0.00)
House Ownership		0.07**	0.09	-0.01	0.05
		(0.03)	(0.05)	(0.30)	(0.08)
HM Fostered Before 15 Yrs Old		0.51***	0.53***	0.44**	0.49***
		(0.03)	(0.05)	(0.20)	(0.06)
Observations	3112	3112	3112	1276	1526

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table C3: Wealth and Increase in Number of Fostered Children (2SLS with controls)

	(1) All	(2) All	(3) Urban	(4) Rural
Wealth	-0.15	-0.22	-0.04	0.19
	(0.10)	(0.18)	(0.12)	(0.28)
Household Size		0.00	0.01**	-0.00
		(0.00)	(0.00)	(0.01)
Number of Clusters		0.02	-0.01	0.04*
		(0.02)	(0.02)	(0.02)
HH is Male		-0.01	-0.02	0.00
		(0.03)	(0.03)	(0.05)
HH is Polygamous		0.05*	0.05	0.07*
		(0.03)	(0.03)	(0.04)
HH Completed Primary School		-0.01	-0.01	0.01
		(0.03)	(0.03)	(0.06)
HM Are Employed		0.02	-0.07	0.04
		(0.06)	(0.09)	(0.07)
HM Have Bank Acct		0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)
House Ownership		-0.06**	-0.06**	-0.08*
		(0.03)	(0.03)	(0.04)
Literacy Rate of HM		-0.01	-0.01	-0.01
		(0.03)	(0.04)	(0.04)
One HM Fostered Before 15 Yrs Old		-0.03	-0.06**	-0.01
		(0.02)	(0.02)	(0.03)
HM Speak Wolof		-0.04	-0.05	0.00
		(0.03)	(0.03)	(0.04)
Observations	1556	1556	818	738
Prob ¿ chi2	0.135	0.004	0.006	0.112

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.

Table C4: Wealth and Decrease in Number of Fostered Children (2SLS with controls)

	(1) All	(2) All	(3) Urban	(4) Rural
Wealth	0.07	0.13	-0.04	-0.20
	(0.10)	(0.16)	(0.13)	(0.24)
Household Size		0.01***	0.01***	0.01***
		(0.00)	(0.00)	(0.00)
Number of Clusters		-0.03**	-0.02	-0.04**
		(0.01)	(0.02)	(0.02)
HH is Male		-0.07***	-0.04	-0.07*
		(0.02)	(0.03)	(0.04)
HH is Polygamous		0.07***	0.07*	0.06*
		(0.03)	(0.04)	(0.03)
HH Completed Primary School		0.01	-0.00	0.06
		(0.03)	(0.03)	(0.05)
HM Are Employed		-0.08	-0.04	-0.04
		(0.05)	(0.09)	(0.06)
HM Have Bank Acct		-0.00	-0.00	0.00*
		(0.00)	(0.00)	(0.00)
House Ownership		0.07**	0.08**	0.05
		(0.03)	(0.03)	(0.04)
Literacy Rate of HM		-0.02	-0.01	-0.00
		(0.03)	(0.04)	(0.04)
One HM Fostered Before 15 Yrs Old		0.19***	0.20***	0.17***
		(0.02)	(0.03)	(0.03)
HM Speak Wolof		-0.01	-0.01	-0.03
		(0.02)	(0.04)	(0.03)
Observations	1556	1556	818	738
Prob ¿ chi2	0.472	0.000	0.000	0.000

* p¡0.1, ** p¡0.05, *** p¡0.01. Standard errors in parentheses.