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Abstract

Using a two-person general equilibrium overlapping generations (OLG) model, this paper studies whether health insurance affects the impact of parental health shocks on child schooling. Individuals choose whether or not they wish to incur a medical cost by seeking care in order to reduce the effect of health shocks on their labour market availability and productivity. The theoretical results show that health shocks negatively affect schooling irrespective of insurance status. However, if the health shock is severe (incapacitating) or sudden in nature, there is a discernible mitigating effect of health insurance on the negative impact of parental ill health on child schooling. The results are tested empirically using data from the third Integrated Household Living Conditions Survey (EICV) for Rwanda, collected in 2011. Empirical findings confirm the theoretical results for health shocks to the father. Shocks to the mother, however, do not appear to significantly affect schooling.

JEL Classification: E21, I13, I25, J22, J24

Keywords: Human Capital, Economic Impact, Health Shocks, Schooling, Overlapping Generations Model, Propensity Scores.

1 Introduction

In the absence of health and disability insurance, health shocks can potentially affect households due to the income uncertainties created (Flores, et al., 2008). Health shocks are unpredictable and lead to both short-term loss of income and poverty traps (Morduch, 1995; Wagstaff, 2007; Sun & Yao, 2010). The greatest economic costs associated with illness are medical care (direct costs) and the loss of income arising from reduced labour supply and reduced productivity (indirect costs), (Gertler & Gruber, 2002; Asfaw & von Braun, 2004). In order to smoothen consumption over time, households tend to rely on several financial coping strategies (Morduch, 1995). Evidence suggests that low income households tend to finance a substantial portion of their healthcare through savings, credit and asset sales. Medical care is financed mainly through labour substitution (Sauerborn, et al., 1996).

Long-term parental health shocks might impact the education of children (Edmonds, 2006) if they are seen as substitutes in the labour market or are required to work at home (family business and domestic chores). This may suggest that, in addition to schooling, some children will be required to work (either at home or elsewhere) to supplement household income (Jacoby & Skoufias, 1997; Dercon & Krishnana, 2000; Johnson & Reynolds, 2013). However, sudden parental health shocks might result in children missing school for a brief period as the household adjusts to the shock.

Health insurance can help eliminate some direct costs, and depending on the effectiveness of treatment, some of the indirect costs mentioned above, making it possible for households to use their savings and other coping mechanisms to finance the sudden loss in revenue. For those with insurance therefore, a very large health shock would be needed to force households below the threshold point (i.e. below the minimum income level required to keep children in school). This threshold point can be described as the point beyond which the household faces catastrophic health expenditure (Xu, et al., 2003).

Although studies on parental health and its impact on children are few and far between, a very large body of literature exists on both the impact of parental death and income shocks on child schooling and household consumption. Studies on the effect of parental death (irrespective of the cause) on child labour find that, in general, the death of a parent has a negative impact on education, and in cases where the cause of death is attributed to ill health, there is a lag in education with erratic school attendance, especially in poorer households (Bicego, et al., 2003; Case, et al., 2004; Yamano & Jayne, 2004; Gertler, et al., 2004; Ainsworth, et al., 2005; Evans & Miguel, 2007; Cas, et al., 2014).

A recent study looking at the impact of parental health shock on schooling finds that only health shocks involving a father negatively affect school attendance while those involving a mother or other household member have no such effect (Alam, 2015). Bratti & Mendola (2014) on the other found that maternal health affects schooling in Bosnia and Herzegovina. Interestingly, Liu (2016) found that health shocks to either the head of the household or the spouse has a negative effect on school enrolment in rural China with insurance playing a mitigating role.

This paper builds on these different strands of literature by examining the effects of health insurance on the schooling for children. A theoretical model is built in which a household is made up of two individuals, a representative parent and a child. The parent works and makes decisions for the household. Health insurance affiliation and healthcare utilisation are treated as optional with a decision on the former taken before any health shocks are experienced. Health shocks affect the time the parent spends working and hence income earned. Theoretical results show that the impact of a parental health shock on the child's schooling depends on the intensity of the shock and whether the parent chooses to seek care or not, with health insurance playing a mitigating role only if the shock severely affects the productivity of the parent. Chronic shocks

(shocks lasting over a month) are not found to have a strong impact on the child's schooling time, irrespective of the parent's insurance status.

We test these results using data from the 2011 Rwandan third Integrated Household Living Conditions Survey (EICV). The focus is on adolescents of secondary school going age (between 13 and 18 years). Propensity scores are used to match children based on the insurance status of their parents. We study the average treatment effects of parental insurance affiliation on schooling, the effect of sudden parental health shocks on children's schooling, and the effect of health shock severity (incapacitating health shocks) on schooling. Empirical results indicate that health shocks to the father have a significant negative effect on schooling when the father is uninsured. The effect is insignificant if the father is insured. In addition, the empirical results indicate that the severity of the disease and its sudden onset are more likely to affect schooling than it becoming chronic.

To our knowledge, this is the first paper to consider the micro-dynamics of health expenditures and their effects on productivity and hence on household spending and incomes. In the presence of health shocks, the first response mechanism of households is to seek medical care in order to reduce the effect these shocks will have on their labour market productivity and hence incomes. Doing so might protect them against falling into a poverty trap. Their productivity might not be affected by the shock, especially if their medical care costs are co-financed rather than self-financed. However, when their medical expenditure is too high, they are more likely to fall into financial difficulty, with the chances of escape being slim if healthcare does not help them to recover fully. Our results add to the growing literature on the impact of parental health on child outcomes.

The rest of the paper proceeds as follows: the next section presents the theoretical model, providing hypotheses which are then tested in section 3. Results are presented in section 4, concluding with a discussion in section 5.

2 Conceptual Framework

Let us consider a two-period overlapping generations (OLG) model in which parents make decisions for their children. The household consists of one parent and one child. The parent invests in the education of their child out of altruism. Children have one unit of time which they spend either in school ($s_t^{x,y}$) or working ($l_t^{x,y}$). Note that child labour in this case includes domestic activities. Thus the time the child spends in school is defined as

$$s_t^{x,y} = 1 - l_t^{x,y} \tag{1}$$

where x, represents the parental insurance status ($u = uninsured, i = insured$) and y the health status ($n = not\ sick, s = sick$). A working child earns a fraction ($0 < \gamma \leq 1$) of the income of the parent for the same hours worked. Thus the monetary earning of the child (ω_t^c) is defined as

$$\omega_t^c = \gamma l_t^{x,y} \omega_t \tag{2}$$

where ω_t is the wage rate and $s_{t-1}\omega_t$ the wage earned by the parent. The parent has one unit of time which he/she spends in the labour market working for a wage. This labour time of the parent is affected by their health status. If they fall sick, the time spent working ($d_t^{x,y}$) can be defined as

$$d_t^{x,y} = 1 - \bar{h} f(m_t^{x,y}) \tag{3}$$

where $\bar{h} \geq 0$ is the exogenous fixed time cost of the health shock, $f(.)$ is the loss in labour time as a result of a health shock and is dependent on treatment costs ($m_t^{x,y}$) with $f'(.) < 0$ and $f''(.) > 0$. In addition, $0 \leq f(.) \leq 1$. When $f(.) = 1$ and $\bar{h} = 1$, the parent does not work, when $\bar{h} = 0$ there is no effect of the health shock on the parent's labour time or there is no health shock. Finally when $(.) = 0$, medical spending has succeeded in eliminating the impact of the health shock on parental labour time. Treatment costs reduce the effect of the health shock on the time available for work. Therefore, in the face of a health shock, parents can choose to either incur a cost in order to minimise the effect of the health shock on their working time or do nothing. The assumption here is that parents invest in their health because of the adverse effect it might have on the education of their children.

Now let us assume the existence of an insurance market where, in order to be insured, the parent will have to pay a premium, q. For this premium, they will receive a payout of $\alpha m_t^{x,s}$ where $0 < \alpha \leq 1$, when they are sick. The premium is independent of the health history of the individual. At the beginning of the period, the parent will have to decide whether to get insured or not. The budget constraints faced by a healthy and a sick uninsured parent are, respectively:

$$c_t^{u,n} = (1 + \rho s_{t-1})\omega_t + \gamma(1 - s_t^{u,n})\, \omega_t - p_t s_t^{u,n} \tag{4}$$

$$c_t^{u,s} = d_t^{u,s}(1 + \rho s_{t-1})\omega_t + \gamma(1 - s_t^{u,s})\, \omega_t - p_t s_t^{u,s} - m_t^{u,s} \tag{5}$$

Healthy and sick insured parents, respectively, face the following constraints

$$c_t^{i,n} = (1 + \rho s_{t-1})\omega_t + \gamma\left(1 - s_t^{i,n}\right)\omega_t - p_t s_t^{i,n} - q \tag{6}$$

$$c_t^{i,s} = d_t^{i,s}(1 + \rho s_{t-1})\omega_t + \gamma\left(1 - s_t^{i,s}\right) \omega_t - p_t s_t^{i,s} - (1 - \alpha)m_t^{i,s} - q \tag{7}$$

All parents have the utility function:

$$U\left(c_t^{x,y}, s_t^{x,y}\right) = u\left(c_t^{x,y}\right) + \theta u\left(s_t^{x,y}\right) \tag{8}$$

where $\theta > 0$ is parental taste for the schooling of a child. The uninsured parent will maximise equation (8) with respect to $c_t^{u,y}$, $m_t^{u,y}$ and $s_t^{u,y}$ subject to equation (4) if he/she is healthy and equation (5) if sick, while the insured parent will maximise equation (8) with respect to $c_t^{i,y}$, $m_t^{i,y}$ and $s_t^{i,y}$ and subject to equation (6) if he/she is healthy and equation (7) if sick. This gives the first order conditions of the uninsured parent as

$$\frac{u'(c_t^{u,n})}{u'(s_t^{u,n})} = \frac{\theta}{\gamma\omega_t + p_t} \tag{9a}$$

$$f'(m_t^{u,s}) = \frac{-1}{\bar{h}(1+\rho s_{t-1})\omega_t}; \quad \frac{u'(c_t^{u,s})}{u'(s_t^{u,s})} = \frac{\theta}{\gamma\omega_t + p_t} \tag{9b}$$

and that of the insured parent as

$$\frac{u'\left(c_t^{i,n}\right)}{u'\left(s_t^{i,n}\right)} = \frac{\theta}{\gamma\omega_t + p_t} \tag{10a}$$

$$f'\left(m_t^{i,s}\right) = \frac{-(1-\alpha)}{\bar{h}(1+\rho s_{t-1})\omega_{t_t}}; \quad \frac{u'\left(c_t^{i,s}\right)}{u'\left(s_t^{i,s}\right)} = \frac{\theta}{\gamma\omega_t + p_t} \tag{10b}$$

Recall that the goal of the paper is to study the possible mitigating effects of health insurance on the impact of parental health shocks on child schooling. Given the complexity of equations (9a) – (10b), there is a need to assume functional forms for both the utility function and the health function. For simplicity let us assume the parent faces a Stone-Geary type utility function where there is subsistence consumption ($\bar{c}$):

$$U\left(c_t^{x,y}, s_t^{x,y}\right) = log\left(c_t^{x,y} - \bar{c}\right) + \varphi log\left(d_t^{x,y}\right) + \theta log\left(s_t^{x,y}\right) \tag{9}$$

Accordingly, the parent obtains utility not from global consumption but from consumption beyond that required to sustain the household, $\bar{c}$. The function $f(m_t^x)$ decreases in m_t^x at a decreasing rate and is bound from below by 0 and above by 1:

$$f\left(m_t^{x,y}\right) = (1 + m_t^{x,y})^{-1} \tag{10}$$

Equilibrium

When a health shock occurs, the amount of time the parent spends working is reduced by $\bar{h}$. This leads to a reduction in parental income. In addition, parents can choose to incur a healthcare cost m_t^x, to reduce the impact of this reduction in working time. Insured parents would have already incurred a cost, which is the premium paid for insurance coverage. This covers a proportion of the cost of healthcare, α. Therefore, the equilibrium medical spending for the uninsured parent and the insured parent can be defined as:

$$m_t^{u,s} = \sqrt{\bar{h}(1 + \rho s_{t-1})\omega_t} - 1 \tag{11a}$$

$$m_t^{i,s} = \sqrt{\frac{\bar{h}(1+\rho s_{t-1})\omega_t}{(1-\alpha)}} - 1 \tag{11b}$$

The equations above indicate that when health shocks have a relatively low impact on parental work time, parents, irrespective of their insurance status, are less likely to spend money on treatment. This is because spending on treatment in this case might take away from the quality of their child's schooling (paying for books, stationery etc.) rather than contribute to reducing the effect of the health shock on their child's schooling. However, as the effects of health shocks on parental labour time increases in severity, insured individuals start to spend on health, most likely due to the fact that a portion of their health spending is refunded. Irrespective of insurance status, spending on treatment increases when health shocks reduce labour time extensively. When this occurs, health spending is more likely to affect schooling positively, as it reduces the effect of the health shock on parental labour supply and productivity.

At moderate levels, parental health shocks lead to positive spending on treatment by the insured, while the uninsured still prefer to remain untreated. However, as the effects of the health shock become more severe, the uninsured start spending on healthcare while the spending of the insured increases, mostly because a percentage is covered by insurance. What remains to be assessed is how parental health shocks affect child schooling in insured and uninsured households.

Turning our attention to child schooling, we first focus on schooling in the absence of a health shock. We obtain the following equilibrium values:

$$s_t^{u,n} = \left(\frac{\theta}{1+\theta}\right)\left(\frac{(1+\rho s_{t-1}+\gamma)\omega_t-\bar{c}}{(\gamma\omega_t+p_t)}\right) \tag{12a}$$

$$s_t^{i,n} = \left(\frac{\theta}{1+\theta}\right)\left(\frac{(1+\rho s_{t-1}+\gamma)\omega_t-q-\bar{c}}{(\gamma\omega_t+p_t)}\right) \tag{12a}$$

The two equilibrium schooling values imply that in the absence of a health shock, paying for insurance reduces schooling time. Note that, in this model it is assumed that the child either stays in school or works. In the ideal case where the child could also spend their time being idle, paying for insurance could simply lead to a reduction in idle time and not schooling time.

The equilibrium schooling times for the uninsured and the insured parents, respectively, are therefore obtained as:

$$s_t^{u,s} = \left(\frac{\theta}{1+\theta}\right)\left(\frac{(1+\rho s_{t-1}+\gamma)\omega_t-\bar{c}-1-2m_t^{u,s}}{(\gamma\omega_t+p_t)}\right) \tag{13a}$$

$$s_t^{i,s} = \left(\frac{\theta}{1+\theta}\right)\left(\frac{(1+\rho s_{t-1}+\gamma)\omega_t-q-\bar{c}-(1-\alpha)-2(1-\alpha)m_t^{i,s}}{(\gamma\omega_t+p_t)}\right) \tag{13a}$$

Proposition 1:

i. *Health shocks negatively affect schooling, i.e.* $s_t^{u,n} \geq s_t^{u,s}$ *and* $s_t^{i,n} \geq s_t^{i,s}$.

ii. *The intensity of the negative effect depends on both the severity of the shock and the parental health status:*

   a. *For relatively low health shocks, the difference in child schooling is the same for those with an uninsured parent and those with an insured parent (it is slightly higher if health premiums are high).*

   b. *For severe health shocks, child schooling is greater when parents are insured.*

Proof:

See mathematical appendix.

The results indicate a nonlinear relationship between parental health shocks and schooling. For uninsured parents, child schooling levels are higher for parents who do not experience health shocks than for those who do. This is in line with intuitive thinking and results obtained in other studies. However, when parents are insured, this effect on child schooling depends on the relative impact of the health shock on parental labour supply, that is to say, the severity of the health shock. When health shocks are low-to-moderate in intensity, their effect on parental labour supply is limited, and in such a case, having insurance will negatively affect child schooling. This is mostly because of the premiums paid relative to the co-payment rate which may lead to a larger reduction in the amount of money available for schooling. However, for severe health shocks, insured households see higher levels of child schooling compared with their uninsured counterparts.

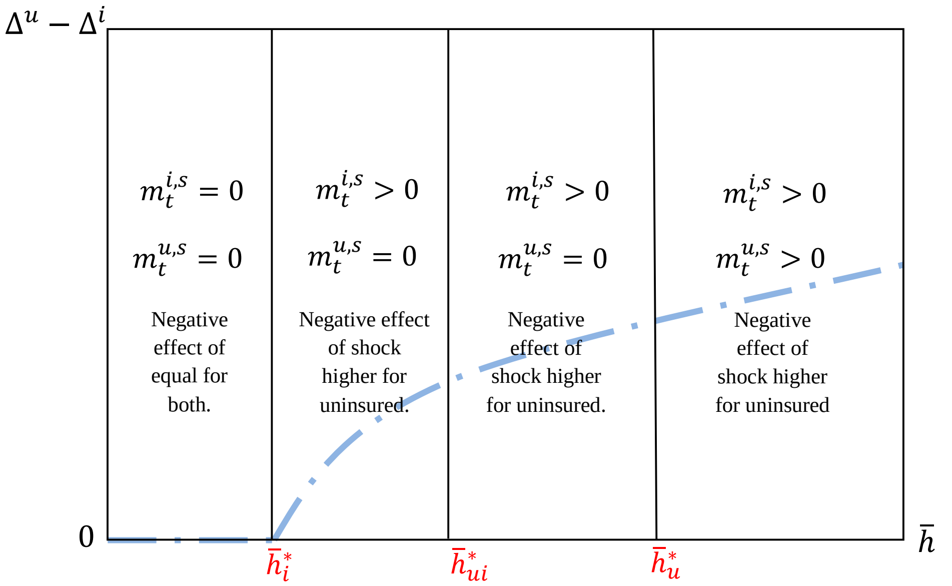

Figure 1: The impact of health shock on differences in schooling among the insured and the uninsured.

Figure 1 illustrates proposition 1 where the x-axis represents the value of the health shock and the y-axis the difference in the effect of the health shock on child schooling depending on the insurance status of the parent where $\Delta^u = (s_t^{u,n} - s_t^{u,s})$ and $\Delta^i = (s_t^{i,n} - s_t^{i,s})$. As we can see, when health shocks are low their negative effect on child schooling is equal for both insured and uninsured households. In addition, none of the parents spend on their own health, that is to say that treatment cost is zero for all groups. For moderate health shocks, the effect on schooling is the same or higher for uninsured households when the co-payment rates are 0 or positive, respectively. In this case, insured parents spend on treatment, while the uninsured do not. For severe health shocks, being insured is associated with a lower likelihood of reduced schooling time compared with being uninsured. At extremely severe health shocks, up to the point where the shock completely prevents the parent from working, schooling levels remain higher among the insured. The blue line depicts an example of the effect of health shocks on the difference in schooling between insured and uninsured households.

3 Empirical Application

From our theoretical model we posit the following: 1) children from insured households are more likely to attend school compared with their uninsured counterparts, 2) severe parental health shocks negatively affect schooling and 3) parental insurance reduces the negative impact of parental health shock on schooling time. That is to say, the slope between schooling time and parental health shock is much higher for children in households in which the parents are insured compared with those in households in which neither parent is uninsured.

3.1 Context: Healthcare Financing in Rwanda

Total health expenditure (THE) per capita in Rwanda continued to increase from approximately US$9 in 2000 to US$34 in 2006. This was largely due to the work of external financing (WHO, 2008; Saksena, et al., 2011). Approximately, 26% of the THE was financed by the households themselves, with 23% of this being OOP.

The government of Rwanda developed a comprehensive health sector plan in the 2000s, focusing on the expansion of health insurance to the informal sector in a bid to improve health access through mutual health insurance (MHI) schemes (Saksena, et al., 2011). By 2007, coverage had reached 74% thanks both the government's actions and to externally financed health insurance scale-up efforts which included the creation of premium subsidies for the vulnerable (Musango, et al., 2009; Saksena, et al., 2011).

For individuals not benefiting from subsided health insurance, a yearly premium of US $1.8[1] is collected by community health workers. This premium is subsequently transferred to the

[1] As of 2006.

respective district level MHI fund and used to pay for both in-patient and out-patient services on a fee-for-service basis (Musango, et al., 2009; Saksena, et al., 2011). Government investment for new health resources have to a large extent been allocated to curative services. Parastatal financing agents, such as *Community-Based Health Insurance Schemes (Mutuelles),* manage approximately 23% of the total health expenditures with external agents covering the remaining 27% (WHO, 2008).

3.2 Data

This analysis uses data from the third Integrated Household Living Conditions Survey (EICV 3) performed in 2011 in Rwanda. The first such survey was first conducted in 2000/01. The aim of this repeated survey is to monitor poverty and living conditions of Rwandans. The third survey sampled approximately 14,308 households. Data collection started in November 2010. Sampled households were distributed across the country to account for regional variations. Households were divided into 10 equally sized samples, (NISR, 2011) to account for seasonal variations in consumption and incomes. The present study focuses on a total of 9667 children aged between 13 and 18, inclusive. Of these, we retain children of the household head whose mother lives in the household, with the household head being in a monogamous marriage. We exclude households with only one parent and those with a polygamous household head, because the dynamics may be different compared with those in our selected sample. Disabled children are excluded as we do not have enough of them in the sample, making them difficult to match. For the same reason, we exclude children with disabled parents. Furthermore, for the effect of health insurance to be better identified, we exclude households with only one MHI affiliated parent and those with other types of insurance. We also exclude children whose school attendance information is unknown. This leaves a total of 2730 children for the analysis. Details on data selection can be found in Table 1.

Table 1: Sample Selection

	Dropped	Not Dropped
Total		9667
Not child of Head	2431	7236
Mother Not in Household	315	6919
Not Monogamous Head	2562	4355
Child Disabled	127	4228
Mother Disabled	197	4031
Father Disabled	307	3709
Only one parent MHI Affiliated or parent with other insurance	491	3233
No Attendance Information	503	2730

Parental Insurance

In order to determine the insurance status of a child's parent, we define the father of the child to be the male household head or the spouse of the household head if the head is female. The mother of the child is defined as the spouse of the male household head or the head of the household as the case may be.

The treatment variable of interest is the insurance status of the child's parent. Thus, a child is classified as coming from an insured household if both of the child's parents are MHI affiliated, and uninsured if neither parent is insured. A total of 75.35% of the children in our sample were from households in which both parents were MHI affiliated.

School Attendance

A child is classified as attending school if he/she did not miss school for reasons other than holidays the week before the interview provided that that they are enrolled in school. 90.18% of the children in our selected sample did not miss school the week before survey interview, accounting for 86.58% and 91.36% of children of uninsured and insured parents, respectively.

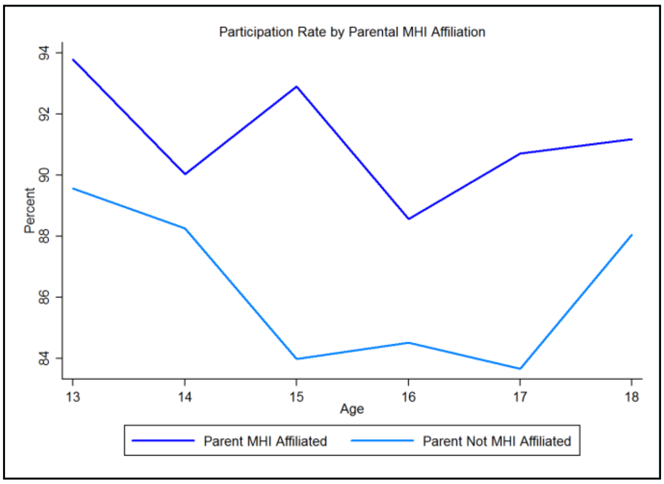

Figure 2: School Attendance Rate by Age and Parental Insurance

Figure 2 shows a decreasing trend in school attendance with increasing age: the older the child, the higher their probability of dropping out of school. In addition, participation rates are lower for children with non-MHI affiliated parents.

Explanatory Variables

Health Related Variables

An individual is defined as having had a health shock if they had a health problem (malaria, internal parasites, respiratory infections, skin disease, accident/injury, diarrhoea, dental problem, gynaecological problems, etc.) during the two weeks before the survey interview. Health shocks continuing for more than one month are classified as chronic. In addition, health shocks which incapacitate the individual are classified as severe. There are therefore two different health shock variables in this analysis, sudden health shocks and severe health shocks.

Using the definition for school attendance above, 87.45% and 91.99% of children with uninsured and insured healthy mothers, respectively, attended school. Similar percentages were found for healthy fathers. School attendance rates of children whose mothers had severe illnesses and those whose mothers had less than severe illnesses - irrespective of MHI affiliation - were approximately the same. Instead, Table 2 shows that for fathers, the severity of the disease had a negative effect on school attendance, this effect being more pronounced when the father was not MHI-affiliated.

Table 2: School Attendance Rates by Parental Insurance Status and Parental Health

	Parents Not MHI Affiliated	Parents MHI Affiliated
Mother Healthy	87.45	91.99
Father Healthy	87.37	91.77
Mother Not Severe Illness	82.87	89.63
Mother Severe Illness	85.66	89.33
Father Not Severe Illness	87.40	91.26
Father Severe Illness	75.96	87.15
Mother Chronic Illness	80.73	89.28
Mother Sudden Illness	81.67	88.48
Father Chronic Illness	92.04	90.04
Father Sudden Illness	78.72	89.66

When we focus on the suddenness of the disease versus its chronicity, we immediately notice that there is a small difference, in terms of the level of their child's school attendance, when either parent is ill and MHI-affiliated, and a very large difference when neither parent is MHI-affiliated. In the latter case, when the father experiences a sudden health shock, he reduces participation by a higher percentage compared with the father having a chronic illness. This difference also exists, albeit to a lesser extent, for mothers who suddenly become ill versus those who are chronically ill.

Gender

Interestingly, female children across all age groups in our sample were more likely to have attended school the week preceding the survey interview (see Table 3). This result is irrespective of the insurance status of the parents. In addition, we notice that children were less likely to have attended school the previous week if their parents were not MHI affiliated, irrespective of their gender.

Table 3: School Attendance Rates by Gender

	Male		Female	
Age	**Parents Not MHI Affiliated**	**Parents MHI Affiliated**	**Parents Not MHI Affiliated**	**Parents MHI Affiliated**
13	84.70	92.36	93.63	95.11
14	87.67	88.74	88.97	91.56
15	85.56	93.56	82.17	92.28
16	80.22	91.12	89.09	85.98
17	78.81	88.42	88.04	92.89
18	86.35	89.99	89.99	92.37
Total	84.58	90.83	88.66	91.89

Other Characteristics

Children of MHI-affiliated parents were, on average, older than their counterparts with non-MHI affiliated parents. Approximately 0.08% of the children in the sample were ill the week before the survey interview, irrespective of parental MHI affiliation. The average child came from a household where 46.3% of its members were children (18 years of age or lower) if their parents were not MHI-affiliated and 44.2% if they were MHI-affiliated. Of the children with MHI-affiliated parents 88.6% were living in rural areas compared to 89.9% of those with non-MHI affiliated parents.

Households were divided into consumption expenditure quintiles and poverty levels based on the food and total poverty lines. A household was classified as extremely poor if their consumption fell below the extreme poverty line, defined as the cost of buying the food consumption basket if nothing is spent on non-food consumption. For the year 2010/2011 this threshold was set at 83,000 Rwandan Franc. Approximately 27.32% of the children in our sample were classified as extremely poor. Table 4 shows that a higher percentage of children with parents not MHI-affiliated came from households classified as extremely poor, compared with children with MHI affiliated parents.

Table 4: Summary Statistics for other Covariates

	Parent Not MHI Affiliated		Parents MHI Affiliated	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Age	14.845	1.535	15.009	1.580
Ill	0.086	0.281	0.084	0.278
Prop. Children in HH	0.463	0.153	0.442	0.165
Rural	0.899	0.302	0.886	0.318
Extremely Poor	0.365	0.482	0.225	0.418
Age of Father	47.929	7.774	48.651	8.467
Age of Mother	43.533	7.179	44.154	7.269
Educated Father	0.766	0.423	0.796	0.403
Educated Mother	0.680	0.467	0.695	0.460
Other HH Member Ill	0.351	0.478	0.317	0.465
Total	672		2058	

The fathers of the children in our sample were on average older than the mothers, with MHI-affiliated parents being slightly older than their non-MHI affiliated counterparts (see Table 4). Fathers were more likely than mothers to have at least primary level education, and affiliated parents were slightly more likely to have at least primary level education. Finally, children from non-MHI affiliated households were less likely to have other ill household members.

3.3 Empirical Strategy

3.3.1 Propensity Score Matching

In the absence of before-and-after data for the same individuals, a selection bias is created, as children of MHI affiliated parents may have certain characteristics in common with each other, and different from those with non-MHI affiliated parents. This bias is eliminated only if exposure to treatment (MHI affiliation) can be considered as purely random. To achieve this, Rosenbaum & Rubin (1983) propose the use of the propensity matching method.

The propensity score is defined as the probability that both parents of the child will be MHI affiliated given some pre-treatment characteristics.

$$p(x) \equiv Pr[MHI\ Affiliation = 1|X]$$
$$= E[MHI\ Affiliation|X]$$

3.3.2 Average Treatment Effects on Treated

Once the propensity scores have been calculated they are used to estimate the average treatment effects on the treated (ATT) using the kernel matching methodology. This is a non-parametric technique where weighted averages of individuals in the control group (uninsured) are used to construct the counterfactual outcome (Becker & Ichino, 2002; Caliendo & Kopeinig, 2008). The main advantage of this matching technique over other techniques is the lower variance thanks to the availability of more information. This however creates the possibility of poor matches. One way to control for this is to specify common support conditions (Caliendo & Kopeinig, 2008), which we do here.

3.3.3 Regression Analysis

To be able to disentangle the effects of parental health shocks we run a probit model to estimate the probability that a child would have attended school the week before the interview despite health shocks to the parent, all else constant. The regression analysis is run on the matched data. If we define the probability that child i attended school two weeks before the interview by π_i^k, then the model of interest is:

$$\pi_i^k = \Phi\big(\alpha + \beta_{1i}^k mother\ chronic_i^k + \beta_{2i}^k mother\ sudden_i^k + \beta_{3i}^k father\ chronic_i^k + \beta_{4i}^k father\ sudden_i^k + \tilde{\beta}_i^k X_i^k\big)$$

where Φ is the probit function and β_{1i}^k, β_{2i}^k, β_{3i}^k and β_{4i}^k are the coefficients of interest. X_{ij}^k is a matrix of other covariates which we control for in our regression, with associated coefficient vector, $\tilde{\beta}_i^k$. Finally k is an indicator variable which is equal to I if the child's parents are MHI affiliated and U they are not.

The following model is run for disease severity

$$\hat{\pi}_i^k = \Phi\big(\hat{\alpha} + \hat{\beta}_{1i}^k mother\ not\ severe_i^k + \hat{\beta}_{2i}^k mother\ severe_i^k + \hat{\beta}_{3i}^k father\ not\ severe_i^k + \hat{\beta}_{4i}^k father\ severe_i^k + \breve{\beta}_i^k X_i^k\big)$$

where $\hat{\beta}_{1i}^k$, $\hat{\beta}_{2i}^k$, $\hat{\beta}_{3i}^k$ and $\hat{\beta}_{4i}^k$ are the coefficients of interest.

3.3.4 Sensitivity Analysis

We are interested in finding out how strong the effects of immeasurable variables are on the inferences made on the treatment effects obtained. Rosenbaum & Rubin (1983) propose a bounding approach which highlights how dependent the results are on the unconfoundedness assumption (Caliendo & Kopeinig, 2008; Becker & Caliendo, 2007; Aakvik, 2001). Based on this approach, if the value for the maximum significance level of the test is above 0.05 then the result is no longer significant at the 5% level.

3.4 Results

<u>Matching and Balance Diagnostics</u>

Results from the propensity score matching are shown in Figures A1 to A3 and in Tables A1 to A3. The matching procedure is carried out by replacement. In the three figures, the propensity score distribution for the three population groups: whole population, males and females, are compared as a function of parental MHI affiliation status. It is immediately evident that there is a significant overlap in the non-affiliated and affiliated groups for all three population groups, for both outcomes of interest (parental health shock chronicity and severity). This would suggest that the characteristics of children with MHI-affiliated parents and those non-MHI affiliated parents are not completely different, and that weighting observations according to the estimates propensity scores may address imbalances between the two (affiliated / non-affiliated) groups. These imbalances can be seen more clearly in the tables where most of the bias in the covariates is no longer significant after matching, irrespective of the outcome of interest.

Impact of Parental MHI Affiliation on School Attendance

We next study the effect of parental health insurance on child school attendance using the kernel matching technique to calculate the ATT. In Table 5 school attendance is lower and statistically significant for the children without MHI affiliated parents, irrespective of gender. This difference appears to be greater for male children.

Table 5: Average Treatment Effect on Treatment by Gender

	Parental MHI	Parental Non-MHI	Difference	t-stat
Male	0.9092	0.8628	0.0464	2.05
Female	0.9197	0.8817	0.0381	1.87
All	0.9145	0.8683	0.0462	3.04

The Mitigating Effects of Health Insurance in the Parental Health Shock- Child Schooling Relationship

Using the matched data, we study the effects of parental health shock on child school attendance based on the child's gender. Marginal effects are presented in Table 6. Complete tables are in the supplementary appendix. Health shocks to the father have a negative and significant effect only if the shock is sudden or very severe. In all other cases, the effect appears to be insignificant. Interestingly, health shocks of any kind to the mother do not have a significant effect on child school attendance. Comparing children of MHI-affiliated and non-MHI affiliated parents, we find a stronger negative effect in the latter on schooling if the father falls suddenly ill or if the father is severely ill.

Interestingly, when focusing on gender subgroups, we find that while paternal health shocks have a negative effect for both males and females - with MHI affiliation playing a mitigating role - sudden health shocks in mothers appear to only negatively and significantly affect female children's school attendance.

Table 6: Impact of Parental Health Shock on School Attendance

	All		**Male**		**Female**	
	MHI Affiliated	**Not MHI Affiliated**	**MHI Affiliated**	**Not MHI Affiliated**	**MHI Affiliated**	**Not MHI Affiliated**
Father Ill over a Month	0.0134	-0.0012	-0.0059	0.0552	0.0249	-0.0891
	(0.0214)	(0.0707)	(0.0386)	(0.0726)	(0.0226)	(0.1228)
Mother Ill over Month	-0.0063	0.0327	-0.0179	-0.0289	0.0039	0.0487
	(0.0232)	(0.0466)	(0.0387)	(0.0819)	(0.0267)	(0.0502)
Father Ill Less than a Month	**-0.0146**	**-0.1191****	**-0.0244**	**-0.1664****	-0.0086	-0.0884
	(0.0175)	**(0.0531)**	**(0.0271)**	**(0.0755)**	(0.0223)	(0.0744)
Mother Ill Less than a Month	-0.0164	-0.0530	-0.0175	0.0229	**-0.0144**	**-0.1336***
	(0.0185)	(0.0469)	(0.0278)	(0.0447)	**(0.0241)**	**(0.0727)**
Father No Severe Illness	0.0008	0.0036	-0.0010	-0.0217	-0.0009	0.0228
	(0.0175)	(0.0438)	(0.0254)	(0.0593)	(0.0244)	(0.0573)
Mother No Severe Illness	-0.0116	-0.0149	-0.0265	0.0347	0.0019	-0.0921
	(0.0181)	(0.0406)	(0.0291)	(0.0409)	(0.0214)	(0.0704)
Father Severe Illness	**-0.0182**	**-0.1949****	**-0.0562**	**-0.2062***	**0.0048**	**-0.2165***
	(0.0231)	**(0.0758)**	**(0.0442)**	**(0.1082)**	**(0.0236)**	**(0.1122)**
Mother Severe Illness	-0.0094	0.0334	-0.0072	0.0273	-0.0102	0.0120
	(0.0182)	(0.0380)	(0.0275)	(0.0502)	(0.0235)	(0.0580)

****p<0.001, **p<0.05, *p<0.1. The numbers in brackets are robust standard errors.*

3.5 Sensitivity Analysis

The results of the sensitivity analysis for the average treatment effect analysis are presented in Table A6 in the supplementary appendix. The values $\boldsymbol{Q^{+}_{MH}}$ and $\boldsymbol{Q^{-}_{MH}}$ are the test statistics, which represent an overestimation and an underestimation of the treatment effect, respectively. If the maximum significance level, $\boldsymbol{P^{+}_{MH}}$ is above 0.05 then the result is no longer significant at the 5% level. Our ATT results have shown that parental MHI affiliation has a positive effect on child schooling. Given that the $\boldsymbol{P^{+}_{MH}}$ values in Table A6 are all below the 0.05 threshold, we can assume that our values are not sensitive to unobserved variables. That is to say that they are robust to any hidden bias.

To check the global robustness of the model, we try different matching methods and also estimate a propensity score weighted regression model using kernel matching. The main results are presented in Table 7. Further results are provided in the supplementary appendix. The first two columns present the results for the radius matching with 0.02 caliper while the next two colums present results for the one-on-one nearest neighbour matching with replacement and a 0.02 caliper.

Table 7: Robustness Check

	Radius Matching		**Nearest Neighbour**		**Propensity Score Weighted**	
	MHI Affiliated	**Not MHI Affiliated**	**MHI Affiliated**	**Not MHI Affiliated**	**MHI Affiliated**	**Not MHI Affiliated**
Father Ill over a Month	0.0128	-0.0391	0.0128	-0.0051	0.0086	0.0017
	(0.0218)	(0.0990)	(0.0218)	(0.0669)	(0.0233)	(0.0663)
Mother Ill over Month	-0.0026	-0.0172	-0.0026	0.0467	0.0006	0.0567*
	(0.0163)	(0.0530)	(0.0163)	(0.0320)	(0.0162)	(0.0298)
Father Ill Less than a Month	**-0.0109**	**-0.3018*** **	**-0.0109**	**-0.1212** **	**-0.0133**	**-0.1246** **
	(0.0203)	**(0.0857)**	**(0.0203)**	**(0.0551)**	**(0.0203)**	**(0.0535)**
Mother Ill Less than a Month	-0.0205	-0.0149	-0.0205	-0.0547	-0.0191	-0.0596
	(0.0186)	(0.0598)	(0.0186)	(0.0502)	(0.0189)	(0.0499)
Father No Severe Illness	0.0045	-0.0999	0.0045	-0.0013	-0.0011	-0.0003
	(0.0195)	(0.0677)	(0.0195)	(0.0451)	(0.0200)	(0.0422)
Mother No Severe Illness	-0.0148	-0.0341	-0.0148	-0.0265	-0.0098	-0.0251
	(0.0188)	(0.0497)	(0.0188)	(0.0428)	(0.0183)	(0.0416)
Father Severe Illness	**-0.0175**	**-0.3701*** **	**-0.0175**	**-0.1780** **	**-0.0158**	**-0.1800** **
	(0.0277)	**(0.1108)**	**(0.0277)**	**(0.0744)**	**(0.0272)**	**(0.0744)**
Mother Severe Illness	-0.0127	-0.0257	-0.0127	0.0180	-0.0110	0.0222
	(0.0195)	(0.0672)	(0.0195)	(0.0442)	(0.0199)	(0.0416)

i. ****p<0.001, **p<0.05, *p<0.1. The numbers in brackets are robust standard errors.*
ii. *Columns 4 and 5 presents the results of the nearest neighbour matching model with replacement and calliper 0.02.*
iii. *Columns 4 and 5 presents the results of the nearest neighbour matching model with calliper 0.02.*

The results are quite similar, with sudden paternal shocks and severe paternal shocks having a negative effect on the child's schooling. Similar results are also found for the kernel matching model with propensity score weighting technique (Rosenbaum & Rubin, 1983; Nichols, 2007). This involves the use of propensity scores as weights for the regression model.

The aim is to make the children with uninsured parents resemble those with insured parents. This strategy is equivalent to inverting the test of randomisation used in experimental designs to generate two groups that look as if they were randomly assigned (DiNardo, et al., 1996; Nichols, 2007). The treated population are weighted by the inverse of the propensity score while the untreated population are weighted by the inverse of 1 minus the propensity score.

3.6 Identification of Impact Pathways

Several studies have highlighted the impact of insurance affiliation on patient consultations. These studies find that the probability that an individual will seek medical consultation when faced with ill health is higher for those with insurance (Saksena, et al., 2011). In Rwanda especially, MHI affiliation is associated with a significant increase in health service utilisation and a lower incidence of catastrophic health expenditure. We are, however, unable to test the full impact of medical consultations in our model, as questions on consultations in the EICV 3 survey were not related to health shocks. Despite the fact that questions about health shocks and about consultations covered the same two-week period before the interview, the information does not necessarily pertain to the actual health shock suffered during this period. In other words, sick individuals may have consulted medical doctors for reasons other than their current health-shock related problem.

Our theoretical results indicate that, as long as the insured seek consultations when ill, a more severe health shock is more likely to affect the schooling of children from uninsured household at a greater magnitude, irrespective of whether they consult health professionals or not. In all other cases, the effect is similar between the two groups (affiliated/non-affiliated).

Health, Hours Worked and Household Incomes

In their work on the impact of parental health on child labour Bazen & Salmon (2010) find that mothers are less likely to work when they are ill. They also find that mothers are more likely to work if fathers are chronically ill. For this income channel to hold, we study the effect of parental health shocks on the hours worked by the father. Both the OLS and instrumental variables (IV) results are presented in Table 8. We run an IV model as there could be factors that affect both paternal health and paternal working hours, leading to a positive effect between the two. To be sure we are truly measuring the effect of the father's health on the number of hours worked, we instrument the various indicators of the father's health by household overcrowding, access to high quality water and the proportion of household members sleeping under bed nets. All three instruments affect the health of the parent without necessarily affecting the working hours of the father. The full results are presented in Table A7 in the supplementary appendix where the Sargan statistic implies that the test of overidentifying restrictions cannot reject the null hypothesis for the case of health shocks. In terms of severity however, the null hypothesis can be rejected. The results of the Durbin-Wu-Hansen endogeneity test show that in the first model, we can treat parental health shock as exogenous but the severity of the shock as endogenous. Thus, while the results of the OLS are sufficient for the first model, the IV results are more relevant for the second model.

Table 8: Impact of Parental Health on the Working Hours of the Father

	Sudden Health Shock		Severe Health Shock	
Variables	**OLS**	**IV**	**OLS**	**IV**
Parents MHI Affiliated	2.3328***	3.6645***	2.3182***	3.7525**
	(0.7699)	(1.2390)	(0.7675)	(1.8598)
Mother Ill over a Month	2.4367**	9.7864**		
	(1.1051)	(4.0269)		
Mother Ill Less than a Month	0.2919	3.6196		
	(1.1299)	(2.3144)		
Father Ill Over a Month	-3.5921**	-41.8136		
	(1.7334)	(32.6886)		
Father Ill Less than a Month	-5.9906***	-58.4498**		
	(1.1256)	(26.4221)		
Mother No Severe Illness			3.0890***	11.4330
			(1.1509)	(8.2874)
Mother Severe Illness			0.6154	6.3458*
			(1.2233)	(3.7990)
Father No Severe Illness			-2.2158*	-57.2622
			(1.2337)	(54.6967)
Father Severe Illness			-11.6599***	-61.7808**
			(1.4261)	(30.7731)

****p<0.001, **p<0.05, *p<0.1.The numbers in brackets are robust standard errors.*

The results in Table 8 indicate that parental health shocks reduce the working hours of the father which might imply a reduction in household income, irrespective of whether the mother works or not. In either case, this reduction in income can translate into children missing school on some days to either replace the mother at home or to take up paid work. Studies have found a negative effect of health shocks on employment and schooling, with one recent study finding that sudden health shocks, as measured by acute hospitalisations, lower employment probability by approximately 7 percentage points in the Netherlands (Garcia-Gomez, et al., 2013).

Health Insurance and Health Care Utilisation

A study on the impact of health insurance on access to healthcare and financial risk protection in Rwanda found an increase in the use of healthcare services among households with MHI compared with those without such cover (Saksena, et al., 2011). If health insurance leads to an increase in healthcare access, then one would expect a reduction in the negative effects of health shocks on hours worked, leading to a reduction in the negative effect on household incomes and consequently on child schooling.

Health and Catastrophic Household Expenditures

Health shocks affect household income, especially if the main earner is the person experiencing the shock and if this shock is severe. When households choose to consult medical professionals in the face of health shocks, they incur a cost. Saksena, et al. (2011) find that in Rwanda, MHI affiliation is associated with a higher financial risk protection with a lower incidence of catastrophic health expenditure. Catastrophic health shocks are bound to affect the children's schooling levels, leading to more absenteesim especially among children from uninsured households.

4 Discussion and Conclusion

This work looks at how health insurance protects the schooling of children against parental shocks. Using both a theoretical and an empirical model, we show that health insurance protects children against severe and/or sudden health shocks to the main earner of the household. In line with the results of Alam (2015), we find that paternal illness, and not maternal illness, negatively affects children's school attendance. One major difference between our work and Alam's (2015) is our focus on both parental insurance and the type of health shock faced. This refinement highlighted the fact that it is the severity and suddenness of illness that leads to the observed negative effect of paternal health shock on schooling. This negative effect is not found if the parents are MHI affiliated.

While Liu (2016) addresses the issue of insurance affiliation, he focuses on the effects of health shocks to either the household head or the spouse on school enrolment. He finds that only health shocks to the head of the household has a negative effect on schooling when the household is uninsured. No effects are found otherwise. The results are not gender-dependent. Liu's (2016) health shock variable is defined as the number of days the individual has been ill in the 4 weeks before the interview. Our model differs from Liu's in that, in addition to being able to link children to their respective parents, we are also able to look at the effect of health shocks that have lasted beyond a couple of weeks (chronic), as well as the severity of the shock.

Interestingly, unlike Liu (2016), we find that it is the suddenness and the severity of the disease that counts. A health shock lasting less than a month has a negative effect on the schooling of children. The effect is no longer visible for health effects which last longer, probably because households may have found other means of adjusting to the health shock, including enrolment in insurance schemes and the setting up of a business by the mother. The results of this current work and those of Alam (2015) and Liu (2016) appear to contradict the results of Bratti & Mendola (2014) who find a significant effect for maternal ill health.

In addition to the fact that our work relies on cross-sectional data, one of the other main limitations of our work is the inability to control for consultations. Our theoretical results point to the importance of consultations in the relationship between parental health shocks and schooling of children. Future work should aim to study how health insurance affects consulations and their subsequent impact on schooling. Performing such an analysis using panel data would add important results to the growing field of parental health and child welfare. The differences regarding MHI affiliation according to income group and residential location are also of interest. Unfortunately, our sample size is too small to adequately access these separately. Despite these limitations, we can draw some important policy implications from our results.

Our results support the argument for universal healthcare coverage. Health insurance not only protects the insured but also helps households keep their children in school in the face of parental health shocks to the main earner. This unintended benefit could help push households out of the vicious cycle of poor health in childhood, low education and low adult outcome such as incomes and health in adulthood. In addition, as Woode, et al. (2014) have shown, there is also a long-term positive effect of health insurance coverage on economic growth, this effect being reinforced through the positive impact on children's school attendance.

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Mathematical Appendix

Proof of Proposition 1

From equations (12a) to (13b) we have that

$$s_t^{u,n} - s_t^{u,s} = \left(\frac{\theta}{1+\theta}\right)\left(\frac{\bar{h}(1+\rho s_{t-1})\omega_t + m_t^{u,s}(1+m_t^{u,s})}{(\gamma\omega_t + p_t)\left(1+m_t^{u,s}\right)}\right)$$

$$s_t^{i,n} - s_t^{i,s} = \left(\frac{\theta}{1+\theta}\right)\left(\frac{\bar{h}(1+\rho s_{t-1})\omega_t + (1-\alpha)m_t^{i,s}\left(1+m_t^{i,s}\right)}{(\gamma\omega_t + p_t)\left(1+m_t^{i,s}\right)}\right)$$

$s_t^{u,n} - s_t^{u,s} \geq s_t^{i,n} - s_t^{i,s}$ iff

$$\left(\frac{\bar{h}(1+\rho s_{t-1})\omega_t + m_t^{u,s}(1+m_t^{u,s})}{\left(1+m_t^{u,s}\right)}\right) \geq \left(\frac{\bar{h}(1+\rho s_{t-1})\omega_t + (1-\alpha)m_t^{i,s}\left(1+m_t^{i,s}\right)}{\left(1+m_t^{i,s}\right)}\right)$$

$$=> \bar{h}(1+\rho s_{t-1})\omega_t\left(1+m_t^{i,s}\right) + m_t^{u,s}(1+m_t^{u,s})\left(1+m_t^{i,s}\right)$$

$$\geq \bar{h}(1+\rho s_{t-1})\omega_t(1+m_t^{u,s}) + (1-\alpha)m_t^{i,s}\left(1+m_t^{i,s}\right)(1+m_t^{u,s})$$

$$=> (1+m_t^{u,s})^2\left(1+m_t^{i,s}\right) + m_t^{u,s}(1+m_t^{u,s})\left(1+m_t^{i,s}\right)$$

$$\geq (1-\alpha)\left(1+m_t^{i,s}\right)^2(1+m_t^{u,s}) + (1-\alpha)m_t^{i,s}\left(1+m_t^{i,s}\right)(1+m_t^{u,s})$$

$$=> (1+m_t^{u,s}) + m_t^{u,s} \geq (1-\alpha)\left(1+m_t^{i,s}\right) + (1-\alpha)m_t^{i,s}$$

$$=> \frac{\alpha}{2} \geq (1-\alpha)m_t^{i,s} - m_t^{u,s}$$

$$=> \bar{h} \geq \left(\frac{1}{(1+\rho s_{t-1})\omega_t}\right)\left(\frac{\alpha}{2\left(1-\sqrt{(1-\alpha)}\right)}\right)^2 \equiv \bar{h}_{ui}^*$$

Q.E.D

Supplementary Appendix

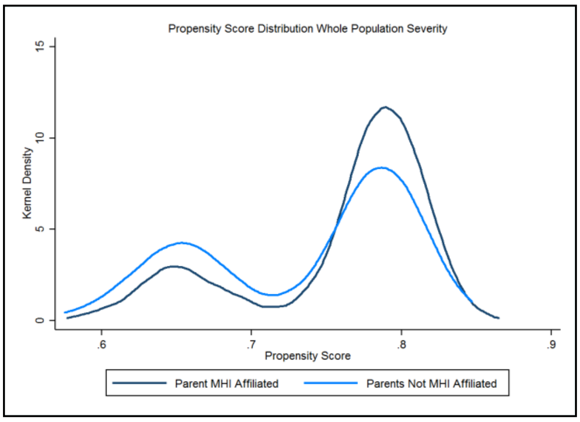
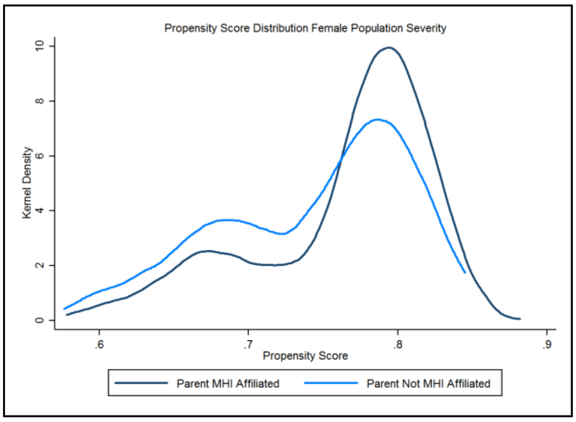


Figure A1: Estimated Propensity Score Distribution Whole Population



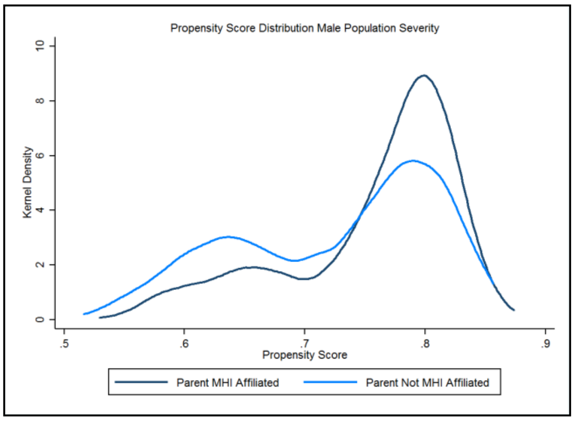


Figure A2: Estimated Propensity Score Distribution Male and Female Population

Table A 1: Balance Statistics for Matching, All Children

Variable	Unmatched Treated	Unmatched Control	Unmatched % bias	Matched Treated	Matched Control	Matched % bias	% Reduction in Bias
Age	15.009	14.845	10.5**	15.009	14.902	6.9**	34.8
Male	0.498	0.51	-2.6	0.498	0.502	-0.8	67.5
Ill	0.084	0.086	-0.8	0.084	0.08	1.6	-99.8
Prop Children in HH	0.442	0.463	-12.8***	0.442	0.453	-6.4**	50.3
Rural	0.886	0.899	-4.2	0.886	0.893	-2.4	41.6
Extremely Poor	0.225	0.365	-31.0***	0.225	0.22	1.1	96.4
Age of Father	48.651	47.929	8.9**	48.651	48.286	4.5	49.4
Age of Mother	44.154	43.533	8.6*	44.154	43.984	2.4	72.6
Educated Father	0.796	0.766	7.1	0.796	0.787	2.2	69.3
Educated Mother	0.695	0.68	3.3	0.695	0.691	0.9	72.0
Other HH Member Ill	0.317	0.351	-7.3	0.317	0.327	-2.2	70.3

***p<0.001, **p<0.05, *p<0.1

Table A 2: Balance Statistics for Matching (Male Children)

Variable	Unmatched Treated	Unmatched Control	Unmatched % bias	Matched Treated	Matched Control	Matched % bias	% Reduction in Bias
Age	15.014	14.878	8.8	15.014	14.965	3.2	63.9
Ill	0.071	0.09	-7	0.071	0.065	2.5	64.9
Prop Children in HH	0.439	0.463	-15.3**	0.439	0.45	-7.2	53.3
Rural	0.902	0.915	-4.6	0.902	0.905	-0.8	81.6
Extremely Poor	0.22	0.373	-34.0***	0.22	0.218	0.5	98.6
Age of Father	48.764	47.557	14.9**	48.764	48.249	6.3	57.4
Age of Mother	44.343	43.344	13.8**	44.343	43.976	5.1	63.3
Educated Father	0.789	0.784	1.2	0.789	0.792	-0.7	43
Educated Mother	0.693	0.673	4.3	0.693	0.69	0.6	85.3
Other HH Member Ill	0.3	0.364	-13.7**	0.3	0.309	-1.9	86.2

***p<0.001, **p<0.05, *p<0.1

Table A 3: Balance Statistics for Matching (Female Children)

	Unmatched			Matched			
Variable	**Treated**	**Control**	**% bias**	**Treated**	**Control**	**% bias**	**% Reduction in Bias**
Age	15.005	14.812	12.3*	15.005	14.908	6.2	50.2
Ill	0.097	0.082	5.1	0.097	0.081	5.6	-10.1
Prop Children in HH	0.446	0.463	-10.4	0.446	0.451	-3.1	70.0
Rural	0.869	0.881	-3.6	0.869	0.873	-1	73.4
Extremely Poor	0.23	0.356	-27.8***	0.23	0.231	-0.3	99.1
Age of Father	48.967	48.316	2.7	48.54	48.517	0.3	89.7
Age of Mother	43.967	43.729	3.3	43.967	44.043	-1	68.2
Educated Father	0.803	0.748	13.2**	0.803	0.797	1.5	88.8
Educated Mother	0.697	0.687	2.2	0.697	0.699	-0.4	83.9
Other HH Member Ill	0.334	0.337	-0.8	0.337	0.329	0.9	-15.2

***p<0.001, **p<0.05, *p<0.1

Table A 4: Marginal Effects for Impact of Parental Health Shock on Schooling (Suddenness)

	All		Male		Female	
	MHI Affiliated	**Not MHI Affiliated**	**MHI Affiliated**	**Not MHI Affiliated**	**MHI Affiliated**	**Not MHI Affiliated**
Age	-0.0059	-0.0132*	-0.0058	-0.0234**	-0.0052	-0.0038
	(0.0036)	(0.0080)	(0.0054)	(0.0110)	(0.0046)	(0.0107)
Male	-0.0168	-0.0177				
	(0.0114)	(0.0260)				
Ill	-0.2248***	-0.1273**	-0.1799***	-0.1478	-0.2550***	-0.1428
	(0.0365)	(0.0638)	(0.0533)	(0.0953)	(0.0494)	(0.0920)
Prop Children in HH	0.0178	-0.0466	0.0173	-0.0369	0.0213	-0.1315
	(0.0418)	(0.1204)	(0.0610)	(0.1557)	(0.0555)	(0.1552)
Rural	-0.0412***	-0.0169	-0.0309	-0.0903**	-0.0477***	0.0418
	(0.0134)	(0.0408)	(0.0239)	(0.0357)	(0.0141)	(0.0590)
Extremely Poor	-0.0289*	0.0008	-0.0219	-0.0254	-0.0315	0.0181
	(0.0150)	(0.0272)	(0.0216)	(0.0375)	(0.0196)	(0.0359)
Age of Father	-0.0012	-0.0003	-0.0025*	-0.0005	0.0003	-0.0009
	(0.0010)	(0.0026)	(0.0014)	(0.0037)	(0.0014)	(0.0034)
Age of Mother	0.0020	0.0036	0.0033*	0.0038	0.0003	0.0029
	(0.0012)	(0.0033)	(0.0018)	(0.0047)	(0.0017)	(0.0043)
Educated Father	0.0128	-0.0184	0.0223	0.0141	0.0036	-0.0228
	(0.0151)	(0.0311)	(0.0225)	(0.0464)	(0.0192)	(0.0417)
Educated Mother	0.0384***	0.0267	0.0425*	0.0582	0.0296	0.0214
	(0.0144)	(0.0319)	(0.0218)	(0.0468)	(0.0185)	(0.0425)
Other HH Member Ill	-0.0057	-0.0193	-0.0251	-0.0588	0.0105	0.0359
	(0.0127)	(0.0290)	(0.0199)	(0.0389)	(0.0161)	(0.0369)
Father Sick over a Month	0.0134	-0.0012	-0.0059	0.0552	0.0249	-0.0891
	(0.0214)	(0.0707)	(0.0386)	(0.0726)	(0.0226)	(0.1228)
Mother Sick over a Month	-0.0063	0.0327	-0.0179	-0.0289	0.0039	0.0487
	(0.0232)	(0.0466)	(0.0387)	(0.0819)	(0.0267)	(0.0502)
Father Ill Less than a Month	-0.0146	-0.1191**	-0.0244	-0.1664**	-0.0086	-0.0884
	(0.0175)	(0.0531)	(0.0271)	(0.0755)	(0.0223)	(0.0744)
Mother Ill Less than a Month	-0.0164	-0.0530	-0.0175	0.0229	-0.0144	-0.1336*
	(0.0185)	(0.0469)	(0.0278)	(0.0447)	(0.0241)	(0.0727)

****p<0.001, **p<0.05, *p<0.1. The numbers in brackets are robust standard errors.*

Table A 5: Marginal Effects for Impact of Parental Health Shock on Schooling (Severity)

	All		Male		Female	
	MHI Affiliated	Not MHI Affiliated	MHI Affiliated	Not MHI Affiliated	MHI Affiliated	Not MHI Affiliated
Age	-0.0059	-0.0124	-0.0056	-0.0211*	-0.0052	-0.0008
	(0.0036)	(0.0081)	(0.0054)	(0.0112)	(0.0046)	(0.0108)
Male	-0.0173	-0.0170				
	(0.0115)	(0.0262)				
Ill	-0.2203***	-0.1557**	-0.1797***	-0.2035**	-0.2515***	-0.1552
	(0.0360)	(0.0682)	(0.0535)	(0.1036)	(0.0481)	(0.0989)
Prop Children in HH	0.0149	-0.0691	0.0066	-0.0770	0.0200	-0.1291
	(0.0420)	(0.1266)	(0.0606)	(0.1650)	(0.0566)	(0.1714)
Rural	-0.0419***	-0.0210	-0.0322	-0.0816**	-0.0476***	0.0120
	(0.0134)	(0.0388)	(0.0239)	(0.0375)	(0.0142)	(0.0521)
Extremely Poor	-0.0276*	-0.0081	-0.0203	-0.0345	-0.0309	0.0114
	(0.0150)	(0.0276)	(0.0220)	(0.0384)	(0.0196)	(0.0370)
Age of Father	-0.0013	-0.0003	-0.0026*	0.0004	0.0004	-0.0014
	(0.0010)	(0.0026)	(0.0013)	(0.0035)	(0.0014)	(0.0032)
Age of Mother	0.0020	0.0031	0.0033*	0.0022	0.0002	0.0024
	(0.0013)	(0.0032)	(0.0019)	(0.0045)	(0.0017)	(0.0040)
Educated Father	0.0123	-0.0124	0.0212	0.0341	0.0024	-0.0336
	(0.0150)	(0.0318)	(0.0223)	(0.0494)	(0.0191)	(0.0408)
Educated Mother	0.0380***	0.0176	0.0422*	0.0437	0.0288	0.0132
	(0.0145)	(0.0313)	(0.0219)	(0.0461)	(0.0185)	(0.0421)
Other HH Member Ill	-0.0068	-0.0215	-0.0268	-0.0745*	0.0088	0.0324
	(0.0129)	(0.0293)	(0.0199)	(0.0416)	(0.0164)	(0.0379)
Father No Severe Health Shock	0.0008	0.0036	-0.0010	-0.0217	-0.0009	0.0228
	(0.0175)	(0.0438)	(0.0254)	(0.0593)	(0.0244)	(0.0573)
Mother No Severe Health Shock	-0.0116	-0.0149	-0.0265	0.0347	0.0019	-0.0921
	(0.0181)	(0.0406)	(0.0291)	(0.0409)	(0.0214)	(0.0704)
Father Severe Health Shock	-0.0182	-0.1949**	-0.0562	-0.2062*	0.0048	-0.2165*
	(0.0231)	(0.0758)	(0.0442)	(0.1082)	(0.0236)	(0.1122)
Mother Severe Health Shock	-0.0094	0.0334	-0.0072	0.0273	-0.0102	0.0120
	(0.0182)	(0.0380)	(0.0275)	(0.0502)	(0.0235)	(0.0580)

****p<0.001, **p<0.05, *p<0.1. The numbers in brackets are robust standard errors.*

Table A 6: Mantel-Haenszel Test Statistics

Whole Population				
γ	Q^+_{MH}	Q^-_{MH}	P^+_{MH}	P^-_{MH}
1	3.599	3.599	0.000	0.000
1.1	2.896	4.309	0.002	0.000
1.2	2.259	4.964	0.012	0.000
1.3	1.675	5.573	0.047	0.000
1.4	1.137	6.144	0.128	0.000
1.5	0.637	6.682	0.262	0.000
1.6	0.169	7.192	0.433	0.000
1.7	0.132	7.676	0.448	0.000
1.8	0.547	8.139	0.292	0.000
1.9	0.939	8.582	0.174	0.000
2	1.312	9.007	0.095	0.000

Male Population				
γ	Q^+_{MH}	Q^-_{MH}	P^+_{MH}	P^-_{MH}
1	3.062	3.062	0.001	0.001
1.1	2.538	3.593	0.006	0.000
1.2	2.062	4.084	0.020	0.000
1.3	1.627	4.540	0.052	0.000
1.4	1.226	4.968	0.110	0.000
1.5	0.854	5.371	0.196	0.000
1.6	0.507	5.754	0.306	0.000
1.7	0.181	6.118	0.428	0.000
1.8	-0.059	6.465	0.524	0.000
1.9	0.232	6.798	0.408	0.000
2	0.509	7.118	0.305	0.000

Female Population				
γ	Q^+_{MH}	Q^-_{MH}	P^+_{MH}	P^-_{MH}
1	1.845	1.845	0.033	0.033
1.1	1.382	2.313	0.084	0.010
1.2	0.960	2.744	0.169	0.003
1.3	0.574	3.144	0.283	0.001
1.4	0.217	3.518	0.414	0.000
1.5	-0.091	3.870	0.536	0.000
1.6	0.221	4.203	0.412	0.000
1.7	0.515	4.520	0.303	0.000
1.8	0.793	4.822	0.214	0.000
1.9	1.056	5.110	0.146	0.000
2	1.306	5.387	0.096	0.000

Table A 7: Results for Impact of Parental Health on the Working Hours of the Father

Variables	OLS	IV	OLS	IV
Rural	-4.9215***	-4.8144***	-5.6655***	-5.1446
	(1.2882)	(1.8314)	(1.2598)	(3.2531)
Household Size	0.9149***	0.6682**	0.7033***	0.5769*
	(0.2108)	(0.3133)	(0.2186)	(0.3481)
Father's Age	-0.2426***	0.0435	-0.2409***	0.0991
	(0.0713)	(0.1851)	(0.0705)	(0.3292)
Educated Father	2.0242**	3.3636**	2.2721**	3.6441**
	(0.9724)	(1.6229)	(0.9775)	(1.6312)
Mother's Age	-0.0917	-0.3141*	-0.0792	-0.3927
	(0.0816)	(0.1907)	(0.0822)	(0.3582)
Educated Mother	1.2537	-1.0843	0.2039	-2.1926
	(0.8668)	(1.6915)	(0.8688)	(2.5205)
Parents MHI Affiliated	2.3328***	3.6645***	2.3182***	3.7525**
	(0.7699)	(1.2390)	(0.7675)	(1.8598)
Father Ill Over a Month	-3.5921**	-41.8136		
	(1.7334)	(32.6886)		
Father Ill Less than a Month	-5.9906***	-58.4498**		
	(1.1256)	(26.4221)		
Mother Ill over a Month	2.4367**	9.7864**		
	(1.1051)	(4.0269)		
Mother Ill Less than a Month	0.2919	3.6196		
	(1.1299)	(2.3144)		
Mother No Severe Illness			3.0890***	11.4330
			(1.1509)	(8.2874)
Mother Severe Illness			0.6154	6.3458*
			(1.2233)	(3.7990)
Father No Severe Illness			-2.2158*	-57.2622
			(1.2337)	(54.6967)
Father Severe Illness			-11.6599***	-61.7808**
			(1.4261)	(30.7731)
Constant	39.5929***	44.9326***	41.6683***	47.8073***
	(3.4683)	(5.5835)	(3.5913)	(6.3705)
Cragg-Donald Wald F statistic		0.98		2.93
Anderson canon. corr. LM statistic		0.2276		0.0122
Stock-Wright LM S statistic		10.83		0.0178
Sargan statistic		0.3206		0.5091
Endogeneity test		0.0378		0.0221

****p<0.001, **p<0.05, *p<0.1. The numbers in brackets are robust standard errors.*

Table A 8: Marginal Effects for Robustness Model (Severity)

	Radius		Nearest Neighbour		Propensity Score Weighted	
	Parent MHI Affiliated	**Parent Not MHI Affiliated**	**Parent MHI Affiliated**	**Parent Not MHI Affiliated**	**Parent MHI Affiliated**	**Parent Not MHI Affiliated**
Age	-0.0065*	-0.0093	-0.0065*	-0.0095	-0.0059*	-0.0104
	(0.0035)	(0.0094)	(0.0035)	(0.0083)	(0.0035)	(0.0080)
Male	-0.0158	0.0026	-0.0158	-0.0150	-0.0174	-0.0213
	(0.0115)	(0.0354)	(0.0115)	(0.0267)	(0.0116)	(0.0257)
Sick	-0.2184***	-0.1045	-0.2184***	-0.1297*	-0.2276***	-0.1544**
	(0.0366)	(0.0913)	(0.0366)	(0.0683)	(0.0372)	(0.0661)
Prop Children in HH	0.0300	-0.2302	0.0300	-0.1582	0.0216	-0.1415
	(0.0456)	(0.1512)	(0.0456)	(0.1281)	(0.0455)	(0.1303)
Rural	-0.0422***	-0.0063	-0.0422***	-0.0295	-0.0420***	-0.0226
	(0.0153)	(0.0519)	(0.0153)	(0.0386)	(0.0155)	(0.0414)
Extremely Poor	-0.0277*	-0.0045	-0.0277*	-0.0038	-0.0284*	-0.0052
	(0.0161)	(0.0376)	(0.0161)	(0.0300)	(0.0160)	(0.0285)
Age of Father	-0.0016	-0.0041	-0.0016	-0.0003	-0.0012	-0.0004
	(0.0011)	(0.0038)	(0.0011)	(0.0027)	(0.0011)	(0.0025)
Age of Mother	0.0025*	0.0051	0.0025*	0.0023	0.0021	0.0025
	(0.0014)	(0.0042)	(0.0014)	(0.0034)	(0.0014)	(0.0031)
Educated Father	0.0088	-0.0027	0.0088	-0.0185	0.0118	-0.0077
	(0.0166)	(0.0399)	(0.0166)	(0.0313)	(0.0166)	(0.0314)
Educated Mother	0.0401**	-0.0082	0.0401**	0.0173	0.0384**	0.0159
	(0.0158)	(0.0357)	(0.0158)	(0.0314)	(0.0157)	(0.0303)
Other HH Member Sick	-0.0057	0.0255	-0.0057	-0.0124	-0.0082	-0.0138
	(0.0135)	(0.0359)	(0.0135)	(0.0317)	(0.0136)	(0.0298)
Father No Severe Health Shock	0.0045	-0.0999	0.0045	-0.0013	-0.0011	-0.0003
	(0.0195)	(0.0677)	(0.0195)	(0.0451)	(0.0200)	(0.0422)
Mother No Severe Health Shock	-0.0148	-0.0341	-0.0148	-0.0265	-0.0098	-0.0251
	(0.0188)	(0.0497)	(0.0188)	(0.0428)	(0.0183)	(0.0416)
Father Severe Health Shock	-0.0175	-0.3701***	-0.0175	-0.1780**	-0.0158	-0.1800**
	(0.0277)	(0.1108)	(0.0277)	(0.0744)	(0.0272)	(0.0744)
Mother Severe Health Shock	-0.0127	-0.0257	-0.0127	0.0180	-0.0110	0.0222
	(0.0195)	(0.0672)	(0.0195)	(0.0442)	(0.0199)	(0.0416)

****p<0.001, **p<0.05, *p<0.1. The numbers in brackets are robust standard errors.*